AN ENERGY EFFICIENT MATHEMATICALLY MODIFIED GLOWWORM SWARM OPTIMIZATION FOR ROUTING IN WSN

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DOI: https://doi.org/10.63001/tbs.2024.v19.i02.S.I(1).pp796-802

KEYWORDS
Sensor network,
optimization,
energy consumption,
swarm intelligence,
and mathematical model.

Received on:

19-09-2024

Accepted on:

26-12-2024

ABSTRACT

WSN is a revolutionary technology that has brought drastic change in the field of environment, health, industry, and smart city [1]. WSNs are wireless networks of spatially distributed sensors that capture, process and forward information about different phenomena of the environment and physical world [2]. These nodes use wireless links to transmit data to a central sink that is responsible for collecting and analyzing collected data. Because of the ability of WSNs to be scalable, flexible, and functional in remote and or risky environments their application is crucial in real time monitoring systems. However, the major constraint emanating from the sensor nodes is the availability of energy that is scarce, which hinders the long-term reliability of such networks [3].
Energy is a major concern in WSNs because most activities in the network including transmitting and receiving data consumes much energy than computation [4]. Low node energy is detrimental to operations because it results to node failures that affect the overall network connectivity and performance. Efficient energy management at each node is crucial to support sustained network longevity, especially in areas that are difficult to reach such as disaster area or industrial facilities where battery replacement is impossible. New optimization methods have brought new ideas to energy efficiency improvement [5].
Algorithms developed from natural inspirations, including Glowworm Swarm Optimization (GSO), considers network conditions and makes routing decisions accordingly. In the same way, Integer Linear Programming (ILP) present a mathematical model for solving the optimization of the energy consuming with certain constraints [6]. While ILP and GSO do not inherently solve each other's problems, hybrid solutions provide reliable and scalable implementations that scale well and cut energy consumption while preserving overall performance [7]. Energy management which prolongs the networks lifetime, cuts expense and lessens the effects on the environment is the fundamental aspect of sustainable WSNs. Through incorporating sophisticated optimization strategies into energy-constrained WSNs, one can achieve scaled up, dynamic and sustainable WSN performance across a broad spectrum of real-world applications [8]. These are critical in managing energy limitations and realizing the WSNs capabilities in the current and emerging technical environment [9].

INTRODUCTION

WSN is a revolutionary technology that has brought drastic change in the field of environment, health, industry, and smart city [1]. WSNs are wireless networks of spatially distributed sensors that capture, process and forward information about different phenomena of the environment and physical world [2]. These nodes use wireless links to transmit data to a central sink that is responsible for collecting and analyzing collected data. Because of the ability of WSNs to be scalable, flexible, and functional in remote and or risky environments their application is crucial in real time monitoring systems. However, the major constraint emanating from the sensor nodes is the availability of energy that is scarce, which hinders the long-term reliability of such networks [3].
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Algorithms developed from natural inspirations, including Glowworm Swarm Optimization (GSO), considers network conditions and makes routing decisions accordingly. In the same way, Integer Linear Programming (ILP) present a mathematical model for solving the optimization of the energy consuming with certain constraints [6]. While ILP and GSO do not inherently solve each other's problems, hybrid solutions provide reliable and scalable implementations that scale well and cut energy consumption while preserving overall performance [7]. Energy management which prolongs the networks lifetime, cuts expense and lessens the effects on the environment is the fundamental aspect of sustainable WSNs. Through incorporating sophisticated optimization strategies into energy-constrained WSNs, one can achieve scaled up, dynamic and sustainable WSN performance across a broad spectrum of real-world applications [8]. These are critical in managing energy limitations and realizing the WSNs capabilities in the current and emerging technical environment [9].
The primary reason leading to this research effort is the need to address unprecedented demand of green and energy efficient WSN deployments. Currently, there is no routing protocol or policy that can enhance energy efficiency, scalability, and performance

concurrently in dynamic network conditions [10]. Shortest-path algorithms are typical, which maximize distance while neglecting energy expenditure, resulting in quick exhaustion of vital nodes. Like many other advanced optimization algorithms, most of them do not consider dynamic feature with respect to network size and topology, which leads to poor performance in real-world application [11].

