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Serp: Scalable And Energy Efficient Routing Protocol For Wireless Sensor Networks

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Abstract

Wireless Sensor Networks (WSNs) are widely used in applications such as environmental monitoring, industrial automation, and smart city infrastructure. Despite their growing adoption, energy consumption and maintenance of battery-operated sensor nodes remain significant challenges that limit network lifetime. This paper proposes a hybrid routing protocol combining the energy efficient LEACH protocol for optimized clustering with Particle Swarm Optimization (PSO) and Q-learning algorithms to enhance energy efficiency, scalability, and adaptability in large-scale network deployments. PSO is utilized to identify initial energy-optimal routing paths, while Q-learning adaptively refines routes in real time based on dynamic factors like remaining node energy, congestion levels, and link reliability. Extensive simulations compare the proposed SERP protocol with GA-UCR and I-OEERP protocols, showing superior results in extending network lifetime, reducing overall energy consumption, improving packet delivery ratios, and minimizing network overhead. These improvements demonstrate the protocol’s potential to support sustainable and efficient communications in large-scale Internet of Things (IoT) environments, making it a promising solution for energy-sensitive WSN applications

Keywords: Wireless Sensor Networks (WSNs); Energy efficiency; Network lifetime; PSO-Q-learning; Intelligent routing.

1. Introduction

Wireless Sensor Networks (WSNs) emerged as one of the most significant technologies driving modern computing and communication paradigms. The widespread applications such as smart cities, environmental monitoring, disaster management, and industrial automation, WSNs are the most significant component of the broader ecosystem of the Internet of Things (IoT) [1]. A WSN consists of many sensors or nodes that cooperatively sense, process, and transmit data from the deployed location to the base station (BS). Despite their versatile nature , the limitations of sensor nodes—particularly their operation on a finite power source [2].

The issue of energy efficient WSN has therefore become a point of active research. Since sensors are often deployed in distant environments, replacing or recharging the nodes is impractical given that a large network is considered. Energy conserving optimized mechanisms must be integrated into the network design to enhance network’s lifetime while maintaining the Quality of Service (QoS) [3-4]. Traditional routing approaches might be unsuitable for large-scale WSNs since they have excessive overhead and poor scalability. To achieve this, hierarchical and clustering-based approaches, such as LEACH (Low-Energy Adaptive Clustering Hierarchy) proposed [5].

Clustering reduces communication distance, energy consumption between nodes, and improves scalability of the network. In the variants of LEACH protocols [6-9], the cluster-heads (CHs) are periodically elected to prevent early node failure. Modern clustering schemes, such as Hybrid Energy-Efficient Distributed clustering [11] and Power-Efficient Gathering in Sensor Information Systems [10], were proposed in an attempt to address these shortcomings by features such as residual energy awareness and chain-based communication. Even though these changes were incorporated scalability and energy efficiency remain an open challenge.

Recent advancements in research has shown the scope of optimization-based clustering methods to overcome the shortcomings of conventional protocols already in use. The new metaheuristic algorithms, including Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and various hybrid approaches, have been extensively applied to perform the task of cluster formation and creating routing paths. For instance, Gunjan et al. [12] proposed GA-UCR, a genetic routing algorithm used unequal clustering mechanism that demonstrated significant enhancements in energy efficiency by addressing the hotspot problem. Similarly, Kumar and Agrawal [13] developed another hybrid C-GSA (Crow–Gravitational Search Algorithm) algorithm, for the tasks of routing, network stability and enhanced lifetime in large-scale deployments. These algorithms highlight the growing potential of hybrid optimization for sustainable WSN's.

In addition to various primary approaches, the application of machine and deep learning algorithms to wireless networks has gained prominence. Reinforcement learning (RL) has emerged as a solution for optimization. Unlike conventional optimization algorithms, which require predefined models, RL helps nodes to dynamically adapt to network conditions by learning the optimal policies. The remainder of this article explore literature review in section 2, followed in section 3 explained the methodology, design aspects. The section 4 analyzes the simulation results of proposed and existing protocols, follows conclusion and scope of this work in future in the section 5.

