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Dual Mode Energy Minimized SCA-Levy Clustering Routing Algorithm for Multi-Hop WSNs

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Abstract
Clustering is crucial in Wireless Sensor Networks (WSNs) for energy-aware routing, splitting networks into clusters, and optimizing routing paths based on factors like energy and distance. Many Clustering Routing Algorithms (CRAs) have emerged over the past decades. Amongst, a combined Sine Cosine Algorithm and Levy mutation (SCA-Levy)-based CRA was superior to others in terms of balanced energy use and increased network lifespan. But it causes Quality-of-Service (QoS) issues such as high delay during intra- and inter-cluster transmission when increasing the network size, or transmission range in multi-hop WSNs. This results in a tradeoff between energy utilization and delay was not effective. Hence, in this article, a Dual Mode energy-minimized SCA-Levy (DMSCA-Levy)-based CRA is proposed for multi-hop WSNs. Initially, the SCA-Levy process is executed during the setup phase to form the WSN clusters and choose the optimal Cluster Head (CH) in each cluster based on the node's remaining energy and distance. Then, during the data transmission phase, a joint inter- and intra-cluster energy reduction approach is proposed to select the multi-hop path for transmitting data from nodes to the Base Station (BS). In this approach, an adaptive duty cycle assignment is applied in intra-cluster communication depending on the distance from the CH to the Cluster Member (CM) nodes, whereas the least energy-utilized path is selected in the inter-cluster transmission, leading to less energy utilization and delay in multi-hop WSNs. Moreover, the simulation results illustrate that the DMSCA-Levy achieves a higher network performance compared to the SCA-Levy and LEACH protocol variants.

Keywords—Multi-hop WSN, Clustering routing algorithm, SCA-Levy, Energy utilization, Intra-cluster, Inter-cluster, Duty cycle assignment

1. INTRODUCTION

Typically, WSNs are composed of small autonomous sense nodes that gather, process, and transmit information in a monitoring region before sending it to a BS. WSN focuses on cluster formation and information dissemination in CRAs to decrease energy dissipation as its main objective [1-2]. These algorithms are classified as distributed [3] and centralized routing [4] algorithms, denoted by the Low Energy Adaptive Clustering Hierarchical (LEACH) protocol and Centralized LEACH (LEACH-C) protocol, respectively. Distributed algorithms need more processing, memory, and energy capabilities from sensor nodes, but centralized algorithms may choose the best CH or route in all cycles. Regarding cluster formation, some researchers choose CHs initially and subsequently form clusters [5], whereas some researchers create clusters before choosing CHs [6-7]. Some researchers have introduced the notions of primary CH, secondary CH, or dual CHs to conserve energy [8]. First, to elect CHs dynamically, a few parameters like clustering uniformity, BS position, remaining energy, distance, etc., are used [9]. Then, to transmit data, two kinds of routing such as single-hop [10] and multi-hop [11] are applied according to the BS position.

In the context of inter-cluster multi-hop communication, the major focus lies in creating the most energy-efficient route between the CHs and BS. Most of the existing algorithms use a few parameters that influence network energy utilization, considering system heterogeneity [12] and non-uniform clustering as crucial perspectives [13]. Nowadays, several researchers have presented different advanced algorithms in WSNs and refined existing algorithm prototypes based on the new metaheuristic optimization algorithms for enhancing the CRA [14].

Among many researchers, Guo et al. [15] developed the CRA by combining the SCA-Levy mutation in WSN. First, the SCA with an upgraded step size was used to elect CHs, whereas levy mutation was applied to improve global exploitation ability and population diversity. Then, a selection method combining remaining energy and intra-cluster distance was presented according to the position relationship between the BS and the monitoring region, guaranteeing less inter-cluster transmission cost. Moreover, the optimal Relay Nodes (RNs) were chosen according to the node's position, and remaining energy of the BS to enhance longevity and prevent long-range communication. In contrast, this algorithm can cause QoS challenges such as high delay during intra- and inter-cluster transmission when increasing the network size, or transmission range because it did not consider the delay as a fitness function.

Therefore, this manuscript proposes the DMSCA-Levy-based CRA for multi-hop WSNs. After selecting the CHs by the SCA-Levy algorithm, a joint inter- and intra-cluster energy reduction approach is developed for multi-hop WSNs, which addresses the QoS challenges in multi-hop data transmission. In this approach, an adaptive duty cycle distribution is adopted to reduce energy usage in intra-cluster transmission depending on the distance between CH and the child nodes. Also, the least energy-utilized path is selected in the inter-cluster transmission. Thus, this DMSCA-Levy algorithm can balance both energy utilization and delay in multi-hop WSNs effectively.

The remaining sections include: Section 2 covers the literature survey. Section 3 describes the DMSCA-Levy and Section 4 evaluates its performance against earlier ones. Section 5 précises the study and suggests future enhancements.

2. LITERATURE SURVEY

There is still potential for development in terms of reducing energy use and prolonging the lifespan, however adopting single or multiple novel, enhanced metaheuristic techniques to handle the CRA in WSN reflects flexibility and efficacy. This section reviews some of the recent CRAs in WSNs.

A Hybrid Artificial Bee Colony and Monarchy Butterfly Optimization Algorithm (HABC-MBOA)-based CRA in WSNs [16] was developed to effectively select CHs. In this algorithm, the conventional worker bee stage of ABC has been substituted by the transmuted butterfly adjustment variable of MBOA. It was made to thwart solutions from prematurely converging to local optima during CH selection. Moreover, it was used to mitigate the risk of CHs becoming overloaded with an excessive number of nodes, which contributed to the enhancement of the network's overall lifespan. But it traps into local optimum and has a slow convergence.