By proposing the ILP-GSO routing algorithm, these major issues in WSN energy management can be solved, and it provides the efficient solution for large scale practical applications. The algorithm saves energy and reduces cases of node death, thus the useful life of WSNs is elongated to support data acquisition and transmission. The combination of mathematical and bio-inspired optimization methodologies offered by the ODAL approach results in sound methods that can handle the challenges of dynamic WSN settings.

The remainder of this paper is organized as follows: Section two discusses previous studies and literature on energy efficient routing protocols and optimization of Wireless Sensor Networks (WSNs). In Section 3, the proposed methodology is described in detail: the ILP formulation and the modified GSO algorithm. Section 4 addresses the issues of applying the hybrid ILP-GSO framework and the result of the simulations are presented. Section 5 offers a comparative study of the proposed method with other state-of-the-art techniques in the literature. Section 6 summarises the paper and highlights possible avenues for the future research.

Related Works

The UWSNs are characterized by challenges such as high power consumption and propagation delays due to the nature of the underwater environment to which the network is exposed. NBEER is a new neighbor-based energy efficient routing protocol that improves the selection of NHN and cooperation schemes. Some simulation results indicate that the proposed NBEER is better than Co-UWSN, CEER in aspects of energy consumption, delay time and network lifetime [6]. The growing importance of clustering routing protocols for WSNs has led to survey studies centred on metaheuristic based approaches. These protocols give the best strategies for selecting the cluster head to reduce energy consumption. The survey has presented the comparative study of the approaches based on the network structure, metaheuristic algorithms and the reported metrics to analyze the new efficient energy solutions in detail [7].

Wearable IoT (WIoT) includes real-time health monitoring through WBANs but it suffers from energy limitation and higher interference. The DECR protocol proposed here uses a distribution two hop clustering technique and MGWO for cluster head selection which has better energy efficiency, connectivity, and performance parameters compared to other similar protocol [8]. The effectiveness of Internet of Things (IoT) for Wireless Sensor Networks (WSNs) is affected by challenges such routing changes and node faults that hinder energy optimization. A novel hybrid ANFIS Reptile Optimization Algorithm defines the best routes, while fault diagnostic approaches provide a stable environment. Studies reveal that the proposed system uses the least amount of energy and has a longer QoS in comparison [9].

EH-WSNs relay energy constraints by employing routing protocols such as HCEH-UC. There is utilization of hierarchical clustering and distributed node alternation for constant target coverage in the protocol. In simulations, long network lifetime and better energy balance are observed with better coverage than usual methods with the same energy [10]. PSO and FL together constitute the E-FEERP protocol which aims at the selection of cluster head and overall data transfer in WSNs. This method improves the throughput, energy per frame, and network lifetime through parallel computing of PSO and fuzzy decision making [11]. Clusterization and routing increase the WSNs energy components and their lifetime. BOA now picks the selective cluster heads while ACO now designates paths. In comparison with other algorithms LEACH and DEEC the usage of the proposed methodology results in higher outcomes in alive nodes and energy consumption [12].

Proposed Methodology - Mathematically Modified Glowworm Swarm Optimization based Routing

The benefits Data mining brings to the ILP framework are the capabilities for more sophisticated analysis. Cluster analysis provides a way of grouping nodes based on the energy consumption and thereby ensures that every node consumes an equal amount of energy than the other node in the network. ordinal that involves regression or time series models, determines rates of energy depletion to guide the early rerouting of nodes in order to avoid network instability. Classification algorithms that are used dynamically segregate the nodes into high energy and low energy so that always the energy efficient paths are preferred. Furthermore, the association rule mining discovers yet unknown patterns of energy usage and delay metrics that help the ILP model prevent certain suboptimal paths and make better routing choices. These contributions improve the energy utility, network durability and the dynamic routing in the WSN settings.

Integer Linear Programming (ILP) Formulation

ILP is employed to model the energy-efficient routing problem. The objective function aims to minimize the total energy consumption while ensuring the constraints of data transmission are satisfied. The objective function is give in below Equation 1.

$$Minimize \sum_{i=1}^{N}\sum_{j=1}^{N} E_{ij}\, x_{ij}$$

where: E_{ij}: Energy consumed in transmitting data from node i to j, x_{ij}: Binary decision variable, where x_{ij}=1 if data is transmitted from i to j, else x_{ij}j=0, and N: Total number of nodes in the network.

