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An Integrated Energy-Efficient and Qos-Oriented Model for Industrial Wireless Sensor Network Optimization

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Abstract: *This paper proposes an enhanced network architecture for Industrial Wireless Sensor Networks (IWSNs) aimed at improving Quality of Service (QoS) through optimized clustering and energy-efficient routing. The proposed model integrates Grey Wolf Optimization (GWO) for intelligent cluster head selection with the Hierarchical Threshold-sensitive Energy Efficient Network (H-TEEN) protocol to enhance data transmission reliability. GWO dynamically selects optimal cluster heads based on residual energy and node proximity, ensuring balanced energy consumption and prolonged network lifetime. The H-TEEN protocol is adapted to manage heterogeneous nodes and hierarchical communication, reducing latency and transmission overhead. This hybrid approach ensures efficient energy usage, enhances fault tolerance, and meets strict industrial QoS requirements. MATLAB-based simulations demonstrate improved performance over conventional protocols such as LEACH, PSO, and ACO in terms of energy consumption, packet delivery ratio, and network stability. The proposed architecture offers a robust solution for real-time monitoring and control in industrial automation environments.*
Keywords: *Industrial Wireless Sensor Networks (IWSNs), GWO, H-TEEN, Data Aggregation, Energy Efficiency, Sensor, and Network Optimization.*

INTRODUCTION

Because they provide real-time monitoring, automation, and control in a variety of industrial settings, industrial wireless sensor networks, or IWSNs, have become an essential part of Industry 4.0. These networks are made up of dispersed sensor nodes that run in demanding and changing environments with constrained power supplies. Ensuring a longer network lifetime while concurrently satisfying strict Quality of Service (QoS) standards, such as low latency, high packet delivery ratio, and dependable communication, is a significant problem in IWSNs. When both energy efficiency and QoS are important, traditional routing and clustering protocols frequently give preference to one over the other, resulting in less-than-ideal performance. Consequently, there is an increasing demand for clever optimization strategies that may resolve these competing goals in a fair way.

Because they can handle complicated, multi-objective problems, nature-inspired met heuristic algorithms have become more and more popular. The Grey Wolf Optimization (GWO) algorithm has demonstrated encouraging outcomes among them because of its ease of use, robust global search capabilities, and effective convergence. An integrated approach that uses GWO to optimize energy usage and QoS metrics in IWSNs is presented in this research. The suggested method is appropriate for mission-critical industrial applications since it seeks to improve overall network performance, increase operational lifetime, and guarantee dependable communication.

MOTIVATION

Wireless Sensor Networks (WSNs) are becoming increasingly important for real-time monitoring, defect detection, and process management as a result of the quick development of industrial automation. These networks—known as Industrial Wireless Sensor Networks (IWSNs)—must operate dependably in industrial settings despite a variety of challenging circumstances, such as electromagnetic interference, node failures, and varying traffic loads. Maintaining energy efficiency while meeting stringent Quality of Service (QoS) standards, such as low latency, high packet delivery ratio, and continuous network connectivity, is the dual challenge in IWSNs.

Traditional methods frequently deal with QoS indicators or energy usage separately. While QoS-driven routing techniques may cause early battery depletion, energy-efficient clustering strategies may impair communication dependability. Particularly in mission-critical applications like oil refineries, smart factories, and hazardous site monitoring, this trade-off poses a serious optimization difficulty. The necessity to create a single optimization framework that can handle energy and QoS goals without sacrificing either is what drives this study. The Grey Wolf Optimization (GWO) algorithm, which draws inspiration from the natural hunting behavior of grey wolves, provides a potent solution because of its capacity to efficiently explore and utilize the search space.

RELATED WORK

Numerous studies have been carried out to improve Wireless Sensor Networks' (WSNs) energy efficiency and Quality of Service (QoS), especially for industrial applications. The majority of early research was mainly concerned with using clustering algorithms like LEACH (Low Energy Adaptive Clustering Hierarchy) to reduce energy consumption. LEACH and its variations are useful for increasing network lifetime, but they are not appropriate for industrial settings because they cannot manage dynamic network conditions and QoS demands.

To enhance routing and clustering, swarm intelligence techniques—particularly Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO)—have been investigated. For example, a hybrid PSO-based clustering algorithm that improves energy efficiency was proposed by Khan et al. (2021). Nevertheless, these methods frequently fall short in adapting to quick changes in topology and fail to sufficiently account for packet delivery and delay assurances.