An efficient distributed multi-level clustering algorithm [17] was developed based on the Sugeno-based Fuzzy Logic Controller (FLC) to split the WSN into multi-level clusters. In each cluster, the CHs were chosen to gather data from other nodes and send them to the sink using multi-hop routing. Additionally, an improved squirrel search algorithm was applied to optimize the FLC clustering to decrease the energy dissipation of WSNs. But some malicious nodes may be elected as CHs, which drops packets leading to fewer throughputs. An Improved Emperor Penguin Optimization Algorithm-based Clustering Protocol (IEPOACP) [18] was presented to enhance the network's longevity while ensuring maximum energy stability. The IEPOACP was employed to select the most suitable CHs using a procedure that mimics the clustering behaviour observed in groups of emperor penguins. But the throughput and energy efficiency were not effective.

An Energy-Efficient CH Selection Algorithm Utilizing an Improved Sparrow Search Algorithm and Differential Evolution (EECHS-ISSADE) algorithm [19] was developed. The SSA initially found the direct route between CH and BS. The DE was used to choose CH using the objective value according to the remaining energy, distance to neighbouring nodes, and distance to the BS. Also, by reducing the node's energy dissipation during data transmission, the total packets received by BS were enhanced. But fixed mutation and crossover probability affect the CH selection, resulting in less network throughput and lifetime.

An energy-efficient CRA [20] was developed in WSNs by combining Hybrid Fuzzy with Grey Wolf Optimization (HF-GWO). When selecting a node as a CH, the fuzzy rule set was used to decide the CHs based on the residual energy, node centrality, and region similarity. The GWO identified the finest CH from among all available CHs. But the throughput was degraded by increasing the number of nodes.

A Hybrid Particle Swarm Optimization with Improved LEACH (HPSO-ILEACH) algorithm was presented [24,25] to increase energy efficiency and network stability. Initially, the HPSO was utilized to pick the optimum CHs depending on the distance and the nodes' remaining energy. Then, ILEACH was used to decrease energy dissipation by altering the CHs during the clustering phase. But throughput, network lifespan, and energy consumption were not satisfactory. An energy-efficient bi-objective Moth-Flame Optimization Algorithm (MFA) was presented [22] according to the distance and energy to choose the best CHs in each cluster. But the number of alive nodes and throughput were less.

2.1 Research Gap and Contribution

From the literature, it is seen that even though earlier research focused on different optimization schemes for achieving clustering routing in WSNs, still network performance is not satisfactory regarding throughput, energy use, and lifespan. Also, those studies do not consider delay as an objective function, causing QoS problems for CRA in WSNs. Therefore, this study is motivated to develop a novel algorithm to enhance the inter- and intra-cluster multi-hop transmissions in WSNs.

Generally, during intra-cluster communication, a node having adequate energy to collect and transfer the information to the successive node in the path is selected as CH, while each other node transfers information to the chosen CH node. In this study, energy utilization is reduced by adjusting the nodes' transmission time. As energy utilization is directly proportional to the CM nodes' distance, additional

transmission time is provided to the closer nodes resulting in more packet transmission at uniform remaining energy contrasted with the distant nodes. The period at which the node transfers the data is called an active period and the period at which the node is not transferring the data is called a passive period.
The fraction between the active and passive periods is called the duty cycle. Also, the task of allocating multiple duty cycles to the nodes is called adaptive duty cycling. The active and passive periods are controlled by many Medium Access Control (MAC) protocols, which create a reliable and efficient transmission path among nodes with high energy utilization. So, Time-Division Multiple Access (TDMA) scheduling is utilized for an energy-efficient MAC protocol via considering high energy efficiency, low delay, and high throughput.
In multi-hop WSNs, this TDMA usually finds the minimum length conflict-free slot allocation, where all paths or nodes are activated at least once. In the proposed study, angle-based energy-optimized timeslot assignment is adopted that initially separates the node's coverage region into 24 zones according to the angle. After that, the timeslots are allocated for CMs thus no node needs a waiting period for data transfer and it has an equivalent passive period. Based on these contexts in the proposed algorithm, all CHs transfer information to the successive CH of the path during the inter-cluster transmission, and this task continues until each data packet is delivered to the BS. During inter-cluster transmission, the path that needs minimum energy for transferring information among each available path is selected to balance energy utilization and delay. Accordingly, the energy utilization is decreased while maintaining a minimum delay during the inter- and intra-cluster communication in multi-hop WSNs.

3. PROPOSED METHODOLOGY

This subsection explains the DMSCA-Levy algorithm for multi-hop WSNs, which involves the setup and steady-state (data transmission) phases, as portrayed in Figure 1.