Flow conservation: The proposal assures that the amount of data that flows into a node is equal to the amount of data that flows out of it, only for the source and sink nodes. On one end, we have the source node, which has a net flow out; at the other end we have the sink node which has a net flow in. It assured that there is a continuous and efficient transfer of data within the network. Ensure that data entering a node equals the data leaving it, except at the source and sink nodes is give in below Equation 2.

$$\sum_{j=1}^{N} x_{ij} - \sum_{k=1}^{N} x_{ki} = \{\begin{matrix} 1 & if\ i\ is\ source, \\ -1 & if\ i\ is\ sink, \\ 0 & oterwise. \end{matrix}$$

Node capacity: Node capacity limits the total energy used by a node to send data to not exceed the energy capacity of that node. This prevents certain nodes from running out of energy rapidly thus conserving the network, and the lifetime of the network while at the same time preventing some nodes from using more energy than other nodes in the network. Limit the energy consumption per node is give in below Equation 3.

$$\sum_{k=1}^{N} E_{ij} x_{ij} \leq \sum\nolimits_{max}^{i} \forall i,$$

Where$\sum_{max}^{i}$ is the maximum energy capacity of node i

Glowworm Swarm Optimization (GSO) Integration

GSO is applied to solve the ILP problem iteratively, finding near-optimal routing paths. Each glowworm represents a potential routing path. Initialize glowworm positions $\{G_1, G_2, \dots, G_m\}$ randomly in the solution space, where m is the number of glowworms. Assign initial luminescence $L_i = f(E_i)$, where $f(E_i)$is a fitness function inversely proportional to energy consumption.

Movement Rule: The movement rule in GSO leads glowworms towards neighbors with higher luminance and is thus associated with more efficient energy paths. The movement is computed as a weighted direction toward the neighboring glowworm towards optimal solutions. This adaptive decision-making metrizes the routing in an optimized manner to enhance the network parameters such as energy per delay. Glowworms move toward neighbors with higher luminescence within a local decision range r_i is give in below Equation 4.

$$G_i(t+1) = G_i(t) + \eta \cdot \frac{G_j(t) - G_i(t)}{\|G_j(t) - G_i(t)\|},$$

where η is the step size, j is the neighbour with higher Lj.

Energy Efficiency Evaluation: The fitness function in energy efficiency evaluation is selected as the total energy consumption and transmission delay. There is also a weighting factor included in the formula to adjust between these measures. Reduced energy consumption and delay lead to high path efficiency and therefore enhances the ability to select the best routing paths that will prolong the lifetime of the network and efficiently deliver the data. Incorporate a mathematical model to evaluate path efficiency is give in below Equation 5.

$$L_i = \frac{1}{E_{path} + \alpha . D_{delay}}$$

where E_{path} is the total energy cost of the path, D_{delay} is the transmission delay, and α is a weighting factor.

Luminescence Update: The quality of a glowworm's position is updated according to the fitness of the new position and the luminescence is updated. A decay constant makes sure that the changes in luminescence are slow so that with the help of glowworms, we are led towards better solutions. The dynamic update process used here enables the adaptive optimization of the system where the energy efficiency and the routing quality increases in subsequent iterations. Update Li based on the quality of the new position is give in below Equation 6.

$$L_i = (t+1) = L_i(t) + (1-p), \text{new fitness}$$

where ρ is a decay constant.

Convergence: Iteratively optimize routing paths until a predefined termination condition is met (e.g., maximum iterations or minimal change in L). It is reached when either fine tuning of luminescence or adjustment of routing paths is done in successive steps up to reaching certain convergence criteria that may be set including a tolerance level in each iteration or a maximum number of iterations allowed. This guarantees near-optimal EE routing paths to be discovered by the algorithm while maintaining computational efficiency for solution quality to cope with dynamic departing networks.

Combined ILP-GSO Framework

The ILP model provides constraints and energy evaluation, while the GSO algorithm dynamically explores the solution space: Paths should be initialized using ILP to meet the constraints to achieve the best solution. They include maximization of energy and minimizing of delay by optimizing path selection using GSO. On the fly power update of the nodes and modification of the routing decisions as the network transforms. The scalability of the ILP-GSO method is therefore achieved by the fact that GSO is iterative and can therefore scale to accommodate for larger networks. Energy consumption is now reduced, and node dead is prevented so that the network lifetime is extended. This approach of operation makes efficient routing, reduces energy consumption, and has the benefits of enhancing the transmission data in a dynamic network environment. The procedure is given in Algorithm 1.

