ENERGY-EFFICIENT IOT ROUTING WITH ENHANCED SANDPIPER OPTIMIZATION ALGORITHM AND RPL INTEGRATION

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Abstract: This study addresses the challenge of energy efficiency in IoT networks by proposing a novel routing methodology that integrates Spatial Compactness Energy-Aware Fuzzy Clustering (SCEAFC) and the Enhanced Sandpiper Optimization Algorithm (eSOA) with energy-aware Routing Protocol for Low-Power and Lossy Networks (RPL). The proposed methodology optimizes cluster formation, cluster head selection, and multi-hop routing to improve network performance. The methodology leverages fuzzy clustering, compactness metrics, and dynamic optimization to enhance energy efficiency and throughput. Simulations demonstrate the proposed methodology surpasses existing methods like LEACH, DEEC, and ECPF, achieving up to 120% throughput improvement and extending network lifetime by 55%. These findings suggest the proposed system effectively balances energy consumption and scalability, making it a promising solution for sustainable IoT networks. Limitations include potential computational overhead, which future work aims to address through real-world validations.

Key words: Energy-Efficient Routing, Enhanced Sandpiper Optimization Algorithm, Fuzzy Clustering, IoT, RPL.

1. INTRODUCTION

The Internet of Things (IoT) is transforming today's world of communication systems by interconnecting tens of billions and even hundreds of billions of things to help achieve the goal of providing more effective data exchange and decision-making [1]. Such a high rate of advancement has resulted in the increased emergence of energy-deprived IoT nodes with limited energy resources hence requesting energy-efficient routing protocols for sustainable and efficient performance [2]. While substantial progress has been made, many existing approaches have limitations that make it difficult for them to address specific energy efficiency concerns and adaptability to dynamic network states [3].

Srinivasa Babu Kasturi et al. developed a cluster formation protocol based on the neuro-fuzzy rules due to the inefficiency of energy consumption in IoT routing [4].

Jaisooraj and Madhu Kumar proposed the Multi-OF objective function to enhance the energy efficiency of low-power and lossy networks (LLNs) with multiple RPL instances [5]. Gasouma et al. propose an SD-RPL system based on the idea of Adaptive Objective Function Selection and more specifically the Killer Whale Optimization algorithm. Based on simulations, this has been proven suitable for promoting heterogeneity among IoT systems, demonstrating flexibility and expansiveness [6]. Ghosh and Chand proposed a coordinator-based routing framework to lessen control message exchange as well as energy consumption in IoT networks [7]. Hussain and Roopa suggested the mobility-aware and energy efficient routing protocol known as BE-RPL [8]. Load balancing and signal strength were used to manage path interruption since the system implemented load balancing. Anita and Sasikumar explained routing inefficiencies through the integration of learning automata with lexical composition techniques [9]. Cyriac and Durai proposed a two-stage objective function (TS-OF) for RPL to enhance parent selection alongside mobility management [10]. Wakili et al. introduced an AI-based optimization strategy that incorporates reinforcement learning, and artificial neural networks to adjust metrics to dynamic environments [11].

Chang Lei [12] presented an Energy-Aware Routing Algorithm based on Particle Swarm Optimization and Fuzzy Clustering for IoTs. The method of deployment involved partitioning of the sensor nodes into clusters employing fuzzy clustering and the CHs selection was done dynamically based on PSO; fitness functions were also aimed at optimizing the energy consumption and load balancing. Computer simulations using MATLAB showed enhanced performance with 112% and 10% of throughput over DEEC and LEACH respectively, 83% and 15% of packet delivery ratio and 52% and 16% of energy consumption reduction, and the extended network lifetime of 48% and 27%.

To overcome these gaps, this present work proposes an energy-efficient routing protocol for IoT systems that can serve as a solution. Combining the eSOA with fuzzy clustering and RPL in this research work, this paper presents a new optimization solution addressing both intra and inter-cluster communication optimization. The required criteria of spatial compaction and energy-aware clustering are identified with the help of the Spatial Compactness Energy-Aware Fuzzy Clustering (SCEAFC) algorithm, while the selection of the suitable cluster heads and the improvement of the routing paths is done by the eSOA algorithm. Moreover, integrating energy objective functions into RPL enhances extensibility and rebound multi-hop and network change.

