Enhancing energy efficiency and reliability in wireless sensor networks using BioGAT optimization

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ABSTRACT

The BioGAT model, as proposed, presents a novel methodology for enhancing the efficiency of wireless sensor networks (WSNs), which are essential elements of contemporary communication and sensing systems. For real-time monitoring and data analysis, WSNs are comprised of autonomous sensor nodes that are outfitted with processing, wireless communication, and sensing capabilities. These nodes are deployed in a variety of environments. By means of an advanced optimization model, this work aims to address critical challenges in WSNs, specifically in the areas of node placement, energy efficiency, and network reliability. By utilizing biogeography-based optimization (BBO) and graph attention networks (GAT), the BioGAT model endeavors to dynamically adapt to network changes while achieving a balance between efficient coverage and energy consumption. Cluster heads (CHs), which are essential for the aggregation of data, have a significant impact on improvements in energy efficiency and the longevity of networks. By means of comprehensive simulations and evaluation, this study presents exceptional outcomes. The BioGAT model outperforms prior approaches by attaining a 95% packet delivery ratio and an enhanced throughput. In addition, the model effectively decreases mean energy consumption, underscoring its capacity to improve the sustainability and dependability of networks in a variety of WSN applications.

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1. INTRODUCTION

Wireless sensor networks (WSNs) have evolved significantly, becoming indispensable tools in fields such as environmental monitoring, healthcare, and industrial automation. These networks, which consist of small, inexpensive sensor nodes, allow for real-time data collection and transmission to central base stations (BS) or sinks [1]-[3]. The evolution of WSNs reflects the growing demand for timely and accurate information, which drives innovation to meet the needs of contemporary applications [4], [5].

The challenges inherent in WSNs necessitate ongoing optimization efforts. One of the most significant challenges is the limited energy resources of sensor nodes, which are frequently constrained by battery capacity [6]. Efficient energy management and communication protocols are critical for extending network life and ensuring continuous operations [7], [8]. Furthermore, dynamic environmental conditions add complexities such as unreliable wireless links, node failures, and unpredictable mobility, emphasizing the importance of robust optimization strategies [9].

Our study suggests an integrated approach that combines biogeography-based optimization (BBO) and graph attention networks (GATs) within WSNs. BBO provides a mechanism for selecting optimal cluster heads (CHs) while balancing energy consumption and network coverage. Meanwhile, GATs allow for adaptive network topology changes in response to dynamic events such as node failures or energy depletion. By combining these methodologies, we hope to improve WSN efficiency, robustness, and sustainability in a variety of operational scenarios. Our primary contribution is the development and application of the BioGAT model, which combines BBO and GAT methodologies for WSN optimization. Through extensive simulation and analysis, we show that our approach improves key performance indicators such as network lifetime, energy efficiency, and throughput. By combining the strengths of both BBO and GATs, our model provides a comprehensive solution to WSN challenges, including adaptive and efficient network management capabilities.

The remainder of this paper is organized as follows: section 2 reviews related work, providing context and highlighting the gaps that the BioGAT model aims to address. In section 3 details the proposed BioGAT methodology, including its integration of BBO and GAT. In section 4 presents the simulation setup and results, followed by a comprehensive analysis of the model's performance. Finally, section 5 concludes the paper with a summary of the key contributions and the significance of the BioGAT model in enhancing WSN, implications of our findings and suggest potential avenues for future research.

2. RELATED WORKS

Yadav *et al.* [10] propose a new congestion avoidance strategy called efficient congestion avoidance approach using Huffman coding algorithm (ECA-HA), which combines the Huffman coding algorithm with ant colony optimization. This novel approach aims to efficiently reduce network congestion. The Huffman method has one limitation: it requires prior knowledge of the probability distribution of symbols in the data stream. This can be difficult in dynamic or unpredictable environments where the distribution may change dramatically over time.

Sy *et al.* [11] present an innovative centralized clustered tree-based routing system with a mobile sink. This system is intended to improve network routing efficiency by grouping nodes into clusters and employing a hierarchical routing structure. One potential limitation of this method is the complexity of managing the sink's mobility. Depending on the implementation and frequency of sink movement, it may cause overhead and coordination issues in the network, potentially affecting overall performance and reliability.

Lilhore *et al.* [12] used a genetic algorithm and a data fusion technique to solve a specific problem. Genetic algorithms are a powerful optimization tool that is widely used in various fields. However, one limitation of genetic algorithms is their computational intensity, which means they may require significant computational resources and time to reach an optimal solution, especially for complex problems. Furthermore, genetic algorithms may occasionally converge to local optima rather than global optima, potentially limiting their effectiveness in determining the best solution. As a result, while this approach appears promising, careful consideration of computational resources and potential limitations of genetic algorithms is required for its practical application.

