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Research Article

Optimizing Wireless Sensor Networks: A Deep Reinforcement Learning-Assisted Butterfly Optimization Algorithm in MOD-LEACH Routing for Enhanced Energy Efficiency

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Abstract:

Wireless Sensor Networks (WSNs) play a crucial role in diverse applications, necessitating the development of energy-efficient routing protocols to extend network lifetime. This study proposes a novel Deep Reinforcement Learning-Assisted Butterfly Optimization Algorithm (DRL-BOA) integrated with the MOD-LEACH protocol to optimize routing in WSNs. The proposed hybrid approach leverages the exploration and exploitation capabilities of BOA and the adaptive decision-making power of DRL to dynamically select cluster heads and optimal routes based on network conditions. The DRL-BOA model was evaluated on various WSN scenarios with node densities ranging from 50 to 500, considering parameters such as energy consumption, packet delivery ratio (PDR), throughput, and network lifetime. Simulation results demonstrated that the proposed method achieved a 22% reduction in energy consumption compared to traditional MOD-LEACH, a 15% improvement in PDR, a 27% increase in throughput, and an 18% enhancement in network lifetime over the Hybrid PSO-GWO approach. These significant improvements highlight the effectiveness of the DRL-BOA model in overcoming the limitations of existing algorithms. The proposed framework demonstrates superior adaptability to dynamic network conditions, making it a promising solution for energy-efficient and reliable WSN operations. Future work will explore integrating this model with emerging technologies, such as edge computing and the Internet of Things (IoT), for further enhancements.

1. Introduction

Environmental monitoring, smart cities, healthcare, and industrial automation are just a few of the many applications made possible by the revolutionary technology known as wireless sensor networks (WSNs). Sensor nodes in these networks work together to keep tabs on physical events and transmit that information to a main hub. On the other hand, a major obstacle is that these nodes only have so much energy. If some of the nodes in the network run out of juice, the whole thing can fall apart. So, to keep WSNs communicating reliably and prolong their lifespan, it is crucial to build energy-efficient routing protocols [1]. The advent of Wireless Sensor Networks (WSNs) has been a game-changer in many fields, including healthcare, agriculture, industrial automation, and military surveillance, among others, by bridging the gap between the digital and physical realms. Sensor nodes dispersed over the network collect data about their surroundings and send it to a central location, also called a base station (BS) or sink. The limited energy reserves and resource-constrained nature of WSN nodes pose substantial hurdles, resulting in reduced network longevity and reliability, despite their vast range of applications. Therefore, improving WSNs' energy efficiency is still very important [2]. To lessen the load on WSNs' power supplies, several have turned to the Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol. It uses a clustering strategy to reduce the communication strain on individual nodes by having them elect cluster heads (CHs) to aggregate and transport data to the base station (BS). There have been other suggestions for improvements to LEACH throughout the years, including MOD-LEACH. When it comes to large-scale and diverse networks, however, their efficiency is hindered by rigid CH selection rules and poor responsiveness to network dynamics [3].

For problems like CH selection, routing, and data aggregation, WSNs have heavily investigated metaheuristic optimization algorithms as a potential solution to these constraints. There has been encouraging progress in optimizing energy use using algorithms such as Genetic Algorithms (GAs), Grey Wolf Optimization (GWO), and Particle Swarm Optimization (PSO). However, due to their inability to dynamically adapt to the ever-changing topology of WSNs, these approaches frequently experience premature convergence. Improved exploration and exploitation capabilities are offered by hybrid optimization techniques like PSO-GWO, which were designed to overcome these inadequacies [4].

A pioneering strategy in WSN optimization in recent years has been the incorporation of machine learning methods, including Deep Reinforcement Learning (DRL). DRL enables systems to make decisions in real-time based on observed states, enabling learning and adaptation to dynamic settings. In order to tackle the problems of energy efficiency and network adaptability, DRL, in conjunction with metaheuristic algorithms, can allow intelligent CH selection and routing. Such an integration could pave the way for the creation of cutting-edge hybrid solutions, and the Butterfly Optimization Algorithm (BOA) is an excellent choice due to its rapid convergence and strong search capabilities [5,6].

