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RESEARCH ARTICLE

An Intelligent Relay Selection with Optimized Cluster Based Routing Algorithm for Multi-Hop Wireless Sensor Networks

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Abstract – Clustering plays a vital role in Wireless Sensor Networks (WSNs) as it enables energy-efficient data collection and transmission. As a result, several Clustering Routing Algorithms (CRAs) were suggested over the years. Amongst, the Sine Cosine Algorithm with Levy Mutation (SCA-Levy)-based CRA achieved a good balance between energy usage and delay in multi-hop WSNs. This algorithm dynamically chose the best Cluster Head (CH) nodes according to the Residual Energy (RE) and intra-cluster distance. In addition, the optimal Relay Nodes (RNs) were decided based on the distance from CHs to the Base Station (BS) and the RE of CHs to circumvent long-range transmission. However, the RN selection process must satisfy constraints on the coverage space, number of nodes and BS position. As the coverage space or the number of nodes increases, the network lifespan decreases. To satisfy these constraints on the RN selection process in multi-hop WSNs, this article proposes a new Relay selection with an optimized SCA-Levy (RSCA-Levy) algorithm. First, the network is clustered, and CH nodes for all clusters are selected by the SCA-Levy scheme. After that, the RN selection challenge is represented as a Markov Decision Process (MDP) and resolved using the Deep Q-Learning (DQL) algorithm. This DQL employs a decentralized scheme with a rectified update function. Using this algorithm, all clusters train their Q-table and elect optimal RNs based on factors like RE, node density, distance to the BS, and coverage space. Furthermore, it transfers data from the Source (S) to the BS via optimal CHs and RNs. The simulation results demonstrate that the RSCA-Levy algorithm achieves 3.76×10^5 packets transferred to the BS, 59J total relaying energy, 5.4% network energy utilization, 35 dead nodes, and 98ms End-to-End (E2E) delay in 1000 rounds with 100 nodes, compared to the existing algorithms such as SCA-Levy, Shortest Path Selection for RN (SPSRN), Enhanced Energy Proficient Clustering (EEPC), Analytic Hierarchy Process (AHP) with Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and Matching Learning-based Relay Selection (MLRS).

Index Terms – WSN, Clustering, SCA-Levy, Relay Selection, Multi-Hop, Markov Decision Process, DQL, Q-Table.

1. INTRODUCTION

Wireless Sensor Networks (WSNs) are an ad hoc network of several sensor nodes, which are small autonomous devices that can cooperate autonomously to gather and send information to the BS or sink node by monitoring a specified area during several events (for example, sound or uniform relocation or monitoring environmental conditions). These nodes have no inherent fixed locations. They can randomly position themselves within a region to transfer data using either a one-hop or multi-hop strategy. These networks include numerous features that have facilitated their rapid progression in various domains like smart farming, weather forecasting, remote healthcare, defense, etc. Notable features include effortless implementation, low expenses for setup, long-range dissemination abilities, and self-configuration ability. However, energy constraints are a major concern in these networks [1]. Each node needs energy to operate, and the dense deployment of nodes makes it difficult to quickly restore the energy of each node. Hence, reducing energy utilization and prolonging the network's lifespan are key challenges in these networks.

To tackle these challenges, WSNs utilize CRAs that include cluster formation and data transmission, which are closely related to energy usage. Given this fact, CRAs have emerged as a significant research area within WSNs, which involves two major stages: (i) CH selection and (ii) data transfer. During CH selection, CRAs hierarchically organize WSNs into several clusters. A head node known as CH is responsible for each cluster, which is decided based on different factors,

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like clustering consistency, BS site, RE, distance, etc. During data transfer, the member nodes of a cluster transfer their information directly to the respective CH or use the multi-hop policy. CH aggregates the received information and sends it directly to the BS or other CHs [2]. Typically, CRAs fall into two groups: distributed (e.g., Low Energy Adaptive Clustering Hierarchical (LEACH)) and centralized (e.g., Centralized LEACH (LEACH-C)) [3]. Centralized CRAs may determine the best CH or path in all rounds, while distributed algorithms require greater computing power, memory, and energy from sensor nodes. In the past centuries, several CRAs have been developed, including different variants of LEACH. Some CRAs create clusters before CH selection, while others follow the reverse process. Also, they used either single-hop or multi-hop routing, depending on the BS site [4]. In the situation of inter-cluster multi-hop transfer, the main goal is to form an energy-efficient route from CHs to BS [5-8]. For this purpose, most current CRAs use factors that affect network energy use [6–8] from the viewpoint of network heterogeneity and non-uniform clustering.

Recently, advanced CRAs have been designed using different metaheuristic algorithms [9-10], such as simulated annealing, genetic algorithm, SCA, etc. However, these algorithms have a few limitations on population diversity and global searchability. Guo et al. [11] developed the CRA to address this issue, combining the SCA and Levy mutation to enhance population diversity and global exploration for optimal CH selection.

Electing CHs was the first stage in using the SCA with an increased step size; improving global exploitation ability and population variety were the goals of levy mutation. Afterward, CH selection was performed by considering the RE and the BS site to minimize the inter-cluster transmission cost. Also, the best RNs were chosen based on the distance from CHs to BS and the RE of CHs, thereby increasing longevity and preventing long-range communication.

1.1. Problem Statement & Objective

In WSNs, selecting the appropriate RNs is essential to conserve more energy and extend network lifespan significantly. However, factors like the coverage space, the number of nodes, and the position of the BS constrain the RN selection process in the SCA-Levy algorithm. As the coverage space or the number of nodes increases, the network energy utilization also increases, leading to a rapid reduction in network lifespan. So, a key goal of this article is to satisfy these constraints while selecting the optimal RNs, ensuring high energy efficiency and network longevity.

1.2. Contributions

This manuscript proposes the RSCA-Levy algorithm for clustering and data transmission in WSNs. The main contributions of this algorithm include:

- Initially, it applies the SCA-Levy algorithm for network clustering and CH selection.
- After CH selection, it initiates the RN selection, which is represented as the MDP and resolved by the DQL procedure. Every cluster utilizes this algorithm to update its Q-table and explores the optimal RN based on various factors, including the inter-cluster Channel State Information (CSI) of each hop, node density, RE, distance to the BS, and coverage space.
- Furthermore, the inter- and intra-cluster communication is performed using the energy-efficient paths that cover the selected CHs and RNs.
- Finally, extensive simulations show that RSCA-Levy achieves maximum network lifetime and energy efficiency by satisfying constraints such as coverage space, number of nodes, and BS position.

The following article is prepared as follows: Section 2 provides a survey. Section 3 explains the RSCA-Levy, and Section 4 assesses the simulation outcomes. Section 5 précises the study and suggests possible future advances.

