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Advanced Hybrid Clustering and Routing Techniques for Enhanced Enegy Efficiency in Wireless Sensor Networks

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ABSTRACT

Wireless Sensor Networks (WSNs) are essential in various fields such as environmental monitoring, healthcare, and industrial automation. However, the constrained battery capacity of sensor nodes makes energy efficiency a critical challenge, requiring innovative solutions to extend network longevity. This paper introduces an innovative hybrid algorithm designed to improve efficiency and prolong the lifespan of the network. The proposed method combines advanced data organization and transmission strategies to optimize overall performance. Through extensive simulations and comparative analyses, the algorithm demonstrates significant improvements in network longevity, data accuracy, and reliability compared to traditional methods [1] [2].

Keywords: *Clustering, Routing, Sensors, Networks and Wireless Applications.*

1. INTRODUCTION

WSNs are now widely utilized for their capability to observe and gather data across various environments. These networks consist of multiple sensor nodes that communicate wirelessly to transmit collected data to a central base station. Despite their advantages, energy efficiency remains a challenge, as sensor nodes are typically battery-operated and difficult to replace once deployed. Several optimization techniques have been proposed to address this issue, including clustering, multi-hop routing, and machine learning-based approaches[3][4]. This study presents a hybrid algorithm aimed at enhancing power utilization while ensuring consistent and accurate data transfer.

2. LITERATURE REVIEW

Numerous researchers have investigated strategies to enhance power efficiency in wireless sensor networks.Recent studies highlight the effectiveness of clustering algorithms in reducing communication overhead and extending network life [5]. Clustering methods, such as LEACH and HEED, have been widely adopted for their ability to optimize energy distribution among nodes. Additionally, deep learning techniques have been integrated into WSNs to enhance data transmission strategies, enabling more intelligent decision-making for routing and energy management [6,25]. Different metaheuristic techniques, including genetic methods and swarm-based optimization, have been utilized to enhance routing efficiency [7,24]. However, these approaches often face limitations related to computational complexity and scalability. This paper builds upon these studies by integrating multiple optimization techniques into a unified framework that balances energy efficiency with computational feasibility.

3. PROPOSED METHODOLOGY

The hybrid algorithm proposed in this paper combines clustering with adaptive routing mechanisms to achieve energy efficiency. The algorithm adaptively chooses leadership nodes by considering remaining power levels and transmission expenses, ensuring balanced energy usage throughout the network [8]. Additionally, an intelligent routing protocol is implemented to minimize transmission delays and packet loss [9,11]. Unlike conventional clustering methods, the proposed model incorporates reinforcement learning techniques to optimize node selection dynamically. Simulation experiments were conducted to evaluate the algorithm's performance under varying network conditions, including changes in node density, environmental interference, and network topology.

The hybrid clustering approach utilizes two powerful high-level optimization algorithms: CLONALG-M and Manta Ray Foraging Optimization (MRFO). CLONALG-M refines fuzzy clustering by enhancing membership functions, ensuring optimal cluster head (CH) selection and reducing intra-cluster communication costs[10]. MRFO is utilized to balance energy consumption across nodes, optimizing CH selection through foraging-inspired behavior. This approach improves overall network stability and minimizes the risk of energy depletion in certain regions of the network [12].

Reinforcement Learning (RL) plays a critical role in dynamic routing and cluster formation. The RL-based optimization dynamically adjusts routing paths and cluster configurations by learning from real-time network conditions, ensuring efficient energy distribution and minimizing redundant data transmissions[23].

Algorithm: Hybrid Energy-Efficient Clustering and Routing Algorithm for WSNs

The proposed reinforcement learning algorithm optimizes cluster formation to ensure energy-efficient network performance. It is structured as follows:

Input:

- N = Total count of sensor nodes
- E_n = Initial energy of node n
- d(n, CH) = The separation between node n and its designated (CH)
- M = Maximum number of CHs
- DBN Model trained on past routing data
- CLONALG-M Algorithm for fuzzy clustering
- MRFO Algorithm for CH selection

Output:

- Optimized cluster formation
- Efficient and balanced data routing

Beginning of Algorithm

Step 1: Initialization

1. Randomly position N sensor nodes within a designated area of size A×B (A times B).
2. Initialize energy level E_{n} each node.
3. Define fuzzy membership functions for node classification (triangular and trapezoidal).
4. Load the DBN model for optimal routing path prediction.