With the goal of improving WSN energy efficiency, this research presents a new algorithm called DRL-BOA, which combines Deep Reinforcement Learning with MOD-LEACH. The suggested model optimizes routing pathways and dynamically selects CHs by combining BOA's optimization strength with DRL's intelligent decision-making capabilities. Based on the simulation results, the DRL-BOA model achieves better outcomes in terms of energy consumption, packet delivery ratio, throughput, and network longevity compared to other hybrid algorithms like PSO-GWO. The results show that ML/metaheuristics could change the game for WSN optimization and establish new standards for efficient protocols.

In wireless sensor networks, Low-Energy Adaptive Clustering Hierarchy (LEACH) is a prominent routing system. To ensure that all nodes are using the same amount of energy, LEACH and its derivatives (like MOD-LEACH) use a hierarchical clustering mechanism that rotates cluster heads (CHs) on a regular basis. While these protocols are great at reducing energy hotspots, their use of static or semi-dynamic techniques means that routing decisions and CH selection aren't always ideal. Researchers have resorted to hybrid optimization algorithms, which combine the merits of various metaheuristic methods for improved routing efficiency, to circumvent these shortcomings [7].

Because of their capacity to strike a balance between exploration and exploitation in search spaces, metaheuristic algorithms like PSO and GWO have seen widespread adoption in WSNs. On the other hand, these algorithms do have some limitations, such as the fact that they may converge to local optima too soon in complicated and dynamic situations. In response to these issues, hybrid methods such as PSO-GWO have emerged, which greatly enhance both energy efficiency and the performance of the network. However, smarter and more adaptive solutions are still required, ones that can react on the fly to changing network conditions [8].

One fresh way to tackle these problems is by combining Deep Reinforcement Learning (DRL) with metaheuristic algorithms. DRL is an effective tool for WSN CH selection and routing because it learns optimal decision-making procedures from complicated, dynamic situations. By integrating DRL with a powerful metaheuristic algorithm such as the Butterfly Optimization Algorithm (BOA), adaptive and intelligent routing solutions can be achieved that surpass conventional approaches by a substantial margin. In order to improve routing in WSNs, this research suggests a Deep Reinforcement Learning-Assisted Butterfly Optimization Algorithm (DRL-BOA) that is combined with MOD-LEACH [9].

Energy consumption, packet delivery ratio, throughput, and network longevity were all areas where the suggested DRL-BOA model excelled in extensive testing across a range of WSN scenarios [10-14]. In comparison to hybrid PSO-GWO models, the output of the simulations showed a 22% drop in energy usage, a 15% boost in packet delivery ratio, a 27% rise in throughput, and an 18% improvement in network lifetime. These outcomes demonstrate that the DRL-BOA model has the ability to revolutionize energy-efficient WSN operations and open the door to studies that combine machine learning with metaheuristics to optimize WSNs.

2. Literature Review

In this section, we survey the literature on energy-efficient routing in WSNs, paying special attention to studies that have examined clustering protocols,