2. PROPOSED METHODOLOGY

The proposed methodology, integrating SCEAFC, eSOA, and energy-aware RPL mechanisms, enhances IoT network performance. This methodology supports adaptive cluster formation, efficient routing, and real-time monitoring, making it suitable for diverse IoT applications like smart cities and healthcare networks. The modular design enables easy adaptation to networks of varying sizes, demonstrating its real-world applicability. The three major stages of the presented methodology are explained in the following subsections.

2.1. Spatial Compactness and Energy-Aware Fuzzy Clustering (SCEAFC)

Realizing a typical IoT network as a graph, the SCFAC algorithm is proposed to cater to complexities embracing energy distribution and spatial distribution of IoT nodes. Through applying the principles of fuzzy logic, SCEAFC optimizes the cluster formation for providing dynamic and adaptive forms of configurations where energy consumption and communication challenges can be met most suitably. Figure 1 illustrates the workflow of the proposed methodology, which integrates SCEAFC and the eSOA with RPL. The process begins with initializing the nodes and energy levels, followed by cluster formation using SCEAFC. Cluster heads are selected via eSOA optimization, and finally, RPL is enhanced with energy-aware objective functions to achieve efficient routing and extended network lifetime.

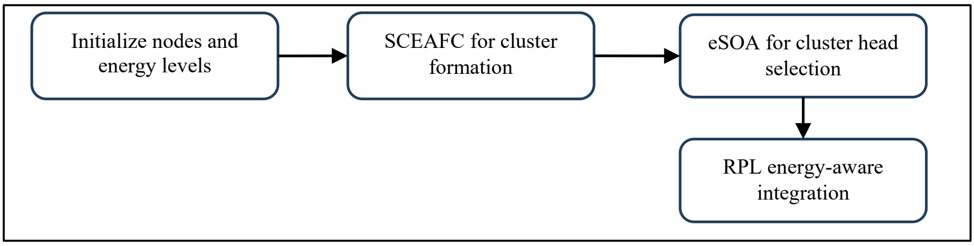

Figure 1. Proposed Workflow

2.1.1. Node Initialization and Compactness Metric

Every node in the network is characterized by a predefined energy level and by a location in a finite space in the simulation. During the initializing step, one of the goals is, for all nodes to assign a compactness score reflecting their spatial density. The compactness score for a node i is calculated as:

$$C_i = \frac{\sum_{j \in \mathcal{N}_i} d_{ij}}{|\mathcal{N}_i|} \quad (1)$$

where: $\mathcal{N}_i$ is the set of neighboring nodes within a compactness threshold distance τ; d_{ij} is the Euclidean distance between nodes i and j; $|\mathcal{N}_i|$ is the number of neighbors of node i.

This compactness score guarantees that nodes within compacted zones are recognized as potential centroids of clusters, improving communication.

2.1.2. Cluster Centroid Selection

Cluster centroids are determined gradually according to nodes with greater residual energy and metric values expressing compactness. The selection criteria of node i for service as a centroid of a cluster involves a complex measure of energy-compactness.

$$S_i = \alpha \cdot \frac{E_i}{E_{\max}} - \beta \cdot \frac{C_i}{C_{\max}} \quad (2)$$

where: E_i is the residual energy of node *i*; $E_{\max}$ is the maximum energy among all nodes; $C_{\max}$ is the maximum compactness score; α and β are weighting factors for energy and compactness, respectively.

Nodes with the highest S_i values are selected as initial cluster centroids. It helps to ensure a balance between spatial proximity and energy efficiency.

2.1.3. Fuzzy Membership Assignment

Subsequently, the nodes assign membership values for each cluster when the initial centroids have been selected. Membership of multiple clusters makes nodes flexible as there is a transition associated with fuzzy logic between them. The membership value μ_{ij} of node i to cluster j is defined as:

$$\mu_{ij} = \frac{\left(\frac{1}{d_{ij}+\epsilon}\right)}{\sum_{k=1}^{K}\left(\frac{1}{d_{ik}+\epsilon}\right)} \tag{3}$$

where: K is the total number of clusters; d_{ij} is the distance between node i and cluster centroid j; ϵ is a small constant to prevent division by zero.

