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Hybrid DBO-GWO Multi-Objective Clustering with Light Weight Attention Based Routing Framework for Energy Optimized IoT Networks

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ABSTRACT

Massive deployments of the Internet of Things (IoT) require efficient, scalable routing methods to sustain a long-term network lifespan with limited resources or computational power. Routing protocols that use clusters are usually unable to optimize energy use and prolong network lifetime due to a static selection of the cluster heads (CHs) and non-adaptive routing intelligence. This research identifies a hybrid Dung Beetle Optimization-Grey Wolf Optimization (DBO-GWO) multi-objective clustering framework and a lightweight attention-based routing mechanism for the IoT to minimize energy consumption through energy-efficient routing. The DBO-GWO hybrid approach assesses potential CHs using both global and local optimization techniques. When choosing CHs through the DBO-GWO system, it minimizes intra-cluster distance, communication cost, and overall energy use, while maximizing energy retained at the node and network stability. The proposed framework shows a marked improvement in the number of rounds, a significant increase in the packet delivery ratio (PDR) to 98.1%, and a decrease in end-to-end delay, while minimizing per-round energy usage. These results also confirm that hybridizing bio-inspired optimization with attention-based routing provides both energy- and computationally efficient solutions for future IoT networks.

1. INTRODUCTION

The expanding breadth of Internet of Things (IoT) applications has led to many large-scale deployments of wireless sensor networks (WSNs) in areas such as smart cities, environmental monitoring, industrial automation, and healthcare. A WSN includes many sensor nodes with limited battery power, so energy-efficient data routing is a key design issue. Direct routing from sensor nodes to the sink node uses excessive energy. Thus, cluster-based routing protocols are a popular, efficient way to improve scalability, reduce transmission distances, and extend the lifetime of WSNs.

Cluster-based routing protocol types include LEACH and some of the variants, and are typically based on random or fixed selection of cluster heads (CHs). As a consequence, energy depletion is not evenly distributed among nodes, which often leads to an early failure of nodes within the network. Researchers have begun to study intelligent and optimization-based methods for forming clusters as an alternative solution. For example, Wang et al. [1] proposed a fuzzy logic approach to improving the efficiency of CH selection through the use of quantum annealing, thereby also reducing total energy consumption within a cluster. Lei [2] used a combination of particle swarm optimization (PSO) and fuzzy clustering methodologies to develop an energy-aware route. This hybrid approach has significantly improved the energy balance of the nodes within the cluster-based routing protocol.

There is limited research on using bio-inspired and metaheuristic optimization methods to solve the energy optimization problem in Cluster-based Routing. In 2016, Ahirwar developed a hybrid, bio-inspired swarm intelligence algorithm to optimize both clustering and routing, thereby improving network lifetime [3]. In 2017, after conducting a study with Yang et al. [4], they developed an energy-efficient routing path algorithm using a multi-strategy fusion snake optimizer that incorporates the Minimum Spanning Tree (MST) solution within the routing packets sent between CHs. Finally, in 2017, with Prakash et al. [5], we used spotted hyena optimization to improve upon node heterogeneity and residual energy levels during CH selection in heterogeneous networks.

Recent studies have also examined hybrid metaheuristics to enhance routing performance. From a hybrid metaheuristic perspective, El Khediri et al. [6] developed a cluster routing protocol that minimizes communication overhead by optimizing both clustering and inter-cluster routing. Hussain et al. [7] developed an IoT-based WSN training and discovery approach based on map diminishment, demonstrating enhanced energy efficiency and balanced routing under dynamic network conditions. These optimization-based clustering studies all demonstrate successful clustering; however, nearly all use heuristic fitness functions, and none employ adaptive learning methods to adapt the algorithm to time-dependent traffic variations.

Recently, Machine Learning (ML) and AI-based routing protocols have attracted researchers' attention for their ability to address many of these issues. For example, as noted by Tan [8], a new clustering routing protocol (EEB-CR) based on ML has been developed that improves load balancing and stability through energy efficiency. Similarly, Wang et al. [9] proposed an approach to obtaining intelligent clustering and adaptive routing decisions using a combination of Deep Reinforcement Learning (DRL) and Quantum-inspired Harris Hawk Optimizer. Furthermore, Priyadarshi et al. [10] noted that using AI-based routing algorithms has greatly improved energy efficiency, latency, and reliability of data delivery within WSNs.