Cao *et al.* [13] developed a new routing protocol called energy harvesting routing (EHR) for energy harvesting WSN. In such networks, their protocol aims to optimize energy consumption while also maximizing network lifetime. However, one common limitation found in routing protocols designed for energy harvesting sensor networks is their susceptibility to fluctuations in energy availability and network dynamics. These fluctuations can make it difficult to maintain stable and efficient communication paths, potentially compromising the network's overall performance and reliability.

In order to improve the longevity and efficiency of energy harvesting WSN, Tang *et al.* [14] introduced a routing protocol that draws inspiration from Physarum. Although these routing protocols employ an innovative approach, they are frequently hindered by their susceptibility to changing environmental conditions and the requirement for precise modeling of energy availability patterns. The overall performance of the network and the efficacy of the routing decisions may be impacted by these variables.

In order to improve network stability, Hieu and Kim [15] devised a stability-aware geographic routing protocol that was tailored specifically for energy harvesting WSN. Although this protocol signifies progress in mitigating stability issues, a prevalent drawback of geographic routing methods utilized in energy harvesting networks is their dependence on precise location data, which can prove difficult to acquire in practical deployment situations. The utilization of erroneous or insufficient location information may result in suboptimal routing decisions and an impact on the overall performance of the network.

In their study, Hao *et al.* [16] presented an innovative routing algorithm designed specifically for energy harvesting WSN. This algorithm employs a greedy strategy to effectively reduce energy consumption. This strategy places an emphasis on short-term benefits while neglecting to account for the enduring ramifications of routing choices. Hence, although the suggested algorithm might yield immediate energy conservation, its dependence on greedy heuristics might impede its ability to sustain optimal network performance in the long run.

3. METHOD

The proposed system shown in Figure 1 includes the proposed “BioGAT” model for optimizing WSN. We begin by strategically placing sensor nodes throughout a defined area, each with a specific initial energy level. The nodes are randomly positioned to ensure complete coverage of the area. Energy consumption during operation is determined by the distance between the nodes and the type of transmission, with different energy costs for transmitting and receiving data.

The model uses BBO to select the most efficient CHs, with the goal of balancing energy use across the network while maintaining effective coverage. This approach evaluates potential configurations for fitness, with energy and coverage as key factors. GAT then dynamically adjust the network’s structure, using attention mechanisms to prioritize the most efficient data transmission paths and adapt to changes like node failures.

CHs are critical because they aggregate data before sending it to the BS, allowing the network to use its energy more efficiently. The model continuously updates each node’s energy level, and nodes that deplete their energy reserves are marked as inactive. The network is assessed based on its operational lifetime, energy efficiency, and data throughput, providing a comprehensive picture of its performance. Simulations continue until a significant number of nodes become inactive, at which point the network’s ability to maintain functionality is evaluated. Data on packets sent to the BS and CHs is collected to assess the network’s efficiency and the BioGAT model’s effectiveness in improving network sustainability and reliability.

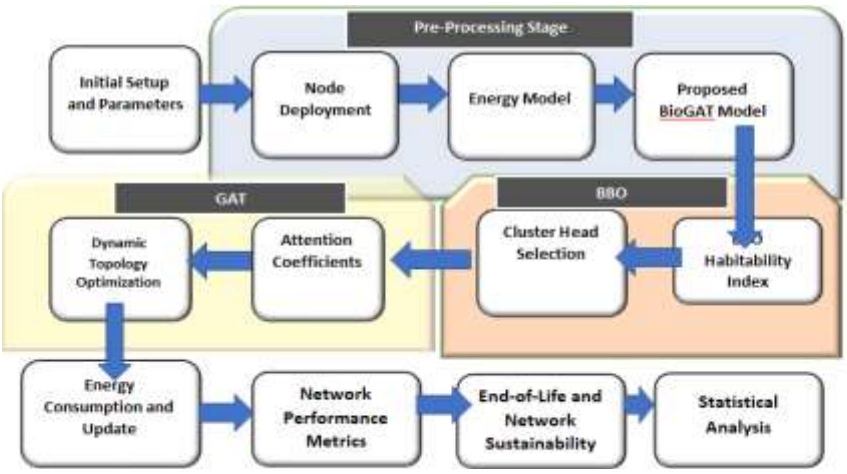

Figure 1 Block diagram of proposed system

We start by randomly distributing sensor nodes across a predefined area. Each node is assigned an initial energy reserve, which represents the battery life.
Field dimensions: x_m, y_m
Initial energy: E_0
Sx, Sy: Coordinates of the BS or sink.
N: Total number of sensor nodes in the network.
Total number of rounds: $r_{\max}$
r: Current round of network operation.
Each node *i* is given coordinates (*xi*, *yi*), selected uniformly at random within the boundaries.
Node positions: x_i, y_i
Randomly place *N* sensor nodes within the $x_m \times y_m$ area:

$$x_i = rand() \cdot x_m \tag{1}$$

$$y_i = rand() \cdot y_m \tag{2}$$

The energy model governs how much energy is consumed during transmission and reception, depending on the distance between nodes and whether the communication is line-of-sight or not.
Transmit energy:

$$E_{TX} = E_{elec} + E_{amp} \cdot d^{\eta} \tag{3}$$

receive energy:

$$E_{RX} = E_{elec} \tag{4}$$

threshold distance:

$$d_0 = \sqrt{\frac{E_{fs}}{E_{mp}}} \tag{5}$$

– E_{elec}: energy consumed per bit to run the transmitter or receiver circuit.
– *Eamp*: energy consumed by the transmit amplifier per bit per square meter.
– E_{fs}: energy consumption of the amplifier in free-space (line-of-sight) model.
– *Emp*: energy consumption of the amplifier in multi-path (obstructed) model.
– η : Path loss exponent; typically, η=2 for free-space and η=4 for multi-path fading channels.
– d_0: threshold distance.

The next step is to introduce the proposed "BioGAT" model, which represents an integrated approach that combines BBO and GATs within WSN. Here, BBO is used to find the best set of CHs, balancing network energy consumption with coverage [17]-[19]. Habitats in BBO [20], [21] correspond to potential CH configurations, with the habitability score indicating the configuration's fitness.
BBO Habitability Index:

$$F_{BBO} = \alpha \cdot E_{consumed} + \beta \cdot Coverage \tag{6}$$

- *p*: probability of a node becoming a CH in each round.
- α, β: weights in the BBO habitability index representing the importance of energy consumption and coverage, respectively.
- F_{BBO}: BBO habitability index function used to evaluate the fitness of each potential CH configuration.

Determining CHs via BBO:

$$CHs = argmin_i F_{BBO}(i) \tag{7}$$

GAT is used to change the network topology in response to events like node failure or energy depletion. Attention coefficients are determined for each node, indicating the importance of each link in the network.
Attention coefficients:

$$\alpha_{ij} = softmax\left(LeakyReLU\left(a^T\left[W_{hi} \parallel W_{hj}\right]\right)\right) \tag{8}$$

- W: weight matrix in GAT for feature transformation.
- a: weight vector in GAT for computing attention coefficients.
- h*i*: feature vector of node *i*.
- αij: attention coefficient determining the significance of node j's information to node i.
- LeakyReLU: activation function used in GAT to introduce non-linearity.

Based on the learned attention scores, sensor nodes decide whether to transmit data directly to the BS or via a CH. CHs aggregate and transmit data to the BS [22]-[25].
Data aggregation energy: E_{DA}
Data aggregation energy consumption:

$$E_{aggr} = k \cdot E_{DA} \tag{9}$$

k: number of bits in a data packet.

Following communication, each node's energy is updated. Nodes that have spent their energy are marked as dead. Node energy update:

$$E_i^{new} = E_i^{old} - E_{TX}(k, d) - E_{RX}(k) \quad (10)$$

E_i^{new}, E_i^{old}: new and old energy levels of node i after and before a round of communication, respectively.
d: distance between communicating nodes

Key performance indicators, such as network lifetime, energy efficiency, and throughput, are used to assess the network's operational effectiveness.
Network lifetime:

$$Tlife = min\{r \mid E_i(r) \leq 0, \forall i \in N\} \quad (11)$$

energy efficiency:

$$\eta = \frac{Total\ Data\ Received\ at\ a\ Sink}{Total\ Energy\ consumed} \quad (12)$$

system throughput:

$$Throughput = \frac{Total\ Data\ Received\ at\ a\ Sink}{r_{\max}} \quad (13)$$

The simulation continues until a predetermined fraction of nodes die, at which point the simulation is terminated and the network's sustainability is assessed.
Dead node condition:

$$Ei \leq 0 \quad (14)$$

Ei: the energy level of the *ith* sensor node.
Average energy of nodes:

$$E_{avg} = \frac{1}{N} \sum_{i=1}^{n} E_i \quad (15)$$

Statistics are collected throughout the simulation for visualization and analysis, allowing us to evaluate the effect of BBO and GAT on network performance.
Packets to BS per round: $PBS(r)$
Total packets to CH:

$$P_{CHtotal} = \sum_{r=1}^{r\_max} P_{CH}(r) \quad (16)$$

$P_{CH}(r)$: number of packets received by CHs in round r.