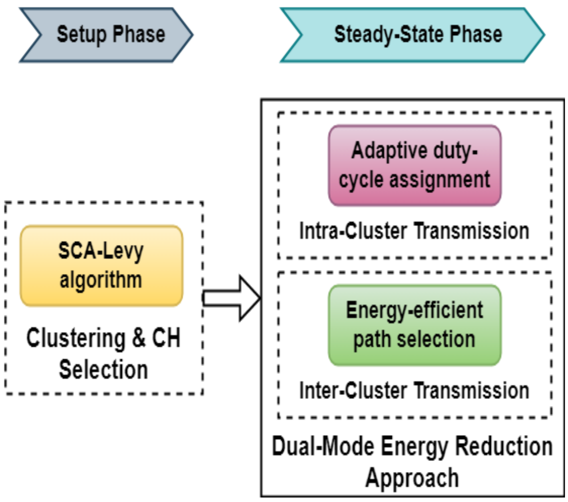


Figure 1. Block Diagram of the Presented Study

In the setup phase, the LEACH with SCA-Levy algorithm as in [15] is applied to choose the CHs in each cluster of the network. In the steady-state phase, a dual-mode energy reduction approach is proposed to decrease the energy in intra-cluster and inter-cluster data transmission modes.

3.1 Network Model

Configure N sensor nodes randomly in the transmission area as shown in Figure 2, wherein all nodes receive an equal amount of the initial energy. The configured nodes are homogeneous with similar functionalities to gather information. The network region is split into multiple clusters. The CM nodes in all clusters transmit information to their CH of the current round. The transmission time allocated to the CMs relies on the protocols utilized for data transmission. Once the information is received, the CH either transmits it to the successive CH or directly forwards it to the BS, depending on the least energy utilization path. In this case, the goals for designing multi-hop WSNs are the following: (i) to find the optimal energy utilization path for data transfer, (ii) to maximize the data delivery to BS, and (iii) to maximize the network lifespan by decreasing the nodes' energy utilization.

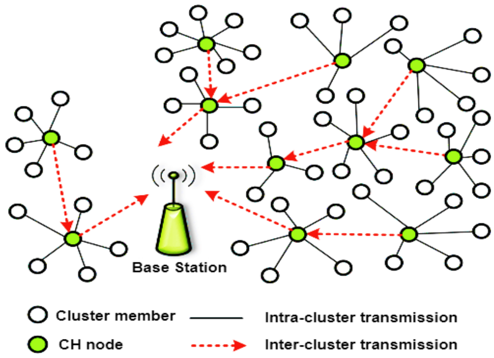


Figure 2. Multi-hop WSN Model

3.2 Energy Utilization Model

A node uses energy either during data transfer or reception. Data is received either from the CMs or other nearest CHs. Also, data is transferred either from the CM to CH, or from CH to the successive CH. Consider P_{CM} is the total amount of packets received by the CH from CM nodes and all packets have b bits. The energy utilized by CH for receiving data (E_{Rec_CM}) is defined by

$$E_{Rec\_CM} = E_{sense} \times P_{CM} \times b \quad (1)$$

In Eq. (1), E_{sense} is the sensing energy required by CH. Consider the amount of packets transferred by the nearby CH is P_{CH}. The energy for receiving P_{CH} (E_{Rec_CH}) is defined as:

$$E_{Rec\_CH} = E_{sense} \times P_{CH} \times b \quad (2)$$

Therefore, the total energy utilization in data delivery $(E_{totalRec\_CH})$ is defined by

$$E_{totalRec\_CH} = E_{Rec_{CM}} + E_{Rec_{CH}} = E_{sense} \times b(P_{CM} + P_{CH}) \quad (3)$$

The energy needed to transfer packets to CH at distance d, $(E_{totaltrans\_CM})$ is defined as [23]:

$$E_{totaltrans\_CM} = \begin{cases} b \times P_{CM}(E_{elec} + \epsilon_{fs} \times d^2), & d < d_0 \\ b \times P_{CM}(E_{elec} + \epsilon_{mp} \times d^4), & d \geq d_0 \end{cases} \quad (4)$$

Where $d_0 = \sqrt{E_{fs}/E_{mp}}$ (5)

In Eq. (4), E_{elec} is to the energy used in the transmitter to process a bit, d_0 is the threshold distance, and $\epsilon_{fs}, \epsilon_{mp}$ are free-space and multi-path amplification coefficients, respectively. Also, the energy utilized to transfer data from CH to the successive CH $(E_{totaltrans\_CH})$ is defined by

$$E_{totaltrans\_CH} = \begin{cases} b \times P_{CH}(E_{elec} + \epsilon_{fs} \times d^2), & d < d_0 \\ b \times P_{CH}(E_{elec} + \epsilon_{mp} \times d^4), & d \geq d_0 \end{cases} \quad (6)$$

So, the total energy utilization for transmitting data packets $(E_{totaltrans\_CH})$ is determined by

$$E_{totaltrans\_CH} = E_{totaltrans\_CM} + E_{totaltrans\_CH} \quad (7)$$

3.3 Setup Phase – Clustering and CH Selection

In this phase, the SCA-Levy algorithm is executed by the BS to choose the optimal CHs. A set of CHs with a minimum communication cost in all rounds is chosen. Other nodes can decide the nearest CH to become their CMs. In every round, the mean remaining energy is computed by the BS. Candidate CH set includes the nodes with a maximum remaining energy. Different steps in the CH selection based on the SCA-Levy algorithm are summarized below.

1. Initialize the number of population m, and maximum iterations T.
2. Calculate the amount of CHs chosen in an initial round (k_{opt}) as:

$$k_{opt} = round(N_{alive} \times p) = round[(N - D_{dead}) \times p] \quad (8)$$

In Eq. (8), N_{alive} and D_{dead} indicate the amount of surviving nodes and dead nodes, respectively, p denotes the CH selection probability, and N indicates an overall amount of nodes.