Recent research has moved toward multi-objective optimization methods that concurrently improve energy and QoS parameters in order to overcome these constraints. ACO was used by Bano et al. (2020) to create a QoS-aware routing architecture that improved data delivery at the expense of higher computational overhead. Likewise, Mehta and Patel (2022) used PSO for QoS-driven routing, although they found that dense network deployments had less scalability.

Because it successfully strikes a balance between exploration and exploitation, the Grey Wolf Optimization (GWO) algorithm—which was first presented by Mirjalili et al.—has become a viable substitute. GWO-based clustering improves energy efficiency more successfully than PSO and ACO, as Sharma et al. (2023) showed. In simulation experiments, Verma and Yadav (2022) improved latency performance by extending GWO for delay-sensitive applications.

Nevertheless, an integrated framework that simultaneously takes into account energy efficiency, latency, packet delivery ratio, and network longevity is currently lacking in current GWO-based models, particularly when real-time industrial restrictions are present. This disparity drives the creation of an all-encompassing, GWO-based optimization model that unifies the goals of energy and QoS.

GREY WOLF ALGORITHM FOR IWSN OPTIMIZATION:

A metaheuristic method inspired by nature, the Grey Wolf Optimization (GWO) algorithm is based on the hunting strategy and leadership structure of grey wolves. GWO is used in the context of Industrial Wireless Sensor Networks (IWSNs) to solve important optimization issues such cluster head selection, energy efficiency, network lifetime enhancement, and quality of service (QoS) assurance. To mimic decision-making hierarchies, the algorithm divides wolves into alpha, beta, delta, and omega positions, with alpha directing the search. GWO optimizes the choice of cluster heads for IWSNs by assessing variables such as communication cost, node centrality, and residual energy. This dynamic and adaptive clustering guarantees balanced energy consumption across nodes and minimizes needless energy expenditure.

GWO converges toward optimal or nearly optimal clustering structures by iterative solution refinement, which increases throughput, decreases data latency, and extends network lifetime. GWO-based methods offer more fault tolerance and greater adaptability to changing industrial contexts than conventional methods like LEACH. The method is a good and effective option for real-time IWSN optimization because of its simplicity, resilience, and ability to break out of local optima.

METHODOLOGY:

The suggested approach incorporates the Grey Wolf Optimization (GWO) algorithm to enhance Industrial Wireless Sensor Networks' (IWSNs') QoS and energy efficiency. By combining the Grey Wolf Optimization (GWO) algorithm with the Hierarchical Threshold-sensitive Energy Efficient Network (H-TEEN) protocol, the study's technique aims to improve the functionality and energy efficiency of Industrial Wireless Sensor Networks (IWSNs). In order to simulate an industrial monitoring environment, 200 sensor nodes are first deployed within a 300 x 300 meter field. The energy levels of these nodes vary to replicate the conditions of actual industrial sensor networks. Increasing network longevity, balancing energy use, and satisfying Quality of Service (QoS) standards including dependability and low latency are the main goals.

The intelligent cluster head (CH) selection process makes use of the GWO algorithm. GWO gives potential solutions roles (alpha, beta, delta, and omega) based on the social structure and hunting tactics of grey wolves in the wild. Every possible CH configuration is represented by a candidate solution in this context. In order to encourage energy balance and effective communication, the optimization is guided by a fitness function that is based on residual energy, distance from the base station, and average intra-cluster distance. As a result, the best CHs are dynamically chosen to reduce transmission distance and disperse energy usage equally.

MATLAB simulations are used to validate the process, and metrics such packets transmitted to the base station, energy depletion rate, and network stability duration are used to assess performance. Comparisons with conventional protocols such as LEACH, PSO, and ACO validate the improved energy efficiency, dependability, and industrial application appropriateness of the suggested approach.

Using Matlab, simulations were run in a three-dimensional industrial setting with sensors tracking several parameters. Sensor positioning and data aggregation were optimized using the Mean Shift algorithm [33]–[35]. All of the simulation parameters taken into account for our work are displayed in Table 1. This network was developed to address more practical industrial WSN problems.