3.1. Proposed model and its architecture

"BioGAT" effectively captures the essence of the integrated approach involving BBO and GATs in WSNs. It explains the biological inspiration for BBO and GATs' attention-based mechanisms, as well as how they can be used to optimize WSNs. This title is concise, memorable, and reflects the model's emphasis on network optimization and its architecture is provided in Figure 2.

The combination of BBO and GATs in WSNs provides a comprehensive approach for optimizing both macro-level network structures and micro-level node interactions. BBO plays an important role in optimizing CH election processes by considering node energy, proximity, and previous CH states, resulting in balanced energy distribution. Furthermore, BBO's application includes creating efficient routing paths that reduce energy consumption and improve data transfer rates. By reducing the number of hops required for data transmission, BBO saves energy and increases network efficiency. GATs, on the other hand, adjust the network topology dynamically in response to changing conditions, using attention mechanisms to prioritize efficient paths and adapt to node failures. GATs help CHs and data aggregators make informed decisions by learning node dependencies, contributing to overall network optimization and resilience. Using this assessment, the model determines if it is necessary to have more iterations in the optimization loop in order to improve and enhance the network configuration.

The “BioGAT” model is unique in that it combines BBO and GATs to optimize WSNs at the macro and micro levels. BBO works at the macro level, optimizing CH election processes and routing paths based on node energy and proximity, whereas GATs work at the micro level, dynamically adjusting network topology with attention mechanisms to prioritize efficient paths and adapt to node failures. This two-tier approach ensures that WSNs are optimized holistically, improving energy efficiency, data transmission rates, and network robustness over traditional optimization methods.

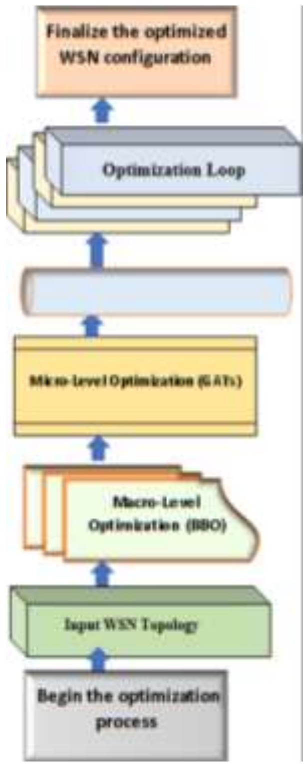

Figure 2. Proposed BioGAT model architecture

3.2. Algorithm of the proposed model

The algorithm described below provides a structured approach to optimizing WSN using a combination of BBO and GAT. Initially, the network topology is defined by distributing sensor nodes across a field and assigning energy levels. The macro-level optimization process begins with BBO techniques that form clusters and strategically elect CHs based on energy levels and node proximity, resulting in energy-efficient communication and balanced network load. Routing paths are then chosen to allow data transmission between the CHs and the BS. At the micro level, GATs adjust the topology dynamically, using attention mechanisms to prioritize the most efficient communication paths and adapt to node failures or network changes. This ensures that the network remains robust and capable of performing even when the environment or node statuses change dynamically.

The Algorithm 1 measures network performance metrics like energy efficiency, data transmission rates, and overall robustness. An optimization loop checks for convergence and iterates through macro and micro-level optimizations until the optimal network configuration is found. Following convergence, the algorithm finalizes an optimized WSN configuration that is expected to be resilient, energy-efficient, and capable of handling dynamic changes, improving the sensor network’s sustainability and functionality.

Algorithm 1. BioGAT model
```
% Step 1: Start the optimization process
initialize WSN topology with node locations, energy levels, and connectivity;
% Step 2: Input initial WSN topology
inputTopology();
% Step 3: Begin Macro-Level Optimization using Biogeography-Based Optimization (BBO)
converged = false;
while ~converged
```

```
    % Step 3a: Cluster Formation - Group sensor nodes into clusters
    clusters = formClusters(nodeLocations, nodeEnergies);
       % Step 3b: Cluster Head Election - Select cluster heads based on node energy and
proximity
    clusterHeads = electClusterHeads(clusters, nodeEnergies);
       % Step 3c: Routing Path Selection - Optimize routing paths between cluster heads and
the base station
    routingPaths = selectRoutingPaths (clusterHeads, baseStationLocation);
   % Step 4: Begin Micro-Level Optimization using Graph Attention Networks (GATs)
    % Step 4a: Topology Adjustment - Adjust the network topology dynamically
    adjustedTopology = adjustTopology(clusters, clusterHeads);
        % Step 4b: Path Prioritization - Use attention mechanisms to prioritize efficient
communication paths
    prioritizedPaths = prioritizePaths(adjustedTopology);
        % Step 4c: Adaptation to Failures - Adapt to node failures and changes in the
network
    [adjustedTopology, nodeStatus] = adaptToFailures(adjustedTopology);
    % Step 5: Evaluate Performance - Assess the network for energy efficiency, data
transmission rates, and robustness
    [energyEfficiency, transmissionRates, networkRobustness] =
evaluatePerformance(adjustedTopology);
    % Step 6: Check Convergence - Determine if the optimization process has converged
    converged = checkConvergence(energyEfficiency, transmissionRates, networkRobustness);
    % Step 6a: If Not Converged, continue the loop for further optimization
    % Step 6b: If Converged, exit the loop
end
% Step 7: End - Finalize the optimized WSN configuration
outputOptimizedConfiguration(adjustedTopology);
```