Algorithm 1. The routing procedure using ILP-GSO

Algorithm: Combined ILP-GSO Framework for Energy-Efficient Routing
Input: Network topology (nodes and links), energy capacities, and routing constraints
Output: Optimized energy-efficient routing paths

1. Initialize Parameters:
   a. Define total nodes N, maximum energy Σ_max, weighting factor α, step size η, decay constant ρ.
   b. Initialize GSO parameters: number of glowworms m, initial luminescence L_i for each glowworm, local decision range r_i.
2. ILP Initialization:
   a. Formulate ILP objective:

$$Minimize \sum_{i=1}^{N}\sum_{j=1}^{N} E_{ij}\, x_{ij}$$

   b. Apply constraints:
      -Flow conservation:

$$\sum_{j=1}^{N} x_{ij} - \sum_{k=1}^{N} x_{ki} = \{\begin{matrix} 1 & if\ i\ is\ source, \\ -1 & if\ i\ is\ sink, \\ 0 & oterwise. \end{matrix} .$$

      -Node capacity:

$$\sum_{k=1}^{N} E_{ij} x_{ij} \le \sum\nolimits_{max}^{i} \forall i,$$

   c. Solve ILP to generate initial feasible paths.

3. GSO Initialization:
   a. Randomly initialize glowworm positions $\{G_1, G_2, \dots, G_m\}$.
   b. Assign initial luminescence: $L_i = \frac{1}{E_{path}+\alpha . D_{delay}}$, where E_path and D_delay are energy and delay for each path.
4. Iterative Optimization:
   while termination criteria not met (e.g., max iterations, minimal change in L):
      a. For each glowworm G_i:
         i. Evaluate neighbors: Identify neighbors within range r_i.
         ii. Movement Rule: Move G_i toward neighbor G_j with higher L_j using:
         $G_i(t+1) = G_i(t) + \eta . \frac{G_j(t) - G_i(t)}{\|G_j(t) - G_i(t)\|}$.
         iii. Update Energy Efficiency: Recalculate L_i using:
         $L_i = \frac{1}{E_{path}+\alpha . D_{delay}}$
         iv. Update Luminescence: Adjust luminescence using:
         $L_i = (t+1) = L_i(t) + (1-p), \text{new fitness}$
      b. Update Decision Range: Dynamically adjust r_i for exploration/exploitation trade-off.
5. Constraint Validation:
   a. Ensure the updated paths satisfy ILP constraints (flow conservation and node capacity).
   b. Discard infeasible paths and reinitialize if necessary.
6. Convergence Check:
   a. Stop iterations if termination criteria are met.
   b. Otherwise, continue the optimization loop.
7. Output Results:
   a. Return optimized routing paths with minimized energy consumption and delays.
   b. Evaluate performance metrics: energy efficiency, network lifetime, delay, and packet delivery ratio.

Result and Discussion

Specification of the simulation models aimed at analyzing the energy-efficient routing protocol in WSNs entails placing the sensing units in a 1000m x 1000m area. Nodes are placed randomly and energy has been modeled using two-ray ground propagation model. CBR traffic pattern is used for the simulation and node mobility is introduced through the random waypoint mobility model. The routing protocol uses Integer Linear Programming (ILP) to determine the initial path; and a variable Glowworm Swarm Optimization (GSO) to update the path. Values including packet size of 512 bytes, transmission range of 250 meters and simulation time of 500 seconds are chosen. It monitors the transmitting, receiving and idle energy models. Evaluation is done based on parameters such as Energy Consumption, Delay, Network Lifetime and Packet Delivery Ratio.

Energy consumption in WSN can be defined as the total consumed energy by the nodes for transmitting, receiving, processing and in idle mode which has a close relationship with the network lifetime. Delay represents the success time that data packets take to travel from the source node to the destination node or the network's ability to respond. Network Lifetime is the functional lifetime of a WSN, which is commonly measured to the time when the first or a significant number of nodes in the network exhaust their energy. Packet Delivery Ratio (PDR) is the ratio of packets received at some desired location to the packets transmitted from source nodes, which is an essential measure of network reliability and integrity.