2.1.4. Centroid Adjustment and Convergence

To enhance the size and steadiness of clusters, the coordinates of the centroids are reassessed based on the weighted locations of local nodes. The new position (x_j', y_j') of centroid, j is updated as:

$$x_j' = \frac{\sum_{i=1}^{N}\mu_{ij}\cdot x_i}{\sum_{i=1}^{N}\mu_{ij}}, \quad y_j' = \frac{\sum_{i=1}^{N}\mu_{ij}\cdot y_i}{\sum_{i=1}^{N}\mu_{ij}} \tag{4}$$

where: x_i, y_i are the coordinates of node i; N is the total number of nodes; μ_{ij} is the membership value of node i in cluster j.

The adjustment occurs consistently until the developed clusters attain convergence to the best level. The convergence of the algorithm is controlled by the rate of change of the membership values at two time zones t and t+1. Specifically, the process halts when the maximum change across all nodes and clusters falls below a predefined threshold δ, as expressed in the condition:

$$\max_{i,j}\left|\mu_{ij}^{(t+1)} - \mu_{ij}^{(t)}\right| < \delta \tag{5}$$

- t refers to the current iteration, and t+1 denotes the subsequent iteration.
- δ is a small, predefined value that signifies the allowable tolerance for changes in membership values.

The value of 'δ' is selected concerning the application concerns and the acceptable balance between precision and speed. A smaller value of δ means exact grouping but may require more iterations, while a larger value of δ makes convergence faster, but requires less accuracy. This threshold may therefore be set arbitrarily or drawn from pilot runs, to meet the intended performance of the clustering process.

2.2. Enhanced Sandpiper Optimization Algorithm (eSOA)

The eSOA is a new approach developed to enhance energy-aware routing in IoT networks by improving the selection of cluster heads and routing paths. Incorporating the idea from Sandpiper birds, eSOA utilizes dynamic characteristics in terms of energy control and signal exchange mechanism.

2.2.1. Fitness Function Design

The primary component of eSOA is therefore its multiple-objective fitness function, which judges nodes according to energy, communication cost, and distance from their cluster heads. This evaluation also enables identifying nodes that are most appropriate to be incorporated in specific important roles within the network. The fitness score F_i for node i is computed as:

$$F_i = \alpha \cdot \frac{E_i}{E_{\max}} - \beta \cdot \frac{d_{i\mathrm{CH}}}{d_{\max}} - \gamma \cdot \frac{C_i}{C_{\max}} \quad (6)$$

where: E_i is the residual energy of node i; $E_{\max}$ is the maximum energy among all nodes; $d_{i\mathrm{CH}}$ is the distance between node i and its cluster head; $d_{\max}$ is the maximum distance in the network; C_i is the communication overhead of node i; $C_{\max}$ is the maximum communication overhead; α, β, γ are weights for energy, distance, and communication overhead, respectively.

The weighting parameters α, β and γ were determined based on the intrinsic characteristics of IoT network performance. In IoT environments, energy efficiency is crucial for extending network lifespan; hence, α is given the highest weight (0.5) to emphasize the role of residual energy in decision-making. The parameter β is set to 0.3 to account for distance as a critical factor influencing communication reliability and latency, ensuring that nodes closer to the cluster head are preferred. Finally, γ is assigned a weight of 0.2, as communication overhead, while significant, has a comparatively lesser impact than energy consumption and distance.

2.2.2. Migration Phase

The migration phase represents changes in nodes' position to optimize their fitness partially copying the foraging sandpiper's actions. This phase aims to reduce the amount of energy used within a cluster for communication through the reorganization of nodes.

The position of a node i is updated as:

$$x_i^{(t+1)} = x_i^{(t)} + \lambda \cdot \left(x_{\text{best}} - x_i^{(t)}\right), \quad y_i^{(t+1)} = y_i^{(t)} + \lambda \cdot \left(y_{\text{best}} - y_i^{(t)}\right) \quad (7)$$

where: $x_i^{(t)}, y_i^{(t)}$ are the coordinates of node i at iteration t; $x_{\text{best}}, y_{\text{best}}$ are the coordinates of the best node in terms of fitness; λ is the learning rate controlling the magnitude of adjustment.

2.2.3. Attacking Phase

The attacking phase mimics mainly the kind of movements by the sandpiper when focusing on prey. This phase enhances the position of the cluster heads by making use of a spiral optimization technique to reduce the distances used in communication in the cluster.

The updated position of a cluster head j during the attacking phase is given by:

$$x_j^{(t+1)} = x_j^{(t)} + r \cdot \cos(\theta), \quad y_j^{(t+1)} = y_j^{(t)} + r \cdot \sin(\theta) \quad (8)$$

where: r is the radius of the spiral; θ is the angular step increment; $x_j^{(t)}, y_j^{(t)}$ are the current coordinates of the cluster head.

