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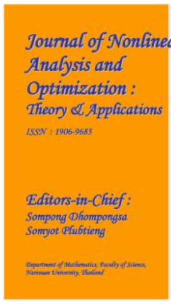

ENERGY EFFICIENT CLUSTER-BASED ROUTING PROTOCOL FOR WSN USING META-HEURISTIC OPTIMIZATION TECHNIQUES

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Abstract
It has been demonstrated that using routing and clustering techniques to conserve energy can significantly and successfully extend the lifespan of wireless sensor networks (WSNs). The proposed method combines the complex meta-heuristic algorithms of Harris Harks Optimization (HHO) and Spotted Hyena Optimization (SHO). This combination technique utilizes HHO's fast exploration to accomplish efficient clustering and optimal Cluster Head (CH) selection. Moreover, SHO's improved manipulation capabilities optimize efficient routing paths. Among the metrics used to measure network performance are packet delivery ratio (PDR), average energy consumption, and network longevity. According to the experimental results, the proposed HHO-SHO technique uses up to 35.5% less energy than existing cluster routing protocols. Moreover, it increases the PDR by up to 11% and the WSN network lifetime by up to 16%.

Keywords:
WSN, energy efficiency, clustering, routing, meta-heuristics algorithms.

1. Introduction

Originally designed for use in military environments, WSNs were simple surveillance networks with numerous scattered sensor nodes. These systems' main goals were the collection, processing, and transfer of data [1]. But with so many energy-constrained sensor nodes for processing, transmission, and storage, along with its highly dynamic, non-replaceable or rechargeable energy features, WSNs have always had to deal with the most important issue: conserving energy to increase the network's longevity. Furthermore, the effectiveness of clustering and routing techniques has been demonstrated. These methods cluster nodes and transfer data to the base station (BS) according to a number of objectives, including as energy efficiency, load balancing, lifetime maximization, and quality of service [2].

Effective routing and clustering algorithms have therefore become essential to the sustainability of WSNs in order to preserve overall network functionality in dynamic network environments and postpone the early depletion of energy. In order to improve WSN efficiency through data routing and energy management, optimization methods have developed over time. Conventional approaches are inadequate in dynamic network topologies, requiring a single intelligent framework for efficient routing across a range of scenarios. Node placement, network routing, and data aggregation are three major WSN difficulties that nature-inspired optimization handles well because of its durability and adaptability. These algorithms offer versatile solutions in complex networks while ensuring sustainability and minimal environmental impact [3].

The main contribution of proposed work is stated below:

- To provide a cluster-based routing protocol for WSN that uses two effective meta-heuristic algorithms and is energy-efficient

- To develop a HHO based clustering mechanism for obtaining best CH selection
- To perform effective routing through SHO algorithm
- To achieve maximum network lifetime and PDR with minimum energy consumption.

2. Literature Survey

A multi-objective Gray-Wolf-Optimization (MOGWO) based data routing scheme is proposed in [4] to prevent premature network death and improve network lifespan performance in WSNs. On the network, there are issues with data congestion, nevertheless. Multi-Criteria Clustering and Bio-Inspired Routing (Moth Flame and Salp Swarm Optimization) is presented in [5] to enhance network lifetime and efficiency in WSNs through energy-efficient routing and robust clustering. Nevertheless, there are challenges in controlling energy use while transmitting data.[6] proposes an Adaptive Sailfish Optimization and Cross-Layer-Based Expedient Routing Protocol (ASFO-E-CERP) to maximize energy efficiency, network lifetime extension, and latency minimization in WSNs by CH selection optimization. However, it uses a lot of power and has more latency problems. [7] proposes the Energy-Efficient Meta-Heuristic Cluster-Based Routing Protocol (EEM-CRP) to maximize energy efficiency in WSNs by optimizing CH selection and routing. However, it has trouble increasing energy efficiency and only explores a small portion of the best CH and route selection techniques. Levy Chaotic Particle Swarm Optimization-based Cluster Routing Protocol (LCPSO-CRP), an improved cluster routing protocol, is created in [8] with the goal of enhancing network longevity and energy efficiency. However, they fail to offer mechanisms that are cognizant of trust and struggle to maintain stability and dependable service quality for a wide range of applications.

