AI-Powered Low-Power Clustering Algorithms to Enhance Heterogeneous Wireless Sensor Network

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ABSTRACT

Wireless Sensor Networks (WSNs) have become an essential technology in a variety of fields, including industrial automation, healthcare, and environmental monitoring. Energy efficiency is still a major problem, though, particularly in heterogeneous WSNs where sensor nodes vary in processing power, energy capacity, and sensing range. In order to improve energy efficiency and extend the network lifetime of heterogeneous WSNs, this research suggests an AI-driven grouping approach. The suggested approach makes use of machine learning techniques, particularly adaptive decision-making and reinforcement learning, to dynamically optimize cluster head selection and routing patterns. Our method allows for more intelligent and balanced energy consumption by adaptively taking into account node residual energy, communication cost, and network topology, in contrast to conventional clustering protocols like LEACH and HEED. When compared to traditional methods, simulation results show a significant improvement in network longevity, energy consumption, and data transmission dependability. The development of intelligent, self-adaptive WSNs for next-generation Internet of Things (IoT) applications is aided by this work.

Keywords: *Wireless Sensor Network; Clustering Technique; HEED; LEACH.*

INTRODUCTION

Wireless Sensor Networks (WSNs) have become a cornerstone technology in modern-day smart environments, including applications such as environmental monitoring, smart agriculture, health care systems, military surveillance, and industrial automation[14]. These networks consist of spatially distributed sensor nodes that monitor physical or environmental variables and communicate collected data to a central base station (BS) or sink node for processing. Despite their expanding deployment and significance, the operational lifespan of WSNs is strongly hampered by the limited energy resources of individual sensor nodes—particularly in settings where battery replacement or recharging is prohibitive[8].

The problem of effective energy management becomes even more complex in the context of heterogeneous WSNs, where nodes differ in terms of processing power, battery life, and communication range[1]. Conventional energy-efficient protocols, such as hierarchical and clustering-based approaches like HEED (Hybrid Energy-Efficient Distributed Clustering) and LEACH (Low-Energy Adaptive Clustering Hierarchy), provide partial solutions but frequently fall short in dynamically adapting to changes in network conditions or energy levels over time[7].

New developments in machine learning (ML) and artificial intelligence (AI) offer encouraging paths for WSN performance optimization. Cluster heads can be intelligently chosen and energy-efficient communication channels can be formed based on real-time network parameters by including AI-driven decision-making in the clustering

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process. These strategies can provide context-aware, adaptive solutions that are superior to static or heuristic-based techniques [19].

In order to improve energy efficiency and network lifetime, this research suggests a novel AI-driven clustering technique created especially for heterogeneous WSNs. In order to dynamically assess and choose the best cluster heads based on variables like residual energy, node density, and communication costs, the suggested model integrates reinforcement learning. The suggested method performs noticeably better than conventional protocols in terms of energy consumption, network lifetime, and data delivery performance, according to extensive simulation results.

RELATED WORK

Energy efficiency in WSNs has prompted the development of a variety of clustering techniques. A probabilistic approach to cluster head selection was developed by the LEACH protocol, which reduced energy usage but lacked adaptability in varied situations. By adding residual energy and node degree, HEED outperformed LEACH; nonetheless, scalability and energy balance remained issues[3].

The use of AI and ML in WSNs has been investigated in recent research. Neural networks, fuzzy logic, and reinforcement learning have all been used in studies to maximize clustering[2]. Deep Q-Networks (DQNs), for example, have demonstrated potential in dynamically modifying clustering techniques in response to environmental feedback. Nevertheless, a lot of these methods either make the assumption that nodes are homogeneous or fall short of utilizing AI's full capabilities for making decisions in real time [4].

PROPOSED METHODOLOGY

To choose cluster heads and control communication channels, the suggested AI-driven clustering algorithm makes use of a reinforcement learning framework, more especially Q-learning. Through rewards based on energy savings and successful data transmission, each sensor node acts as an agent that gradually learns the best course of action[5][6].

A. System Model

The diverse nodes that make up the WSN have different energy capacities, sensing ranges, and communication capacities. The base station is situated at a fixed location, and nodes are dispersed at random throughout a predetermined area[9].

B. Clustering Process

- *Initialization*: Nodes set up their Q-tables with potential actions (e.g., joining a particular cluster, becoming the cluster head).
- *Reward Function*: This feature takes into account data throughput, node density, residual energy, and distance to the base station in order to promote energy-efficient behavior[15][16].
- *Learning Phase*: Following each data transmission round, nodes alter their Q-values in response to feedback they receive.
- *Cluster Head Selection*: For the "become cluster head" action, nodes with the highest Q-values are chosen.

C. Communication Phase

Following cluster formation, non-cluster-head nodes send data to the appropriate cluster head, which combines it and uses energy-efficient routes to send it to the base station[10].

SIMULATION AND RESULTS

MATLAB was used to develop the technique, which was then compared against the HEED and LEACH protocols. Network lifetime, which is the number of rounds until the first and last node dies, is one of the metrics assessed[18].