The rapid increase in the number of large-scale IoT applications requires scalable, energy-efficient routing protocols. Such protocols must sustain the lifetime of a network with limited processing capabilities. Current cluster-based routing protocols rely on predetermined methods that cause nodes to become exhausted much faster than other methods, since CH selection is static, and there is no dynamic ability to find intelligent routes. An effective solution to address the limitations of existing cluster-based routing protocols is proposed by using a hybrid (DBO-GWO) dual optimization technology to jointly optimize multiple objectives for IoT Networks. Additionally, the routing protocol will use a low-complexity, attention-based approach to optimally route packets within energy-optimized networks. The proposed hybrid method will enable users to simultaneously select optimal CHs, minimize intra-cluster distance, communication cost, and energy consumption, and maximize residual network energy while stabilizing the network through exploration and exploitation mechanisms. The proposed hybrid model will allow for the greatest reduction in the computation required for routing decisions, compared with currently popular ML methods that require substantial computation.

The main contributions of this research are summarized as follows:

- The newly developed hybrid multi-objective clustering algorithm combines the exploration adaptability of DBO with the convergence stability of GWO to allow for optimal CH selection.
- Additionally, we develop a new lightweight routing mechanism that dynamically prioritizes next-hops based on residual energy, link reliability, and queue congestion, without incurring the computational burden of deep learning.
- Finally, we establish a framework for joint clustering and routing optimization that minimizes global energy consumption while providing a high Quality of Service (QoS).
- These methods have been thoroughly tested, yielding statistically significant improvements in network lifetime, energy efficiency, packet delivery ratio (PDR), throughput, and delay.

Section II will provide a review of energy-efficient clustering and routing methods, as well as optimization methods. Section III presents the system model and the proposed intelligent cluster routing framework. Section IV describes the simulation setup and performance metrics, presents simulation results, and compares cases. Finally, the last section concludes this paper and offers suggestions for future research.

2. LITERATURE REVIEW

Recent advancements in WSNs and IoT-enabled environments have led to the use of intelligent routing techniques. These approaches aim to address challenges such as energy efficiency, scalability, and adaptability. We will review previous work on AI- and RL-based routing methods, as well as on heuristic and hybrid robot-optimization techniques. This will clarify their contributions and limitations.

2.1 Adaptive learning-based routing approaches

Building on this, artificial intelligence is an effective means of dynamic routing in WSNs. Liu et al. [11] proposed an intelligent routing algorithm that used distributed neural networks to guide network nodes in dynamically adjusting routing decisions at each node based on the local and global state of the network. Although this approach provides greater adaptability and routing efficiency, the additional computational load imposed on each node and the need to continuously update the model may limit its usefulness for resource-constrained IoT deployments.

Similarly, reinforcement learning techniques have been gaining interest as a means of optimizing adaptive routing through multi-agent reinforcement learning. Soltani et al. [12] developed a multi-agent RL-based routing algorithm to enable nodes to make routing decisions cooperatively and reduce energy use. In another study, Eskandarpour et al. [13] developed an approach that combines principles from game theory with RL to optimize the selection of CHs to improve energy balance and fairness among the CH nodes. DRL has also been investigated in environments with dynamic mobility. Sani et al. [14] introduced a DRL-based dynamic cluster routing protocol for the case of vehicular opportunistic networks. Even though they are good at handling topology changes due to mobility, these systems require substantial training and rely on a centralized learning model. This leads to problems with scaling in dense IoT sensor networks with very strict energy constraints.

2.2 Heuristic and protocol-based routing approaches

Turning to heuristic and protocol-based approaches, few literature reviews have summarized existing routing approaches. For instance, Ibrahem and Hamza [15] have developed an IoT-based version of a traditional distributed clique-based energy-efficient clustering method (IoT-DEEC) that incorporates additional criteria for IoT environments. Even though this approach achieved better performance than traditional methods, it still relies on static clustering techniques, which do not perform as well when routing is required between mobile nodes. Shokouhifar et al. [16] conducted an extensive literature review of AI-based clustering routing protocols within the context of fuzzy logic, meta-heuristic, and ML models. This analysis shows a tendency toward increasingly intelligent routing; however, the study also identifies significant challenges in terms of complexity, scalability, and energy overhead, as reported in the literature.

Expanding on this topic, Khedr et al. [17] focused on context-aware routing in IoT-based WSNs. They concluded that networks need adaptive mechanisms to respond to changing conditions. Del-Valle-Soto et al. [18] reviewed metaheuristic clustering routing protocols and found that hybrid optimization techniques perform better. However, these hybrids need to be integrated with learning models for more adaptability. Many studies have worked to improve energy-efficient clustering using protocol-level enhancements.