2. LITERATURE SURVEY

This section presents studies on CH and RN selection in wireless networks, organized by publication year. Zhang et al. [12] developed a technique for selecting a CH with a Mobile Sink (MS) and selecting a relay with a Multi-User Multi-Armed Bandit (MU-MAB). The WSN was initially clustered using the K-means algorithm. The CH selection mechanism was devised with MS to optimize and balance energy consumption within the cluster. Then, a Virtual Head (VH) was created for MS to gather data. The MU-MAB was implemented to solve the RN selection permutation problem efficiently. Moreover, stable matching theory and the marginal utility principle were used to assign optimal one-to-one combinations for improved energy efficiency. However, it solely focused on energy utilization for RN selection, neglecting other constraints on distance, node density, etc.

Shukla & Tripathi [13] deployed the nodes in the hierarchical cluster structure. Then, they adopted the Effective RN Selection (ERNS) technique to determine the suitable RNs for all clusters by considering node density and minimum distance, as well as the consecutive RN based on the transmission range as a threshold distance. They also integrated the ERNS technique into the Minimum Energy-Consumption Chain-Based routing Protocol (ME-CBCCP) for data transmission. However, the total energy depletion remained high. Also, they observed that the number of RNs moderately increased when increasing the coverage space and the number of nodes. Xie et al. [14] proposed a new technique for RN localization and energy-efficient routing in heterogeneous WSNs. They formulated the RN node localization problem as a non-deterministic polynomial hard problem, taking into account the presence of unreachable regions in the network. Then, they used adaptive whale optimization to regulate the cost of RNs and reduce energy consumption. However, they did not evaluate energy usage and longevity.

Rathore et al. [15] proposed the SPSRN method to decrease energy consumption in WSNs. The goal of CH selection was to minimize energy usage and enhance network lifespan using the SPSRN concept. To maintain normal energy depletion, the chosen trajectory cluster was initiated. The SPSRN approach ensured that data from each node was transmitted to the nearest nodes in the shortest path. However, as the network size increased and multiple RNs were present, the network lifespan deteriorated, rendering the method unsuitable.

Guleria et al. [16] developed the EEPC scheme for selecting RNs in heterogeneous WSNs. The network consisted of static and mobile nodes. Static nodes transmitted data and mobile nodes selected a CH from the static nodes based on their placement and energy level. Mobile nodes then transferred information to the CH. RNs were discovered using the EEPC scheme based on their velocity and position. The selected intermediate RNs transferred the collected data to the BS using the sensor information fusion scheme. However, it solely chose the RNs based on their velocity and position, neglecting the coverage and energy constraints.

Bilandi et al. [17] proposed a fusion technique incorporating the AHP and TOPSIS for selecting RNs in wireless networks. They considered factors such as remaining power, node count, location, Signal-to-Noise Ratio (SNR), distance, and node criticality. They ranked the nodes, and the top-ranked node was elected as the RN. However, the RE was low, and they did not consider the coverage space constraints of the RN selection. Wang et al. [18] presented the MLRS scheme for WSNs using the Upper Confidence Bound (UCB) and similarity concept to decrease power usage. It enabled optimal RN selection by merging knowledge-based identical choice indexes and similarity-based disagreement decisions. However, having more RNs can lead to similarity disagreements in UCB, which can reduce the network's performance.

Wan & Chen [19] developed the RN selection scheme for energy collection WSNs. They analyzed the energy consumption and solar energy state of sensor nodes in a solar WSN. They adjusted the cooperation probability with the interruption probability threshold and managed the RNs participating in cooperative transmission to conserve energy. They used a multi-criteria RN selection method based on solar energy status, network energy balance, SNR ratio, and outage probability of RN. However, the efficiency of balancing energy utilization at nodes was low. Zhou & Tang [20] suggested the RN selection for wireless networks that prioritize long lifespan and high reliability. They periodically chose a node with a strong channel condition as the RN at constant intervals, taking into account computation errors and power consumption. This can prevent excessive energy utilization at the RN. However, this method only accounted for a single RN, potentially affecting network performance in scenarios with multiple RNs. Loukil [21] introduced an energy-saving multi-relay scheme for WSNs to reduce energy usage in clustered WSNs. It involved clusters where sensors cooperatively transmitted data to the CH according to the Bit Error Probability (BEP). The best RN was chosen according to the least transmission energy in the source-target and RN-target connections when maintaining the BEP. However, this scheme did not take into account the impact of node location and RE on the selection of optimal RNs. Table 1 summarizes the above-studied CRAs in terms of their merits, and demerits.

Table 1 Comparison of Earlier CRAs in WSNs

Ref. No.	Algorithms	Merits	Demerits
[12]	MU-MAB	It achieved high energy efficiency and network lifetime.	It solely focused on energy utilization for RN selection.
[13]	ERNS and ME-CBCCP	It achieved uniform energy utilization across each cluster.	The total energy depletion remained high. Also, they observed that the number of RNs moderately increased when increasing the coverage space and the number of nodes.
[14]	Adaptive whale optimization	It reduced RN cost significantly under situations, where the RN was not located in an unreachable area.	While their goal was to decrease energy consumption and prolong the network's lifespan, they did not evaluate energy usage and longevity.
[15]	SPSRN	It achieved a minimum E2E delay and a maximum throughput.	As the network size increased and multiple RNs were present, the network lifespan deteriorated, rendering the method unsuitable.

[16]	EEPC algorithm	It increased the network lifespan and reduced energy utilization.	It solely chose the RNs based on their velocity and position, neglecting the coverage and energy constraints.
[17]	AHP-TOPSIS	It achieved a higher network lifespan and throughput.	The RE was low, and they did not consider the coverage space constraints of the RN selection.
[18]	MLRS	It efficiently reduced mean energy utilization.	The optimal RN selection probability remained low. Also, having more RNs can lead to similarity conflicts in UCB, which can reduce the network's performance.
[19]	Multi-criteria RN selection method	It efficiently chosen RNs with better channel and energy states.	The efficiency of balancing energy utilization at nodes was low.
[20]	RN selection algorithm based on channel condition	It effectively extended the network longevity.	It only focused on a single RN, potentially affecting network performance in scenarios with multiple RNs.
[21]	Energy-saving multi-relay scheme	It achieved significant energy efficiency and network lifespan.	It did not take into account the impact of node location and RE on the selection of optimal RNs.

This literature highlights the significance of choosing the best RNs for WSNs to extend their lifespan, taking into account various factors such as the distance between nodes and the BS and the energy consumption of nodes. However, the RN selection process still faces challenges due to constraints like limited network coverage, a fixed number of deployed nodes, and the specific position of the BS. Simply increasing the coverage space or node count without proper energy management can lead to decreased network lifespan due to higher energy usage for communication and increased overhead. To tackle these challenges, this paper introduces the RSCA-Levy algorithm, which takes into account constraints related to node count, coverage space, and BS location during the RN selection process. By optimizing RN placement within these constraints, the RSCA-Levy algorithm aims to enhance the network's energy efficiency, balance energy distribution, and reduce the risk of premature node failure, thereby extending the network's lifespan.