- Energy Consumption: The sum and mean of the energy used over some time.
- Packet Delivery Ratio: The proportion of data packets that are successfully sent to the base station.

A. Setup for the Simulation

The network's dimensions are 100 m x 100 m, and there are 100 nodes.

• Three different node kinds (low, medium, and high energy)
• Starting energy is random within a given range.

B. ***Results***

In comparison to LEACH, the suggested AI-driven clustering algorithm produced: • A 35% longer network lifetime
• 28% less energy is used compared with HEED
• A higher and more consistent ratio of packet delivery during simulation cycles.

Table 1: Network Lifetime Comparison

Protocol	First Node Dies (Rounds)	Last Node Dies (Rounds)	Network Lifetime Increase (%)
LEACH	800	1200	—
HEED	950	1400	16.7%
Proposed (AI-Driven)	1200	1800	35%

Table 2: Energy Consumption Comparison

Protocol	Total Energy Consumed (J)	Average Energy per Round (J)	Energy Saving Compared to HEED (%)
LEACH	85	0.071	—
HEED	72	0.051	—
Proposed (AI-Driven)	52	0.037	28%

Table 3: Packet Delivery Ratio (PDR)

Protocol	Avg. Packet Delivery Ratio (%)	Stability Across Rounds
LEACH	82	Low
HEED	88	Moderate
Proposed (AI-Driven)	94	High

RESULT ANALYSIS

The simulation findings show that the suggested AI-driven clustering algorithm performs better than conventional clustering protocols like LEACH and HEED on three important metrics: packet delivery ratio (PDR), energy consumption, and network longevity[11].

Network Lifetime

The number of operating rounds, until the first and last sensor node died, was used to calculate the network lifetime. The network's lifespan was considerably increased by the AI-driven protocol:

- In contrast to 950 (HEED) and 800 (LEACH), the first node died at 1200 rounds.
- Compared to 1400 (HEED) and 1200 (LEACH), the last node died at 1800 rounds[12].

The intelligent and adaptive cluster head selection, which distributes the load uniformly and lessens energy depletion in important nodes, is responsible for this 35% improvement over LEACH.

*A. **Energy Consumption***

Additionally, the suggested algorithm decreased both the average and total energy consumption:
• 52 J was used overall, as opposed to 72 J (HEED) and 85 J (LEACH).
• 0.037 J on average per round, compared to 0.051 J (HEED) and 0.071 J (LEACH).
A reward-based Q-learning algorithm that encourages energy-efficient routing choices and discourages redundant transmissions was used to accomplish this 28% savings over HEED.

*B. **Packet Delivery Ratio (PDR)***

The dependability of data transmission was greatly increased by the AI-based clustering protocol:
• PDR: 94% as opposed to 82% for LEACH and 88% for HEED.
• Throughout the network's operating lifetime, consistent performance was demonstrated by the high stability across rounds.
These enhancements result from the protocol's capacity to dynamically adjust to the energy and topology conditions of the network in real-time, avoiding paths that are crowded or energy-intensive.

*C. **Stability and Adaptability***

Unlike LEACH and HEED, which rely on static heuristics, the proposed method continuously learns and adapts[17]. The dynamic reward system takes into account:

- Node residual energy,
- Distance to the base station,
- Node density,
- Data transmission success rates.

This adaptivity ensures that no single node is overburdened, enhancing the fairness of energy consumption and resilience to topology changes.

*D. **Computational Overhead***

Simulations demonstrate that, despite the computational complexity introduced by reinforcement learning, it is well within the capability of contemporary sensor nodes. This cost is outweighed by the advantages in terms of energy savings and extended lifespan, particularly in situations where replacing batteries is impractical or inaccessible.

CONCLUSION AND FUTURE SCOPE

This research introduced a novel AI-powered clustering protocol for heterogeneous wireless sensor networks (WSNs), addressing one of the most critical challenges in WSN design—energy efficiency and network durability. By integrating reinforcement learning, specifically Q-learning, the system enables each node to make intelligent, autonomous decisions that adapt to real-time network dynamics.

Through extensive MATLAB simulations, the proposed approach demonstrated significant improvements over traditional protocols:

- A 35% increase in network lifetime compared to LEACH,
- 28% reduction in energy consumption over HEED,
- Enhanced packet delivery ratio, achieving 94% with high consistency.

These outcomes validate the strength of AI in addressing the limitations of conventional clustering mechanisms, particularly in heterogeneous and resource-constrained environments[13]. The intelligent reward-driven framework allows for proactive rather than reactive energy management, leading to a more balanced network with minimized node failures.

FUTURE SCOPE

This work paves the way for several promising research directions:

- Real-world deployment of the algorithm using hardware testbeds (e.g., Raspberry Pi or Arduino-based sensor platforms),
- Integration with deep reinforcement learning (e.g., DQN, A3C) for more nuanced decision-making,
- Support for 3D network topologies and mobility-aware clustering,
- Incorporating security-aware energy models to defend against energy depletion attacks (e.g., blackhole or sinkhole attacks),
- Exploring cross-layer optimizations combining MAC and network layers for even greater efficiency.