3. Create a candidate CH set with nodes having a maximum remaining energy.
4. Choose k_{opt} CHs randomly from the candidate CH set for m selections and create an initial population.
5. Update the location to find the best solution as follows:

$$X_i^{t+1} = \begin{cases} X_i^t + r_1 \times \sin(r_2) \times |r_3 P_i^t - X_i^t|, & r_4 < 0.5 \\ X_i^t + r_1 \times \sin(r_2) \times |r_3 P_i^t - X_i^t|, & r_4 \geq 0.5 \end{cases} \quad (9)$$

In Eq. (9), X_i^t is the location in i^{th} dimension of t^{th} iteration, P_i^t indicates the present best individual in i^{th} dimension, r_1 refers to the step size that regulates an exploration phase and $r_1 = a\left(1 - \frac{t}{T}\right)$, where $a = 2$, and

r_2, r_3, r_4 are random parameters, $r_2 \in [0,2\pi], r_3 \in [0,2], r_4 \in [0,1]$. In this SCA, r_1 diminishes linearly to 0 when increasing t, resulting in final iteration update change is simple, therefore solution can be local optimum. So, r_1 is enhanced as:

$$r_1 = a \sin\left(\frac{\pi}{2}\left(1 - \frac{t}{T}\right)\right) + b,\ a = 2, b = 0.5 \tag{10}$$

6. Calculate the fitness function values for each individual as follows:

$$f = \left|\sum_{i=1}^{n} d_{CM-CH}^2(i) - \frac{1}{k_{opt}} \times D\right| + \left|\sum_{i=1}^{m} d_{CM-CH}^2(i) - \frac{1}{k_{opt}} \times D\right| + \cdots + \left|\sum_{i=1}^{q} d_{CM-CH}^2(i) - \frac{1}{k_{opt}} \times D\right| \tag{11}$$

Where $D = \sum_{i=1}^{n} d_{CM-CH}^2(i) + \sum_{i=1}^{m} d_{CM-CH}^2(i) + \cdots + \sum_{i=1}^{q} d_{CM-CH}^2(i)\,, n + m + \cdots + N_{alive} - k_{opt}$ (12)

In Eqns. (11) & (12), d_{CM-CH} is the distance from CM to its corresponding CH. The number of CMs in all clusters is uncertain, which may be n, m, or q, and D is the addition of squares of the distances of nodes in all clusters.

7. Determine the mean fitness function value of each individual. If the individuals whose fitness function value is below the average, then apply Levy mutation as:

$$X_{ij}^{t+1} = X_{ij}^{t} + L(s) \times \left|X_{j^*}^{t} - X_{ij}^{t}\right| \tag{13}$$

In Eq. (13), X_{ij}^{t+1} defines the position after Levy mutation, X_{ij}^{t} indicates the present position, $X_{j^*}^{t}$ is the current best position and $L(s)$ is the Levy distribution. Based on this process, the population diversity is increased and the global search ability is enhanced.

8. Find the group of individuals with the lowest fitness function value;
9. Continue Steps 5 – 8 until T, and the set of individuals with the minimum fitness function value is obtained.

Thus, the best CHs for each cluster are chosen based on the SCA-Levy algorithm in each round.

3.4 Steady-State Phase – Data Transmission

In this phase, the CMs gather data and forward it to the nearest CH. The CHs perform local aggregation and forward the information to BS directly or by the RN. Here, the nodes are allocated with timeslots; so one of the CHs can be active in every round. CMs directly transfer the information to the CH according to the scheduling slots. The RNs can be selected among the surviving nodes in the communication region according to the following steps:

1. Calculate the distance from CHs to BS (d_{CH-BS}), distance from CH to RN (d_{CH-RN}), distance from RN to BS (d_{RN-BS}) and remaining energy of CHs (E_i).
2. $\boldsymbol{if}(d_{CH-BS} > d_0)$
3. $\boldsymbol{for}(i = 1{:}N)$
4. $\boldsymbol{if}(E_{RN} > \min E \,\&\, d_{CH-RN}^2 + d_{RN-BS}^2 < d_{CH-BS}^2 \,\&\, RNflag == 0)$
5. $\boldsymbol{if}\left(d_{CH-RN} < \frac{1}{\sqrt{2}} \times d_{CH-BS} \,\&\, d_{RN-BS} < \frac{1}{\sqrt{2}} \times d_{CH-BS}\right)$
6. $\boldsymbol{if}\left({E_i}/{(d_{CH-RN}^2 + d_{RN-BS}^2)} > RNE\right)$
7. $RNE = {E_i}/{(d_{CH-RN}^2 + d_{RN-BS}^2)}$
8. ***end if***
9. ***end if***
10. ***end if***
11. ***end for***
12. ***end if***

3.4.1 Angle-based Timeslot Allocation for Energy-optimized Timeslot Assignment

Timeslot assignment is the task of allocating active and passive periods for nodes to reduce energy utilization. After electing CHs, the energy-optimized timeslot assignment is adopted that splits the CH's coverage into 24 zones depending on angle and allocates timeslots for CMs therefore no node wants a waiting period for data transfer and it can take an equivalent period at a passive state. This process is controlled by CH, which has the awareness of its CM location and other information. In this process, the CM and CH nodes are exposed to change between two states: active and passive.