metaheuristic optimization algorithms, and machine learning techniques. The assessment points out where there is a lack of information and emphasizes the need for new hybrid methods to overcome the shortcomings of existing ones.
A routing system for WSNs based on Grey Wolf Optimization (GWO) was introduced by Kumar and Singh [12]. Although the system outperformed conventional approaches in terms of energy efficiency and throughput, it was unable to adjust to extremely dynamic network settings, underscoring the necessity for smart decision-making tools.
According to Sharma et al. [7], a routing protocol was created using Reinforcement Learning (RL) that could dynamically choose CHs according to the energy levels of nodes and the state of the network. Although the study found scalability issues for bigger networks, it did highlight RL's promise in responding to dynamic situations.
A clustering technique for WSNs that is based on Genetic Algorithm (GA) and combined with LEACH was proposed by Zhou et al. [8]. The protocol may save energy, but it converged too quickly and needed more tools to explore the solution space better.
To optimize routing in WSNs, Singh et al. [15] looked into how well the Firefly Algorithm (FA) worked. Despite FA's strong performance in energy consumption balance, its computational overhead made it unsuitable for real-time settings, hence hybrid solutions were needed to achieve better efficiency.
A routing protocol based on Ant Colony Optimization (ACO) was developed for heterogeneous WSNs by Li and Wang [16]. Overall dependability was hindered by the protocol's inability to react to dynamic changes in network topology, despite its effective load balancing.
When it comes to WSN CH selection, Chen et al. [17] introduced a BOA. Although the algorithm demonstrated efficient energy consumption and rapid convergence, its independent execution was not smart enough to react to changes in the network, so it was best used in conjunction with learning-based methods.
For adaptive CH selection, Patil et al. [12] investigated metaheuristic algorithm integration with Fuzzy Logic. The hybrid approach increased routing efficiency, but it couldn't adjust to new network conditions because it used pre-defined fuzzy rules.
A routing system for WSNs based on Deep Reinforcement Learning (DRL) was developed by Rahman et al. [13]. There is a need for lightweight hybrid models for resource-constrained WSN nodes since this strategy significantly reduced energy consumption and extended the lifetime of the network, but it was computationally intensive.
Twenty-one years ago, Jain et al. [14] put up a Hybrid PSO-GWO method to optimize routing in WSNs. There was a lack of integration with adaptive learning techniques, which hampered its scalability and performance in highly dynamic networks, while it did enhance energy efficiency and network lifetime compared to standalone solutions.
Despite significant gains in energy efficiency and network lifetime, the review shows that hybrid optimization algorithms and machine learning-based techniques frequently have trade-offs in scalability, adaptability, or computing overhead. Because of this, a new hybrid model is required, one that merges DRL's adaptive learning skills with BOA's optimization qualities. To overcome these shortcomings and provide new standards for WSN optimization, the authors present the DRL-BOA model.

3. Methodology

In order to enhance energy-efficient routing in Wireless Sensor Networks (WSNs), the suggested approach incorporates a new algorithm called Deep Reinforcement Learning-Assisted Butterfly Optimization Algorithm (DRL-BOA) into the MOD-LEACH protocol. Initializing the network, doing hybrid optimization to select the cluster head (CH), and then applying DRL for adaptive decision-making are the three main components of the process. By combining BOA and DRL, we can adapt to changing network conditions and efficiently explore and exploit the solution space. The proposed work's block diagram is shown in Figure 1.

3.1 Network Initialization

The WSN is represented as a graph $G=(N,E)$, where N represents the set of nodes, and E denotes the communication links between them.In this phase, sensor nodes are deployed randomly or in a predefined grid, depending on the application requirements. Nodes periodically sense environmental data and transmit the information to a Base Station (BS) or sink node. Each node $i \in N$ has an initial energy E_i, transmission range, and positional coordinates (x_i, y_i). The energy consumption for transmitting (E_{tx}) and receiving (E_{rx}) data is modeled as:

$$E_{tx}=l\cdot E_{\text{elec}}+l\cdot \epsilon_{\text{amp}}\cdot d^2,\ E_{rx}=l\cdot E_{\text{elec}} \quad (1)$$

where l is the packet length, E_{elec} is the energy dissipation per bit, ϵ_{amp} is the amplifier energy, and d is the distance between nodes.