3. Proposed Methodology

A hybrid approach combining Harris Hawks Optimization (HHO)for clustering and Spotted Hyena Optimization (SHO) for optimal routing to enhance energy efficiency and extend the lifetime of WSN.Figure 1 represents the overview of proposed HHO-SHO technique.

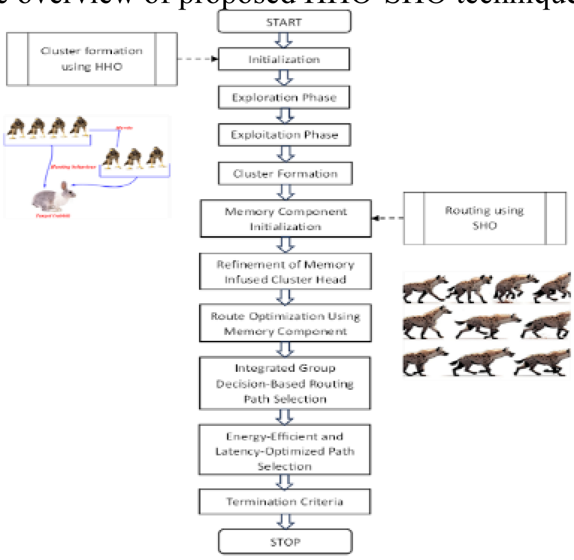

Figure 1. The overview of proposed HHO-SHO technique

3.1. System model

In the proposed HHO-SHO algorithm, uniformly distributed sensor nodes with identical capabilities and initial energy estimate their distance from the BS and adjust transmission power accordingly. The BS, an unconstrained node with a fixed location and unique ID, and all nodes remain static after deployment.

3.2. Proposed HHO-SHO technique

HHO [9] involves a population of hawks (candidate solutions) that cooperate to hunt a prey (optimal solution). The algorithm iterates through several phases, including exploration (searching for potential solutions) and exploitation (refining the solutions).

3.2.1. Initialization

Each hawk (candidate CH) is initialized with parameters such as position, energy levels, and other relevant attributes. The initial positions of hawks are distributed randomly across the sensor network.The fitness function evaluates each hawk based on criteria essential for effective CH selection. The fitness function considers:residual energy, distance to BS and distance to neighboring nodes.The fitness function is defined as Eq. (1):

$$Fitness(i) = \alpha \cdot \frac{E_{residual}(i)}{E_{initial}} + \beta \cdot \left(\frac{1}{d(i,BS)}\right) + \gamma \cdot \left(\frac{1}{\sum_{j\in neighbors} d(i,j)}\right) \quad (1)$$

Where, $E_{residual}(i)$ is the residual energy of node i,$E_{initial}$ is the initial energy of node i,$d(i,BS)$ is the distance from node i to the BS,$d(i,j)$ is the distance from node i to its neighbor j,α, β, and γare weighting factors.

3.2.2. Exploration Phase

During the exploration phase, hawks randomly explore the search space to identify potential CHs. This phase encourages diversity in the solutions and helps avoid local optima. The exploration behavior is governed by Eq. (2):

$$X(t+1) = X(t) + r_1 \cdot \left(X_{rand}(t) - X(t)\right) \quad (2)$$

Where, X(t) is the position of the hawk at iteration t,$X_{rand}(t)$ is a randomly selected hawk's position,r_1 is a random number in the range [0, 1].

3.2.3. Exploitation Phase

In the exploitation phase, hawks focus on converging towards the optimal solution by exploiting the best solutions found so far. This phase involves different strategies based on the energy of the prey (potential CH):

1. Soft Besiege: When the prey's energy is high, hawks perform a soft besiegeas Eq. (3):

$$X(t+1) = X_{best}(t) - r_2 \cdot | X_{best}(t) - X(t) | \quad (3)$$

2. Hard Besiege: When the prey's energy is low, hawks perform a hard besiege as Eq. (4):

$$X(t+1) = X_{best}(t) - r_3 \cdot | X_{best}(t) - X(t) |^2 \quad (4)$$

Where, $X_{best}(t)$is the position of the best hawk at iteration t,r_2 and $r_3$are random numbers in the range [0, 1].

Hawks switch between exploration and exploitation based on the probability PPP calculated as Eq. (5):

$$P = e^{-\frac{E_{Prey}}{E_{max}}} \quad (5)$$

Where, E_{Prey} is the energy of the prey,$E_{max}$is the maximum energy.If P is greater than a threshold, the algorithm favors exploration; otherwise, it favors exploitation.