2. Literature Review

A hybrid efficient clustering and routing mechanism tailored for large-scale wireless sensor networks. By combining adaptive cluster-head selection with optimized multi-hop data forwarding, the approach minimizes communication overhead and improves network stability. The results demonstrate extended network lifetime, reduced energy variance across nodes, and better packet delivery reliability, making it effective for IoT-driven WSN applications.

In [14], a Q-learning topology routing protocol (QTAR) was proposed for underwater WSN to enhance energy efficiency and reduce delay. Hybrid swarm intelligence clustering protocol proposed in [15] integrating Grey Wolf Optimizer (GWO) with Genetic Algorithm (GA) to improve cluster head (CH) selection and achieve efficient energy distribution. A dual phased optimization hybrid framework routing integrating Sailfish Optimization (SFO) and Spotted Hyena Optimization (SHO) [16]. In [17], a reinforcement learning routing protocol is introduced for Software-Defined WSNs (SDWSNs). The hybrid PSO-Q-learning algorithm developed [18-20] to overcome slow convergence in path planning. The Q-learning mechanism [21] producing shorter and smoother paths. In [22], the authors developed an efficient routing protocol using dynamic objective selection and reinforcement learning.

The authors [23] introduced an optimal rate control strategy that offers Firefly Optimization combined with Ant Colony Optimization inspired routing techniques to maximize throughput. The I-OEERP protocol [24] focuses on extending the lifetime of WSNs by employing a C-GSA framework. In the framework, clusters are formed using Crow Search Algorithm (CSA) and the Gravitational Search Algorithm (GSA) for selecting remaining nodes. Another study, GA-UCR [9], presents a genetic algorithm routing scheme utilizing unequal clustering, where the genetic algorithm optimizes CH election and data forwarding towards base station, enhancing overall network performance. The protocol [25] employs PSO to explore and categorize potential routes in the network. Q-learning framework refines and optimizes these routes once they categorized with the help of using real-time feedback from the network.

Despite these advances, integrating metaheuristic algorithms with RL for a comprehensive, scalable, and energy-efficient routing solution remains an open challenge. This paper proposes a novel hybrid routing framework that synergizes Particle Swarm Optimization with Q-learning to deliver congestion-aware, energy-efficient, and scalable routing for large-scale WSNs. The key contributions are:

- The proposed protocol uses optimized K-means clustering for efficient resources.
- Developed PSO based Route Optimization with relay fitness function to improve energy balance, conservation, and reduce congestion.
- Q-learning adapts routing to dynamic network conditions, enhancing real-time decision-making and reliability.

3. Proposed SERP Protocol

The proposed SERP protocol presented combines clustering based on the LEACH protocol, relay node optimization through PSO and adaptive routing using Q-learning to enhance energy efficiency and support scalability in sensor networks. The approach begins with selecting cluster heads (CHs), followed by evaluating relay nodes using multiple criteria. Initial routing paths are optimized via PSO, and these routes are further refined with reinforcement learning techniques.

3.1 Network Model and Assumptions

The *N* static sensor nodes are deployed randomly and uniformly across a two-dimensional sensing region of area *A*. Each node is equipped with limited battery energy E_0 and has a unique identifier. The nodes are assumed to be stationary post-deployment, and the Base Station (BS) is positioned either centrally inside or externally outside the sensing area, based on deployment scenarios. The network model shown in the figure 1.

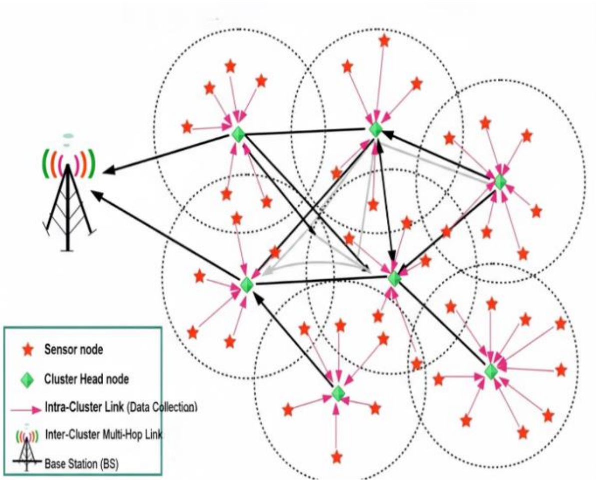

Figure. 1. WSN network model.