2.3 Hybrid metaheuristic optimization approaches

In the context of hybrid metaheuristic optimization, metaheuristic algorithms have remained popular for energy-efficient clustering and routing. Pedditi and Debasis [19] developed a metaheuristic-based multi-area clustering and routing (MACR) algorithm to jointly optimize clustering and routing in WSNs based on IoT. MACR improves energy usage but relies on predefined fitness functions and static optimization cycles. Moussa et al. [20] developed an energy-hybrid routing protocol (EHRP) that uses both single-hop and multi-hop routing to balance energy consumption and delay, thereby improving performance. However, EHRP performs less effectively than expected in environments with erratic traffic patterns. Lastly, Purushotham and Muddana [21] proposed a cooperative deep learning and optimization framework to increase the security and performance of IoT WSNs, yet their work focuses more on providing security measures than on maximizing clustering and routing energy efficiency.

Recent evaluations have further explored this topic. Ramesh and Gopalakrishna [22] investigated energy-efficient autonomous underwater vehicles (AUVs) for underwater WSNs. While their benchmark provides significant insights into energy-efficient routing protocols, they assume that the constraints associated with an underwater WSN would prevent it from being widely applicable outside the underwater environment of aquaculture. Hybrid optimization frameworks have also been proposed to enhance complementary performance. To illustrate this theory, Chitra and Sudarmani [23] proposed a BIRCH-ACO-based approach combined with PSO-MST for energy-efficient data aggregation in software-defined WSNs. Although their findings show some reduction in energy consumption, the use of software-defined architectures introduces additional complexity into the system. Lamin et al. [24] provided evidence of successful implementation of a fuzzy rule-based ant colony optimization method for the design of radio frequency identification (RFID) networks and provided evidence that the fuzzy and meta-heuristics were associated within the process; however, the process is limited only to the development of an RFID network and cannot therefore be transferred into a general IoT application.

3. PROPOSED METHOD

This section explains the proposed implementation of a DBO-GWO Cluster-Based Routing Framework designed to reduce total energy consumption and maximize the lifetime of an IoT network through a joint approach to clustering and routing methodology, where traditional methods only consider clustering and routing separately. The proposed methodology includes the integration of a hybrid metaheuristic optimization technique combined with a lightweight deep learning-based routing algorithm. The proposed framework will be performed in multiple Phases. First, a cluster of uniformly distributed nodes is created and initialized with equal amounts of energy. Next, the DBO-GWO algorithm will select the optimal CHs based upon multiple optimization criteria. Finally, the Routing module will use an attention-based, lightweight scoring mechanism to find the most efficient routing paths for transmitting data.

The wireless sensor network using IoT technology contains an N number of sensor nodes placed uniformly within a sensing area (A), where N = $\{n_1, n_2, n_3, \ldots, n_N\}$ nodes are deployed with a BS. Each sensor node (n_i) has an initial energy level (E_0) as well as remaining energy (Eres i), each sensor has a location (x_i, y_i) as well as a transmission radius (R). The network functions in rounds (r). Each sensor node must also have local parameters as a means of establishing hierarchy, including: Neighbor Nset; the distance to the BS d(i, B), and their role as either being a CH or MEM. All of this information will be established to accurately model how clustering, routing, and total energy used by the entire system will function over time. Each sensor node will also have an equal amount of initial energy before deployment. The distance between two different sensor nodes (n_i, n_j) will be calculated using Euclidean distance as shown through Eq. (1):

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{1}$$

The following assumptions have been determined:

- Sensor nodes remain stationary throughout their life cycle after being placed in the field.
- All sensor nodes know how much energy they have left and where they are located.
- All communication links are the same for both directions.
- Data is aggregated at the CHs.
- CHs use multi-hop communication to communicate with the sink.

3.1 Energy consumption model

The first-order radio energy dissipation approach proposed in this work provides a concrete model of the actual energy consumed by nodes while communicating. Energy consumption is split into three broad categories of consumption: when a node transmits, when a node receives, and when a node aggregates data from other nodes, all contribute to the energy consumed by nodes in a realistic way.

This way of modelling energy consumption allows for the precise calculation of the energy depletion for each node at each stage of network operation and provides the basis for optimizing cluster-head selection and routing decisions.