Iterative Update and Convergence: The algorithm iteratively updates the positions of hawks, alternating between exploration and exploitation, until a stopping criterion is met. The final positions of the hawks represent the selected CHs, which balance energy consumption and ensure effective communication within the network.

3.2.4. Cluster Formation

Once the CHs are selected, the rest of the nodes join the nearest CH based on signal strength, forming clusters. Each CH manages the data aggregation and communication with the BS, thereby optimizing the overall network performance.

This algorithm, which draws inspiration from the social coordination and cooperative hunting strategies of spotted hyenas, aims to strike a balance between exploring to uncover new solutions and refining those that already exist. With memory-infused cluster head selection and improved routing strategy, the SHO algorithm improves decision-making capabilities by building on the foundations established by HHO's high speed energy conscious clustering. The following succinct description of this novel method's intricate procedure is possible:

3.2.5. Memory Component Initialization

The routing paths are shown in SHO as "hyenas," or potential solutions. In the beginning, a population of hyenas is created at random to symbolize potential routes from the base station (BS) to the Cluster Heads (CHs). The beginning position of each hyena in the search space corresponds to a possible route. Usually, the starting positions are chosen at random to accommodate a wide variety of potential solutions.

3.2.6. Refinement of Memory Infused Cluster Head

In order to improve refinement, SHO includes memory components during the initialization step. Every hyena keeps a record of its best-found solutions, which are the shortest and most energy-efficient routes found to date. This memory enables the algorithm to enhance and optimize previously found effective solutions, which helps direct the exploration and exploitation stages. The memory element makes sure that in later iterations, the optimal pathways are given priority.

3.2.7. Route Optimization Using Memory Component

SHO optimizes routing pathways by using the memory component. Hyenas change their locations in the search space by using their recollection of the best solutions, striking a balance between discovering new paths and taking advantage of well-known, profitable ones. Hyenas's memory affects their update rules, improving convergence towards the best routing paths. The update of a hyena's position, considering memory, is given by Eq. (6):

$$X(t+1) = X(t) + r_1 \cdot (X_{best\_memory}(t) - X(t)) \quad (6)$$

where $X_{best\_memory}(t)$ represents the best solution stored in the memory at iteration t.

3.2.8. Integrated Group Decision-Based Routing Path Selection

SHO uses a group decision-based strategy in the decision-making process. Hyenas cooperate by exchanging knowledge on the optimal routes that the populace has found. The routing paths are further refined with the use of this common knowledge. Through the use of various hyenas to determine which paths are ideal, the group decision framework ensures robustness and dependability in the routing paths.

3.2.9. Energy-Efficient and Latency-Optimized Path Selection

SHO's fitness function for routing takes latency and energy usage into account. While the latency criterion reduces transmission delays, the energy-aware criterion guarantees that paths with the least amount of energy consumption are given priority.

The combined fitness function is in Eq. (7):

$$Fitness(r) = \alpha \cdot \left(\frac{E_{total}(r)}{E_{max}}\right) + \beta \cdot \left(\frac{d_{total}(r)}{d_{max}}\right) \quad (7)$$

where $E_{total}(r)$ is the total energy required for the path r, and $d_{total}(r)$ is the total distance of the path. Weights αand β balance the importance of energy and latency.

3.2.10. Termination Criteria

Up until a halting condition is satisfied, the SHO algorithm repeatedly cycles through the exploration and exploitation stages. One basis for the stopping criterion is:

- Maximum Number of Iterations: The algorithm stops after a predefined number of iterations.
- Convergence Threshold: The algorithm stops when the improvement in fitness function values falls below a certain threshold, indicating that the solution has converged.

The final routing paths selected by SHO represent the optimal routes from CHs to the BS, ensuring efficient energy use and minimal latency. These paths are used for data transmission, enhancing overall network performance and extending the network's lifetime.

4. Result and Discussion

The 100x100 square meter experimental setting is used to assess how feasible the suggested work is. Ten square meter grids have been divided up into multiple areas inside this network space. The number of deployed nodes can vary from 100 to 500, and the number of nodes that are actively operating can vary from three to ten, in order to evaluate how well the suggested plan performs. An initial supply of energy equal to sixty joules is given to each node. The PDR, average energy consumption, and network lifetime of the suggested HHO-SHO approach are evaluated and compared to the EEM-CRP [7] and LCPSO-CRP [8] as benchmarks.