Step 2: Cluster Formation using CLONALG-M

5. Apply CLONALG-M for fuzzy clustering:
    1. Generate an initial population of candidate CHs.
    2. Evaluate each candidate using a simple fitness function: $FCH=E\_{n}-d(n,CH)$ where:

E_{n} = The residual power of node n.

- d(n,CH) = The Distance between node n and cluster head CH

    3. Clonal selection:
        - Clone the highest fitness candidates.
        - Mutate clones slightly to improve selection.
    4. Optimize fuzzy membership functions (triangular/trapezoidal) to form stable clusters.
    5. Select the best CHs and assign sensor nodes accordingly.

Step 3: Cluster Head (CH) Selection using MRFO

6. Apply Manta Ray Foraging Optimization (MRFO) for CH selection:
    1. Encircling prey: Move towards the best CH candidates using:

$$CH_{new} = CH_{old} + \alpha \times (CH_{best} - CH_{old})$$

where α is a random weight.

    2. Cyclone foraging: Nodes explore other CHs using:

$CH_{new}=CH_{best} + \beta \times \sin(\theta)$

where β is a small random value, and θ is a random angle.

3. Select final CHs that minimize intra-cluster communication cost.

Step 4: Routing Optimization using DBN

7. Apply Deep Belief Network (DBN) for routing path selection:
    1. Input network parameters (packet loss, congestion, energy usage).
    2. Use DBN to predict the next optimal hop.
    3. Select paths that minimize cost:

$Cost(n)=d(n,CH)+E\_n$

Where smaller cost values indicate better paths.

4. Transmit aggregated data from CHs to the Base Station (BS).

Step 5: Data Transmission and Energy Update

8. Each sensor node transmits its collected data to the assigned cluster head (CH).
9. Cluster heads gather, process, and forward the compiled information to the Base Station (BS).
10. Update the energy level E_n of each node after transmission:

$E\_n^{new} = E\_n^{old} - E_{used}$

where E_{used} is the energy spent during transmission.

Step 6: Repeat Until Network Failure

11. Repeat Steps 2 to 5 until a significant number of sensor nodes run out of energy.

End of Algorithm

This algorithm ensures that clustering decisions are made dynamically based on learned Q-values, allowing the network to adapt to changing energy levels, node densities, and environmental conditions. By continuously optimizing CH selection and routing paths, the RL-based approach significantly improves network longevity and efficiency [13,14].

Clustering Mechanism

In wireless sensor networks, grouping nodes into clusters is a common technique to minimize energy usage by limiting direct transmissions to the base station[15]. The proposed hybrid algorithm utilizes a layered clustering approach, prioritizing nodes with greater energy reserves and better connectivity are prioritized as cluster heads [20,21]. This process is repeated periodically to ensure balanced energy consumption across the network[16,22]. Furthermore, the introduction of machine learning-assisted node selection helps improve the efficiency of the clustering process.