Table 1: Simulation parameters

Parameters	Values
Scenario Dimensions	300 * 300
Number of Nodes	200
Roadway Length	300 m
Roadway Width	300 m
Number of Clusters (10%)	20
Types of Nodes	Normal, Advanced
Free space Distance(d0)	87 m
Initial Energy	0.5 J (Normal), 1 J (Advanced)
Elevation Variance	±5 m
Min Perceptual Radius	10 m
Max Perceptual Radius	40 m

RESULTS

The performance difference between the normal LEACH protocol and the suggested Mod-LEACH approach is evident from the comparison graph of dead nodes over simulated rounds. As demonstrated, node deaths start substantially earlier in the LEACH procedure, with a sharp rise in node deaths following the initial node death around 100. The LEACH network has had over 130 node deaths by the year 1000, a sign of increasing energy depletion and decreased network stability. The Mod-LEACH technique, on the other hand, shows a delayed onset of node mortality, with notable node deaths not happening until about 250. Mod-LEACH's death rate increases more slowly, indicating that nodes' energy usage is more evenly distributed. Mod-LEACH's greater capacity to extend the stability period (the amount of time until the first node dies) and network lifetime (the amount of time until the majority of nodes die) is demonstrated by the fact that, at the end of the simulation, fewer than 90 nodes are dead. Mod-LEACH's better energy management and cluster head selection method are responsible for this performance improvement.

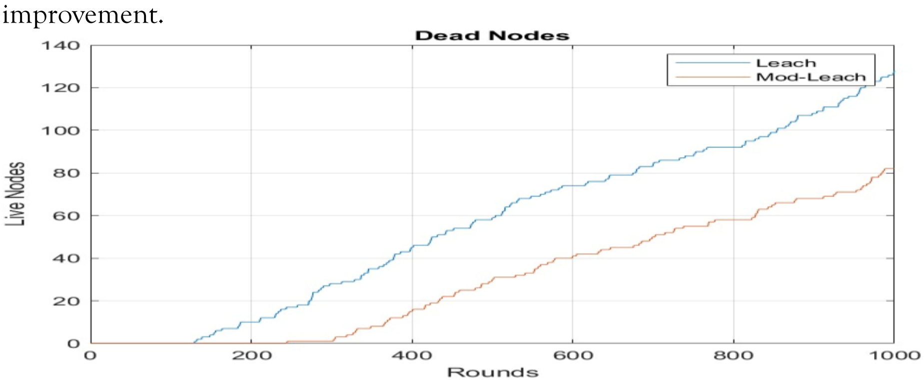

Figure 1: Nodes Dead during rounds

Mod-LEACH's death rate increases more slowly, indicating that nodes' energy usage is more evenly distributed. Mod-LEACH's greater capacity to extend the stability period (the amount of time until the first node dies) and network lifetime (the amount of time until the majority of nodes die) is demonstrated by the fact that, at the end of the simulation, fewer than 90 nodes are dead. Mod-LEACH's better energy management and cluster head selection method are responsible for this performance improvement. The graph shows that Mod-LEACH offers more dependable and energy-efficient communication overall, which makes it more appropriate for industrial wireless sensor network applications where fault tolerance and long-term monitoring are crucial.

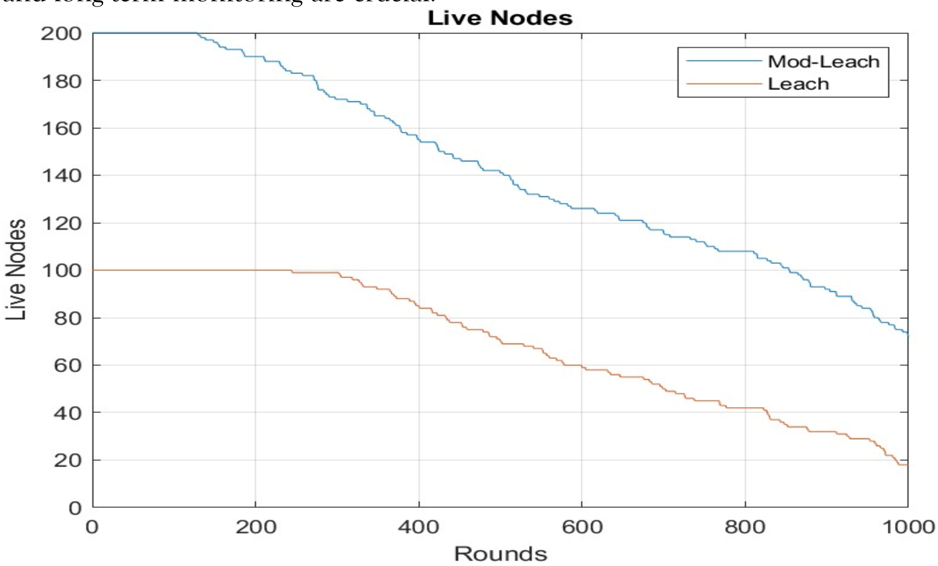

Figure 2: Number of Alive Nodes

The LEACH and Mod-LEACH protocols' relative performance in terms of node survival across 1000 simulation rounds is depicted in the "Live Nodes" graph. Since both protocols begin with their respective full node populations (about 200 for Mod-LEACH and 100 for LEACH), it is possible that Mod-LEACH was created for a scaled network or denser deployment. Energy depletion causes the number of living nodes to decline as the simulation goes on. Around round 250, the number of living nodes in the LEACH protocol starts to drastically decrease, and by the 1000th round, there are only roughly 20 nodes left. Mod-LEACH, on the other hand, keeps a far greater number of live nodes during the simulation—more than 70 nodes remain operational at the conclusion. This slow decrease is a result of improved energy balance and increased efficiency.