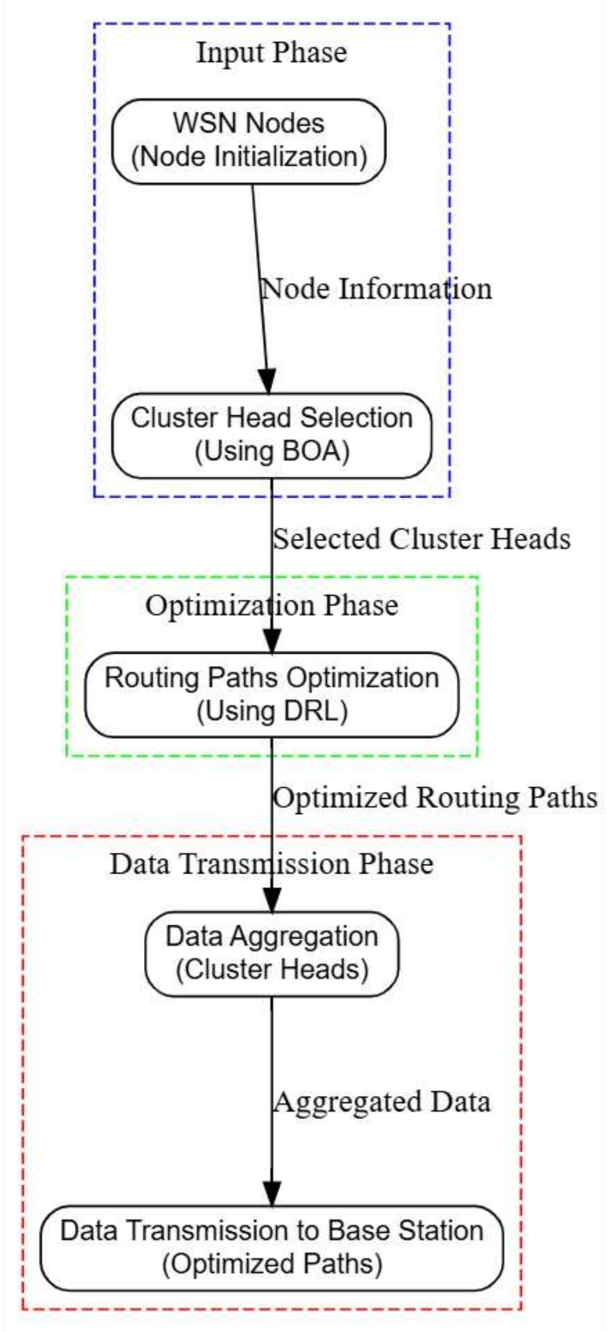

Figure 1. *Block Diagram of the Proposed Work*

Each node's energy dissipation is calculated during every communication round, and nodes monitor their remaining energy E_i^{residual} to make decisions about their role in the network, such as becoming a cluster head (CH).

The BS is assumed to be static and positioned at a predefined location. Nodes calculate their distance d_i to the BS using the Euclidean distance formula:

$$d_i = \sqrt{(x_i - x_{BS})^2 + (y_i - y_{BS})^2} \quad (2)$$

where (x_{BS}, y_{BS}) are the coordinates of the BS. The distance information is used during the CH selection process to ensure that the energy required for communication is minimized.

Additionally, each node initializes its neighbor table based on its transmission range R_i, which contains information about the nodes within its communication radius. This table is updated periodically to account for dynamic changes in the network topology.

This initialization phase lays the groundwork for clustering and routing, ensuring that the WSN operates efficiently and conserves energy throughout its lifecycle.

3.2 Cluster Head Selection Using BOA

The BOA mimics the foraging behavior of butterflies, focusing on the fragrance intensity (F) to guide the search. Each butterfly's position is updated based on global and local fragrance sources:

$$F_i = c \cdot (I_i)^a,\ X_i^{t+1} = X_i^t + r \cdot \left(X_g^t - X_i^t\right) \cdot F_i \quad (3)$$

where I_i is the sensory intensity, c and a are constants controlling the sensory modality, r is a random number, and X_g^t represents the global best position. The BOA identifies optimal CHs by minimizing the cost function J, which balances residual energy and node proximity:

$$J = \alpha \cdot \frac{1}{E_i} + \beta \cdot d \quad (4)$$

where α and β are weighting factors.