Communication between nodes follows the standard radio energy model, accounting for both free-space and multipath fading channel losses. Nodes have a fixed communication radius, and all nodes within this radius can directly communicate. The network assumes reliable bidirectional links with no node mobility. Additionally, sensors can perform in-network data aggregation to reduce redundant transmissions.

3.2 Optimized Cluster Formation

Before the cluster head (CH) selection phase, optimized cluster formation is performed to enhance cluster stability and equilibrium energy consumption among the network. Unlike pure random clustering, the proposed method forms clusters based on both geographical proximity and remaining energy of the sensor nodes, ensuring prolonged network lifetime and reducing the likelihood of cluster instability. Each sensor node exchanges limited neighbor information and initially forms clusters based on node positions.

A K-means clustering algorithm is applied to assign nodes to clusters such that the intra-cluster distance is minimized. Each node is assigned to the cluster with the nearest centroid as

$$k^* = \arg \min_{k\in\{1,2,\ldots,K\}} d_{i,ck} \quad (1)$$

where $d_{i,ck}$ Euclidean distance of node i and centroid of cluster k (C_k). Clusters are adjusted by considering nodes' remaining energy to avoid early cluster head death, ensuring balanced energy distribution and prolonged network lifetime. The fitness of each cluster can be defined to jointly account for energy and compactness:

$$F_{cluster}(C_k)= \frac{1}{|Ck|}\sum_{i=Ck} Ei - \frac{1}{|Ck|}\sum_{i=Ck} d_{i,ck} \quad (2)$$

Maximizing $F_{cluster}(C_k)$ ensures clusters are compact (low intra-cluster distance) and energy-balanced (high average residual energy). This optimized cluster formation reduces the likelihood of uneven cluster sizes and excessive energy consumption in large clusters.

3.2 Cluster Head Selection

The deployed nodes are once portioned into groups, then Cluster Head selection process initiated. For the CH selection, we used an enhanced LEACH variant [7-9]. The cluster head election considers both the residual energy of the sensor node and its distance to the BS, defined by the probability function:

$$P_{CH}(n) = \begin{cases} \dfrac{p}{1-p\times\left[r\,mod\left(\frac{1}{p}\right)\right]}\times\left(\dfrac{E_{res}}{E_{int}}\right)\times\left(1-\dfrac{d(n,BS)}{d_{max}}\right) & \forall\, i\in G \\ 0 & other\ wise \end{cases} \quad (3)$$

where: *P* is percentage of nodes to become CHs, E_{res} (*n*) is the node’s residual energy, *d* (*n*, *BS*) is the euclidean distance from node *n* to the BS, d_{max} is the maximum distance between any node and the BS in the network.

This weighted probability favours nodes with higher residual energy and those nearer to the BS, aiming to reduce energy-expensive long-distance transmissions. A node with a random number smaller than P_{CH} (*n*) elects itself as CH in the current round. Once the nodes selected as CH, it broadcast advertisement messages, and other nodes join the CH with the highest RSS (Received Signal Strength). This process reduces direct long distance communication to the BS and saves energy.

3.3 PSO-Based Route Optimization

Particle Swarm Optimization (PSO) is employed to categorize energy-efficient and reliable initial routing paths before reinforcement learning fine-tunes them. Each particle in the swarm encodes a candidate routing path from source nodes to the base station. The particles iteratively update their positions (routes) and velocities (search directions) to maximize the route fitness. The fitness is evaluated based on energy, delay, and link quality. The fitness function of a path p is expressed as:

$$F(p) = \alpha.\frac{1}{E_{res}(p)} + \beta.\frac{1}{LQ(p)} + \gamma.Delay(p) \qquad (4)$$

where $E_{avg}(p)$ is the residual energy of nodes in path p, $LQ(p)$ denotes the average link quality, and $Delay(p)$ represents end-to-end latency.