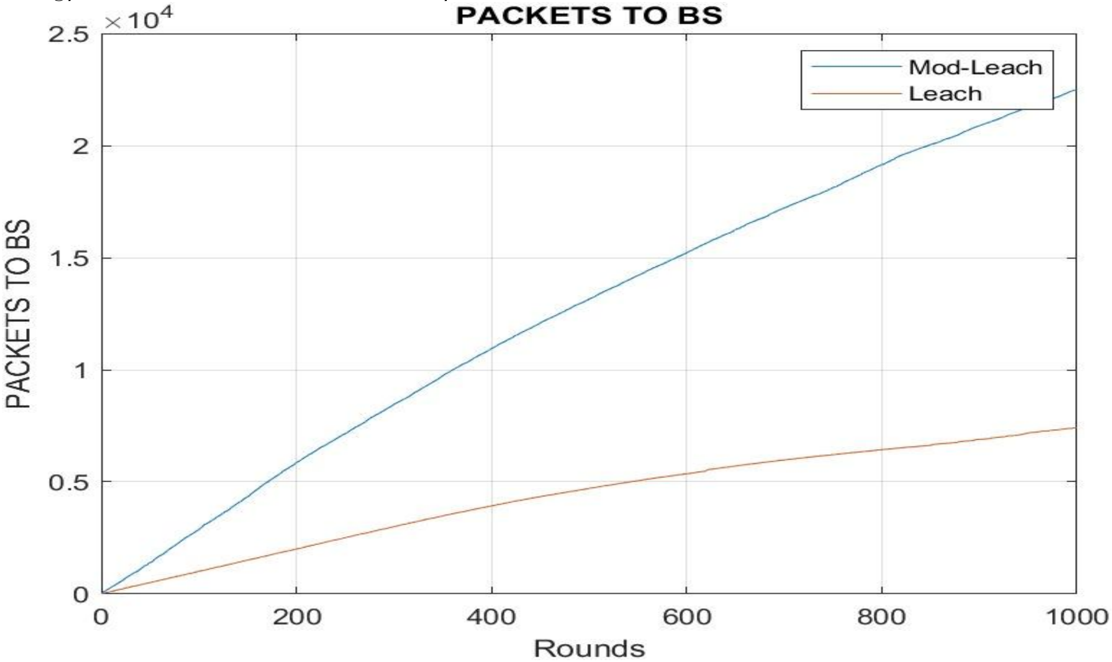

Figure 3: Packets sent to the base station

The cumulative number of data packets sent to the base station by the LEACH and Mod-LEACH

protocols during 1000 simulation rounds is compared in the Packets to BS (Base Station) graph. The y-axis, which is within the range of $\times 10^4$, displays the total number of packets that were successfully delivered, while the x-axis indicates the number of rounds. Mod-LEACH shows a substantially steeper slope than LEACH right away, which suggests a lot higher data throughput. Mod-LEACH sent almost 2.4×10^4 packets by the end of the simulation, while LEACH sent less than 1.0×10^4 packets.
This outcome demonstrates the Mod-LEACH protocol's higher data transport capacity and network dependability. Its intelligent cluster head selection is largely responsible for the improvement, as it distributes the energy load evenly among nodes and increases their operational lifetime. More nodes survive longer as a result, continuously providing the base station with data.