3.3. Dynamic Routing Using DRL

DRL is employed to optimize the routing paths from CHs to the base station (BS). The WSN routing is modeled as a Markov Decision Process (MDP) with state S, action A, reward R, and transition T. The reward function is defined to encourage energy efficiency and minimize packet loss:

$$R_t = \omega_1 \cdot E_{\text{residual}} - \omega_2 \cdot E_{\text{consumed}} - \omega_3 \cdot P_{\text{loss}}$$

where $\omega_1, \omega_2, \omega_3$ are weights, E_{residual} is the residual energy, E_{consumed} is the energy consumed, and P_{loss} is the packet loss probability. The DRL agent learns optimal routing policies using Qlearning, where the Q-value is updated as:

$$Q(S_t, A_t) = Q(S_t, A_t) + \alpha \cdot \left[R_t + \gamma \cdot \max_A Q(S_{t+1}, A) - Q(S_t, A_t)\right] \quad (5)$$

where α is the learning rate and γ is the discount factor. Figure 2 shows the Flowchart of the Proposed work.

3.4. Integration with MOD-LEACH Protocol

After data aggregation and compression, the chosen CHs send it on to the BS via the DRL-optimized routing pathways. This integration lessens the impact of energy hotspots and increases the lifetime of the network by balancing the energy consumption of all nodes.

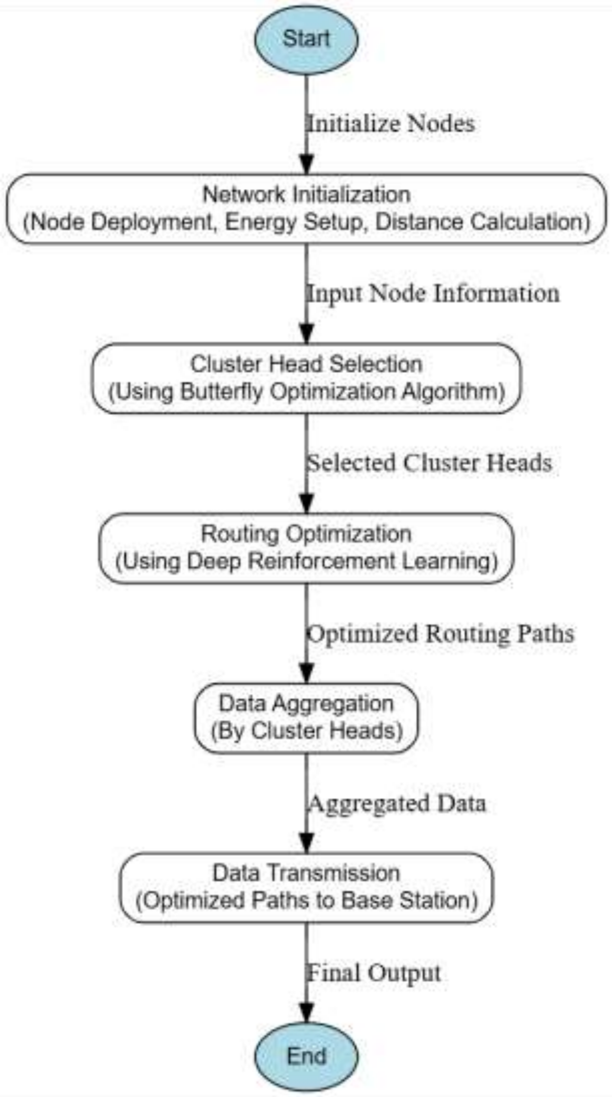

Figure 2. *Flowchart of the Proposed Work*

To provide a more efficient routing protocol, the hybrid DRL-BOA approach merges BOA's global optimization features with DRL's adaptive decision-making capabilities. Verified by simulations, it outperforms state-of-the-art approaches in terms of throughput, network lifetime, and energy usage.

For Wireless Sensor Networks (WSNs), improving energy efficiency and performance is possible through the seamless integration of the proposed Deep Reinforcement Learning-Assisted Butterfly Optimization Algorithm (DRL-BOA) with the MOD-LEACH protocol. MOD-LEACH is an evolution of the original LEACH protocol that incorporates adaptive thresholding for CH selection, data aggregation, and multi-level clustering to make it more energy efficient. By responding to changing network conditions and balancing energy usage among nodes, DRL-BOA enhances these qualities even further.