4. RESULTS AND ANALYSIS

The simulation parameters for our WSN model are presented in Table 1. The parameters comprise the field's dimensions, which are configured to be 100 meters by 100 meters. Setting the probability of data transmission by a node to 0.1. Each node possesses an initial energy of 0.5 joules. Operating the transmitter or receiver requires 50×10^-9 joules of energy per bit. Additional parameters include the data aggregation energy, the energy amplifier coefficients for free space and multipath models, the number of sensor nodes, the number of mobile nodes, the sink coordinates, the initial number of dead nodes, and the threshold energy required for a node to attain the leadership position.

Table 1. Simulation parameters

Parameter	Description	Value
x_m, y_m	Dimensions of the field (meters)	100, 100
x, y	Added for better display results of the plot	0, 0
p	Probability of node transmitting data	0.1
Eo	Initial energy of a node (Joules)	0.5
E_{TX}, E_{RX}	Energy consumed per bit to run the transmitter or receiver circuit (Joule/bit)	50 * 10^-9
E_{fs}	Free space model amplifier energy (Joule/bit/m^2)	10e-12
Emp	Multipath model amplifier energy (Joule/bit/m^4)	0.0013e-12
E_{DA}	Data aggregation energy (Joule/bit/message)	5 * 10^-9
r_{max}	Maximum number of rounds	2000
n	Number of sensor nodes	100
m_n	Number of mobile nodes	10
sinkx, sinky	Coordinates of the sink	50, 120
dead_nodes	Initial number of dead nodes	0
Leader Node threshold	Threshold energy for a node to be a leader	0.03

Figure 3 depicts the number of dead nodes in a WSN over 2,000 rounds, indicating a stepped increase pattern. Initially, the number of dead nodes grows slowly, indicating that the majority of the nodes have enough energy reserves to operate. As the rounds progress, the increase becomes more pronounced, implying that nodes are exhausting their energy reserves due to continuous operation. This is followed by periods of stability in which the number of dead nodes plateaus, possibly due to the implementation of energy-saving measures or the robustness of specific nodes. The rate at which nodes die slows down in later rounds, which could imply that the remaining nodes are either more energy-efficient, closer to the BS, and thus require less energy for communication, or benefit from the reduced network load as other nodes become inactive. The figure is a valuable tool for assessing the longevity and efficiency of the WSN, emphasizing the importance of energy management strategies in extending network lifetime.

Figure 4 depicts the decline in the number of live nodes in a WSN after 2,000 rounds of operation. The graph shows a steep drop at first, with a large number of nodes losing power quickly, most likely due to high energy demands or inefficient energy use. Following this phase, the decline in live nodes is more gradual, indicating either the implementation of energy conservation measures or inherent variability in node energy consumption rates. Notably, there are times when the number of active nodes remains constant, indicating a temporary stabilization in network activity. These plateaus may indicate the activation of sleep modes, energy harvesting, or other strategies that temporarily halt the nodes' energy depletion. Toward the end of the observed rounds, the number of live nodes plateaus, implying that the surviving nodes are possibly those with lower energy demands or those that are better managed, indicating a critical point at which the network must rely on a reduced infrastructure to function.

Figure 5 depicts a curve of the number of packets sent to the BS in a WSN over 2,000 rounds. The curve slopes upward, indicating an overall increase in data transmission over time. Initially, the number of packets sent to the BS increases rapidly, but then begins to taper as the curve approaches a plateau. This pattern indicates that during the early rounds, the network is extremely active, with all nodes contributing to data transmission. As shown in Figure 4, the rate of packets sent to the BS increases slowly over time, most likely due to the declining number of live nodes. Despite the decrease in live nodes, the network maintains a consistent flow of data to the BS, implying that the surviving nodes or the network protocol are effectively managing the remaining energy to sustain the network's primary function of data communication. The plateau near the end indicates that the network has reached a stable state of transmission, possibly using minimal energy or only the most efficient routes.