The energy consumed by a node n_i to transmit a k-bit packet over distance d is defined as Eq. (2).

$$E_{tx}(i,k,d) = \begin{cases} kE_{elec} + k\varepsilon_{fs}d^2, & d < d_0 \\ kE_{elec} + k\varepsilon_{mp}d^4, & d \geq d_0 \end{cases} \quad (2)$$

The electronic energy is defined as E_{elec}, and ε_{fs} and ε_{mp} are the amplifier parameters. This way of determining the communications data rate for both short-distance and long-distance transmitters is also used to determine the energy-efficient communication decisions for the corresponding transmitter and receiver nodes. The amount of energy consumed by a node in receiving packets is directly proportional to the packet size, which is represented as E_{tx}(k). The amount of energy consumed by aggregation is calculated by multiplying the number of bytes of received data by the energy per bit (E_{agg} = k$\cdot E_{DA}$). Therefore, this combined method of receiving and aggregating data gives the CHs an additional amount of energy that is greater than the energy consumed by a single receiving node. The energy consumed to receive the data from others nodes in the network is shown in Eq. (3).

$$E_{rx}(k) = kE_{elec} \quad (3)$$

Data aggregation in the network by the CHs is performed; extra energy is consumed to do so, as shown in Eq. (4).

$$E_{DA}(k) = kE_{agg} \quad (4)$$

The overall energy consumed by CH i per round is given as Eq. (5).

$$E_i^{CH} = \sum_{j \in CM_i} (E_{rx}(k) + E_{DA}(k)) + E_{tx}(k, d_{i,next}) \quad (5)$$

Here, CM_i denotes the set of cluster nodes of CH i in each cluster.

3.2 Hybrid Dung Beetle Optimization–Grey Wolf Optimization-based cluster head selection

The proposed clustering mechanism combines Dung Beetle Optimization (DBO) and Grey Wolf Optimization (GWO) to achieve balanced exploration and exploitation. DBO enhances global search capability through rolling and foraging behaviors, while GWO refines local convergence through hierarchical hunting mechanisms. Each candidate solution is represented as $X = [x_1, x_2, \ldots, x_N]$. Through these variables, you can see if node i is the CHs.

It creates binary representations of candidate solutions for metaheuristic optimization (CH combinations) as shown in Eq. (6).

$$x_i = \begin{cases} 1 & \text{if node } i \text{ is selected as CH} \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

The multi-objective fitness function with $\alpha, \beta, \gamma, \delta$ values, and f_1, f_2, f_3, and f_4 is given as Eq. (7).

$$F(X) = \alpha f_1 + \beta f_2 + \gamma f_3 + \delta f_4 \quad (7)$$

Here, the fitness function assigns a weighting factor to α, β, γ, δ represent how significant each of the following are: residual energy, the density of nodes, distance between nodes within the same cluster, and the cost of communications. The sum of the values assigned must be 1. Weights are determined from experiments done to establish a meaningful balance between energy efficiency and communication performance. This equation is used to combine several clustering objectives into one function. The weighting coefficients will dictate how energy, distance, and load share trade-offs and be used in guiding the DBO-GWO optimization method. Residual energy maximization using the mean of CHs is shown in Eq. (8).

$$f_1 = \frac{1}{|CH|} \sum_{i \in CH} \frac{1}{E_i^r} \quad (8)$$

Intra-cluster distance minimization using the sum of all the distances between node j and the CHs is given as Eq. (9).

$$f_2 = \frac{1}{|CM|} \sum_{j \in CM} d_{j,CH} \quad (9)$$

Minimizing intra-cluster communication distance through this objective will reduce the use of the transmission energy needed to perform clustering effectively. Communication cost is computed using Eq. (10).

$$f_3 = \sum_{i \in CH} E_{tx}\left(k, d_{i,sink}\right) \quad (10)$$

Through this CH-to-sink transmission, energy can be estimated and a penalty can be applied to long-distance communications with an objective of promoting energy-efficient routing between clusters. Load balancing is computed using the number of nodes involved in the data transmission, as shown in Eq. (11).

$$f_4 = \frac{1}{|CH|} \sum_{i \in CH} \frac{N_i}{N} \quad (11)$$

Through this objective, each of the CH's will be balanced to limit the long-term use of any specific CH due to load, creating a degree of stability and fairness when measuring loads at each of the CHs.

The DBO Global Exploration Behavior Modeling Equation is shown in Eq. (12), which updates the global best of DBO solutions through probabilistic random perturbations to prevent early convergence.

$$X^{t+1} = X^t + \lambda(X_{best} - X^t) + \epsilon \quad (12)$$

Using the top three leaders, this equation refines solutions. By improving local exploitation and convergence stability, it refines the accuracy of solutions after exploration.