3. PROPOSED METHODOLOGY

This section describes the RSCA-Levy algorithm in detail. Figure 1 portrays an outline of this work. In the setup stage, LEACH with SCA-Levy selects CHs in each cluster. DQL-based RN selection chooses optimal RNs in multi-hop WSNs. In the steady-state phase, an energy-efficient inter- and intra-cluster transmission is performed.

3.1. Network Model

This study examines a multi-hop network model, which consists of S, a destination (D) node, i.e., BS, and N clusters of nodes represented by $C_1, \dots, C_N$. Each cluster (C_n) contains k_n decode-and-forward RNs denoted as $R_1^n, R_2^n, \dots, R_{k_n}^n, n = 1, \dots, N$. For simplicity, assume that C_0 represents S and C_{N+1} represents D, with K_0 and K_{N+1} both equal to 1. Neither the RNs nor S have direct communication with D, except for the nodes in C_N. The data transferred by S is relayed to D through a route that includes N RNs chosen from C_n. The multi-hop communication begins with S transmitting its information to C_1. Certain participant of C_1 is chosen to get the information and then forwards it to C_2. This process continues until the information is transmitted by D.

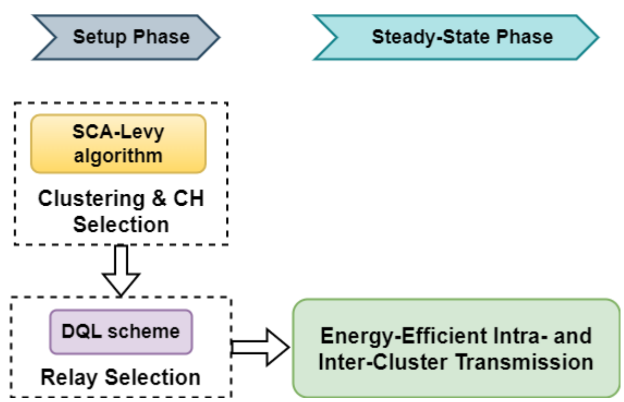

Figure 1 Outline of this Work

3.2. Channel Model

The network's wireless channels undergo Rayleigh fading and the noise at all receivers is a complex Gaussian random parameter with 0 average and σ^2 difference. The inter-cluster complex channel factors from $R_{k'}^{n-1}$ to R_k^n are represented by $h_{k'k}^n$. If $n = N + 1$, then $h_{k'k}^{N+1} = h_{k'D}^{M+1}$. Consider the

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transferring power of $R_{k'}^{n-1}$ is P_{n-1}, obtained SNR of R_k^n is defined by equation (1).

$$\Gamma_{k'k}^n = \frac{P_{n-1}\left|h_{k'k}^n\right|^2}{\sigma^2}, n = 1, \dots, N+1 \quad (1)$$

E2E SNR and E2E rate of the multi-hop transmission are defined by equations (2) and (3), respectively.

$$\Gamma_E = \min_n \Gamma_{k'k}^n, n = 1, \dots, N+1 \quad (2)$$

$$R_{E2E} = \frac{1}{N+1}\log(1 + \Gamma_E) \quad (3)$$

3.3. Energy Model

A node spends energy either while transmitting or getting information. Information is obtained either from the Cluster Member nodes (CM) or from other neighboring CHs. Information is transmitted either between CMs and CHs or CHs and CHs. Let P_{CM} denote the overall quantity of packets delivered to the CH from CMs, with every packet including b bits. The energy consumed by CH for packet reception $\left(E_{Rec_{CM}}\right)$ is specified in equation (4).

$$E_{Rec_{CM}} = E_{sense} \times P_{CM} \times b \quad (4)$$

In equation (4), E_{sense} represents the energy utilized by CH during data sensing. Let P_{CH} represent the quantity of packets sent by the neighboring CH. The energy utilized to receive P_{CH} $\left(E_{Rec_{CH}}\right)$ is specified in equation (5).

$$E_{Rec_{CH}} = E_{sense} \times P_{CH} \times b \quad (5)$$

So, a sum of energy utilized in data reception $\left(E_{totalRec_{CH}}\right)$ is determined as equation (6).

$$E_{totalRec_{CH}} = E_{Rec_{CM}} + E_{Rec_{CH}} = E_{sense} \times b(P_{CM} + P_{CH}) \quad (6)$$

The energy utilized for sending packets to CH at distance d, $\left(E_{totaltrans_{CM}}\right)$ is specified in equations (7) and (8).

$$E_{totaltrans_{CM}} = \begin{cases} b \times P_{CM}\left(E_{elec} + \epsilon_{fs} \times d^2\right), & d < d_0 \\ b \times P_{CM}\left(E_{elec} + \epsilon_{mp} \times d^4\right), & d \geq d_0 \end{cases} \quad (7)$$

$$\text{Where } d_0 = \sqrt{\epsilon_{fs}/\epsilon_{mp}} = 87.71 \quad (8)$$

In equations (7) and (8), E_{elec} indicates the energy utilized in the transmitter, d_0 represents the threshold distance, and $\epsilon_{fs}, \epsilon_{mp}$ define free-space and multi-path amplification constants, respectively. The energy spent for sending packets between CHs $\left(E_{totaltrans_{CH}}\right)$ is specified in equation (9).

$$E_{totaltrans_{CH}} = \begin{cases} b \times P_{CH}\left(E_{elec} + \epsilon_{fs} \times d^2\right), & d < d_0 \\ b \times P_{CH}\left(E_{elec} + \epsilon_{mp} \times d^4\right), & d \geq d_0 \end{cases} \quad (9)$$

As a result, a sum of energy spent for data transfer $\left(E_{totaltrans_{CH}}\right)$ is calculated in equation (10).

$$E_{totaltrans_{CH}} = E_{totaltrans_{CM}} + E_{totaltrans_{CH}} \quad (10)$$

3.4. Optimal CH Selection Using SCA-Levy Algorithm

The BS uses the SCA-Levy algorithm [11] in the CH selection process to choose optimal CHs with minimal communication cost. This SCA-Levy algorithm involves several steps. First, the population size and maximum iterations are initialized. Then, the number of CHs is calculated based on the surviving and dead nodes. A candidate set of nodes with the maximum RE is formed. A subset of CHs is randomly chosen, and their locations are updated iteratively using SCA dynamics. The step size is adjusted for exploration, and Levy mutation enhances global search ability and diversity. Fitness values are computed based on intra-cluster distances, and nodes with the lowest fitness are selected as CHs. This process continues iteratively until optimal CHs with minimum communication cost and balanced energy usage are identified.