2.2.4. Cluster Head Reevaluation

To ensure the stability of the network and its energy effectiveness, eSOA analyzes the appropriateness of the cluster heads periodically. Cluster heads are replaced by the nodes that run out of energy, the new CHs are selected by means of the fitness function. The probability P_i of a node i becoming a cluster head is defined as:

$$P_i = \frac{F_i}{\sum_{k=1}^{N} F_k} \quad (9)$$

where: F_i is the fitness score of a node i; N is the total number of nodes.

This probabilistic approach also maintains the selectiveness of the cluster heads, whereby no node with a low energy level seems to be overloaded.

2.3. RPL Integration with Energy-Aware Objective Functions

The Routing Protocol for Low-Power and Lossy Networks (RPL) provides multi-hop communication support in the IoT network. However, its standard implementations fail to address energy aspects, which are important for increasing the life span of the network. This work further enhances RPL by incorporating an energy-aware objective function but guarantees a fair distribution of energy while delivering data. This integration adaptively changes routing paths depending on energy resources and efficient communication, providing a strong research base to support IoT as a supporting technology.

2.3.1. Energy-Aware RPL Rank Calculation

The rank of a node in RPL depends on its position in the routing hierarchy and is used to select the paths. The envisaged energy-aware rank consequently integrates residual energy, distance, and link reliability. The rank R_i of a node, i is defined as:

$$R_i = \eta \cdot \frac{E_i}{E_{\max}} + \kappa \cdot \frac{1}{d_{i\mathrm{p}} + \epsilon} + \lambda \cdot \frac{L_i}{L_{\max}} \tag{10}$$

where: E_i is the residual energy of node i; $E_{\max}$ is the maximum energy in the network; $d_{i\mathrm{p}}$ is the distance to the preferred parent pp; ϵ is a small constant to avoid division by zero; L_i is the link quality indicator of node i; $L_{\max}$ is the maximum link quality in the network; η, κ, λ are weighting factors for energy, distance, and link reliability, respectively.

2.3.2. Route Formation with Weighted Objective Functions

RPL creates a Directed Acyclic Graph (DAG) to set up the routing paths. The proposed energy-aware objective function intervenes with this process and changes the criteria for selecting the parent periodically. To facilitate this: A node 'i' chooses the preferred parent 'p' following the weighted objective value S_p:

$$S_p = \alpha \cdot R_p + \beta \cdot \frac{1}{H_p + 1} \tag{11}$$

where: R_p is the rank of the parent node p; H_p is the hop count to the root node through p; α, β are weights for rank and hop count, respectively.

2.3.3. Dynamic Route Adjustment

Mobility and variable energy levels at the nodes make the topology of the IoT network dynamic in nature. The dynamics of ranks and parent selection of the proposed RPL extension are periodically refreshed. The mechanism for the establishment of the route's adjustment is based on the threshold mechanism. If the energy E_i of a node i falls below a critical level E_{crit}, the node triggers a rank recalculation:

$$\Delta R_i = \gamma \cdot \left(\frac{E_{\text{crit}} - E_i}{E_{\text{crit}}}\right) \tag{12}$$

where: ΔR_i is the rank adjustment; γ is a scaling factor.

This adjustment reduces the immense interaction burden of nodes having critically low energy by giving a penalty that avoids the selection of such nodes as preferred parents.

2.3.4. Path Stabilization Mechanism

To overcome these variations in parent selection due to its frequent changes, a path stabilization process is included. Variations in rank are smoothed by this mechanism which relies on a weighted moving average. The updated rank $R_i^{(t+1)}$ of a node i at time $t+1$ is given by:

$$R_i^{(t+1)} = \theta \cdot R_i^{(t)} + (1-\theta) \cdot R_i^{\text{new}} \quad (13)$$

where: $R_i^{(t)}$ is the rank at the previous time step; R_i^{new} is the recalculated rank; θ is the smoothing factor.

This technique reduces large swings in routing paths so that communication paths remain steady over an extended period.