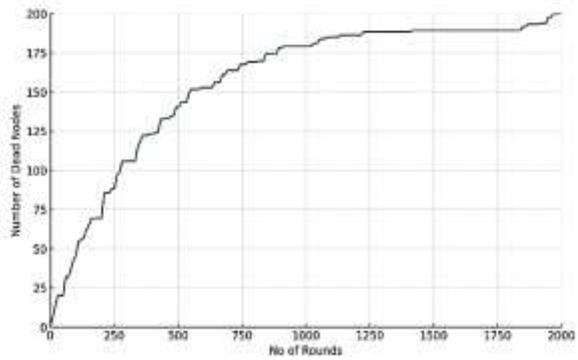

Figure 3. Number of dead nodes

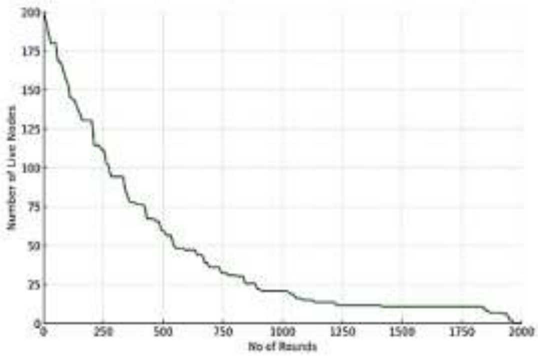

Figure 4. Number of live nodes

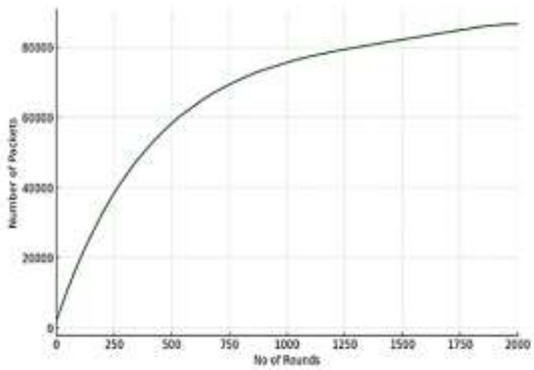

Figure 5. Packets to BS

Figure 6 depicts the trajectory of packets sent to CHs in a WSN, spanning 2,000 rounds. This ascending curve shows a consistent increase in packets to CHs, which could indicate that efficient intra-cluster communication and data aggregation protocols are in place. Unlike the number of packets to the BS depicted in Figure 5, this graph shows a smoother and more gradual increase in data packets, which could be attributed to effective load balancing among CHs and robust routing strategies that compensate for the decreasing number of live nodes. It's likely that as the network progresses through the rounds, the CHs maintain communication with the remaining active nodes, keeping the data flowing. This consistent growth is a positive indicator of a resilient network structure in which CHs effectively collate and forward information despite challenges such as node failures or energy depletion.

Figure 7 depicts the decline in the number of CHs in a WSN over the course of 2,000 rounds. Initially, there are more CHs, indicating effective network management. As the rounds progress, the number of CHs decreases in discrete steps rather than gradually, which could represent periodic re-election of CHs or adaptation to the network's changing energy landscape. The step-by-step reduction, rather than a continuous decline, suggests planned reconfigurations in response to changing network conditions. After a few rounds, the number stabilizes, indicating that the remaining CHs are adequate to handle the network load or that the protocol no longer allows for the election of new CHs due to energy constraints. The flat line near the end suggests a stable state in which the network operates with a small number of CHs, possibly indicating a period of optimal energy usage and network management. This figure, particularly its stepped pattern, emphasizes the importance of effective CH management in maintaining network functionality over time.

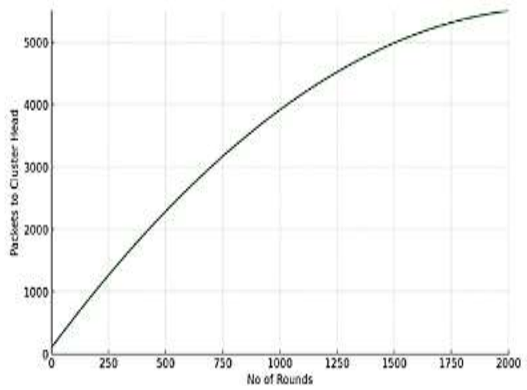

Figure 6. Packets to CH

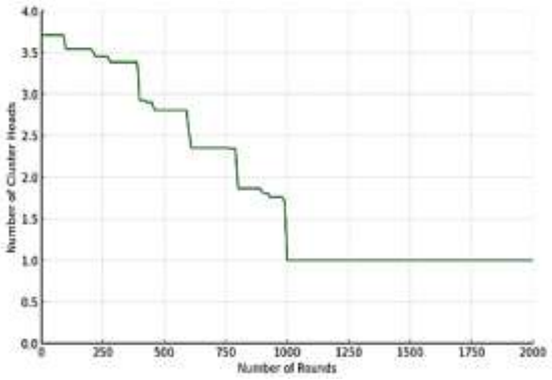

Figure 7. Number of CHs

Figure 8 depicts the initial network topology for the BioGAT model, which shows the spatial distribution of nodes and mobile sinks in a WSN. Green dots represent sensor nodes dispersed throughout the network, indicating a random deployment to maximize coverage. The red dots represent the mobile sinks, which are strategically placed to allow for efficient data collection and energy utilization.