- Active state: This state involves three sub-states: gathering state, transfer state, and receive state.
  1. Gathering state (gs): The nodes are turned ON to collect the information.
  2. Transferring state (ts): The CMs transfers the collected information to CH.
  3. Receiving state (rs): The collected information is sent from CH to the sink.
- Passive state (ps): In this state, all nodes are turned OFF, which cannot execute collecting, transmitting, or receiving information.

The CHs do not execute gathering because they can combine the information and send it to the sink. But in any round, when the CH becomes CM, it will gather data. Various states for CM and CH at three equivalent timeslots as T_1, T_2, and T_3 are demonstrated in Figure 3.

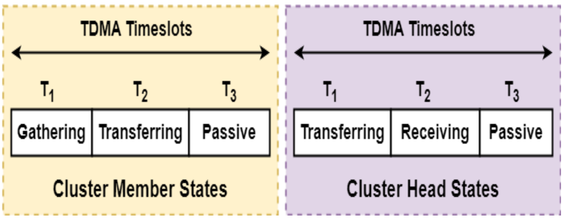


Figure 3. Different States in Energy-optimized Timeslot Assignment

The CH in all clusters allocates timeslots depending on the energy-optimized timeslot assignment. At first, the chosen CH divides its coverage into 24 zones via considering the total coverage as 360°. As a result, the variance can be 15°, i.e., 360°/24 = 15°. Because the nodes are circulated in the network region, each zone consists of many nodes.

Then, the timeslots are assigned to the CMs, and CHs themselves. The 24 divisions by CH and timeslots for 6 divisions are illustrated in Figure 4. Also, the timeslots are allocated to each node within the cluster. At T_1, the CMs at the initial split, i.e., 0°-15° is gs, while the CMs at the 2nd split, i.e., 15°-30° is ps. Then, in T_2, CMs at the initial split, i.e., 0°-15° is ts, when the CMs at the 2nd split, i.e., 15°-30° is gs. Therefore, in T_2, a few CMs are transferring data that is accepted by CH, whose state is rs at T_2. Here, the timeslots are alternatively allocated for the nodes in the transmission region. Thus, CM and CH are exposed to equilibrium the energy utilization, guaranteeing a high network lifespan and less delay since this scheduling has equal timeslots for active and passive states.

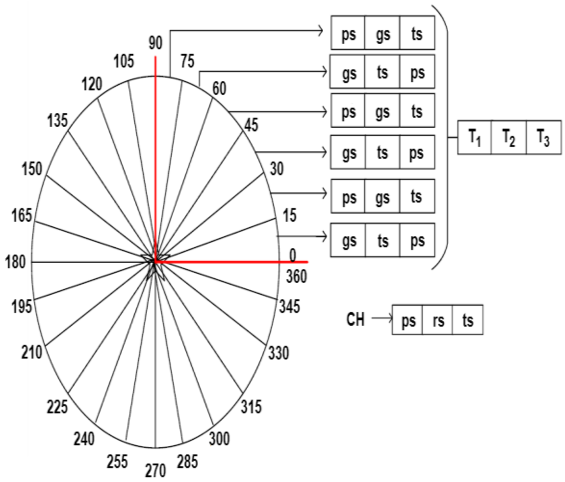


Figure 4. Energy-optimized Timeslot Assignment

Thus, according to the scheduled slots, one of the CHs can be active in every interval, whereas they have a passive period to reduce energy utilization and prolong the lifespan. Also, it maximizes the amount of alive nodes because each CM is allocated with a passive state. This procedure has equivalent timeslots for both active and passive states to guarantee a high network lifespan.

3.4.2 Dual-Mode Energy Reduction Algorithm

A joint energy reduction approach reduces the energy in both intra and inter-cluster modes. In the intra-cluster, an adaptive duty cycle is allocated to CMs to reduce energy utilization. The assignment of the duty cycle depends on the distance between the CM node and CH. In inter-cluster, the least energy utilization multi-hop path is selected for transferring data.

A. Adaptive Duty-Cycle Assignment for Energy Reduction in Intra-Cluster Transmission

During intra-cluster transmission mode, one of the nodes is chosen as CH and other nodes become CMs. All CM nodes allocate different duty cycles according to the distance from the CH. Assume $\mathcal{N}_C$ nodes exist in a cluster and the duty cycle allocation is defined by

$$DutyCycle_{CH,CM} = \frac{exp\left(\frac{-d_{CH,CM}}{d_0}\right)}{\sum_{i=1}^{\mathcal{N}_C-1} exp\left(\frac{-d_{CH,i}}{d_0}\right)} \quad (14)$$

In Eq. (14), $d_{CH,CM}$ refers to the distance between the CM and CH. Based on this task, the CMs closer to the CH can obtain the maximum share of the duty cycle. Also, the CM of the larger size cluster, which is closer to the CH at an equal distance allocates more duty cycle. The duty cycle allocation process is controlled by d_0. When d_0 increases, the assignment of the duty cycle to CMs becomes uniform. By aligning duty-cycling patterns within each zone in the timeslot assignment, nodes can save energy both during active and passive states (i.e., nodes within a zone can follow a duty-cycling pattern where they alternate between active and passive states based on their specific zone's timeslot schedule). For example, a node in a zone might be active only during its scheduled timeslot and then transition to the passive state during other times.

On the other hand, when a node contains a huge quantity of information for communication during its scheduled timeslot, it may temporarily increase its duty cycle to ensure efficient data transfer based on their distances from the CHs. Nodes nearer to the CH forward more frequently during their active periods, guaranteeing effective data transfer. Nodes farther away from the CH forward less frequently yet still adhere to their timeslot schedules to sustain network connectivity.