Table 1. Comparison of Energy Consumption (J)

Nodes	HCEH-UC	E-FEERP	ILP-GLO
50	1.44	2.48	0.98
100	2.31	3.21	1.30
150	3.30	5.98	2.45
200	4.98	7.69	3.12

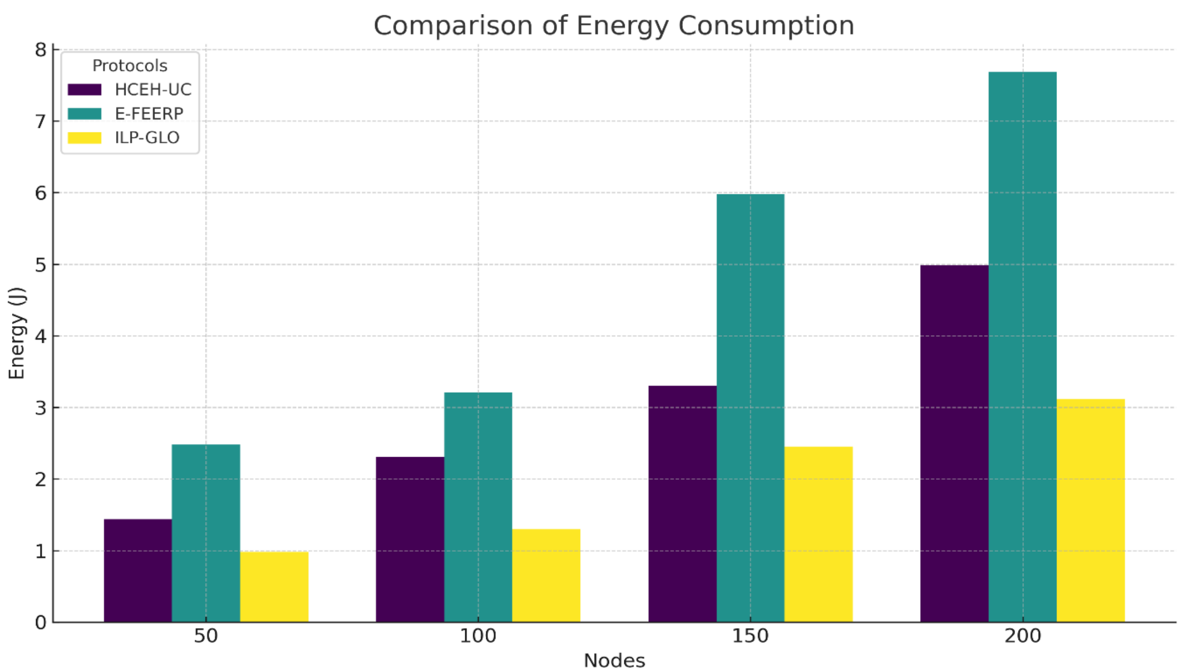

Figure 1. Comparison of Energy Consumption (J)

The energy consumption values for ILP-GLO show consistent improvements over HCEH-UC and E-FEERP for all node counts. For 50 nodes, ILP-GLO consumes 0.98 J compared to 1.44 J and 2.48 J for HCEH-UC and E-FEERP, respectively, marking a reduction of 32% and 60%. As the network scales to 200 nodes, ILP-GLO maintains its efficiency, consuming 3.12 J versus 4.98 J for HCEH-UC and 7.69 J for E-FEERP. Figure 1 highlights the scalability of ILP-GLO, which has a linear increase in energy consumption compared to the more pronounced growth for other protocols.

Table 2. Comparison of Delay (s)