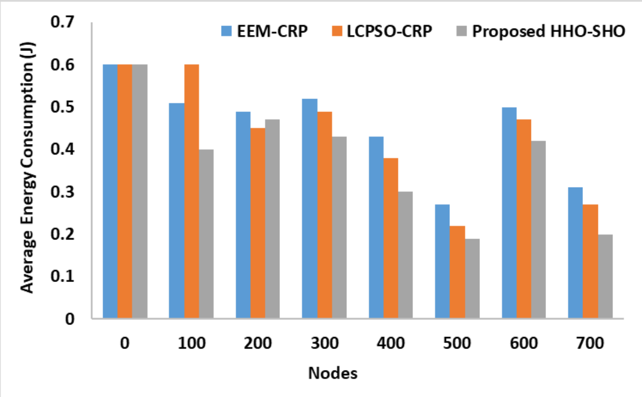

Figure 2. Comparison of average energy consumption

Figure 2 shows the comparison average energy consumption. It shows that the proposed HHO-SHO protocol consistently uses less energy than the EEM-CRP and LCPSO-CRP protocols across various node counts in WSNs. For instance, at 100 nodes, HHO-SHO reduces energy consumption by 21.6% and 33.3% compared to EEM-CRP and LCPSO-CRP, respectively. Even as the number of nodes increases to 700, HHO-SHO achieves a 35.5% and 25.9% reduction in energy use compared to EEM-CRP and LCPSO-CRP, respectively. This demonstrates that the HHO-SHO protocol significantly improves energy efficiency and network lifetime over its counterparts.

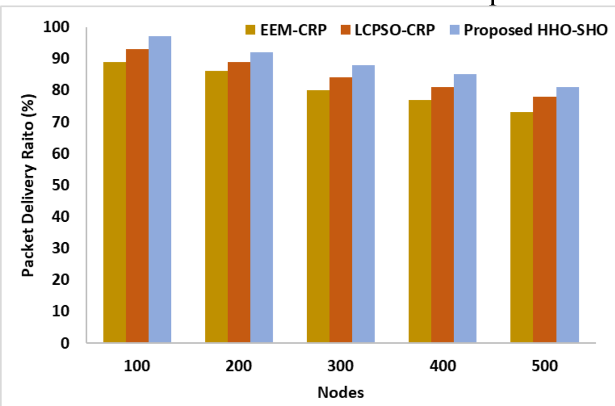

Figure 3. Comparison of packet delivery ratio

Figure 3 shows the comparison of PDR, it shows that the proposed HHO-SHO protocol improves the PDR over EEM-CRP and LCPSO-CRP at different node counts in WSNs. For 100 nodes, HHO-SHO improves PDR by 9% over EEM-CRP and 4.3% over LCPSO-CRP. At 200 nodes, the improvement is 7% over EEM-CRP and 3.4% over LCPSO-CRP. With 300 nodes, HHO-SHO enhances PDR by 10% compared to EEM-CRP and 4.8% compared to LCPSO-CRP. For 400 nodes, the improvement is 10.4% over EEM-CRP and 4.9% over LCPSO-CRP. Lastly, at 500 nodes, HHO-SHO improves PDR by 11% over EEM-CRP and 3.8% over LCPSO-CRP. Overall, the proposed HHO-SHO consistently achieves higher PDR, indicating better reliability in data transmission.

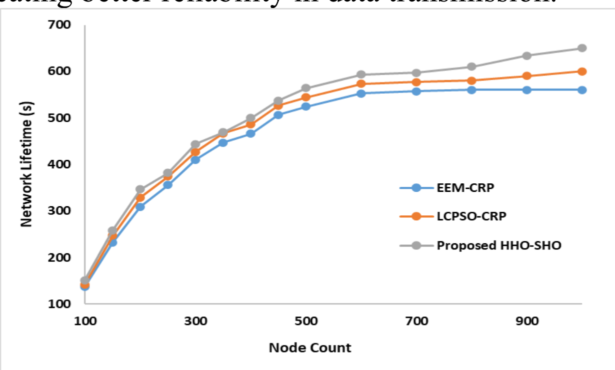

Figure 4. Comparison of network's lifetime

Figure 4 shows the comparison of network's lifetime, it shows that the proposed HHO-SHO protocol significantly extends network lifetime compared to EEM-CRP and LCPSO-CRP in WSNs. For 100 nodes, HHO-SHO increases lifetime by 10.2% over EEM-CRP and 6.3% over LCPSO-CRP. At 200 nodes, the improvement is 12.3% over EEM-CRP and 5.5% over LCPSO-CRP. For 300 nodes, HHO-