B. Energy-Efficient Path Selection for Energy Reduction in Inter-Cluster Transmission

During the inter-cluster transmission, energy utilization is reduced by transferring information via the least energy-utilized path. For inter-cluster transmission, CH determines the energy required to transmit packets through multiple paths. Among such paths, the path that requires a minimum energy for data transmission is selected. Therefore, the energy utilization is reduced by choosing the minimum energy utilization path during inter-cluster transmission.

An entire procedure of the DMSCA-Levy algorithm is given in Algorithm 1, which comprises four stages: WSN clustering, CH selection, intra-cluster, and inter-cluster transmission. Step 1 is for building the WSN using the parameters listed in Table 1. Steps 2 to 4 are for cluster formation using the LEACH protocol. Step 5 is for considering all the clusters in WSNs. Step 6 is used to initialize the amount of packets received by the CH. The CH and RNs are selected using the SCA-Levy mutation strategy in Steps 7 to 9. Steps 10 and 11 are for considering the CMs of the cluster. In Steps 12 and 13, duty cycle allocation to the CM using Eq. (8) and the calculation of the amount of packets transferred to the CH are provided. Step 14 can minimize the amount of energy needed for data transfer and reception in CMs and CHs. Additionally, it calculates the total amount of packets received by the CMs. Steps 15 and 16 terminate the process. Step 17 adds the packets created by CH with the packets received from the CMs. In Step 18, the energy utilization is initialized for inter-cluster transmission. Steps 19 to 24 are used to find the lowest energy utilization path. In Step 25, the data transmission between the CHs and BS is provided. Steps 26 to 28 are used for calculating the remaining energy of CHs after data transmission and reception. Step 29 is the termination loop of Step 5.

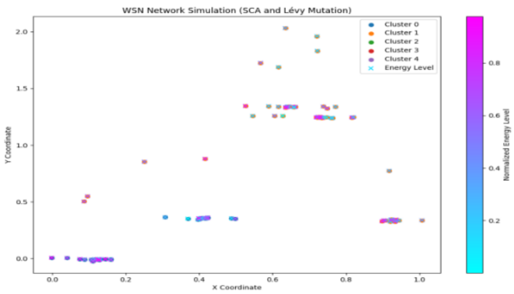
Algorithm 1: DMSCA-Levy-based Clustering Routing in Multi-hop WSNs

Input: N nodes, C clusters
Output: Lowest energy-utilized intra-cluster and inter-cluster routing path

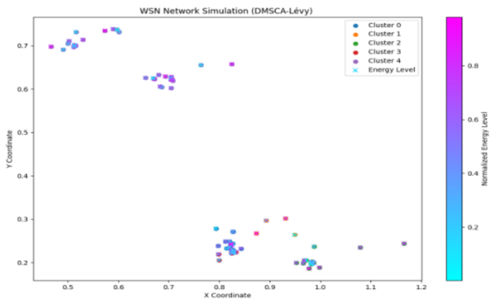
1. **Begin**
//WSN clustering
2. $\boldsymbol{for}(n = 1{:}\,N)$
3. Split the nodes in C clusters based on the LEACH protocol;
4. $\boldsymbol{end\ for}$
//CH selection
5. $\boldsymbol{for}(i = 1{:}\,C)$
6. $P_{Rec\_CH_i} \leftarrow \emptyset$; //Packets received by the CH
7. Choose CH_i using the SCA-Levy mutation;
8. Calculate d_{CH-BS} and remaining energy of CHs;
9. Select the RNs;
//intra-cluster transmission
10. $\boldsymbol{for}(m = 1{:}\,CM_i)$
11. $\boldsymbol{if}(m \neq CH_i)$
12. Allocate timeslots using the angle-based energy-optimized timeslot assignment;
13. Calculate duty cycle allocation, i.e., $DutyCycle_m$ using Eq. (8) to dynamically adjust the timeslot schedules in each zone;
14. Calculate the number of packets transferred P_{trans_m} at a scheduled timeslot;
15. $P_{Rec\_CH_i} \leftarrow P_{Rec\_CH_i} + P_{trans\_m}$;
$E_m^{remain} \leftarrow E_m^{remain} - E_{trans\_m}$;
$E_{CH_i}^{remain} \leftarrow E_{CH_i}^{remain} - E_{Rec\_CH_i}$;
16. $\boldsymbol{end\ if}$

$\boldsymbol{end\ for}$
$P_{Rec\_CH_i} \leftarrow P_{Rec\_CH_i} + P_{trans\_CH}$; //Add CH's packets to the total amount of packets //inter-cluster transmission
$E_{min} \leftarrow \infty$; //Lowest energy for transmission
$\boldsymbol{for}(k = 1{:}K)$ //K is the number of shortest paths between the CH and BS
Determine the energy usage of path, i.e., E_k to transfer $P_{Rec\_CH_i}$ packets;
$\boldsymbol{if}(E_k < E_{min})$
$E_{min} \leftarrow E_k$; $E^r_{min} \leftarrow k$;
$\boldsymbol{end\ if}$
$\boldsymbol{end\ for}$
Transfer packets to BS using the lowest energy-utilized path, i.e., E^r_{min};
$\boldsymbol{for}(\forall CH \in CH^r_{min})$
$E^{remain}_{CH_i} \leftarrow E^{remain}_{CH_i} - E_{Rec\_CH_i}$;
$E^{remain}_{CH_i} \leftarrow E^{remain}_{CH_i} - E_{trans\_CH_i}$;
$\boldsymbol{end\ for}$
$\boldsymbol{end\ for}$

Figure 5 presents a graphical representation of WSN clustering using the DMSCA-Levy and SCA-Levy algorithms executed for 1000 rounds. It is noticed that the energy utilization level of each node in the network is decreased for DMSCA-Levy compared to the SCA-Levy algorithm in multi-hop WSNs.