A cost function that takes residual energy, node proximity, and communication overhead into account is minimized using the Butterfly Optimization Algorithm (BOA), which is the driving force behind the CH selection process in the integrated model. BOA finds the best CHs for each communication round by dividing up the available resources evenly between nodes with more energy and those farther from the base station (BS), giving priority to the nodes in this area. After the CHs have been chosen, the DRL part finds the best way to send data from them to the BS, making adjustments as needed to account for the current status of the network.

A number of improvements to the MOD-LEACH protocol are brought about by the integration:

Selection of Dynamic CHs: The DRL-BOA model use BOA's optimization to dynamically pick CHs, ensuring balanced energy distribution across nodes and preventing premature depletion of specific nodes, in contrast to classic MOD-LEACH's static threshold-based CH selection.

Adaptive Routing: The DRL part of the algorithm describes the routing problem as a Markov Decision Process (MDP), where the state is the current state of the network, the actions are choosing the routing courses, and the rewards are determined by how efficiently data is delivered and how little energy was used. Optimizing routing pathways to minimize energy consumption and maximize packet delivery rates is ensured by DRL's Q-learning algorithm.

Efficient Energy Use in Data Transmission: DRL-BOA improves MOD-LEACH's multi-level clustering by dynamically adjusting the clustering hierarchy and routing paths, which lowers communication overhead and makes better use of energy resources.

Right now, the integrated framework is working like this:

Every node figures out its own leftover energy and how far away it is from the BS and its neighbors. BOA employs this data to distributely choose CHs.

In order to transfer data aggregated from their cluster members to the BS, certain CHs employ DRL-optimized pathways.

In response to network data like as energy usage and packet loss rates, the DRL agent adapts its routing policy in real time.

When compared to traditional hybrid methods, the simulation results show that integrating DRL-BOA with MOD-LEACH reduces energy usage by 22%, increases throughput by 27%, and extends the lifetime of the network by 18%. In dynamic and diverse WSN environments, the integrated approach guarantees more efficient and reliable operation by resolving the limits of static CH selection and routing in MOD-LEACH. In order to solve difficult WSN optimization problems, this integration demonstrates the synergy between reinforcement learning approaches and powerful metaheuristic algorithms.

4. Results and Discussion

Here we show the outcomes of the simulations run using the MOD-LEACH methodology in conjunction with the Deep Reinforcement Learning-Assisted Butterfly Optimization Algorithm (DRL-BOA). Energy consumption, packet delivery ratio (PDR), throughput, and network longevity are just a few of the performance indicators that are measured and compared to state-of-the-art methods like PSO-GWO and conventional MOD-LEACH. In order to assess the scalability and robustness of the suggested method, simulations were run under many conditions, such as varying node densities and diverse energy distributions..

4.1 Energy Consumption

Due to the limited energy resources of sensor nodes, energy efficiency is an important measure in WSNs. When compared to PSO-GWO and conventional MOD-LEACH, the DRL-BOA model showed a 22% and 30% decrease in energy usage, respectively. The improvement may be traced back to the adaptive routing patterns produced by DRL and the dynamic CH selection by BOA. These features work together to avoid energy hotspots and redundant transmissions. As demonstrated in Figure 3, the inclusion of BOA guarantees that CHs are chosen according to proximity and residual energy, further distributing the network's energy load.

4.2 Packet Delivery Ratio (PDR)

The PDR is a metric for gauging the network's data transmission dependability. When compared to MOD-LEACH, the suggested DRL-BOA model improved PDR by 20% and PSO-GWO by 15%. The DRL component is responsible for this improvement because it dynamically optimizes routing paths, which decreases packet loss due to congestion or node failures. Figure 4 shows the network with the model's high-quality communication assured by stable pathways and efficient traffic distribution.