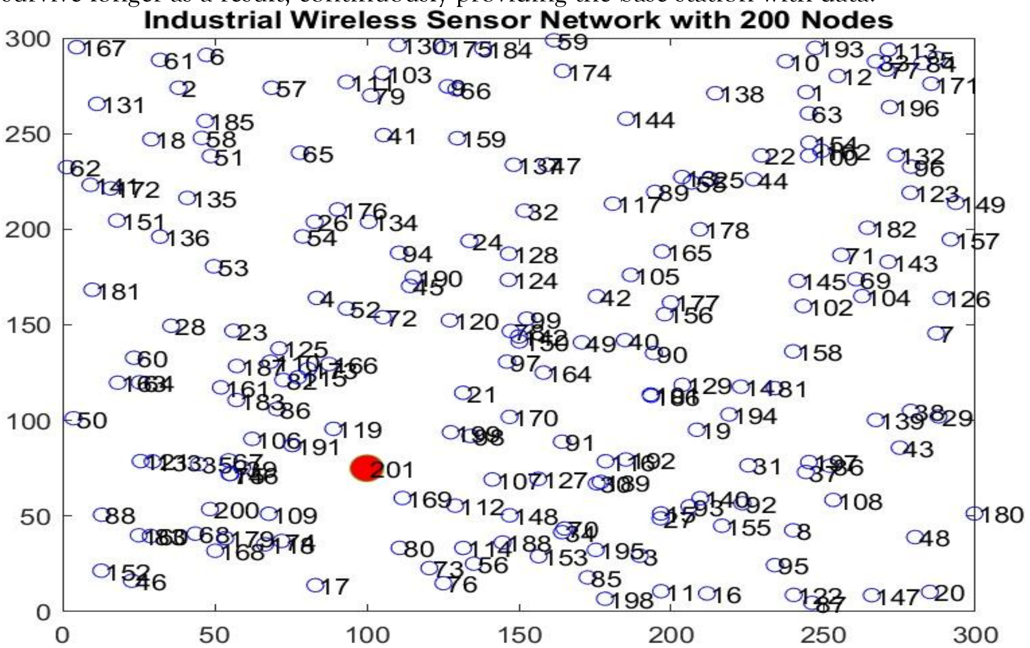

Figure 4: Industrial Network with Heterogeneous Nodes
An Industrial Wireless Sensor Network (IWSN) with 200 randomly placed nodes is seen in figure 4. The base station is represented by the red dot (node 201), and each node has a numerical identification. This configuration mimics a common industrial deployment scenario for protocol testing and performance analysis in simulation environments.

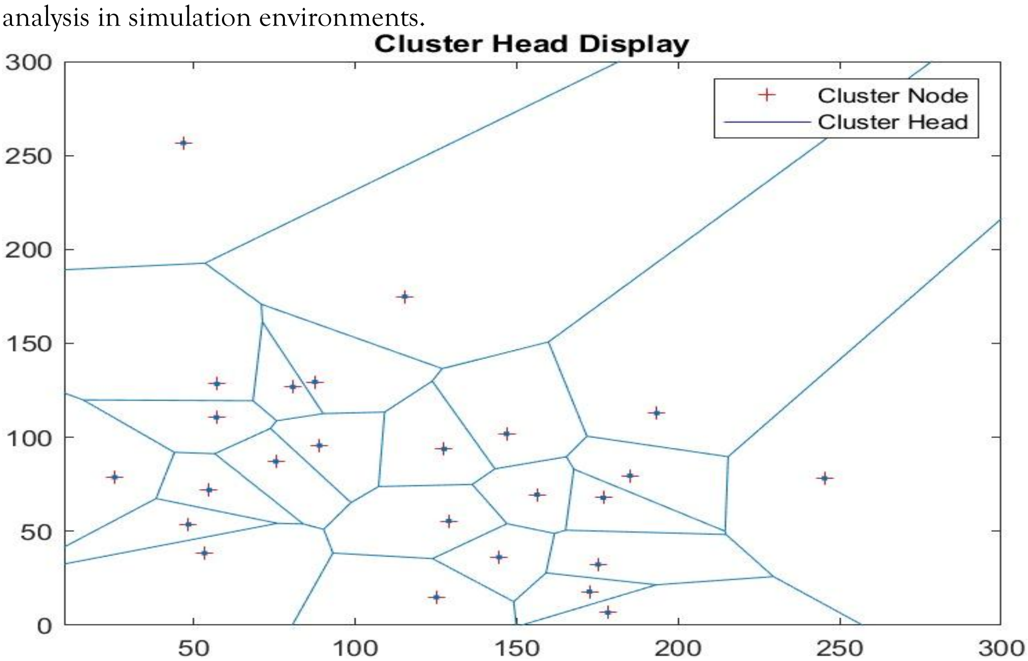

Figure 5: Cluster Head Nodes Display
The cluster head formation in a Wireless Sensor Network (WSN) is depicted in this diagram. With one cluster head per area, the blue lines delineate the boundaries of each cluster, while the red crosses stand in for the cluster nodes. In order to optimize energy consumption, these cluster heads are in charge of gathering data from the sensor nodes in their respective regions and sending it to the base station.