3.5. Optimal Relay Node Selection Based on Deep Q-Learning

After the optimal CHs are chosen, each cluster simply needs data from former and consecutive clusters, making multi-hop communication naturally Markov. In this study, a multi-hop RN selection is devised as MDP and a decentralized relay selection method based on DQL is introduced to select the best RNs. The method consists of setup, learning and prediction stages. All clusters, with D, preserves both Q and reward tables. Learning and prediction stages are decentralized to all clusters, as well as done in a sequential way from C_1 to C_N. The Q-tables are restructured for several episodes until convergence and utilized to explore the optimal RNs.

A typical DQL scheme for a multi-hop WSN is illustrated in Figure 2. Basic definitions of this scheme are presented, using the algorithm on the n^{th} cluster (C_n) as an example.

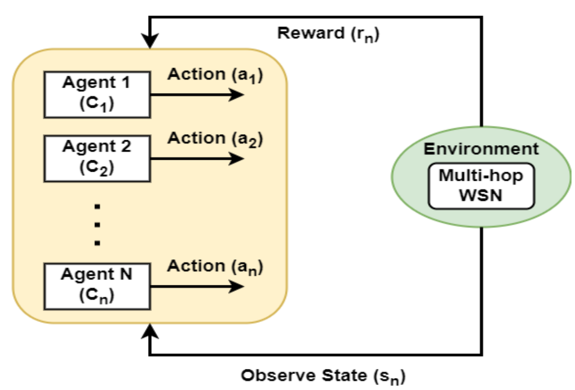

Figure 2 Structure of Typical DQL for Multi-Hop WSNs

- State (s_n): It denotes the chosen RN of cluster C_{n-1} that transfers the information-carrying signal to C_n.

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- Action (a_n): It denotes the RN chosen from C_n that can obtain the signal transferred from s_n. For $s_n = R_{k'}^{n-1}$, potential activities contain each RN of C_n, i.e., $a_n \in \{R_k^m | k = 1, \dots, K_m\}$.
- Reward $r_n(s_n, a_n)$: It represents the reward of s_n if a_n is reserved, and kept in the reward table of C_n. If $s_n = R_{k'}^{n-1}$, and $a_n = R_k^m$, then $r_n(s_n, a_n)$ is described by the SNR from s_n to a_n, i.e., defined in equations (11) and (12).

$$r_n(R_{k'}^{n-1}, R_k^m) = \Gamma_{k'k}^m \tag{11}$$

$$Q_n(s_n, a_n) = \begin{cases} (1-\alpha)Q_n(s_n, a_n) + \alpha\big(r_{n+1} + \gamma Q_{max}(m+1)\big), & n \le N, r_n(s_n, a_n) > r_{n+1} \\ (1-\alpha)Q_n(s_n, a_n) + \alpha\big(r_n(s_n, a_n) + \gamma Q_{max}(m+1)\big), & n \le N, r_n(s_n, a_n) < r_{n+1} \\ r_n(s_n, a_n), & n = N+1 \end{cases} \tag{12}$$

- Q-value $Q_n(s_n, a_n)$: It represents the Q-value for a corresponding (s_n, a_n) pair that is described to calculate the total s_n. $Q_n(s_n, a_n)$ is kept in the Q-table of C_n and attained by iterative updating.

Here, factors comprise training rate α, reduction γ, and error threshold ε. Figure 3 depicts the DQL scheme design used in this study.

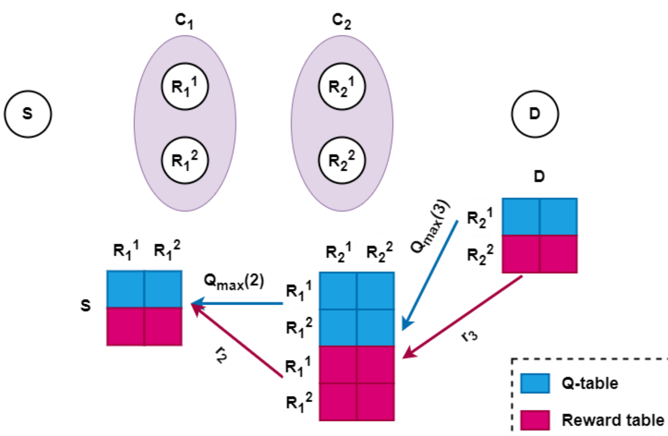

Figure 3 DQL-Based Multi-Hop Relaying

3.4.1. Setup

The reward table and Q-table of C_n are set using $K_{n-1} \times K_n$ tables, where $n = 0,1, \dots, N+1$, as defined in Tables 2 and 3, respectively. The reward table accumulates r_n for each (s_n, a_n) pair. To set the reward table, C_n calculates the CSI from all nodes of C_{n-1} to all nodes of its own, and determines the reward by equation (11). The Q-table accumulates the Q-values for each (s_n, a_n) pair. Each row and column in the Q-table signifies a node in C_{n-1}, and C_n, respectively. The Q-values for tables from C_1 to C_N are set to zero. The Q-table of D is static and reproduced from D's reward table.

Table 2 Reward Table of n^{th} Cluster

$s_n \backslash a_n$	R_1^n	R_2^n	$\cdots$	$R_{K_n}^n$
R_1^{n-1}	Γ_{11}^n	Γ_{12}^n	$\cdots$	$\Gamma_{1K_n}^n$
R_2^{n-1}	Γ_{21}^n	Γ_{22}^n	$\cdots$	$\Gamma_{2K_n}^n$
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
$R_{K_{n-1}}^{n-1}$	$\Gamma_{K_{n-1}1}^n$	$\Gamma_{K_{n-1}2}^n$	$\cdots$	$\Gamma_{K_{n-1}K_n}^n$

Table 3 Q-Table of n^{th} Cluster

$s_n \backslash a_n$	R_1^n	R_2^n	$\cdots$	$R_{K_n}^n$
R_1^{n-1}	$Q_n(R_1^{n-1}, R_1^n)$	$Q_n(R_1^{n-1}, R_2^n)$	$\cdots$	$Q_n(R_1^{n-1}, R_{K_n}^n)$
R_2^{n-1}	$Q_n(R_2^{n-1}, R_1^n)$	$Q_n(R_2^{n-1}, R_2^n)$	$\cdots$	$Q_n(R_2^{n-1}, R_{K_n}^n)$
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
$R_{K_{n-1}}^{n-1}$	$Q_n(R_{K_{n-1}}^{n-1}, R_1^n$	$Q_n(R_{K_{n-1}}^{n-1}, R_2^n$	$\cdots$	$Q_n(R_{K_{n-1}}^{n-1}, R_{K_n}^n$

3.4.2. Training

During training, the Q-tables of all clusters are updated iteratively until convergence. The main problem with learning is the updation. If the normal updation is used, merely the rate of the present hop is considered. However, with DF multi-hop relaying, the end-to-end rate cannot be determined by the rate of a single hop alone. Therefore, considering every hop in the update function is not cost-effective and may not produce good performance.