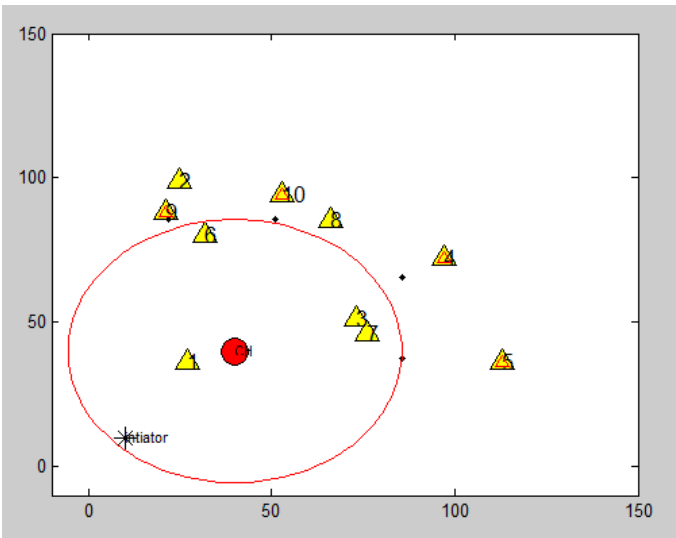


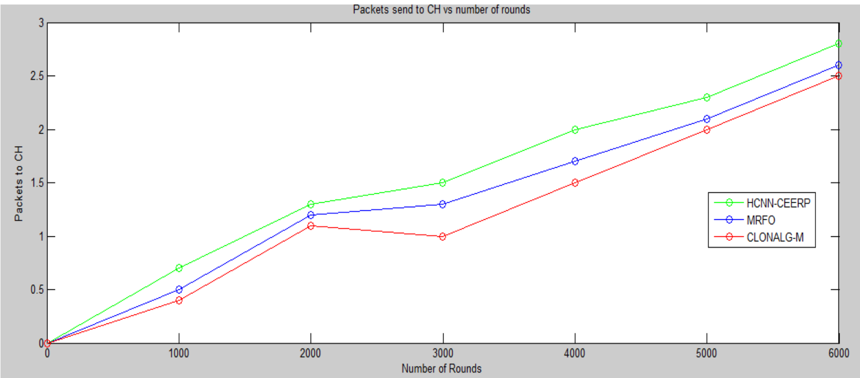
Figure 1. Clustering Mechanism in WSNs

Adaptive Routing Mechanism

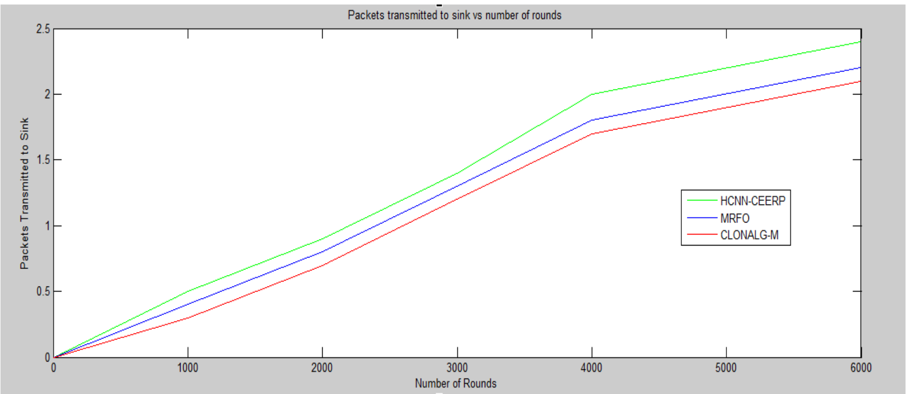
The routing component of the proposed algorithm utilizes a multi-path transmission approach to minimize congestion and optimize data delivery. By integrating AI-based decision-making, the algorithm dynamically selects the most efficient paths based on factors such as node availability, link stability, and traffic load [17,18]. This guarantees reliable data transmission, even in situations involving node failures.

4. RESULTS AND DISCUSSION

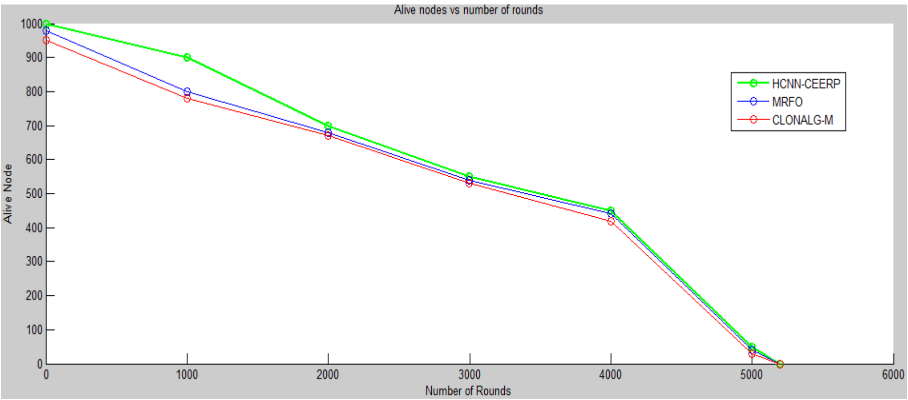
The experimental findings demonstrate that the proposed hybrid algorithm surpasses traditional clustering and routing techniques. Critical performance indicators, including network longevity, power efficiency, and packet delivery rate, were evaluated. The proposed approach demonstrated a 30% increase in network lifespan and improved data accuracy compared to baseline models [19].