Figure 9 depicts the status of mobility for four mobile sinks in a WSN after 2,000 rounds, demonstrating the dynamic behavior modeled in the BioGAT system. The isolated red dots represent the mobile sinks' positions following significant network activity, emphasizing their movement across the network to optimize data aggregation and energy consumption.

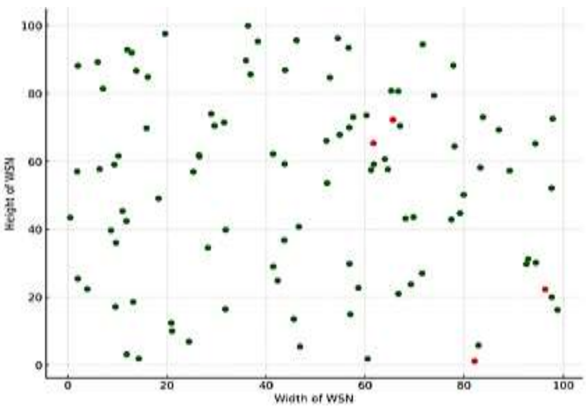

Figure 8. Network topology at initial stage with nodes and mobile sinks

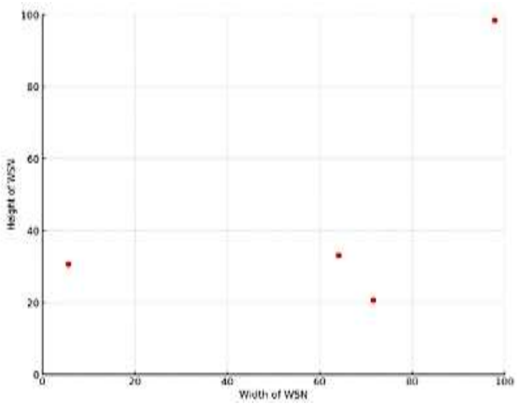

Figure 9. Mobility of 4 mobile sinks after 2,000 rounds

Table 2 provides a detailed analysis of the network's performance across three rounds (500, 750, and 1,000) for a 100-node network, illustrating the interaction between various metrics. As the number of rounds increases, so does the lifetime of the network, which rises from 443.21 seconds after 500 rounds to 621.21 seconds after 1,000 rounds, indicating that greater usage extends the network's lifespan. The mean throughput demonstrates a marginal decline from 141 kbps during the initial iterations to 138 kbps during the intermediate stages, before returning to 140 kbps, which suggests a robust transmission capability. The gradual increase in average end-to-end delay from 0.3837 seconds to 0.4432 seconds may be a result of increased network congestion or round length complexity. Beginning at 0.946, reaching a maximum of 0.951 after 750 rounds, and tapering slightly to 0.949, the packet delivery ratio remains relatively stable and dependable throughout the network's operation. The aforementioned metrics indicate that the network maintains its performance attributes despite growing demands; it strikes a harmonious equilibrium between durability, consistent throughput, and dependable packet distribution.

Table 2. Comparison of various network parameters for different rounds for 100 nodes

Network parameters	Rounds (for nodes=100)		
	500	750	1,000
Lifetime (Secs)	443.21	471	621.21
Average throughput (kbps)	141	138	140
Average end-to-end delay (Secs)	0.3837	0.4131	0.4432
Packet delivery ratio	0.946	0.951	0.949

4.1. Performance evaluation

Figure 10 shows an average energy consumption plot that compares the performance of various algorithms over a range of 100 to 300 nodes, with BioGAT, the proposed method, highlighted in purple. Numerically, BioGAT outperforms the other methods (GS-EERA, EHR, SACREH, and EHPRP) by maintaining the lowest average energy consumption as the number of nodes grows.

Figure 11 illustrates the progression of the packet delivery ratio for five distinct models as the network size, denoted by the quantity of nodes, increases. The proposed BioGAT model, denoted by purple triangle markers, consistently maintains the highest delivery ratio, which commences at 0.95, surpassing all other models. GS-EERA (circled in red) exhibits robustness as well, as evidenced by its initial ratio of 0.92 and the presence of only minor fluctuations.