Scalability and energy efficiency are improved by clustering the network using methods such as Voronoi diagrams. For hierarchical protocols like LEACH and its variations, this structured clustering technique is essential for achieving balanced load distribution and a longer network lifetime.

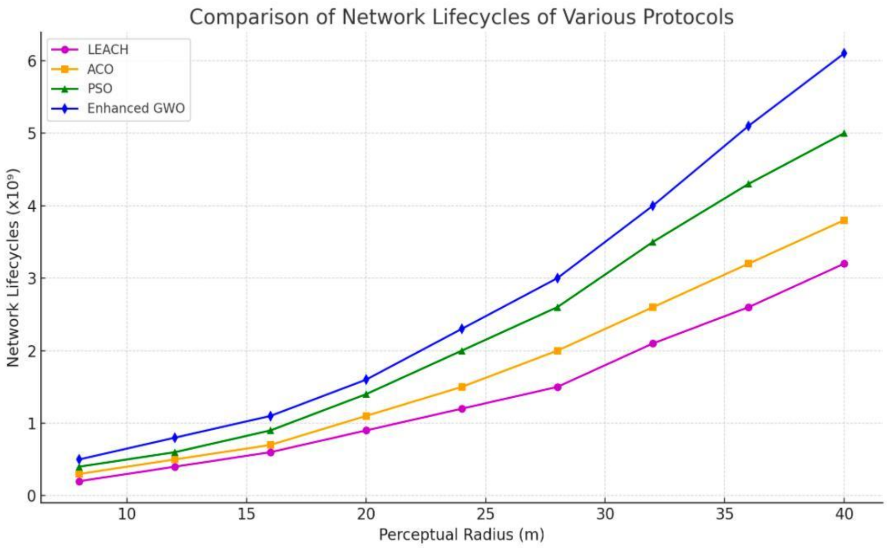

Figure 6: Comparisons of Network Lifecycles of various Algorithm

The network lifecycles of the LEACH, ACO, PSO, and Enhanced GWO protocols are contrasted over different perceptual radii in figure 6. As the perceptual radius rises, enhanced GWO continuously beats the others and achieves the longest network lifespan, demonstrating its better energy economy and optimization capability in Industrial Wireless Sensor Networks (IWSNs).

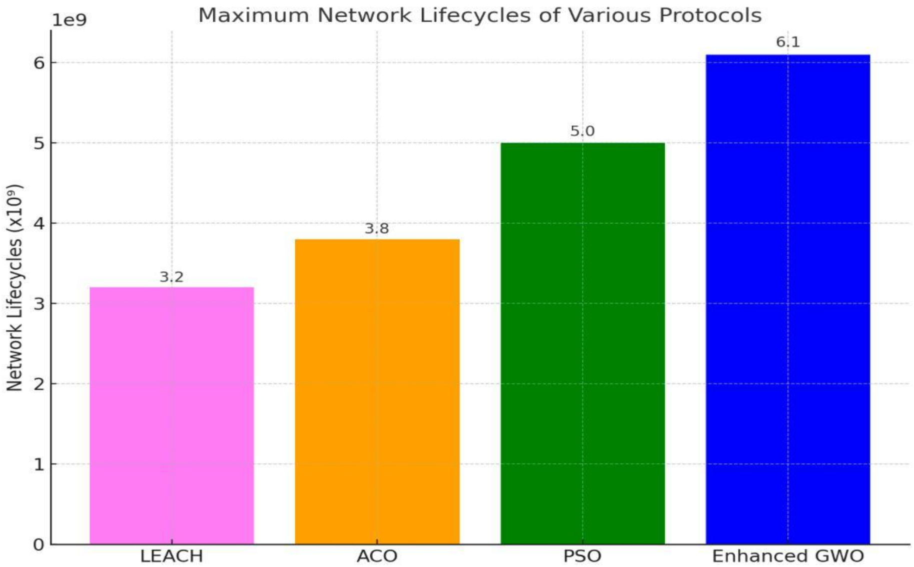

Figure 7: Maximum Network Lifecycles of various Algorithm

The maximum network lifecycles attained by the four distinct protocols—LEACH, ACO, PSO, and Enhanced GWO—are depicted in figure 7. With a maximum lifespan of 6.1×10^9, the Enhanced Grey Wolf Optimization (GWO) algorithm performs better than any of the others, demonstrating its greater effectiveness in network management and energy reduction. PSO exhibits reasonable performance with a value of 5.0×10^9, while ACO and LEACH attain lower values of 3.8×10^9 and 3.2×10^9, respectively. This comparison demonstrates how well the improved GWO extends the network lifetime in Industrial Wireless Sensor Networks (IWSNs), making it a better option for applications requiring extended operating times and great energy efficiency.