The velocity and position of particles are updated using:

$$v_i(p+1) = \omega v_i(p) + a_1 r_1\big(pbest_i - x_i(p)\big) + a_2 r_2(gbest - x_i(p)) \qquad (5)$$

$$x_i(p+1) = x_i(p) + v_i(p+1) \qquad (6)$$

Here, ω is the inertia weight, a_1 and a_2 are acceleration constants, while $pbest$ and $gbest$ represent personal and global best solutions respectively. This mechanism helps PSO quickly converge towards near-optimal paths.

3.4 Q-Learning Based Routing Refinement

After initial optimization, routing is refined dynamically using Q-learning. Each node learns from its environment and adapts routing choices.

State (S): current node and neighbour information obtained by

$$\delta_t = \{E_{\mathrm{res}}(p), v(p), LQ(p), C\mathrm{k}(\mathrm{p})\} \qquad (7)$$

Action (A): selecting the next-hop relay by

$$\Theta_t = \{\text{CH\_Election,Cluster\_Join, Data\_Relay, Sleep\_Mode}\}$$

Reward (R): a function of residual energy, link quality, delay, and energy cost:

$$R(s,a) = \lambda_1.f_{RE} + \lambda_2.f_{LQ} - \lambda_3.Delay - \lambda_4.Energy\ Cost \qquad (8)$$

The Q-values are updated iteratively as:

$$Q(s,a) \leftarrow Q(s,a) + \alpha[R(s,a) + \gamma\max_{a'} Q(s',a') - Q(s,a)] \qquad (9)$$

where α is rate of learning and γ is the discount factor. Over multiple interactions, the policy converges towards energy-efficient routing.