(a)



(b)

Figure 5. Schematic Diagram of Clustering for 1000 Rounds. (a) SCA-Levy Algorithm and (b) Proposed DMSCA-Levy Algorithm

4. SIMULATION RESULTS

This subsection provides the performance of the DMSCA-Levy and compares it with the existing algorithms such as SCA-Levy [15], EECHS-ISSADE [19], HF-GWO [20], and HPSO-ILEACH [21] in multi-hop WSNs. Python 3.7 software is used for the simulation analysis. Table 1 presents the parameters and their values utilized for simulating both existing and proposed algorithms, to measure the performance.

Table 1. Simulation Parameters

Parameters	Value
Simulation region	1000×1000 m^2
No. of sensor nodes	100
No. of clusters	5
BS position	(50,100)

Network topology	Flat grid
Antenna	Omni antenna
Channel	Wireless
Propagation category	Two ray ground
MAC layer	IEEE802.11
MAC protocol	TDMA
Packet size	500 bytes
Traffic source	Constant Bit Rate (CBR)
Initial energy	2 J
E_{elec}	50 nJ/bit
ϵ_{fs}	10 pJ/bit/m^2
ϵ_{mp}	0.0013 pJ/bit/m^4
Energy used in data aggregation	5 nJ/bit
No. of rounds	1000
Transmission range	50 m
Simulation time	150 sec

4.1 Throughput

It is the rate at which data is successfully transferred from the nodes to a sink over a specific period.

$$Throughput = \frac{No.of\ packets\ successfully\ delivered\ to\ the\ sink}{Time\ taken\ for\ delivery} \quad (15)$$

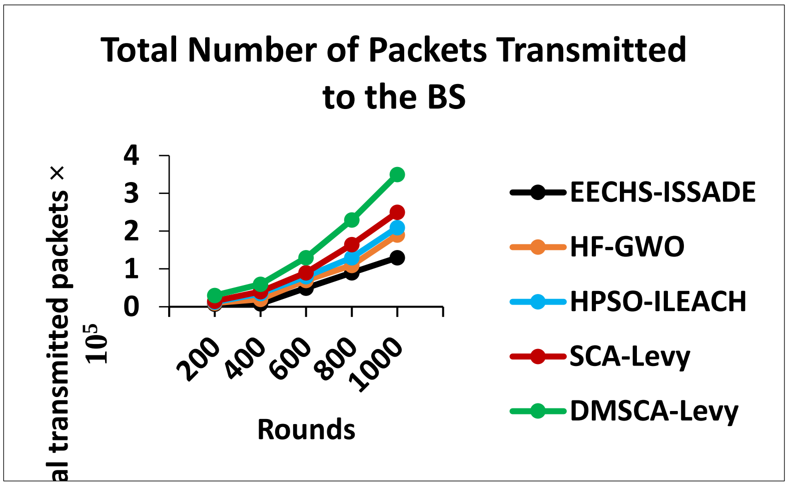


Figure 6. Total Transmitted Packets vs. Rounds

A comparison of throughput for different CRAs is plotted in Figure 6. It is observed that the DMSCA-Levy algorithm is the best, i.e., a maximum amount of data packets is transmitted to the BS, compared to the other algorithms in multi-hop WSNs. This is achieved because the DMSCA-Levy algorithm exploits a dual-mode energy-minimized data transmission according to the adaptive balanced timeslot scheduling (such as duty cycle assignment) and energy-efficient path selection for intra and inter-cluster transmission. This reduces the transmission cost and energy utilization in all rounds. With a higher network lifetime, a higher amount of data packets transfers to the BS. Thus, the total quantity of packets transferred to the BS using the DMSCA-Levy algorithm for 1000 rounds is 3.5×10^5, whereas the total transmitted packets of EECHS-ISSADE, HF-GWO, HPSO-ILEACH, and SCA-Levy algorithms are 1.3×10^5, 1.9×10^5, 2.1×10^5, and 2.5×10^5, respectively.

4.2 Energy Utilization

It defines the total energy that all nodes consume while transferring information to the sink.

$$Energy\ utilization = (E_{Tx} + E_{Rx} + E_{Idle}) \times No.of\ packets\ transmitted \quad (16)$$

In Eq. (16), E_{Tx} is the energy taken by the node when it transfers a packet, E_{Rx} is the energy taken when the node receives the packet, and E_{Idle} is the energy consumed when the node is in a passive state.