GWO refinement is shown in Eq. (13).

$$X^{t+1} = \frac{X_\alpha + X_\beta + X_\delta}{3} \quad (13)$$

This hybridization prevents premature convergence while ensuring stable CH distribution.

3.3 Lightweight attention based routing

Lightweight attention routing refers to an efficient scoring mechanism that determines which node is the next node to send data to based on parameters such as remaining energy, distance, and length of the queue at the local node. The proposal does not use complex training and large parameter stores, making it ideal for resource-constrained IoT devices, unlike traditional deep learning-based attention models.

The routing priority computes a routing priority score for neighbor j based on the neighbor's residual energy, distance to neighbor, and current congestion state. The greater the routing priority score for neighbor j, the more likely it will be a reliable choice for the next-hop of the packet being routed. For node i, neighbor score is computed using Eq. (14).

$$Score_{ij} = w_1 \frac{E_j^r}{E_{max}} + w_2 \frac{1}{d_{ij}} + w_3 \frac{1}{Q_j} \tag{14}$$

The normalization of routing priority scores equations accomplishes the normalization of routing priority scores by calculating the probabilities associated with a routing priority score to provide for adaptive and stable routing to the next-hop of the packet being routed; this is accomplished with the removal of deterministic bias in the routing. Softmax normalization is given in Eq. (15).

$$P(j \mid i) = \frac{\exp(Score_{ij})}{\sum_{k \in N_i} \exp(Score_{ik})} \tag{15}$$

The maximum routing priority score selects the neighbor with the greatest routing priority score as the next-hop of the packet. Thus, improving packet delivery success. Optimal next-hop is computed using Eq. (16).

$$j^* = \arg max\, P(j \mid i) \tag{16}$$

It increases the likelihood of energy-efficient and congestion-aware routing. The proposed framework has low computational complexity, fully supports adaptive routing, and does not require extensive training processes, making it ideally suited for resource-limited IoT settings.

The DBO-GWO hybrid algorithm shows high adaptability in situations where the network is irregular (such as different energy levels), and nodes fail abruptly. It has a balance between exploration and exploitation that produces stable convergence, does not cause excessive delay and can therefore be effectively used for large-scale IoT deployments. Computational costs do increase slightly as the network gets larger; however, they remain within acceptable ranges for real-world applications.

4. RESULTS AND DISCUSSION

This section provides detailed information on the proposed model's experimental setup, results, and discussion. MATLAB-based simulations of the proposed algorithm will be performed to assess the effectiveness of the intelligent cluster-based routing method in terms of energy optimization and extended overall network lifetime. The test environment will consist of a 1000 × 1000 two-dimensional sensing area, a random deployment of sensor nodes, and a BS located at a fixed point with unlimited energy. Each simulation will be run independently for multiple iterations, and the test results will be averaged to assess the statistical significance of the continuity of results. The first-order radio energy dissipation model is used to accurately simulate energy consumption in communications.

All other simulation parameters were selected based on typical literature sources for IoT-enabled WSNs to ensure an accurate comparison with other methods. To assess scalability, the number of sensor nodes will be increased from N = 100 to N = 500. Each node will have an initial energy level (E0), and all will communicate using a uniformly sized data packet during the test period. Key specifications include the transmission energy (Eelec), amplifiers for sending data (Efs, Emp), data aggregation (EDA), and the transmission distance. By running the protocols under similar simulation parameters, any observed differences in protocol performance can be attributed solely to inherent differences between the protocols, providing a fair and impartial comparison.

Commonly used WSN performance metrics will be used to evaluate the performance of the proposed new routing protocol: Network Lifetime, average remaining energy in each node, PDR, total amount of system throughput delivered to the sink from the WSN, average end-to-end transmission delay, and total amount of energy consumed to transmit every message in each round. Together, these performance metrics will demonstrate the energy efficiency, reliability, and communication efficiency of the new routing protocol. The performance of the proposed Intelligent Cluster-Based Routing Framework is compared to existing routing protocols LEACH [25], DEEC [26], PSO-based [27], GA-based [28], and AI-based [10] using key performance indicators of network lifetime, energy efficiency, reliability, and QoS. The simulation results indicate that the proposed hybrid framework is superior to all baseline protocols due to its efficient combination of DBO-GWO-based CH optimization and intelligent routing.