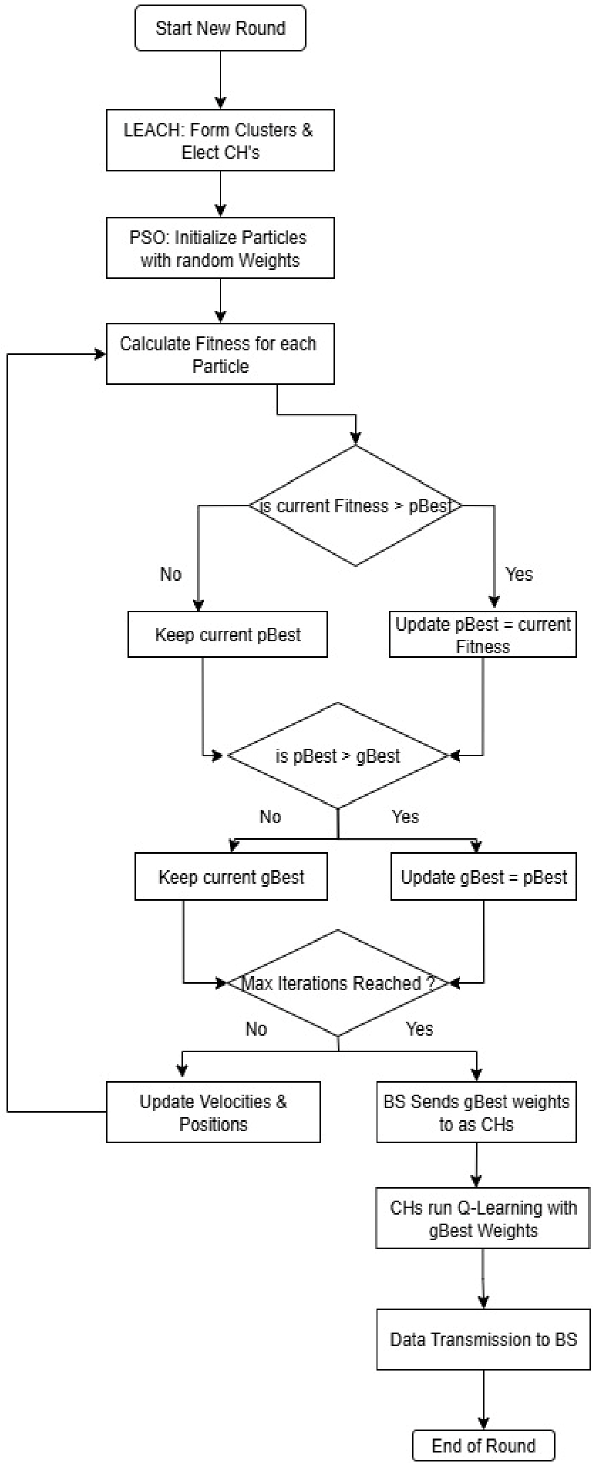

Figure 2. Flowchart of Proposed Routing Protocol

Figure 2 illustrates the complete routing protocol workflow, starting with the optimized cluster formation enhancing cluster stability, followed by energy-aware cluster head selection, PSO-based relay node selection to optimize communication paths, and Q-learning based adaptive routing to adjust dynamically based on network conditions. Algorithm 1 provides the understanding of proposed protocol methodology.

Algorithm 1: PSO-QLR-Based Routing

Input: Sensor nodes *N*, initial clusters
Output: Optimized routes and adaptive next-hop selection

1. For each node *n* in the network:
2. Participate in route selection phase.
3. Compute fitness value for each path *p*:
4. For each particle in PSO swarm,
Estimate p_{best} and G_{best}
If current fitness >> previous p_{best}: update p_{best}.
If current p_{best} > G_{best} : update G_{best}.
5. Update velocities and particle positions
6. Repeat steps 5-6 until stop condition is met.
7. Store best route corresponding to G_{best}.
8. For data transmission, starting from the source node:
While current node ≠ sink node
9. Gather available neighbour information (state *S*).
10. For each neighbour (possible next-hop, action *A*):
11. Calculate expected reward *R* as a function
12. Update Q-value
13.Choose next-hop relay (action) with highest Q-value.
14. Forward data to selected relay and repeat until data reaches the base station

This enhanced methodology provides a more detailed network model, integrates an optimized clustering approach for improved balance and stability, and upgrades the CH election process into an energy-aware model tailored for longer network lifespan.

4. Results and Analysis

The performance analysis of SERP was conducted using NS-2.35 simulator to validate the protocol's effectiveness. The simulation setup span of a 500 m × 500 m network area with sensor nodes randomly distributed across the field. To examine scalability aspects, the node density was varied from 100 to 600 nodes. Constant Bit Rate traffic was generated using User Datagram Protocol for data transmission. The simulation configuration parameters are summarized in Table 1. The evaluation metrics of proposed protocols with existing mechanisms is illustrated in Figures. 3–7.

Table 1: Simulation Parameters:

Parameter	Specification
Deployment Area	500 x 500
Node Count Variation	50 to 600 Nodes
Node Initial Energy	1.5 Joules
Size of Data Packet	512 bytes
Propagation Model	Two-Ray Ground
Routing Comparisons	I-OEERP,GA-UCR, Proposed

4.1 End-to-End Delay Performance

The end-to-end delay performance analysis, depicted in Figure 3, highlights improvements achieved by the proposed protocol compared to existing approaches.

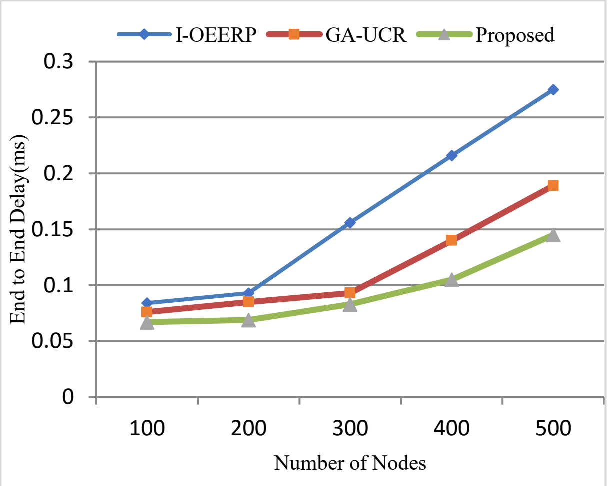

Figure 3. Performance Evaluation of End-to-end Delay

The end-to-end delay performance analysis, depicted in Figure 3, highlights improvements achieved by the proposed protocol compared to existing approaches. SERP reduces end-to-end delay by 16% to 39%, a substantial gain attributable to its hybrid routing mechanism. This hybrid nature facilitates the selection of optimized routing paths contributes to lower transmission and queuing delays within the network.