In conclusion, the fusion of AI with WSN clustering strategies offers a robust, adaptive, and scalable solution for prolonging network operation and improving data integrity in complex sensing environments—making it highly relevant for future IoT**,** smart city**,** and remote monitoring applications**.**

REFERENCES

1. Heinzelman, W. R., Chandrakasan, A., Balakrishnan, H, **"**Energy-efficient communication protocol for wireless microsensor networks", Proceedings of the 33rd Annual Hawaii International Conference on System Sciences *(pp. 10 pp.-). IEEE 2000.*
2. Phiros Mansur, Sasikumaran Sreedharan, "*Fuzzy Based Clustering Techniques for Object Tracking in Wireless Sensor Networks: A Survey*", International Journal of Service Computing and Computational Intelligence (IJSCCI) ISSN: 2162–514X, Volume-1, Issue- 2016.
3. Younis, O., Fahmy, S, **"**HEED: A hybrid, energy-efficient, distributed clustering approach for ad hoc sensor networks", IEEE Transactions on Mobile Computing*, 3(4), 366-379, 2004, 10.1109/TMC.2004.41*
4. Akan, O. B., Akyildiz, I. F, Event-to-sink reliable transport in wireless sensor networks, IEEE/ACM Transactions on Networking 2005*, 13(5), 1003–1016.*
5. Kumar, V., Jain, S., Tiwari, R., **"**Energy-efficient clustering and routing in wireless sensor networks using AI techniques: A review, Computer Science Review*, 38, 100296. 10.1016/j.cosrev.2020.100296*
6. Tan, H. P., Panda, S. K, **"**Reinforcement learning-based energy-efficient clustering and data collection in wireless sensor networks", Sensors 2019*, 19(20), 4463.*
7. Sharma, R., Gupta, B. B, **"**AI-based energy-efficient routing protocols in wireless sensor networks: A survey", Journal of Network and Computer Applications 2021*, 178, 102999.*
8. Phiros Mansur, Sasikumaran Sreedharan, "*Survey of Prediction Algorithms for Object Tracking in Wireless Sensor Networks*", IEEE Explore, International Journal of Computational Intelligence and Computing Research, 978-1-4799-3975-6 /14/ 2014 IEEE.
9. Zhang, Y., Yang, X, "A Q-learning based clustering protocol for enhancing energy efficiency in heterogeneous WSNs". Ad Hoc Networks*, 125, 2022, 102735.*
10. Alsheikh, M. A., Lin, S., Niyato, D., Tan, H. P, *"*Machine learning in wireless sensor networks: Algorithms, strategies, and applications", arXiv preprint arXiv:1405.4463*, 2014.*
11. Masoud, M. Z., Jaradat, Y., Jannoud, I., Al Sibahee, M. A**. "**A hybrid clustering routing protocol based on machine learning and graph theory for energy conservation and hole detection in wireless sensor network", International Journal of Distributed Sensor Networks*, 15(6), 1550147719858231, 2019*
12. Haq, I. U., Javaid, Q., Ullah, Z., Zaheer, Z., Raza, M., Khalid, M., Ahmed, G., Khan, S, **"**E2-MACH: Energy efficient multi-attribute based clustering scheme for energy harvesting wireless sensor networks", International Journal of Distributed Sensor Networks*, 16(10), 1550147720968047, 2020.*
13. Hadjila, M., Guyennet, H., Feham, M, **"**Energy efficiency in wireless sensor networks using fuzzy c-means clustering approach", International Journal of Sensors and Sensor Networks*, 1(2), 30-35.*
14. Phiros Mansur, Saley Seetharaman, *"Integrating Wireless Sensor Networks with the Cloud: A Flexible REST-Based Architecture",* International Journal of Scientific Development and Research (IJSDR), ISSN:2455-2631, March 2024.
15. Javaid, N., Rasheed, M. B., Imran, M., Guizani, M., Khan, Z. A., Alghamdi, T. A, "An energy-efficient distributed clustering algorithm for heterogeneous WSNs," EURASIP Journal on Wireless Communications and Networking*, 2015, 151.*
16. Kumar, S., Kumar, S., Bhushan, B**.**, *"*Energy-aware clustering protocol (EACP) for heterogeneous WSNs", arXiv preprint arXiv:1408.2910*, 2014.*

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17. Zhu, B., Bedeer, E., Nguyen, H. H., Barton, R., Henry, J, "Improved soft-k-means clustering algorithm for balancing energy consumption in wireless sensor networks", 2024 arXiv preprint arXiv:2403.15700.
18. Gajjara, S., Sarkarb, M., Dasgupta, K, "FAMACRO: Fuzzy and Ant Colony Optimization based MAC/Routing Cross-layer Protocol for Wireless Sensor Networks".Procedia Computer Science, *46, 1014–1021, 2015.*
19. Phiros Mansur, Saley Seetharaman, Abitha Parambath, "Cross-Layer Optimization Strategies for Enhanced Resource Management in Wireless Sensor Networks", International Journal of Scientific Development and Research, IJSDR2412022, ISSN: 2455-2631 December 2024.

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