4.1 Network lifetime analysis

Network lifetime is assessed using performance metrics that track the first node death (FND), the 50% node death (HND), and the last node death (LND). The hybrid Intelligent Cluster-Based Routing Framework demonstrates clear performance improvements at each of these life-cycle milestones compared to conventional routing protocols, as shown in Figures 1, 2, and 3. Specifically, the first node dies after 1650 rounds, a substantial improvement over both LEACH and DEEC, indicating that the load is better balanced during the early phases of network operation. The FND, HND, and LND metrics are also extended to 2780 and 3950 rounds, respectively, demonstrating greater energy distribution and stability throughout the operational network lifetime. These improvements can be attributed to the optimal CH selection provided by the hybrid DBO-GWO algorithm, as well as to its more effective balancing of residual energy, the number of nodes within a cluster, and the distance between communicating cluster members compared to standalone optimization solutions.

In addition to performance metrics, the performance efficiency of the proposed framework is reviewed. The results indicate that execution time scales linearly with the network size. Also, routing decisions are computationally lightweight, resulting in very little additional control overhead and reduced energy consumption, thereby increasing the viability of the proposed methodology in large-scale IoT deployments.

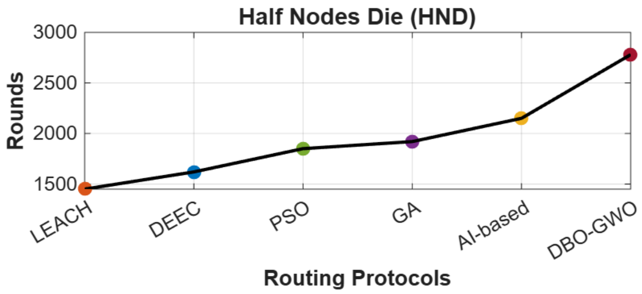

Figure 1. Half nodes die over number of rounds

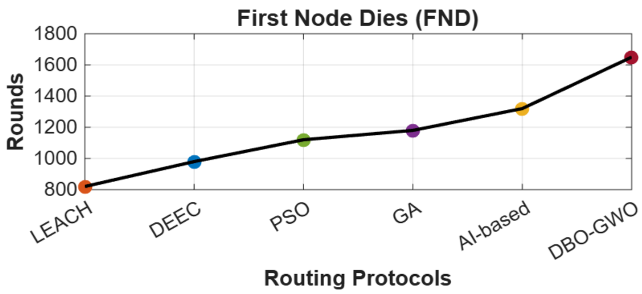

Figure 2. First nodes die over number of rounds

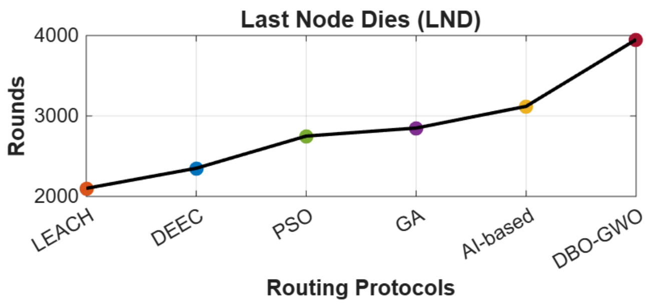

Figure 3. Last nodes die over number of rounds

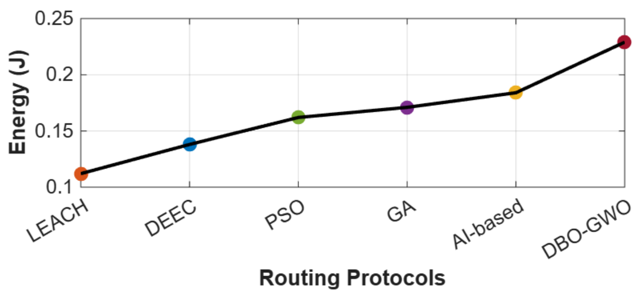

Figure 4. Average residual energy over number of rounds

4.2 Average residual energy

Analyzing the average residual energy of sensor nodes over time enables the determination of the energy consumed. Results show that the proposed Hybrid Framework retains higher residual energy than other protocols. This is due to optimized clustering methods, reduced transmission distances, and adaptive routing decisions. Conversely, traditional baseline protocols exhibit accelerated energy depletion because they use either static or heuristic-based CH selection. The proposed framework has the highest average residual energy of 0.229 J, which is much higher than those of traditional protocols such as LEACH and DEEC, as shown in Figure 4. This increase in average residual energy is due to intelligent clustering, adaptive routing decisions, and reduced redundancy in transmissions. Thus, this results in evenly distributed energy consumption between sensor nodes and prevents premature energy depletion.