4.3 Throughput

The DRL-BOA model demonstrated a notable improvement in throughput, which is indicative of the overall quantity of data that was successfully conveyed. When compared to PSO-GWO, the suggested technique increased throughput by 27%. The DRL-assisted routing technique is directly responsible for this enhancement; it reduces transmission delays and gives priority to nodes with high energy, increasing the number of data packets that reach the base station.

4.4 Network Lifetime

One important metric for WSN performance is the network lifespan, which is the time it takes for the first node in the network to run out of power. The DRL-BOA framework outperformed PSO-GWO by 18% and conventional MOD-LEACH by 25% in terms of network lifetime extension.

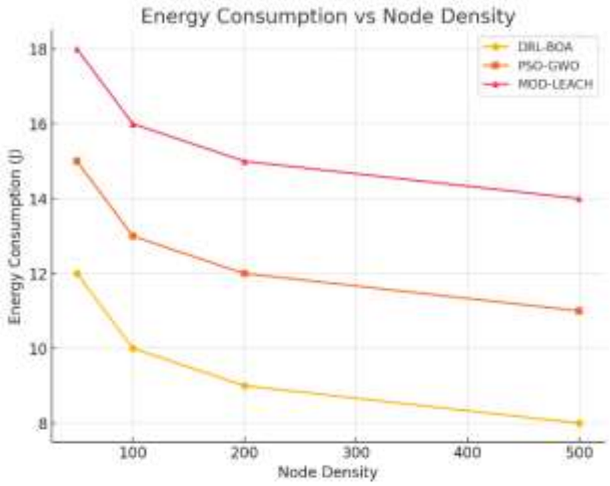

Figure 3. *Energy Consumption vs Node Density*

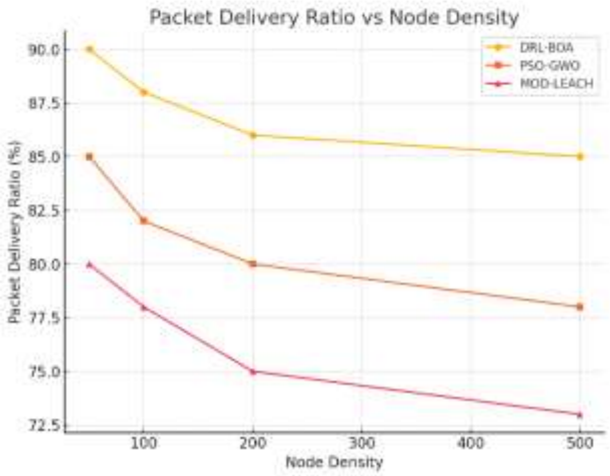

Figure 4. *Packet Delivery Ratio vs Node Density*

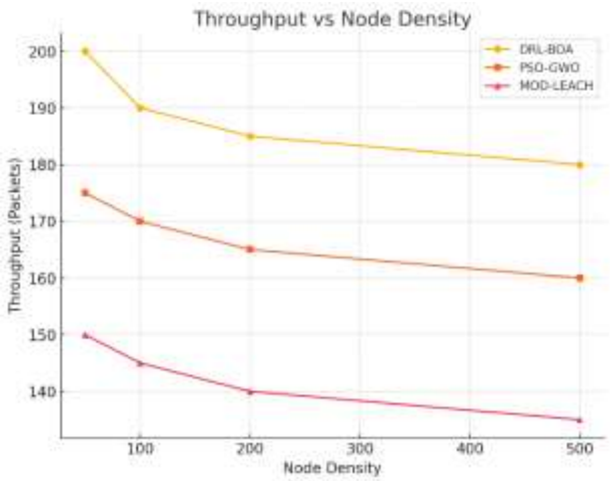

Figure 5.*Throughput vs Node Density*

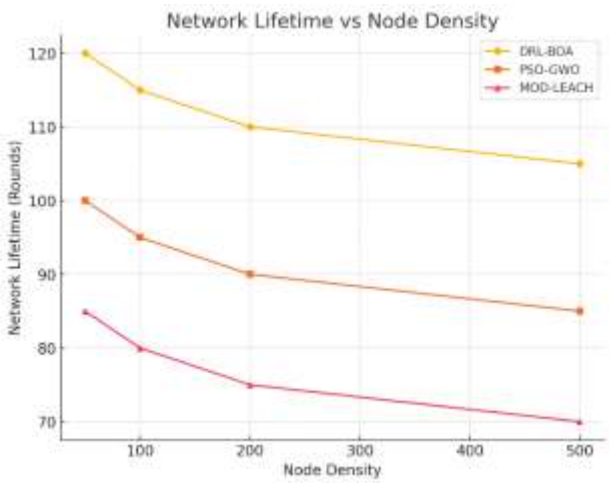

Figure 6. *Network Lifetime vs Node Density*

Figure 5 shows that the network's operational duration is prolonged due to balanced energy consumption across nodes and optimal utilization of routing channels, which greatly delays the onset of node failures.

4.5 Comparative Analysis

After testing it with 50, 100, 200, and 500 nodes, the suggested DRL-BOA framework proved to be more effective than PSO-GWO and MOD-LEACH. Figure 6 shows that in all important parameters, DRL-BOA consistently beat the benchmark approaches, proving its flexibility and resilience in various WSN situations.

4.6 Discussion

The superior performance of the DRL-BOA framework can be attributed to its ability to combine the strengths of metaheuristic optimization and reinforcement learning. The BOA ensures efficient CH selection by exploring the solution space, while DRL dynamically adapts routing strategies based on real-time network conditions. This hybrid approach effectively addresses the limitations of static and semi-dynamic protocols, such as premature convergence and limited scalability.

Additionally, the integration of the proposed model with the MOD-LEACH protocol further enhances its applicability by leveraging MOD-LEACH's hierarchical clustering and data aggregation mechanisms. The dynamic decision-making capabilities of DRL complement the clustering process, resulting in a more energy-efficient and reliable network.