Furthermore, the adaptive nature of Q-learning allows adaptive routing decisions based on node residual energy and link quality, reduces delay. As node density increases, the routing model efficiently balances the traffic load, preventing bottlenecks that typically exacerbate delay. Collectively, these design elements enable SERP to deliver faster and more reliable data communication suitable for time-sensitive applications in large-scale wireless sensor networks.

4.2 Energy Consumption Performance

The performance of energy consumption metric for the proposed SERP protocol is illustrated in Figure 4. Results indicate that SERP expends between 22% and 36.4% less energy than existing routing protocols under varying node densities. This significant reduction in energy drainage is attributed to SERP's hybrid design, which strategically balances the network's load through intelligent cluster formation and adaptive routing decisions. As node density increases, SERP's integration of PSO with Q-learning-driven adaptive forwarding, allows the network to dynamically fine-tuned for changing conditions and avoid congested or energy-drained nodes. This adaptive behavior conserves energy, making SERP highly effective for large-scale wireless sensor network deployments that demand both scalability and sustainable operation.

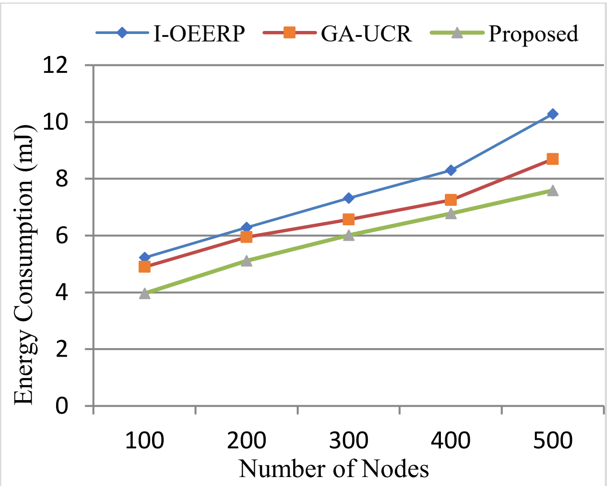

Figure 4. Performance of Energy Consumption

4.3 Packet Delivery Ratio Performance

As illustrated in Figure 4, the SERP protocol achieves a packet delivery ratio that is 29% to 43% higher than comparable state-of-the-art routing protocols. This improvement is primarily due to SERP's congestion-aware routing mechanism, which dynamically identifies and avoids overloaded paths, effectively reducing packet loss and retransmissions. SERP ensures that data packets are routed through paths with optimal link quality and residual energy. The selective forwarding minimizes the risk of node failure or buffer overflow along the transmission path.

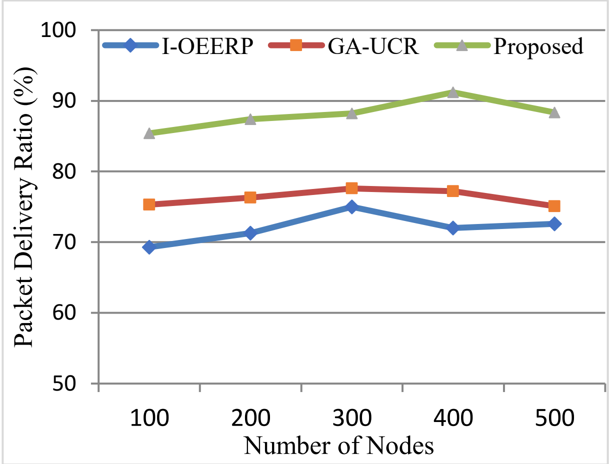

Figure 5.Performance of Packet Delivery Ratio

These features collectively contribute to more reliable communication and enhanced robustness, making SERP well-suited for applications requiring dependable data delivery in large-scale wireless sensor networks.

4.4 Network Throughput Performance

The throughput comparison presented in Figure 5, demonstrates throughput improvement ranging from 28% to 41% over existing routing mechanisms. This significant increase in data throughput is facilitated by SERP's efficient data forwarding technique, which reduce redundant transmissions and optimize the use of available bandwidth.