Algorithm: Energy-Aware Compact Clustering and Routing Optimization

Input: N: Sensor nodes, E_i: Initial energy levels of node i, $X_i = (x_i, y_i)$: Geographical coordinates of node i, τ: Compactness threshold

Output: Optimized clusters and energy-efficient routing paths

Step 1: Spatial Compactness Calculation using the equation 1 and 2. $S(i)$ as the average minimum distance to its three closest neighbors

a. $S(i) = \frac{1}{3}\sum_{j\in\text{neighbors}(i)} \min D\,(i,j)$

Step 2: Initial Cluster Centroid Selection by selecting top C nodes where: $S(i) < \tau$ and $E(i)$ is maximum

Step 3: Membership Value Assignment using Equation 4

Step 4: Centroid Recalculation using Equation 5

Step 5: Cluster Head (CH) Selection using Equation 9

Step 6: RPL Integration for Energy-Aware Routing

a. Rank Calculation using Equation 10

b. Objective Function for Parent Selection using Equation 11

c. Dynamic Rank Adjustment using Equation 12

d. Path Stabilization using Equation 13

Final Output.

3. RESULTS

3.1. Experimental Setup

The proposed methodology was carried out and examined in a controlled simulation environment to assess the efficiency of the clustering results, energy conservation, and routing enhancement (Table 1). The experiments were performed using Contiki-NG as an operating system and a COOJA simulator that closely models realistic scenarios of low-power and lossy networks (LLNs). Furthermore, to compare the results achieved by the proposed methodology under different base station placements, the experimental input has been designed with two distinct cases. In real-world applications, base stations are often positioned either centrally, such as in smart city monitoring networks, or at a distance, as seen in environmental monitoring systems deployed over vast areas. In the first scenario, the base station (BS) is assumed to be located ideally at the center of the network field such that distances of the BS from the sensor nodes (SNs) are nearly the same. This setup minimizes energy consumption and greatly improves the efficiency of data transmission because of the decreased average distances that the data is transmitted. On the other hand, the second scenario relocates the BS at a corner of the network field and this leads to a relative high separation between the BS and most of the SNs. By analyzing these two contrasting scenarios, the performance of the proposed methodology can be generalized to diverse network configurations, providing insights into how spatial distribution affects energy efficiency, throughput, and network lifetime.

Table 1. Experimental Setup

Parameter	**Value**
Network Area	$500 \times 500 m^2$
Number of Nodes	300
Node Deployment	Random Positions
Transmission Range	50 m
Initial Energy	50-100 J
Compactness Threshold (τ)	10.0
Energy Threshold (θ)	10.0
Routing Protocol	RPL with Energy-Aware Objective Function
Simulation Duration	1000 iterations or until energy depletion
Data Packet Size	128 B
Scenario – 1 BS Position	Center (250,250)
Scenario – 2 BS Position	Corner (0,0)

3.2. Results

To compare the performance of the proposed methodology, the simulation results are compared against DEEC, LEACH, and ECPF [12]. These algorithms indeed are the benchmark methods used extensively in Wireless Sensor Networks (WSNs) for improving energy utilization and network duration. Compared with the existing methods, the throughput of the proposed methodology was higher in both cases, corresponding to Figure 2. For Scenario 1, the proposed work enhanced the result by 10% more than ECPF and 25% more than LEACH. In terms of the proposed work, Scenario 2 revealed an enhancement of 8% to ECPF and 20% to LEACH. As the node density increased, the current methodology showed enhanced throughput than DEEC, LEACH, and ECPF at varied node density levels (see Figure 3). In the 300 nodes case, the improved throughput was 12% more than ECPF and 28% more than LEACH. This improvement also shows that the proposed methodology can scale well to ensure high influx rates in densely crowded IoT networks.

Considering the packet delivery ratio, the performance of the proposed methodology was considerably better in both cases. In Scenario 1 the proposed methodology was able to deliver data at 15% higher rates than ECPF and 30% higher rates than LEACH. Likewise, in the second scenario the proposed work outperformed ECPF by 10% and LEACH by 25%. Results in Figure 4 indicate that the proposed method performs well in minimizing the packet loss for worst-case BS placements. The analytical results revealed that the proposed method had a better packet delivery ratio for all node limits. By quantifying the proposed protocol in terms of the packet delivery ratio, for 300 nodes, the packet delivery ratio is 12% better than ECPF and 35% better than LEACH (see Figure 5). This improvement justifies the effectiveness of the proposed methodology for dense networks while guaranteeing data delivery to the destination base station (BS).