Nodes	HCEH-UC	E-FEERP	ILP-GLO
50	0.69	1.12	0.54
100	2.15	4.65	1.97
150	6.68	9.51	5.04
200	8.92	11.54	7.02

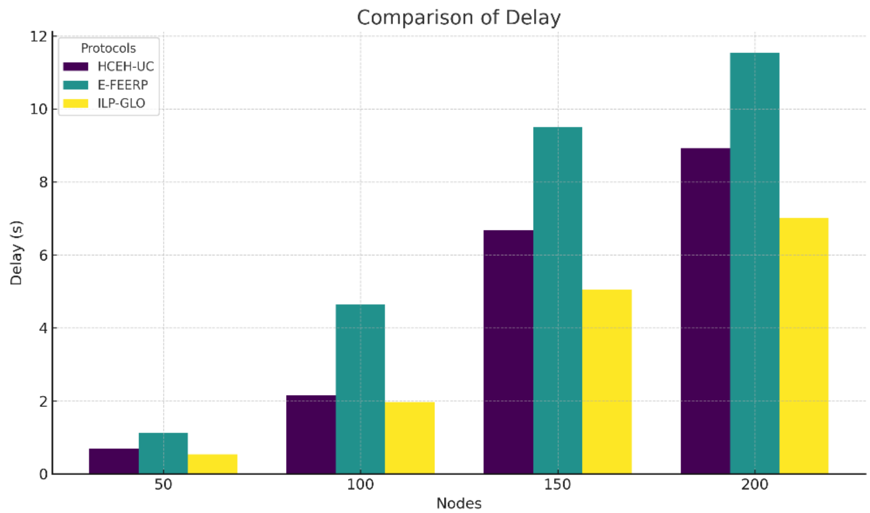

Figure 2. Comparison of Delay (s)

ILP-GLO demonstrates the lowest delay across all node densities, making it the most time-efficient protocol. For 50 nodes, ILP-GLO achieves a delay of 0.54 s compared to 0.69 s for HCEH-UC and 1.12 s for E-FEERP. As the node count increases to 200, ILP-GLO sustains better performance with a delay of 7.02 s, whereas HCEH-UC and E-FEERP exhibit delays of 8.92 s and 11.54 s, respectively. Figure 2 further reinforces the superior delay management of ILP-GLO, which scales more gracefully in dense networks.

Table 3. Comparison of Network Lifetime (s)

Nodes	HCEH-UC	E-FEERP	ILP-GLO
50	71.69	57.48	73.67
100	62.15	53.21	64.58
150	56.68	25.98	58.87
200	28.92	17.69	30.53

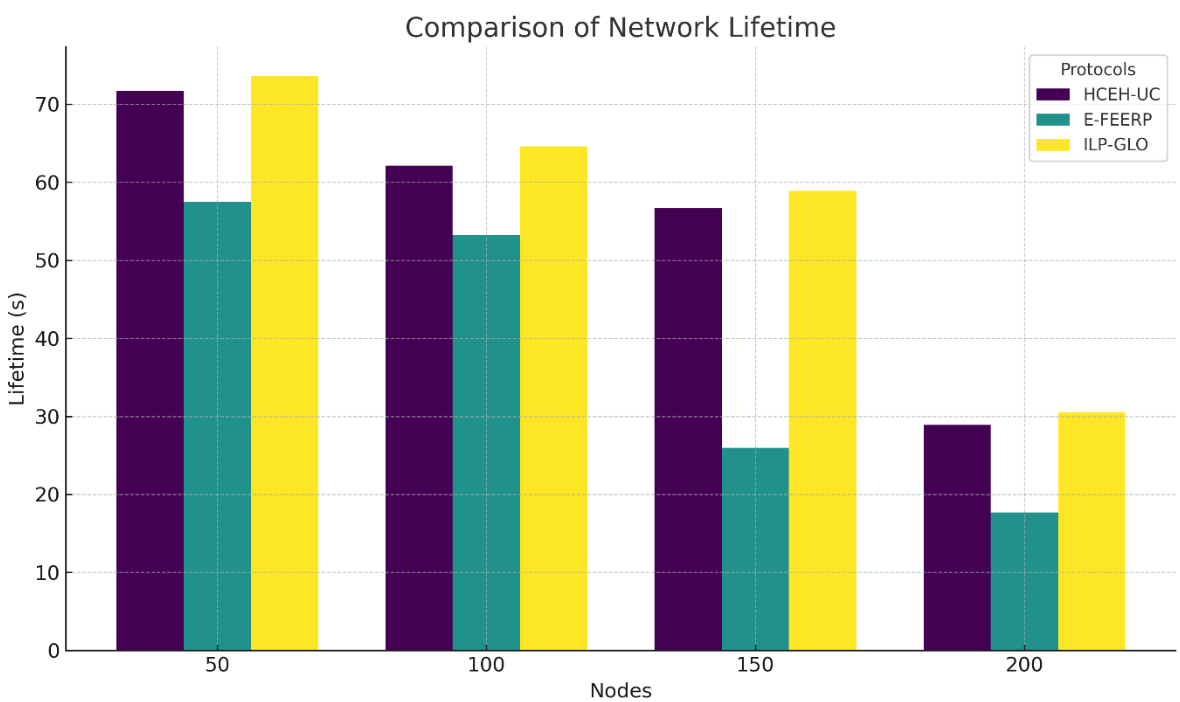

Figure 3. Comparison of Network Lifetime (s)