Instead, the update function is modified to select the larger reward between the previous hop and the current one. This maximizes the E2E rate. The novel updation is provided in equation (12). At the starting of t^{th} updating episode, $s_1 = S$ and a_1 is chosen arbitrarily from C_1. Then, C_2 selects the optimal action a_2' using equation (13):

$$a_{n+1}' = \underset{a_{n+1}}{\operatorname{argmax}}\, Q_{n+1}(a_n, a_{n+1}) \tag{13}$$

Additionally, the Q-value and reward of a_2' are computed using equations (14) and (15), respectively.

$$Q_{max}(n+1) = Q_{n+1}(a_n, a_{n+1}') \tag{14}$$

$$r_{n+1} = r_{n+1}(a_n, a_{n+1}') \tag{15}$$

After that, $Q_{max}(2)$ and r_2 are transferred to C_1, and utilized to modify $Q_1(S, a_1)$ using equation (12).

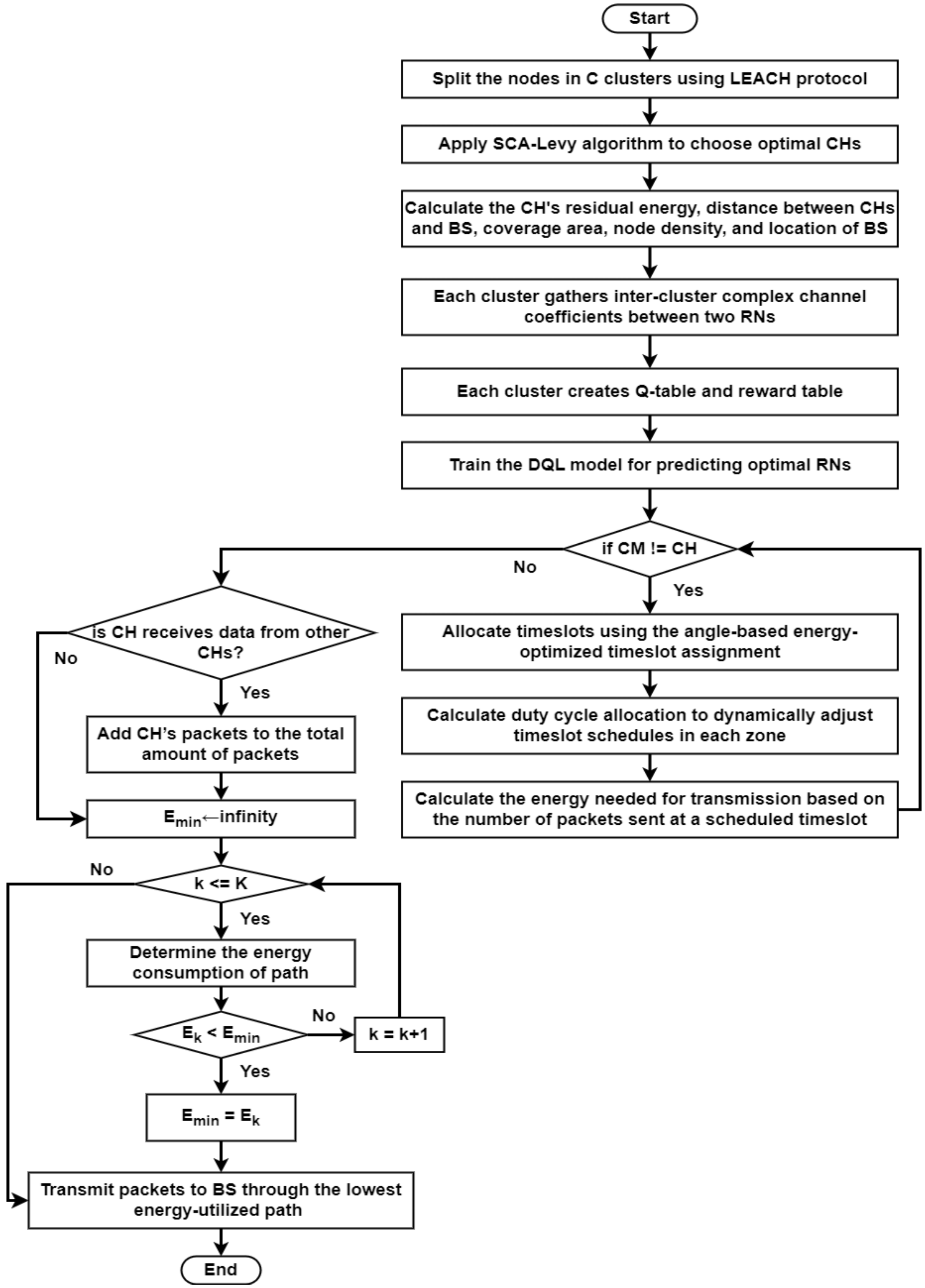

Figure 4 Flow Diagram of RSCA-Levy for Multi-Hop WSNs

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For C_2, $s_2 = a_1$ and a_2 are arbitrarily chosen from C_2. The remaining processes are analogous as C_1, and $Q_2(s_2, a_2)$ is modified. This updating process for all clusters is reiterated until the E2E rate error is smaller than ε, indicating that the Q-tables have converged and learning is completed. If the error is still larger than ε, a fresh episode of updation is begun.

3.4.3. Prediction

Each cluster, starting from C_1 to C_n, explores its Q-table and chooses the optimal RN. Initially, C_1 explores its 1-row Q-table and chooses a with the maximum Q-value as the best RN. This is defined in equation (16).

$$n^* = \underset{a \in C_n}{\operatorname{argmax}} Q_n((n-1)^*, a), n = 1, \dots, N \tag{16}$$

C_2 searches its Q-table for the corresponding row of 1^* and obtains 2^*. Once each cluster completes its RN selection, a multi-hop route is created to deliver data from S to D using energy-efficient inter- and intra-cluster transmission scheme. A pseudocode for this DQL-based multi-hop RN selection is given in Algorithm 1, and its flow chart is displayed in Figure 4.