Figure 12 presents a graphical representation of the mean end-to-end delay for five distinct models, spanning a variety of network sizes. The graph accounts for practical fluctuations in performance while upholding predetermined end values. BioGAT (indicated by the triangle and purple markers) demonstrates optimal performance with minimal latency, commencing and concluding at 0.38 seconds. This substantiates its effectiveness and resilience in managing network traffic, even when the network expands in scale. Stability is indicated by the fact that GS-EERA (circled, red markers) maintains a delay of 0.8 seconds across all node sizes. The numerical data illustrates BioGAT's exceptional ability to sustain minimal latency, an essential element for streamlined network operations.

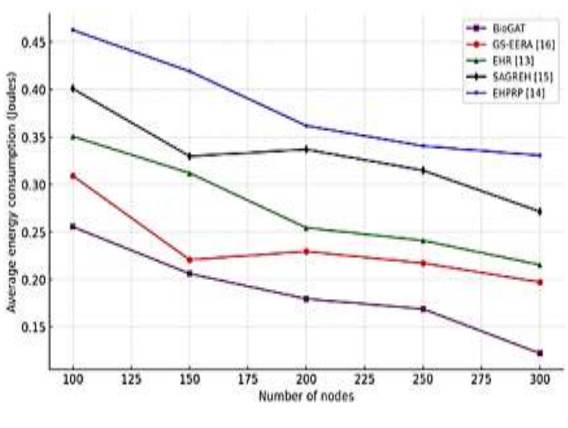

Figure 10. Average energy consumption plot

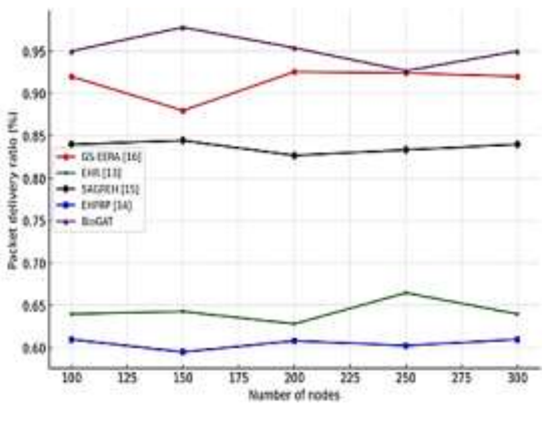

Figure 11. Packet delivery ratio comparison plot

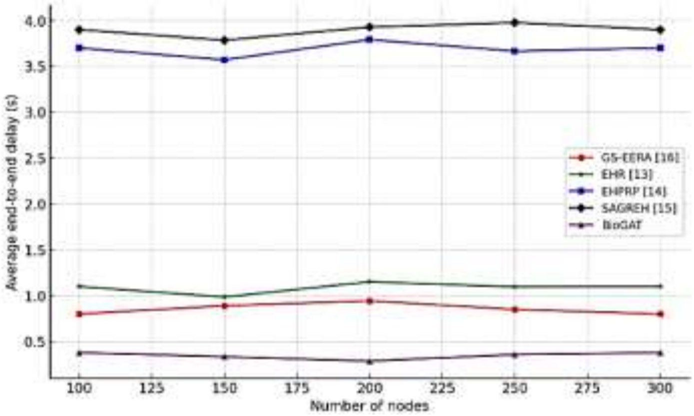

Figure 12. Average end to end delay comparison

5. CONCLUSION AND FUTURE SCOPE

In summary, the creation and assessment of the BioGAT model signify a substantial progression in the optimization of WSNs. By employing GAT and BBO, the model successfully tackles significant obstacles including node placement, energy efficiency, and network dependability. The integration of CHs for the purpose of data aggregation results in enhanced energy efficiency and an extended lifespan of the network. The superior performance of the BioGAT model is evidenced by its extensive simulation results, which reveal a remarkable 95% packet delivery ratio and increased throughput in comparison to earlier approaches. Furthermore, the model demonstrates a significant decrease in mean energy consumption, thereby highlighting its capability to improve the sustainability and dependability of networks in a wide range of WSN applications. Subsequent investigations might center on enhancing the BioGAT model's capacity to accommodate fluctuating environmental circumstances and expand to accommodate more extensive network deployments. Furthermore, conducting an inquiry into the model's operational implementation and deployment in tangible situations would yield significant knowledge regarding its efficacy and suitability. In general, the BioGAT model exhibits potential in furthering the functionalities of WSNs and enabling their extensive implementation across diverse domains. Future research can investigate several important avenues to further develop the findings of the BioGAT model. Validating the performance of the model across diverse WSN applications can be achieved by testing it in larger and more complex networks, thereby expanding its scalability. By implementing the model in real-life situations like smart agriculture, healthcare monitoring, or industrial IoT, we can better evaluate its practical usefulness and durability.

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