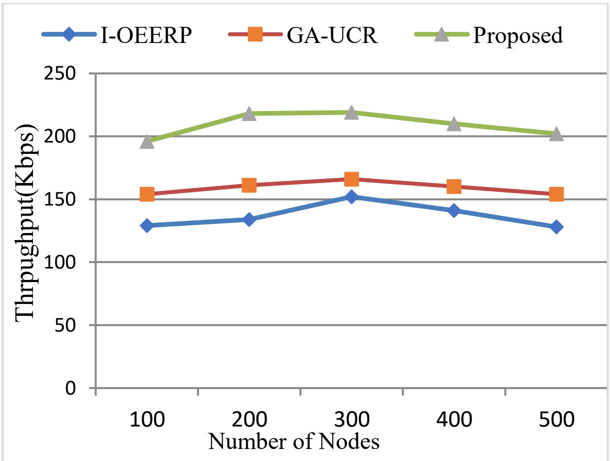

Figure 5.Performance of Throughput

Proposed protocol identifies optimal routing paths that minimize communication overhead and delay. The protocol dynamically selects high-quality links, balancing network load and minimizing packet loss due to congestion or node failure with the use of Q-learning-based adaptive routing. Collectively, these mechanisms enable SERP to sustain higher data rates, making it particularly suitable for applications with demanding bandwidth and reliability requirements in large-scale wireless sensor networks.

4.5 Network Overhead Performance

Figure 6 illustrates performance on Network overhead of proposed and existing protocols. Network overhead is a crucial factor which influencing the efficiency and longevity of wireless sensor networks, as excessive control messaging can drain node energy and congest the network.

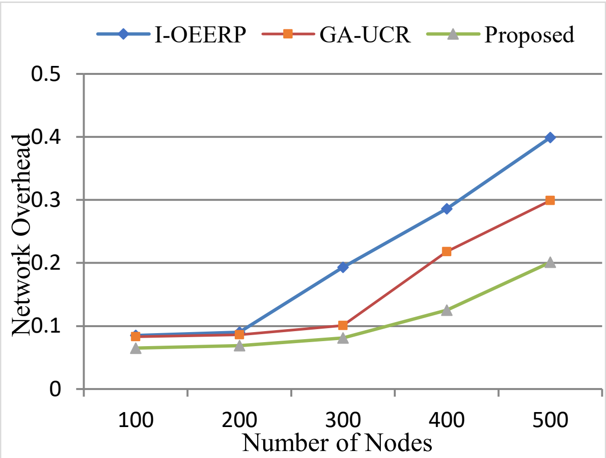

Figure 6.Performance on Network overhead

In SERP-WSN, simulations reveal that the protocol reduces control packet transmissions by approximately 22-37% compared to existing protocols over various node densities. The overhead is minimized via the synergy of intelligent clustering and adaptive routing. The protocol's use of Particle Swarm Optimization streamlines cluster head selection, reducing frequent re-clustering and associated control traffic. Additionally, Q-learning guides routing decisions with localized learning, avoiding excessive broadcast overhead typically involved in route maintenance. This efficient overhead management not only conserves the limited energy of sensor nodes but also mitigates network congestion, thereby preserving bandwidth for higher throughput and reducing packet delay

5. Discussion

This paper introduced a novel hybrid protocol SERP, combines LEACH-based clustering with Particle Swarm Optimization guided by Q-learning for route refinement. The extensive simulation results confirm that the proposed protocol significantly improves major performance metrics. The energy consumption reduced by approximately 21.6%, extends network lifetime between 30% and 35%, increases packet delivery ratio by 15.6%, and decreases end-to-end delay by nearly 39%. By utilizing PSO for global path optimization and Q-learning to adaptively select relays in a dynamic network environment, the protocol achieves reliable, scalable, and energy-effective communications within large sensor deployments. These improvements affirm proposed protocol as a promising solution for high-demand wireless sensor network scenarios. Future research will focus on extending support for mobile nodes and integrating security features to bolster robustness.

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