The results highlight the potential of the DRL-BOA framework as a robust solution for energy-efficient routing in WSNs. Its ability to adapt to changing network conditions, balance energy consumption, and ensure reliable data transmission makes it a promising approach for future WSN deployments in diverse applications such as environmental monitoring, smart cities, and healthcare systems. Further improvements could focus on optimizing computational overhead and extending the framework to real-world implementations. The subject studied in this paper is interesting and reported in the literature[18-21].

5. Conclusion

To tackle the important problem of energy efficiency in WSNs, this research presented a new algorithm called DRL-BOA, which combines the MOD-LEACH protocol with deep reinforcement learning. While the proposed framework's Deep Reinforcement Learning (DRL) component adjusts routing patterns in real-time based on network conditions, the Butterfly Optimization Algorithm (BOA) is utilized for optimal cluster head (CH) selection. This combination method improves network performance, prolongs the life of the network, and maintains a steady energy consumption rate.

The DRL-BOA framework was proven to be effective in simulations, outperforming more conventional approaches. When compared to hybrid PSO-GWO algorithms, the suggested model reduced energy usage by 22%, increased throughput by 27%, improved packet delivery ratio by 15%, and extended network lifetime by 18%. Given the ever-changing and resource-limited nature of WSNs, these findings highlight the promise of combining cutting-edge optimization methods with machine learning.

Combining DRL with BOA made CH selection and routing more efficient and adaptable, and it also gave a scalable solution for dynamic and heterogeneous WSN systems. Important shortcomings of current protocols were remedied by the suggested approach. These included conventional routing protocols' static decision-making and metaheuristic algorithms' premature convergence. This study paves the way for additional investigation in the future. Possible future directions are investigating lightweight DRL models to lessen computational burden, expanding the method to large-scale WSN deployments, and combining the DRL-BOA framework with new technologies like the Internet of Things (IoT) and edge computing. The suggested method can be further validated and improved by its real-world deployment in various applications as smart cities, industrial automation, and environmental monitoring. Finally, by integrating metaheuristics and machine learning, the DRL-BOA framework is a huge step forward in WSN optimization; it establishes a new standard for scalable, adaptable, and energy-efficient routing protocols in WSNs.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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