Phase 1: Setup

$\mathrm{for}(n = 1{:}N+1)$

C_n assesses and gathers $h^n_{k'k}$ for each k' and k;

C_n creates a $K_{n-1} \times K_n$ reward table and sets it by equation (11);

C_n creates a $K_{n-1} \times K_n$ Q-table;

$\mathrm{if}(n = 1, \dots, N)$

Each Q-value is assigned to be zero;

else

Duplicate Q-values from reward table;

end if

end for

Phase 2: Training

$t = 1, R_0 = 0;$

while(1)

$s_1 = S;$

$\mathrm{for}(n = 1{:}N)$

C_n chooses a_n arbitrarily from C_n;

Request $Q_{max}(n+1)$ and r_{n+1} from C_{n+1};

Modify $Q_n(s_n, a_n)$ by equation (12);

$s_{n+1} = a'_{n=1};$

end for

Calculate end-to-end rate R_n;

$\mathrm{if}(R_n - R_{n-1} < \varepsilon)$

Break;

else

$t = t + 1;$

end if

end while

Phase 3: Prediction

Consider $0^* = S;$

$\mathrm{for}(n = 1{:}N)$

C_n searches in its Q-table and chooses the optimal RN n^* by equation (16);

Notify n^* to C_{n+1};

$R^n_{n^*}$ receives the signal transferred from $R^{n-1}_{(n-1)^*}$, and forwards it to C_{n+1};

end for

Algorithm 1 DQL-Based Multi-Hop RN Selection

4. SIMULATION RESULTS

The efficiency of the RSCA-Levy algorithm was evaluated with existing algorithms, including SCA-Levy [11], SPSRN [15], EEPC [16], AHP-TOPSIS [17], and MLRS [18], in multi-hop WSNs. Python language is used for simulating proposed and existing CRAs, using the parameters provided in Table 4 to ensure a fair investigation.

Table 4 Simulation Specifications

Parameters	Range
Simulation region	1000×1000 m2
# of sensor nodes	100
# of clusters	5
BS coordinates	(50,100)
Topology	Flat grid
Antenna	Omni antenna
Channel	Wireless channel
Propagation	Two ray ground
MAC layer	IEEE802.11

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MAC protocol	Time Division Multiple Access (TDMA)
Size of packet	500 bytes
Traffic class	Constant Bit Rate (CBR)
Starting energy	2 J
E_{elec}	50 nJ/bit
ϵ_{fs}	10 pJ/bit/m2
ϵ_{mp}	0.0013 pJ/bit/m4
Energy spent for information fusion	5 nJ/bit
# of rounds	1000
Communication distance	50 m
Simulation duration	150 c

4.1. Throughput

It measures the number of successful packet transfers over a given period from nodes to a sink. This is calculated by equation (17).

$$Throughput = \frac{No.of\ packets\ successfully\ delivered\ to\ the\ sink}{Time\ taken\ for\ delivery} \quad (17)$$

Figure 5 compares the throughput values of various CRAs. The RSCA-Levy algorithm has a throughput of 3.76×10^5, while existing algorithms such as SPSRN, EEPC, AHP-TOPSIS, MLRS, and SCA-Levy have throughputs of 1.81×10^5, 2×10^5, 2.19×10^5, 2.33×10^5, and 2.5×10^5, respectively.

This shows that the RSCA-Levy algorithm increases the overall quantity of transmitted data to the BS compared to the others in multi-hop WSNs, by selecting the optimal CHs and RNs based on different network parameters.

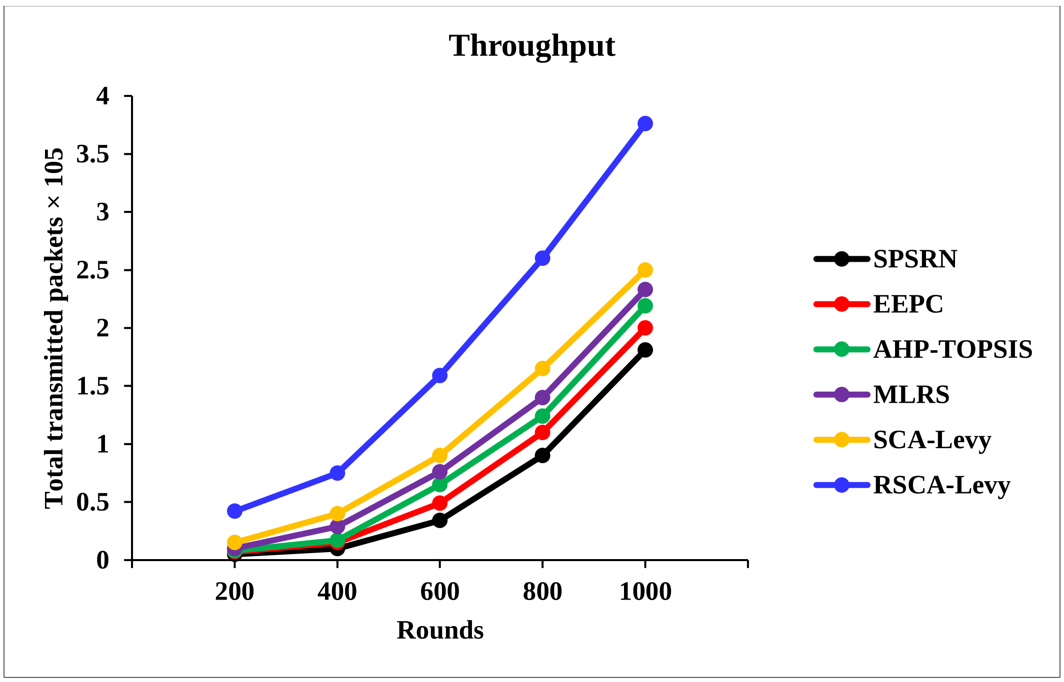

Figure 5 Total Transmitted Packets vs. Rounds

4.2. Total Energy Use for Relaying

It quantifies the energy spent by all nodes in accepting packets from the neighboring CHs and forwarding it to the subsequent CH/BS through the RN. This is calculated by equation (18).

$$E_{total} = \sum_{i=1}^{M} E_{totaltrans\_i} + E_{totalRec\_i} \quad (18)$$

In equation (18), M is the number of nodes, $E_{totaltrans\_i}$ represents the overall energy spent by node i during packet transfer, and $E_{totalRec\_i}$ denotes the overall energy spent by i for accepting packet from neighboring node.

Figure 6 compares the total energy utilization for relaying using different CRAs with varying numbers of rounds. The RSCA-Levy algorithm reduces the total relaying energy by 55.64%, 53.54%, 50.83%, 49.14%, and 45.37% compared to

SPSRN, EEPC, AHP-TOPSIS, MLRS, and SCA-Levy, respectively. This leads to the longest network lifetime achieved by the RSCA-Levy algorithm compared to the others.