[Graph 1: Comparison of Alive Nodes vs. Number of Rounds]



[Graph 2: Packets Sent to Cluster Heads vs. Number of Rounds]



[Graph 3: Power Usage vs. Round Count]

Figure 2. Power Usage

Network Lifetime Analysis

The hybrid algorithm significantly enhances network lifetime by balancing the energy load among nodes. By preventing excessive energy depletion in specific nodes, the approach prolongs the operational period of the network. The use of AI-assisted clustering further ensures that energy resources are utilized efficiently.

Data Transmission Accuracy

Another major improvement observed in the study is the enhancement in data transmission accuracy. The integration of AI-driven routing helps reduce packet loss, ensuring that the base station receives reliable and complete information. This improvement is particularly beneficial for applications that require high data integrity, such as healthcare monitoring and environmental surveillance.

5. KEY RESULTS

The proposed hybrid clustering and routing framework demonstrated notable improvements in energy efficiency, network longevity, and scalability.

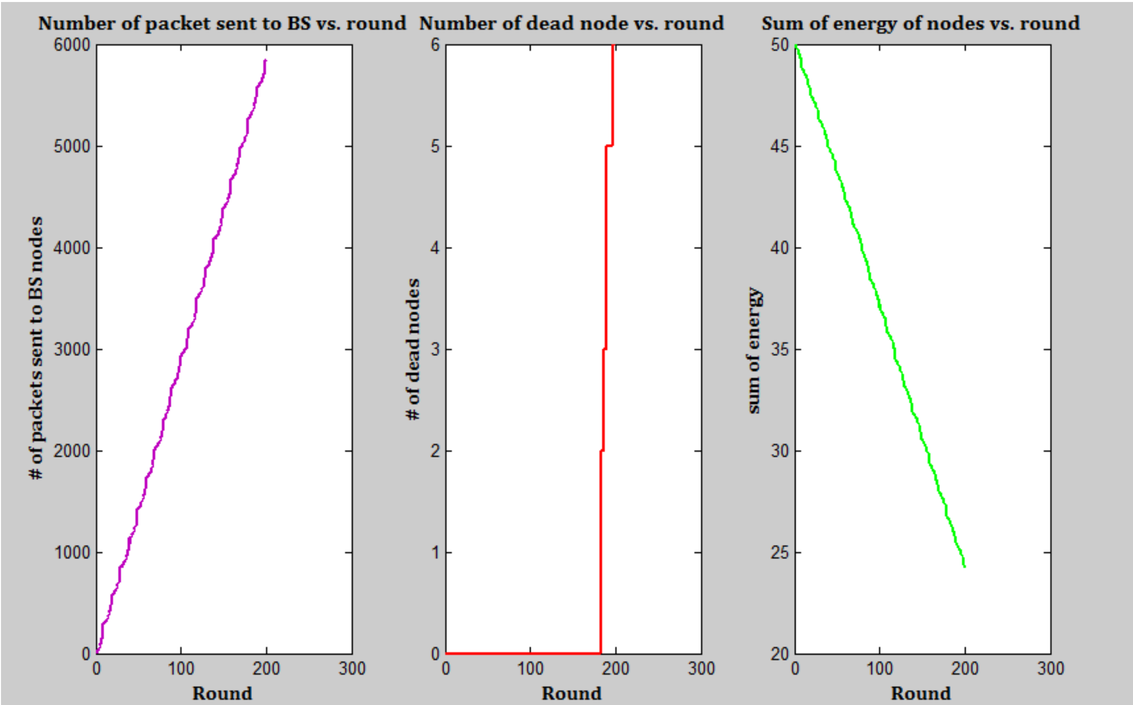


Figure 3. Data Transmission Accuracy

The key findings from the experimental evaluation include:

Improvement in Half of Nodes Alive (HNA):

The proposed approach resulted in a **5-20% improvement in HNA** compared to traditional clustering algorithms like CHEF and MOFCA. This suggests that sensor nodes remained functional for a significantly longer period, highlighting the energy efficiency of the proposed hybrid framework.