SHO extends lifetime by 12.4% over EEM-CRP and 4% over LCPSO-CRP. The trend continues, with HHO-SHO showing a 16.1% longer lifetime than EEM-CRP and 8.3% longer than LCPSO-CRP at 1000 nodes. Overall, HHO-SHO consistently enhances network longevity.

5. Conclusion
The integration of Harris Hawks Optimization (HHO) and Spotted Hyena Optimization (SHO) in the proposed technique effectively enhances clustering and routing in WSNs. By combining HHO's exploration strength with SHO's exploitation capabilities, the methodology significantly improves energy efficiency, network lifetime, and PDR. Experimental results validate that the HHO-SHO technique outperforms other cluster routing protocols, reducing energy consumption up to 35.5%, extending network lifetime up to 16%, and increasing PDR up to 11%. This innovative approach demonstrates a substantial advancement in optimizing WSN performance.Future enhancements could integrate machine learning for optimizing clustering and routing, and explore hybrid meta-heuristic algorithms for complex, dynamic network conditions in WSNs.

References
[1] Yang, L., Zhang, D., Li, L., & He, Q. (2024). Energy efficient cluster-based routing protocol for WSN using multi-strategy fusion snake optimizer and minimum spanning tree. Scientific Reports, 14(1), 1–24. https://doi.org/10.1038/s41598-024-66703-9
[2] Jing, D. (2024). Harris harks optimization-based clustering with fuzzy routing for lifetime enhancing in wireless sensor networks. IEEE Access: Practical Innovations, Open Solutions, 12, 12149–12163. https://doi.org/10.1109/access.2024.3354276
[3] Roberts, M. K., Thangavel, J., &Aldawsari, H. (2024). An improved dual-phased meta-heuristic optimization-based framework for energy efficient cluster-based routing in wireless sensor networks. Alexandria Engineering Journal, 101, 306–317. https://doi.org/10.1016/j.aej.2024.05.078
[4] Ojha, A., & Chanak, P. (2022). Multiobjectivegray-wolf-optimization-based data routing scheme for wireless sensor networks. IEEE Internet of Things Journal, 9(6), 4615–4623. https://doi.org/10.1109/jiot.2021.3105425
[5] Vellaichamy, J., Basheer, S., Bai, P. S. M., Khan, M., Kumar Mathivanan, S., Jayagopal, P., & Babu, J. C. (2023). Wireless sensor networks based on multi-criteria clustering and optimal bio-inspired algorithm for energy-efficient routing. Applied Sciences (Basel, Switzerland), 13(5), 2801. https://doi.org/10.3390/app13052801
[6] Cherappa, V., Thangarajan, T., Meenakshi Sundaram, S. S., Hajjej, F., Munusamy, A. K., & Shanmugam, R. (2023). Energy-efficient clustering and routing using ASFO and a cross-layer-based expedient routing protocol for wireless sensor networks. Sensors (Basel, Switzerland), 23(5), 2788. https://doi.org/10.3390/s23052788
[7] Chaurasia, S., Kumar, K., & Kumar, N. (2023). EEM-CRP: Energy-efficient meta-heuristic cluster-based routing protocol for WSNs. IEEE Sensors Journal, 23(23), 29679–29693. https://doi.org/10.1109/jsen.2023.3322631
[8] Luo, T., Xie, J., Zhang, B., Zhang, Y., Li, C., & Zhou, J. (2024). An improved levy chaotic particle swarm optimization algorithm for energy-efficient cluster routing scheme in industrial wireless sensor networks. Expert Systems with Applications, 241(122780), 122780. https://doi.org/10.1016/j.eswa.2023.122780
[9] Ramadan, A., Kamel, S., Korashy, A. et al. An enhanced Harris Hawk optimization algorithm for parameter estimation of single, double and triple diode photovoltaic models. Soft Comput 26, 7233–7257 (2022). https://doi.org/10.1007/s00500-022-07109-5