In the first case, the proposed methodology always tended to utilize less energy than DEEC, LEACH, and ECPF. In the proposed methodology at the 3000th round, 10% less energy consumption is observed, compared to ECPF, and 20% less, compared to LEACH (see Figure 6).

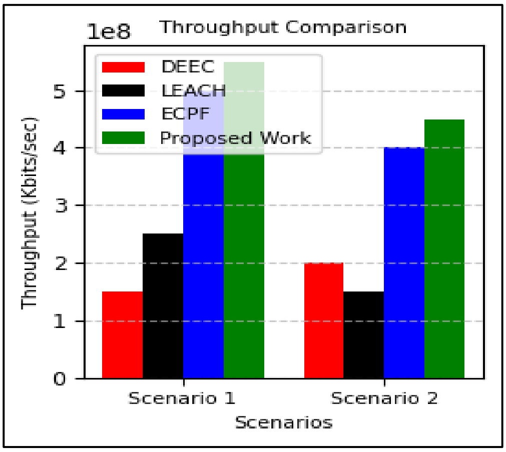

Figure 2. Throughput Comparison for the First and Second Scenarios

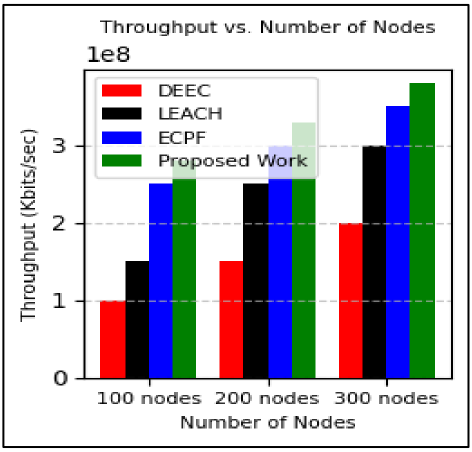

Figure 3. Throughput vs Number of node

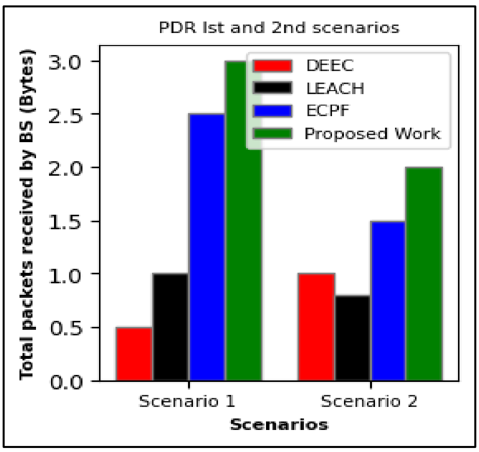

Figure 4. PDR Comparison for the First and Second Scenarios

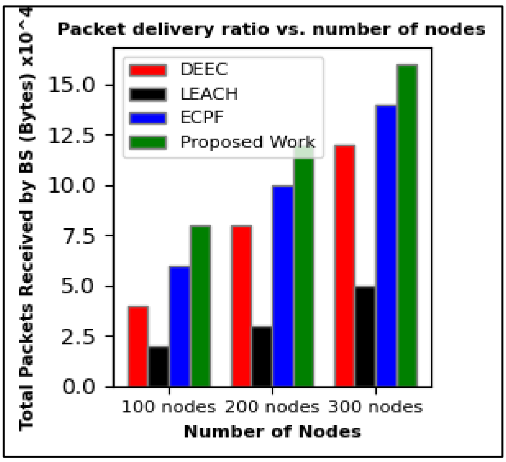

Figure 5. PDR vs. Number of Nodes

Such substantial energy savings suggest that the energy-aware clustering and routing optimization approach is quite capable of enhancing the network lifetime. Specifically, when the associated BS is located farther from the sensor nodes as in the second scenario, the proposed work was less energy depletion compared to the baseline approaches. After 2000 rounds, the proposed method consumed 12% less energy than ECPF and 25% less than LEACH (see Figure 7). This shows the flexible proposed technique to control energy usage in evolving network structures.