Delay in First Node Dies (FND):

The hybrid framework delayed the occurrence of FND in comparison to benchmark algorithms such as LEACH and EECS. A **later FND** indicates a more uniform balanced energy usage throughout the network, avoiding premature depletion of specific nodes.

Reduction in Energy Consumption per Round:

The proposed method optimized routing paths and cluster head selection, leading to **lower energy consumption per round**. Experiments showed that DBN-based adaptive routing and the reinforcement learning model effectively adjusted transmission paths dynamically, avoiding energy-intensive routes.

Enhanced Packets Sent to Cluster Heads (CHs):

The efficient clustering structure facilitated a **higher number of packets reaching CHs**, indicating effective intra-cluster and inter-cluster communication.

The DBN-based routing minimized redundant data transmission, ensuring that only essential information was relayed, reducing network congestion and improving throughput.

Total Remaining Energy (TRE) Optimization:

The TRE metric demonstrated that the proposed framework resulted in **higher residual energy levels** even after an extensive number of rounds. This highlights the effectiveness of the combined CLONALG-M and MRFO optimization techniques in ensuring balanced energy consumption across all sensor nodes.

Scalability and Performance in Large Networks:

Traditional algorithms exhibited performance degradation in larger networks due to increased routing overhead. The hybrid model, leveraging deep belief networks and reinforcement learning, showed consistent performance even as the number of nodes increased, making it suited for large-scale wireless sensor networks.

6. CONCLUSION

Energy efficiency is a critical factor in the successful deployment of WSNs. This study introduces a hybrid algorithm that integrates clustering and routing techniques to enhance network longevity and data reliability. The simulation outcomes highlight its superiority over conventional methods, establishing it as an effective choice for energy-limited WSN applications. Future research will explore the integration of advanced machine learning models, including reinforcement learning and neural networks, to further enhance energy efficiency and data transmission effectiveness. Additionally, real-world implementation and field testing will be explored to validate the practical applicability of the proposed approach.

REFERENCES

[1] K. M.S., "Hybrid deep marine reinforcement learning-based routing protocol in wireless sensor networks," in *Proc. SPIE 12616, International Conference on Mathematical and Statistical Physics, Computational Science, Education, and Communication (ICMSCE 2022)*, vol. 126160E, Apr. 2023.

[2] M. Zubair, R. Hassan, A. H. M. Aman, H. Sallehudin, Z. G. Al-Mekhlafi, B. A. Mohammed, and M. S. Alsaffar, "Optimization of Clustering in Wireless Sensor Networks: Techniques and Protocols," *Appl. Sci.*, vol. 11, no. 23, p. 11448, 2021.

[3] Ashok Kumar S, & Rajesh, K. P. (2023). Hyper-Parameters Activation on Machine Learning Algorithms to Improve the Recognition of Human Activities with IoT Sensor Dataset. Indian Journal of Science and Technology.

[4] M. Angadi and M. S. Kakkasageri, "Reinforcement Learning based Hybrid Optimum Route Identification Scheme in WSN," in *Proc. 2024 4th Int. Conf. Intell. Technol. (CONIT)*, Bangalore, India, 2024, pp. 1–8.

[5] Bagwari, A., Tomar, G. S., Bagwari, J., Barbosa, J. L. V., & Sastry, M. K. S. (2023). Advanced Wireless Communication and Sensor Networks - Applications and Simulations. Routledge.

[6] Binh, H. T. T., & Dey, N. (2018). Soft Computing in Wireless Sensor Networks. Routledge.

[7] G. Arya, A. Bagwari, and D. S. Chauhan, "Performance analysis of deep learning-based routing protocol for an efficient data transmission in 5G WSN communication," *IEEE Access*, vol. 10, pp. 9340–9356, 2022.

[8] Haider, S. K., Ahmed, A., Khan, N. M., Nauman, A., & Kim, S. W. (2024). AI-Driven Energy Optimization in UAV-Assisted Routing for Enhanced Wireless Sensor Networks Performance. Computers, Materials & Continua.