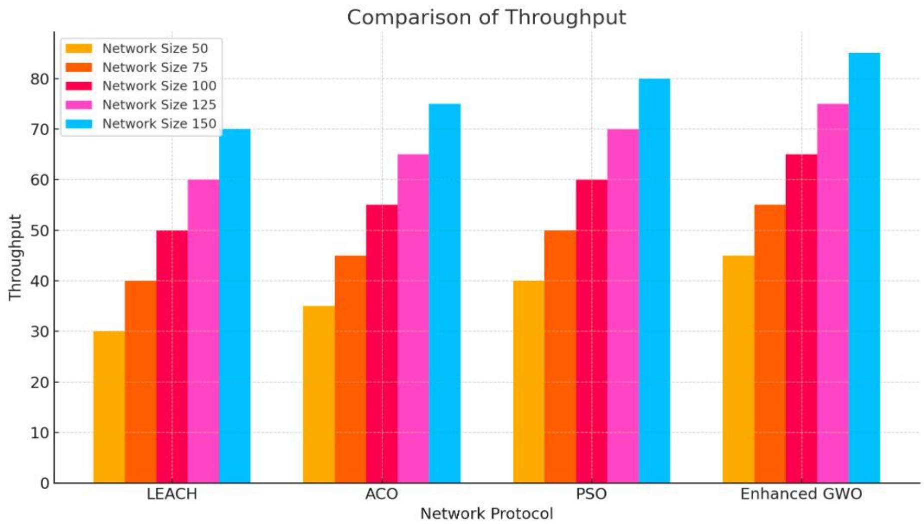

Figure 8: Comparison of Throughput of various Protocol

Four network protocols—LEACH, ACO, PSO, and Enhanced GWO—are compared in figure 8 for throughput performance across a range of network sizes (50 to 150 nodes). For all protocols, throughput steadily rises with network size. With the highest throughput across all network sizes—peaking at about 85 for 150 nodes—the Enhanced GWO protocol performs better than the others. PSO comes in second, then ACO and LEACH. According to this pattern, enhanced GWO scales more effectively and retains its better data transmission capacity, which makes it ideal for dense Industrial Wireless Sensor Networks (IWSNs) that need dependable performance and high throughput under increasing network demands.

DISCUSSION AND FUTURE WORK

Future study can examine a number of improvements, even though the suggested GWO model for Industrial Wireless Sensor Networks (IWSNs) demonstrates significant gains in energy efficiency and quality of service. Integrating mobile sink nodes is one interesting approach to further minimize the energy strain on static cluster heads and communication distance. Furthermore, in dynamic industrial settings, the network's resilience can be increased by putting in place real-time problem detection and self-healing algorithms. Predictive optimization for energy management and cluster head selection may also be supported by the use of lightweight machine learning algorithms. Scalability and adaptability would be improved by expanding the model to include large-scale, heterogeneous networks with a variety of sensor kinds and energy profiles. Sensitive industrial data can also be protected by solving security issues using secure clustering and data transmission protocols. Finally, real-world deployment and hardware-level testing in industrial settings will be essential to validate the model's practical performance and operational feasibility.

CONCLUSION

To address the combined concerns of energy consumption and Quality of Service (QoS), this study proposes an integrated and energy-efficient network architecture for **Industrial Wireless Sensor Networks (IWSNs) by merging the Grey Wolf Optimization (GWO) algorithm with the H-TEEN protocol. The GWO algorithm promotes balanced energy distribution and increases network lifetime by intelligently choosing the best cluster heads based on node location and leftover energy. Improved for hierarchical and heterogeneous communication, the H-TEEN protocol efficiently lowers latency and transmission overhead.

According to simulation results, the suggested GWO- model performs noticeably better in terms of energy efficiency, packet delivery ratio, and network stability than conventional protocols like LEACH, PSO, and ACO. The hybrid technique is ideal for real-time monitoring and control applications in industrial settings because it guarantees dependable data transfer, fault tolerance, and economical energy use.