ILP-GLO consistently extends network lifetime compared to HCEH-UC and E-FEERP. For a network with 50 nodes, ILP-GLO achieves a lifetime of 73.67 s, surpassing HCEH-UC by 2.77% and E-FEERP by 28.16%. Even with 200 nodes, ILP-GLO retains an advantage with 30.53 s compared to 28.92 s for HCEH-UC and 17.69 s for E-FEERP. Figure 3 confirms ILP-GLO's stability and efficiency in maintaining a longer network lifespan even under increasing node density.

Table 4. Comparison of Packet Delivery Ratio (%)

Nodes	HCEH-UC	E-FEERP	ILP-GLO
50	78.56	82.02	99.02
100	75.38	87.76	96.70
150	79.09	84.57	90.45
200	76.39	80.23	87.12

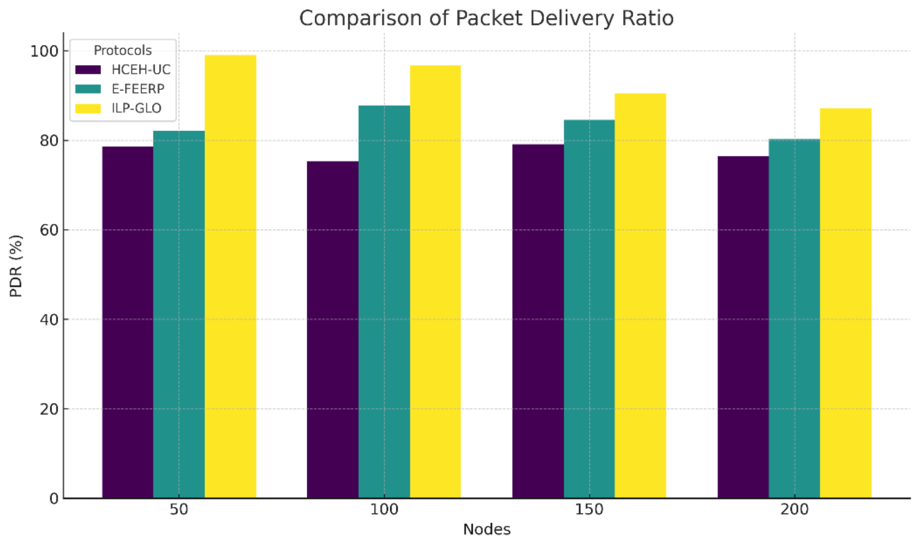

Figure 4. Comparison of Packet Delivery Ratio (%)

ILP-GLO exhibits the highest packet delivery ratio (PDR) among all protocols. For 50 nodes, ILP-GLO achieves 99.02% PDR, which is 26.07% higher than HCEH-UC and 20.74% higher than E-FEERP. As the network size grows to 200 nodes, ILP-GLO sustains a PDR of 87.12%, outperforming HCEH-UC and E-FEERP, which achieve 76.39% and 80.23%, respectively. Figure 4 illustrates the robustness of ILP-GLO in maintaining high data delivery efficiency across varying network scales.

ILP-GLO surpasses HCEH-UC and E-FEERP across all metrics, offering superior energy efficiency, lower delay, extended network lifetime, and higher packet delivery ratio. This robust performance, particularly in dense network environments, demonstrates the effectiveness of combining ILP with GSO for dynamic routing optimization.

CONCLUSION

Energy conservation is an important area in the efficient use of Wireless Sensor Networks (WSNs) since energy in sensor nodes is severely limited. This research proposes the use of techniques in optimization like ILP and modified GSO as keys to energy-conscious routing. The proposed approach can effectively decrease energy utilization, decrease delay, and enhance the lifetime of the network compared to other techniques prevalent in the existing state. Throughput and packet delivery ratio show that the proposed hybrid routing protocol is efficient in providing reliable network operation under different scenarios. The future work could extend this by exploring how collision-aware routing mechanisms can be integrated to improve energy efficiency even further. Interference in WSNs causes data packet collisions and results in retransmission procedures which in turn produce wastage of energy and reduced performance of the network. More energy can be saved and latency reduced by extending effective collision avoidance schemes through adaptive protocols for channel selection and interference avoidance.

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