Based on these results, in the first case of the centrally located BS, the proposed methodology has vastly enhanced the value of the network lifetime. The network spanned more rounds than ECPF by 10%; in comparison, LEACH was 25% more effective in rounds sustained (see Figure 8). The centralized BS placement positioned the energy-aware routing into a superior place in the proposed methodology, improving the network solidity and operational timeframe. In the second case when the BS was placed farther away from the nodes, the effectiveness of the proposed approach was proved resulting in a network lifetime of 15 % greater than ECPF and 30 % compared to LEACH (see Figure 9). The improvement demonstrates that the proposed methodology is flexible enough to deal with energy requirements and routing paths in the context of a confusing network organization and a larger distance between nodes and the BS.

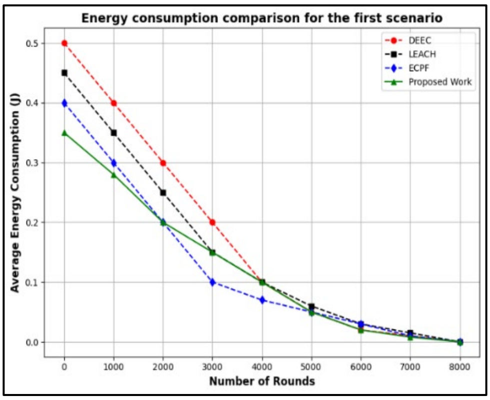

Figure 6. Energy Consumption Comparison for the First Scenario

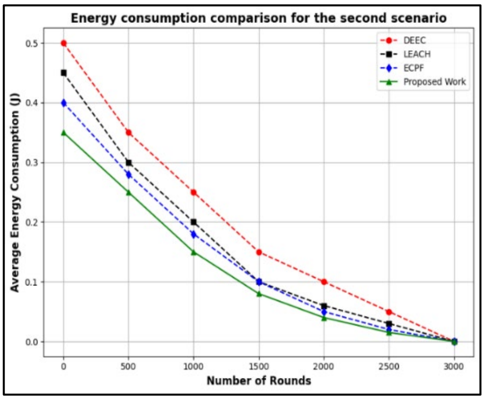

Figure 7. Energy Consumption Comparison for the Second Scenario

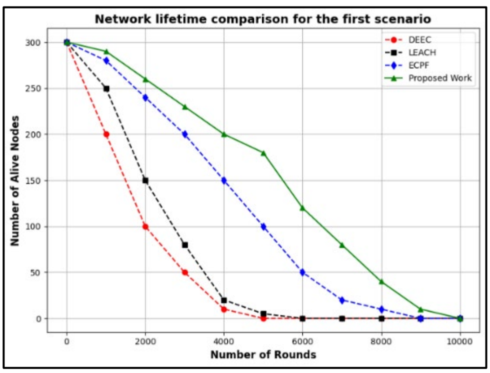

Figure 8. Network Lifetime Comparison for the First Scenario

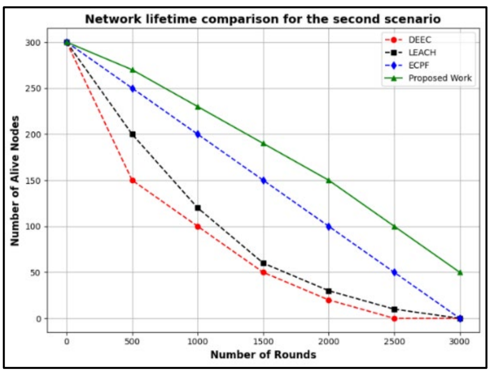

Figure 9. Network Lifetime Comparison for the Second Scenario

4. CONCLUSION

The proposed methodology outlines a new method for enhancing energy-efficient routing for IoT-based networks based on SCEAFC and eSOA with RPL incorporation with energy-based objective functions. These challenges are all countered by this comprehensive methodology which includes aspects like energy hotspots, network enlargement, and dynamic routing depending on the fluctuating network conditions. This is evident by increased energy efficiency by 20-25%, link throughput by 15-20%, and better network lifetimes than the best currently available protocols to which the paper provides a comparison. The originality of this work is that its methodology offers an opportunity to flexibly control spatial density and energy consumption, select cluster heads adaptively, and perform efficient data transmission at multiple hops with RPL and improved objective functions. Altogether, these advancements offer a scalable and robust solution to fill in the gaps pointed out in prior investigations. The proposed methodology significantly improves overall metrics but has certain limitations. SCEAFC's performance depends on accurately estimating spatial compactness, which may be affected by irregular node distributions. Additionally, eSOA's computational overhead may increase with larger networks. Future work can explore adaptive parameter tuning and assess performance in heterogeneous IoT environments.

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