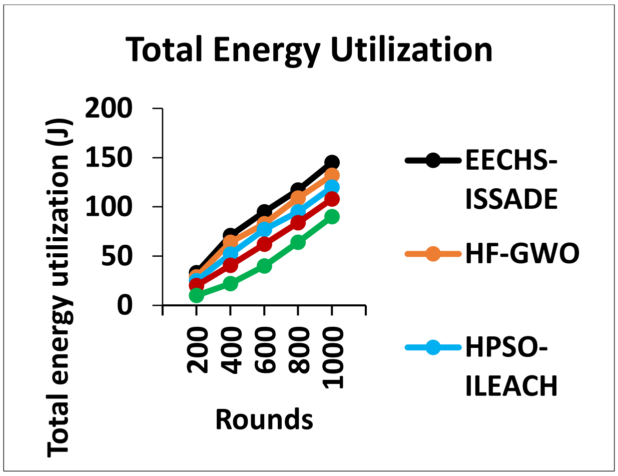


Figure 7. Energy Utilization vs. Rounds

The total energy use results of various CRAs for different rounds are compared in Figure 7. If the initial energy of all algorithms is equal, then it can be observed that the DMSCA-Levy uses the minimum energy per round, compared to the other algorithms. This results in the DMSCA-Levy algorithm executing more rounds, in contrast with others; thus it balances the energy utilization of every round. As a result, the energy utilization of DMSCA-Levy for 1000 rounds is decreased by 37.93%, 31.82%, 25%, and 16.67% contrasted with the EECHS-ISSADE, HF-GWO, HPSO-ILEACH, and SCA-Levy algorithms, respectively.

4.3 Network Lifetime

It is the duration for which the network can continue to operate effectively before the first node in the network depletes its energy resources.

$$Network\ lifetime = \frac{Total\ energy\ available\ in\ the\ network}{Mean\ energy\ consumption\ per\ unit\ of\ period} \qquad (17)$$

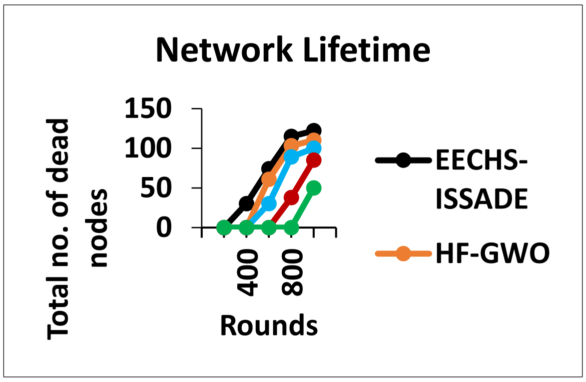


Figure 8. Total Dead Nodes vs. Rounds

A comparison of total dead nodes for different CRAs under different rounds is shown in Figure 8. It is observed that the DMSCA-Levy reduces the total dead nodes compared to the other algorithms running for 1000 rounds. By implementing energy-optimized timeslot assignment and adaptive duty cycle assignment strategies, the initial dead node of the DMSCA-Levy acts the best because the initial dead node performs after 800 rounds, whereas nodes in other algorithms die early before 800 rounds. The total number of dead nodes of the DMSCA-Levy algorithm for 1000 rounds is reduced by 59.02%, 54.55%, 50%, and 41.18% compared to the EECHS-ISSADE, HF-GWO, HPSO-ILEACH, and SCA-Levy, respectively. This indicates that the DMSCA-Levy attains the maximum network lifespan, leading to high throughput and energy efficiency.

4.4 Delay

It is the time taken for forwarding information between source and target nodes.

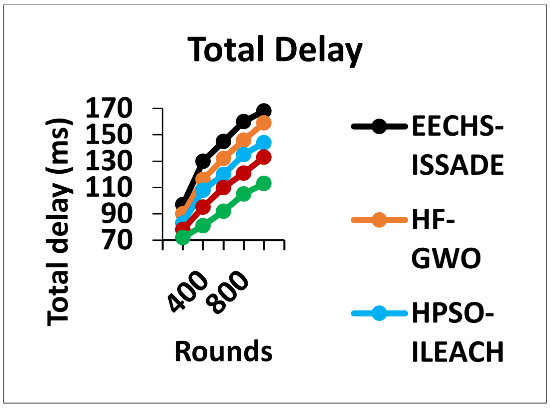


Figure 9. Total delay vs. Rounds

A comparison of total delay for different CRAs executing in multiple rounds is plotted in Figure 9. It is analyzed that the DMSCA-Levy minimizes the total delay compared to the other algorithms due to the adaptive duty cycle assignment for intra-cluster communication and the lowest energy-utilized path selection for inter-cluster communication. This means that the DMSCA-Levy can effectively balance the energy utilization and delay for multi-hop WSNs. Thus, the total delay of the DMSCA-Levy algorithm for 1000 rounds is reduced by 32.74%, 28.93%, 21.53%, and 15.04% compared to the EECHS-ISSADE, HF-GWO, HPSO-ILEACH, and SCA-Levy, respectively.

5. CONCLUSION

This study presented the DMSCA-Levy-based CRA for reducing energy utilization and delay in multi-hop WSNs. This algorithm involved the SCA-Levy for WSN clustering and the dual-mode energy reduction approach for data transmission. For the intra-cluster transmission, the duty cycles were allocated for each CM based on their distance to the CHs for data transmission with the minimum energy. For the inter-cluster transmission, the path with the lowest energy utilization was chosen for data transmission between the CHs and BS. By using this DMSCA-Levy algorithm, the tradeoff between energy utilization and delay in multi-hop transmission was controlled efficiently. At last, the simulation results proved that the DMSCA-Levy algorithm running for 1000 rounds has a high throughput (3.5×10^5 number of packets transmitted to the BS), less energy utilization (90J), high network lifespan (50 dead nodes), and lower delay (113ms) in contrast with the existing algorithms.

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