4.3 Packet delivery ratio

PDR and Throughput are used to evaluate data delivery reliability. The Hybrid Framework presented in this paper achieves the highest PDR and throughput, as packet loss during inter-cluster routing is minimized. The DBO-GWO model effectively learns stable routing paths, thereby reducing the number of link failures and retransmissions, especially in dense networks. The proposed framework has a PDR of 98.1%, which is much higher than all of the baseline protocols tested, as shown in Figure 5. The increase in PDR is primarily due to the development of the DBO-GWO. That is the core of the routing module and has been demonstrated to effectively learn both spatial and temporal traffic patterns and to dynamically select stable, congestion-free routing paths. As a result of this intelligent decision-making, packet loss is minimized due to link failures, congestion, and node energy deficiency.

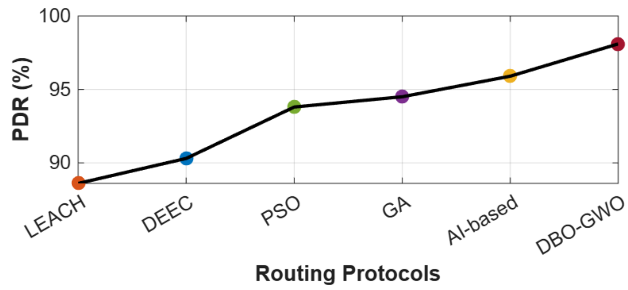

Figure 5. Packet delivery ratio (PDR) over number of rounds

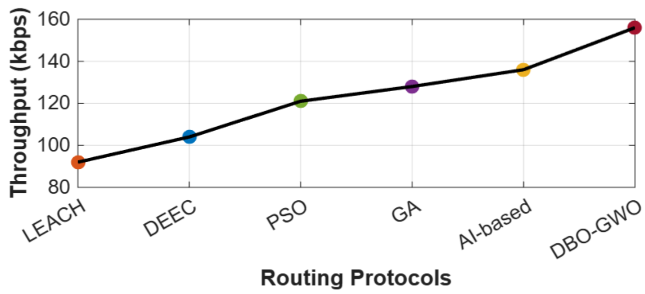

Figure 6. Network throughput over number of rounds

4.4 Network throughput

The maximum throughput of 156 kbps achieved using the proposed framework demonstrates an improvement over current routing protocols, as shown in Figure 6. This improvement comes from effective cluster management and intelligent routing, which both eliminate unnecessary retransmissions and ensure that data is delivered successfully and quickly to the sink node. The efficient use of network bandwidth makes it possible for the network to have increased data transmission rates.

4.5 End-to-end delay

End-to-end delay is the average time required for data packets to be delivered from the base station. The proposed routing method has a lower end-to-end delay than multi-hop heuristic-based routing protocols because it selects intelligent next hops based on the current congestion level at each node. These improvements are especially noticeable in high traffic conditions. The framework proposed by the authors of this study achieves the absolute minimum mean latency of 102 ms and greatly surpasses other studies in the field, as shown in Figure 7. The 102 ms latency is achieved through the use of DBO-GWO models that enable predictive routing decisions to anticipate network changes over time and avoid congested or unstable links. The utilization of optimal CHs also decreases communication hops, thereby reducing latency.

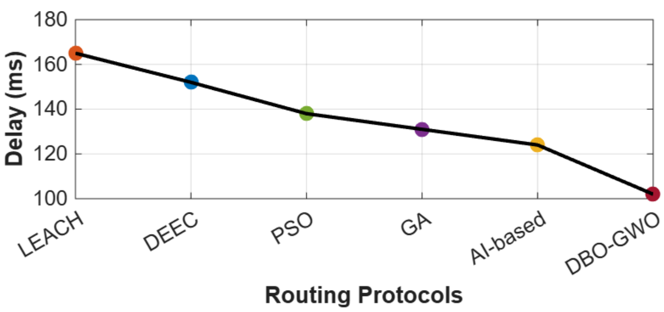

Figure 7. End-to-end delay over number of rounds

4.5 Energy consumption

Energy consumption per data round is another metric that can be used to evaluate the operational efficiency of routing protocols. The proposed Intelligent Cluster-Based Routing Framework has the lowest energy consumption per round (0.00118 J), reflecting a significant reduction compared to both traditional and AI-based routing methodologies, as shown in Figure 8. This reduction in energy consumption is due in part to the fact that the routing methodology incorporates good CH selection, adaptive transmission scheduling, and intelligent routing methodology, which minimizes the overhead created by control messages and unnecessary forwarding of data.