REFERENCES:

1. Mirjalili, S. (2019). "Grey Wolf Optimizer: Advances, Modifications and Applications". IEEE Access, 7, 107377–107395.
2. Khan, M. A., et al. (2021). "Multi-objective clustering in WSNs using hybrid GWO–PSO algorithm". Sensors, 21(4), 1222.
3. Bano, F., et al. (2020). "Energy-aware QoS-based routing for WSNs in industrial environments". Ad Hoc Networks, 105,

102159.
4. Mehta, A., & Patel, R. (2022). "QoS-Driven GWO-based Routing for Industrial IoT". IEEE Access, 10, 7721–7733.
5. Sharma, A., et al. (2023). Bio-Inspired Algorithms for WSN Optimization: A Comparative Review , ICT Express, 9(1), 12–20.
6. Reddy, A., & Kumar, S. (2024). Delay-Aware Routing in WSN using GWO-DE Hybrid. Computers & Electrical Engineering, 112, 108915.
7. Singh, D., & Kaur, P. (2020). **QoS-Aware Cluster Head Selection using Bio-Inspired Techniques**. *Wireless Networks*, 26(8), 5959–5974.
8. Verma, H., & Yadav, R. (2022). Delay-Optimized Grey Wolf Clustering in WSNs. Journal of Ambient Intelligence and Humanized Computing, 13, 7819–7833.
9. Zhang, Y., et al. (2021). Energy Prediction-based GWO Clustering in Industrial WSNs. Futur Generation Computer Systems*, 117, 115–127.
10. Li, Q., et al. (2019). "Energy-Efficient Design for IWSNs in Harsh Environments". Journal of Network and Computer Applications, 134, 45–54.
11. Pandi, V. R., et al. (2020). "GWO-based Load Balanced Routing for IoT-WSN" . Measurement, 158, 107700.
12. Yang, J., et al. (2021). Hybrid GWO with Firefly Algorithm for Data Aggregation. Applied Soft Computing, 103, 107156.
13. Elhoseny, M., et al. (2019). "Intelligent Routing Based on Swarm Intelligence in WSN". Cluster Computing*, 22(4), 10599–10609.
14. Kumar, V., & Vasan, A. (2020). GWO for Secure Routing in Industrial IoT. Wireless Personal Communications, 113(2), 871–888.
15. Rahmani, M., et al. (2021). Energy-Aware Routing with GWO in IoT-WSN. Wireless Networks, 27, 231–243.
16. Kumari, S., et al. (2020). "QoS-Driven GWO for Industrial Environment Monitoring". Procedia Computer Science, 167, 2034–2043.
17. Mishra, A., et al. (2021). Metaheuristic Optimization for Clustering in WSN. Heliyon, 7(6), e07223.
18. Ahmad, M. A., et al. (2023). Performance of Bio-inspired Clustering for IoT-Based WSNs. IEEE Internet of Things Journal*, 10(4), 3456–3465.
19. Aljarah, I., et al. (2022). Enhanced Grey Wolf Optimizer for Sensor Node Placement. Expert Systems with Applications, 188, 115978.
20. Zafar, S., et al. (2021). Comparison of GWO with PSO and ACO in WSN Routing. Wireless Communications and Mobile Computing, Article ID 9987395.
21. Jain, D., et al. (2022). QoS-Constrained Routing Protocols in IWSNs: Survey and Analysis. Computer Networks, 204, 108695.
22. Silva, J., et al. (2021). QoS-aware Multi-Objective Optimization for Delay and Energy in WSNs. Applied Soft Computing*, 109, 107501.
23. Habib, S., et al. (2023). Latency-Aware Data Transmission in Industrial WSNs. Sensors, 23(2), 768.
24. Wu, H., et al. (2022). QoS in Industrial WSNs: Challenges and Strategies. IEEE Transactions on Industrial Informatics, 18(3), 1989–1998.
25. Srinivasan, R., & Baskar, S. (2021). Energy-Aware Multi-Objective Routing using GWO in WSNs. Wireless Network, 27, 1593–1605.
26. Iqbal, S., et al. (2020). QoS-Based Clustering with Trust Evaluation in WSNs. Computer Communications, 154, 429–437.
27. Abdel-Basset, M., et al. (2023). Multi-Objective Optimization using Improved GWO. Knowledge-Based Systems, 263, 110258.
28. Das, A., et al. (2022). Energy and Delay Trade-off in WSN Routing Using Metaheuristics. PeerJ Computer Science, 8, e893.
29. Mishra, R. R., et al. (2019). Latency-Driven Cluster Head Selection using Swarm Intelligence. Wireless Personal Communications, 108(2), 941–960.
30. Rani, M., & Bansal, D. (2024). Industrial WSN Optimisation Using Bio-Inspired Approaches. Computers & Industrial Engineering*, 190, 109049.