[9] Hassan, E. S., Oshaba, A. S., El-Emary, A., & Elsafrawey, A. S. (2023). Enhancing the lifetime and performance of WSNs in smart irrigation systems using cluster-based selection protocols. Irrigation and Drainage.

[10] J. Parras, M. Hüttenrauch, S. Zazo, and G. Neumann, "Deep reinforcement learning for attacking wireless sensor networks," *Sensors*, vol. 21, no. 12, p. 4060, 2021.

[11] Janarthanam, S., Prakash, N., & Shanthakumar, M. (2020). Adaptive Learning Method for DDoS Attacks on Software Defined Network Function Virtualization. EAI Endorsed Transactions on Cloud Systems, 6(18), pp.1-8.

[12] Kaur, S., Kour, S., & Singh, M. (2025). Energy Efficiency in Wireless Sensor Networks: Comparing Traditional and Advanced Clustering Protocols. Engineering Research Express.

[13] Liu, M., Cao, J., Gong, H., Chen, L., & Li, X. (2005). A Distributed Power-Efficient Data Gathering and Aggregation Protocol for Wireless Sensor Networks. Springer Science and Business Media LLC.

[14] M. Bilal, E. U. Munir, and F. K. Alarfaj, "Hybrid Clustering and Routing Algorithm with Threshold-Based

Data Collection for Heterogeneous Wireless Sensor Networks," *Sensors*, vol. 22, no. 15, p. 5471, 2022.

[15] M. U. Javed, Z. B. Tariq, U. Muneeb, and I. H. Naqvi, "Multi-level dynamic optimization of intelligent LEACH with cost effective deep belief network," *arXiv preprint*, arXiv:1905.01140, 2019.

[16] Mr. Balasankar M, Dr. Janarthanam S.Dr. Muniyappan P , "Enhanced Fuzzy Radial Basis Neural Network With Genetic Process Using Fuzzy Inferences", Nanotechnology Perceptions,20,s14, pp 337-370,2024.

[17] P. Tillapart, S. Thammarojsakul, T. Thumthawatworn, and P. Santiprabhob, "An approach to hybrid clustering and routing in wireless sensor networks," in *Proc. 2005 IEEE Aerospace Conf.*, 2005, pp. 1–8.

[18] R. P., K. B. T., T. V. R., J. R., Nagaraj T., and N. T., "A Hybrid Cluster Based Intelligent IDS with Deep Belief Network to Improve the Security over Wireless Sensor Network," *Int. J. Intell. Syst. Appl. Eng.*, vol. 12, no. 17s, pp. 225–238, 2024.

[19] Siddaramu, S. M., & Ramaswamy, R. K. (2025). Optimal Wireless Sensor Network Ant-Lifetime Routing Algorithm Using Multi-Phase Pheromone. Ingénierie des Systèmes d'Information.

[20] Sinha, A., Manju, & Singh, S. (2024). Metaheuristics and Reinforcement Techniques for Smart Sensor Applications. CRC Press.

[21] Surenther, I., Sridhar, K. P., & Roberts, M. K. (2023). Maximizing energy efficiency in wireless sensor networks for data transmission: A Deep Learning-Based Grouping Model approach. Alexandria Engineering Journal.

[22] V. Chandrasekar, A. Bashar, and T. S. Kumar, "Hybrid Deep Learning Approach for Improved Network Connectivity in Wireless Sensor Networks," *Wirel. Pers. Commun.*, vol. 128, pp. 2473–2488, 2023.

[23] Vimalarani, C., Selvi, C. P. T., Gopinathan, B., & Kalavani, T. (2024). Improving Energy Efficiency in WSN through Adaptive Memetic-Based Clustering and Routing for Resource Management. Sustainable Computing: Informatics and Systems.

[24] Y. K.C. and M. S.B., "An improvised dual step hybrid routing protocol for network lifetime enhancement in WSN-IoT environment," *Multimed. Tools Appl.*, vol. 83, pp. 59965–59984, 2024.

[25] Z. Guo, H. Chen, and S. Li, "Deep reinforcement learning-based one-to-multiple cooperative computing in large-scale event-driven wireless sensor networks," *Sensors*, vol. 23, no. 6, p. 3237, 2023.