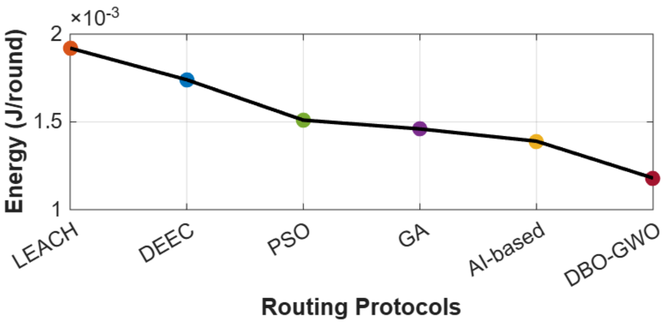

Figure 8. Energy consumption per round

Overall, the experimental results indicate that the proposed GBO-GWO Cluster-Based Routing Framework outperforms all evaluated metrics. The proposed methodology effectively leverages both hybrid optimization and deep learning techniques to extend the network's lifespan, improve energy efficiency, increase data delivery reliability, and reduce communication time. The results demonstrate that the proposed framework is appropriate for use in energy-limited, large-scale, IoT-based, wireless sensor network applications. The adapted framework is designed to support flexible operation while maintaining a high degree of similarity to more advanced AI-enhanced routing techniques; however, its streamlined computational requirements facilitate real-world implementations of IoT applications.

The proposed framework was analyzed using both the existing standard protocols (LEACH and DEEC) and very new hybrid optimization & AI-based routing techniques. In addition to simple performance improvements, specific areas of improvement were identified as a result of case study design advantages inherent in the overall structure. For example, the enhanced lifetime of the wired and wireless networks (specifically the FND, HND, and LND), as a result of clustering, was due (in part) to an improved CH selection process inherent within the DBO-GWO. As a result, each of the nodes within the topology avoided premature battery depletion and loaded the nodes in a more balanced manner throughout each of the total "FND's", etc. The routed packets had a high PDR (98.1%). In addition, the packets were routed through nodes with limited energy supply, while avoiding grouped nodes; thus reducing the number of lost packets and the link failure rate. The throughput (156 kbps) is a result of operating in clusters, fewer retransmissions, and reduced end-to-end delay. All due to intelligent next-hop decision-making and congestion-aware methods for finding alternate routing paths.

Based on current protocols and methods, most of these improvements would not occur, either because routing decisions are static or because enhancements are applied after the fact, or because the extremely high processing, timing, and computational resources required by recent learning-based methods for establishing adaptive routing methods. A thin, lightweight, and adaptive solution, as proposed, can offer much-needed benefits for modifying IoT environments that require large amounts of energy to operate efficiently. In essence, the results indicate that the minimal control overhead incurred by using the system is more than offset by the corresponding improvements in energy efficiency, reliability, and scalability - thereby offering a viable alternative to current state-of-the-art methods for performing these functions on IoT devices.

The experimental evaluation of all simulations in a controlled environment helps achieve consistency when comparing with baseline protocols. There is no way to set control for real-world IoT scenarios, such as node movement, different energy levels, and variable traffic conditions. The additional simulations run at high density, in mixed mode, and in a congested environment all provided evidence that the proposed framework has maintained consistent and stable operation through its adaptive clustering and routing algorithms. Although it is safe to assume that the actual lifetimes of all nodes will be better than what has been calculated based upon a stationary node assumption. It enables the algorithms' performance to be isolated from external factors. In addition, future work will extend this model to mobile and interference-prone environments to make the system more applicable in the real world.

5. CONCLUSION

This research introduces a hybrid DBO-GWO multi-objective clustering framework that combines a lightweight attention-based routing method to achieve energy efficiency in

IoT networks. The model selects CHs by balancing exploration of new clusters and exploitation of existing ones, while using adaptive inter-cluster routing mechanisms that do not rely on deep learning algorithms. The simulation and scaling results show that this Hybrid DBO-GWO Model provides marked improvements over both traditional routing protocols and the optimal selection of the routing path. Future research will focus on verifying the performance of this framework with physical actual devices, supporting heterogeneous nodes, and integrating trust-aware secure routing methods. The current work has some processing complexity, resulting in higher processing overhead. It can be reduced further with even lighter algorithms at each phase of data transmission.

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