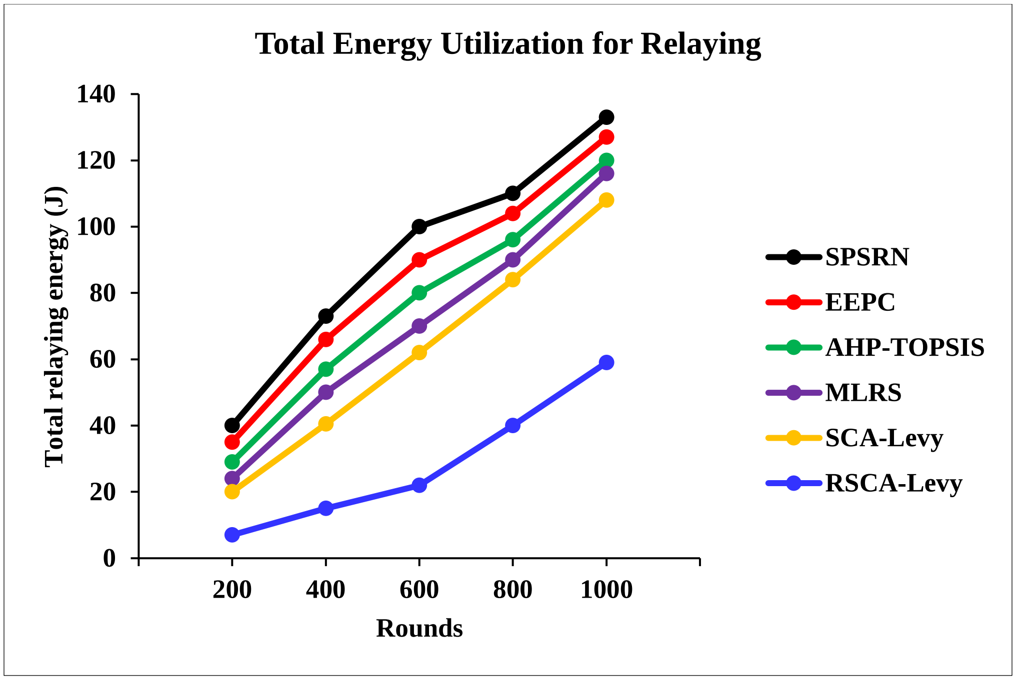

Figure 6 Total Relaying Energy vs. Rounds

4.3. Network Energy Use

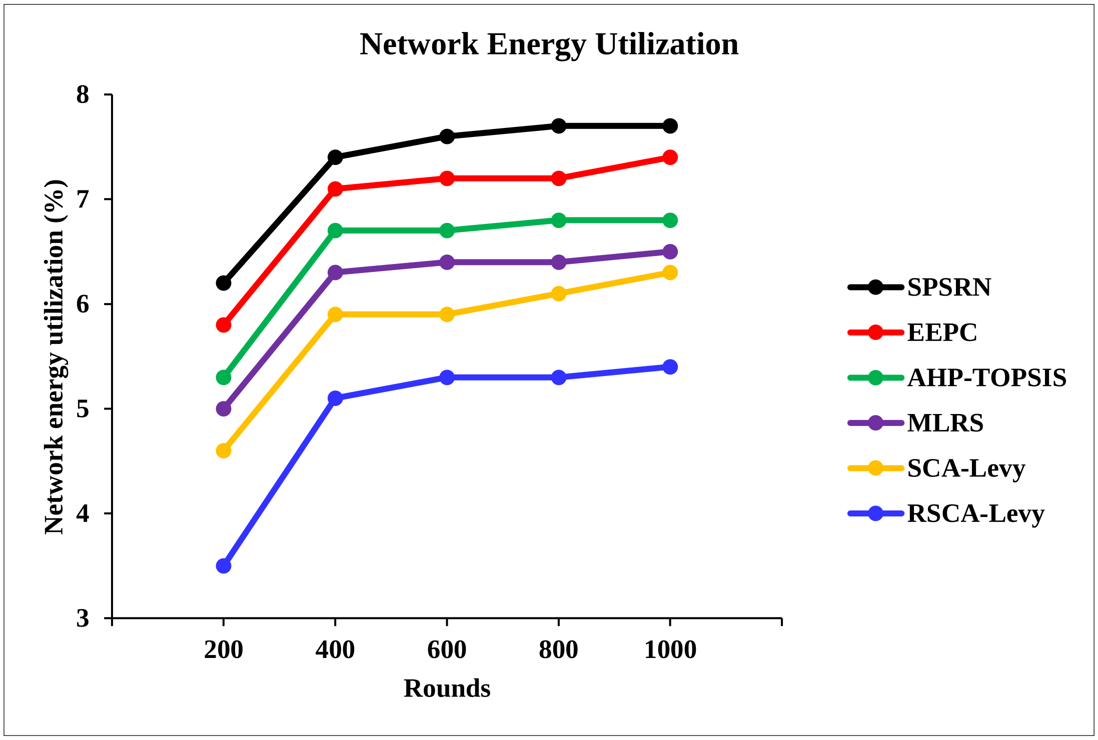

Figure 7 Network Energy Use vs. Rounds

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It signifies the fraction of energy spent by the nodes during placement to their initial energy levels. It is calculated using equation (19).

$$Network\ energy\ utilization = \frac{\sum_{i=1}^{M} E_{used\_i}}{\sum_{i=1}^{N} E_{initial\_i}} \quad (19)$$

In equation (19), E_{used_i} signifies the energy spent by i during its placement, and $E_{initial\_i}$ denotes the opening energy of i.

Figure 7 compares the network energy use of different CRAs with varying numbers of rounds. The RSCA-Levy algorithm attained high energy efficiency due to its uniform energy consumption mechanism. It reduces network energy utilization by 29.9%, 27.03%, 20.59%, 16.92%, and 14.29% compared to SPSRN, EEPC, AHP-TOPSIS, MLRS, and SCA-Levy, correspondingly.

4.4. Network Lifetime

It defines the duration in which the network can function effectively before the primary node depletes its energy. It is determined by equation (20).

$$Network\ lifetime = \frac{Total\ energy\ available\ in\ the\ network}{Mean\ energy\ consumption\ per\ unit\ of\ period} \quad (20)$$

Figure 8 evaluates the network lifetime values of different CRAs for varying number of rounds. The RMSCA-Levy algorithm decreases the network lifetime by 72%, 70.09%, 67.89%, 65%, and 58.82% compared to SPSRN, EEPC, AHP-TOPSIS, MLRS, and SCA-Levy, respectively. The RSCA-Levy algorithm has the longest network longevity with optimal CH and multi-hop RN selection strategies in WSNs, resulting in high throughput and energy efficiency.

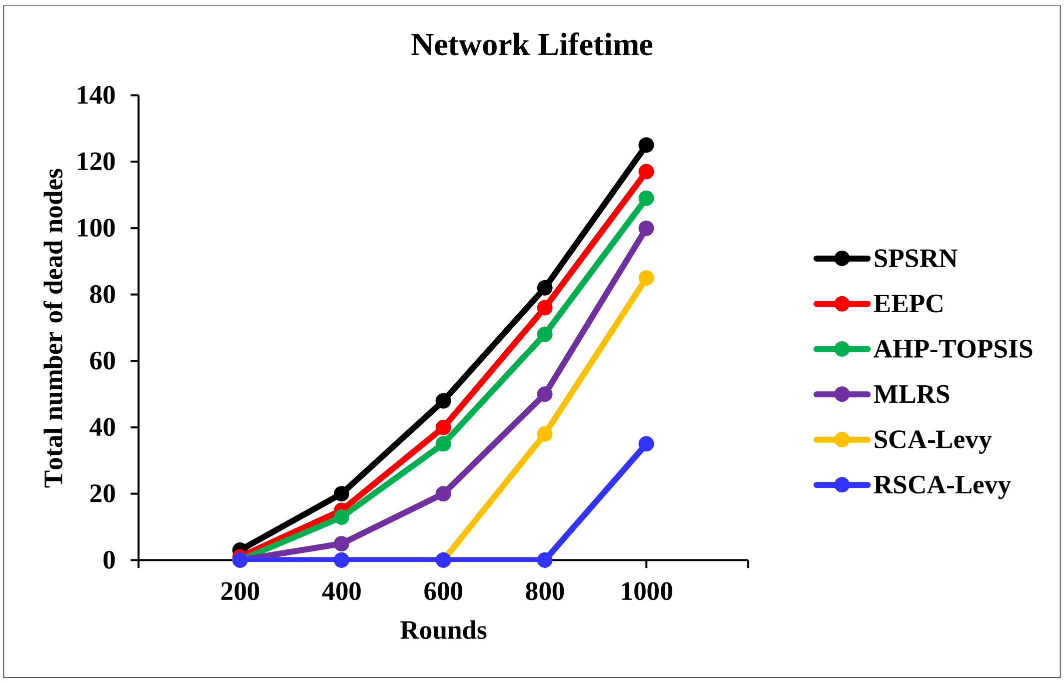

Figure 8 Total Dead Nodes vs. Rounds

4.5. Delay

It refers to the interval spent to transfer packets from S to D. It is calculated by equation (21).

$$E2E\ delay = \frac{\sum_{y=1}^{p}(R_y - S_y)}{n} \quad (21)$$

In equation (21), p indicates the overall quantity of packets received by the BS, R_y denotes the accepting time of the packet y and S_y indicates the forwarding time of y.

Figure 9 compares the E2E delay values of different CRAs for varying number of rounds. The RSCA-Levy algorithm reduces the total delay by 40.96%, 37.97%, 33.33%, 28.99%, and 26.32% compared to SPSRN, EEPC, AHP-TOPSIS, MLRS, and SCA-Levy, respectively. This reduction in delay is achieved by transmitting data through the optimal CH and RNs to the BS in WSNs, resulting in a higher number of successfully transmitted packets.

4.6. Discussion

Based on the simulation results, it is clear that the RSCA-Levy algorithm outperformed SPSRN, EEPC, AHP-TOPSIS, MLRS, and SCA-Levy in improving network performance. By considering coverage space, node count, and BS position constraints, it effectively balanced energy utilization and lifespan of the network. This led to robust communication through optimal CHs and RNs, resulting in higher throughput and lower E2E delay. Hence, this algorithm is suitable for various WSN applications requiring energy efficiency and reliable communication, such as environmental monitoring, industrial automation, smart transportation, healthcare systems, and disaster management. It also enhances military and surveillance operations and improves renewable energy grids by facilitating efficient data transmission.

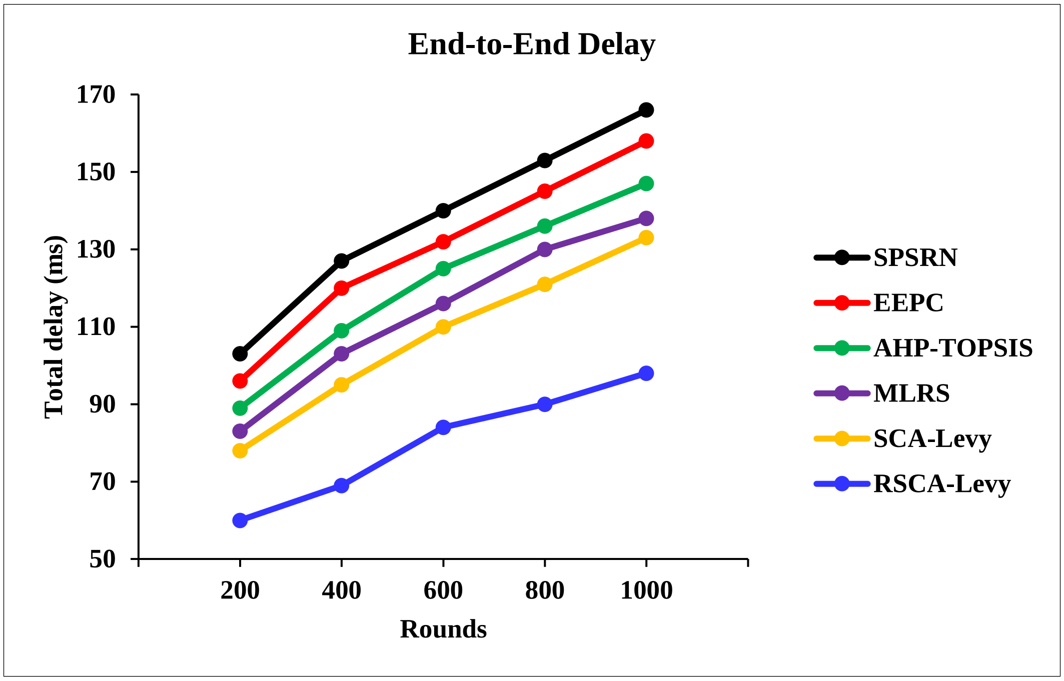

Figure 9 Total Delay vs. Rounds

5. CONCLUSION

This article presents the RSCA-Levy algorithm, a novel solution for multi-hop WSNs. The algorithm uses DQL scheme to efficiently select RNs based on factors including RE, node density, distance to the BS and coverage space. Each cluster trains its Q-table, enabling optimal RN choices for energy-efficient data transmission within and between clusters. Simulation results proved that the RSCA-Levy algorithm outperforms existing algorithms, achieving maximum throughput, network lifetime and energy efficiency. The RSCA-Levy achieves 3.76×10^5 packets transferred to the BS, 59J total relaying energy, 5.4% network energy utilization, 35 dead nodes, and 98ms E2E delay in 1000 rounds with 100 nodes, compared to the conventional CRAs.

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