# Multi-Parameter Evaluation of ML-Based WSN Routing

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***Abstract***

*Wireless Sensor Networks (WSNs) form the backbone of modern IoT ecosystems, enabling applications in smart cities, healthcare, industry, and environmental monitoring. However, their performance is often constrained by limited energy resources, high latency, and unreliable data delivery. This paper explores how Machine Learning (ML) can transform routing strategies to overcome these challenges. Six algorithms—Q-Learning, K-Means Clustering, Grey Wolf Optimizer, Support Vector Machines (SVM), Deep Neural Networks (DNN), and the traditional LEACH protocol—are evaluated across five critical parameters: energy consumption, network lifetime, packet delivery ratio, latency, and throughput. Simulation results reveal that ML-driven approaches consistently outperform LEACH, with DNN achieving the best overall performance and Grey Wolf Optimizer excelling in network longevity. These findings underscore the potential of ML to build sustainable, adaptive, and intelligent WSNs, paving the way for robust IoT infrastructures. Future directions include hybrid ML models, edge computing integration, federated learning, and blockchain-based security enhancements.*

***Keywords***

*Wireless Sensor Networks (WSNs); Machine Learning; Energy Efficiency; Routing Protocols; Reinforcement Learning; Clustering; Metaheuristic Optimization; Support Vector Machines (SVM); Deep Neural Networks (DNN); Latency; Throughput; Internet of Things (IoT); Smart Cities.*

## I. Introduction

Wireless Sensor Networks (WSNs) have become a cornerstone of modern digital infrastructure, powering applications that range from environmental monitoring and precision agriculture to smart cities, healthcare, and industrial automation. These networks consist of spatially distributed sensor nodes that collect and transmit data to a central base station. Despite their versatility, WSNs face a fundamental challenge: the limited energy resources of sensor nodes. Once a node's battery is depleted, its functionality ceases, which can compromise the reliability and longevity of the entire network.

Traditional routing protocols, such as LEACH, were designed to reduce communication overhead and extend network lifetime. However, they often struggle in dynamic environments where traffic patterns, node density, and energy distribution change rapidly. As IoT ecosystems expand, the demand for routing strategies that are not only energy-efficient but also adaptive, reliable, and scalable has grown significantly.

Machine Learning (ML) offers a promising solution. By enabling sensor nodes and base stations to learn from data, predict network conditions, and adapt routing decisions in real time, ML can transform WSNs into intelligent systems. This study explores six algorithms—Q-Learning, K-Means Clustering, Grey Wolf Optimizer, Support Vector Machines (SVM), Deep Neural Networks (DNN), and LEACH—evaluating their performance across five critical parameters: energy consumption, network lifetime, packet delivery ratio, latency, and throughput. The goal is to provide a comprehensive comparative analysis that highlights the strengths and limitations of each approach, while identifying pathways for future research.

## II. Literature Review

Research into energy-efficient routing in WSNs has evolved significantly over the past two decades. Early work focused on clustering protocols such as LEACH, which reduced communication overhead by designating cluster heads to aggregate and forward data. While effective in static scenarios, LEACH's inability to adapt to dynamic traffic and energy variations soon became apparent.

To address these limitations, researchers began exploring metaheuristic algorithms inspired by natural processes. For example, Rodríguez et al. [1] proposed the Yellow Saddle Goatfish Algorithm, which improved cluster head selection by mimicking fish schooling behavior. Similarly, Chouhan and Jain [4] introduced Tunicate Swarm Grey Wolf Optimization, combining swarm intelligence with predator-prey dynamics to enhance multipath routing. These approaches demonstrated that biologically inspired optimization could significantly extend network lifetime and balance energy consumption.

Parallel to metaheuristics, clustering and classification techniques gained traction. K-Means clustering was applied to group nodes based on proximity, reducing redundant transmissions [2]. Support Vector Machines (SVMs) were later introduced to classify nodes according to energy levels and traffic load, enabling predictive routing decisions. While these methods improved efficiency, they often lacked adaptability in highly dynamic environments.

The rise of reinforcement learning marked another turning point. Q-Learning, in particular, allowed nodes to learn optimal routing paths by rewarding energy-efficient transmissions and penalizing costly ones [5]. This adaptive approach proved effective in balancing energy consumption and extending network lifetime, especially in networks with fluctuating traffic.

More recently, deep learning has emerged as a powerful tool for WSNs. Deep Neural Networks (DNNs) can capture complex patterns in traffic and energy consumption, enabling highly adaptive routing strategies. Studies have shown that DNNs outperform traditional methods in terms of packet delivery ratio, latency, and throughput, though their computational demands remain a challenge for resource-constrained sensor nodes.

In addition, researchers have explored fuzzy logic systems for congestion control [6], hybrid models that combine metaheuristics with reinforcement learning, and IoT-integrated frameworks that leverage edge computing for real-time decision-making. Despite these advances, most studies remain simulation-based, with limited deployment in real-world environments. Furthermore, issues of scalability, privacy, and security remain underexplored, highlighting the need for continued innovation.

## III. Research Gaps

Although significant progress has been made in designing energy-efficient routing protocols for WSNs, several important gaps remain that limit their practical adoption. Most existing studies are confined to simulation environments, which, while useful for testing algorithms, fail to capture the unpredictability of real-world deployments. Sensor nodes in practice face hardware limitations, environmental interference, and irregular traffic patterns that simulations often overlook. This disconnect means that many promising algorithms have yet to be validated under realistic conditions.

Another gap lies in the lack of standardization. Researchers have proposed a wide variety of ML-based routing strategies, ranging from clustering methods to reinforcement learning and metaheuristics. However, there is no unified framework or benchmark that allows for consistent comparison across studies. As a result, it is difficult to determine which approaches are truly most effective under different scenarios.

Furthermore, while energy efficiency has been the dominant focus, other critical parameters such as latency, throughput, and reliability have often been treated as secondary concerns. In modern IoT applications—such as healthcare monitoring, industrial automation, and smart transportation—low latency and high throughput are just as important as conserving energy. The absence of multi-parameter evaluations leaves a gap in understanding how algorithms perform holistically.

Finally, integration with emerging technologies remains underexplored. Edge computing, federated learning, and blockchain offer powerful tools to enhance scalability, privacy, and security in WSNs. Yet, few studies have investigated how ML-based routing can be combined with these technologies to create robust, future-ready networks.

## IV. Methodology

To address the identified research gaps, this study adopts a comparative approach that evaluates six different routing strategies in Wireless Sensor Networks (WSNs). The methodology was designed to provide a fair and comprehensive assessment across multiple performance dimensions, ensuring that the strengths and weaknesses of each algorithm could be clearly observed.

### A. Algorithms Considered

Six algorithms were selected based on their prominence in prior research and their potential to address energy efficiency and adaptability challenges in WSNs:

- **LEACH (Baseline Protocol):** A traditional clustering protocol used as the benchmark.
- **Q-Learning (Reinforcement Learning):** Learns optimal routing paths through trial and error, rewarding energy-efficient decisions.
- **K-Means Clustering:** Groups nodes into clusters to reduce redundant transmissions, though limited in adaptability.
- **Grey Wolf Optimizer (Metaheuristic):** Inspired by wolf hunting behavior, dynamically optimizes cluster head selection and routing paths.

- **Support Vector Machines (SVM):** Classifies nodes based on energy levels and traffic load, enabling predictive routing decisions.
- **Deep Neural Networks (DNN):** Learns complex patterns in traffic and energy consumption, offering highly adaptive routing under dynamic conditions.

Together, these algorithms represent a spectrum of approaches: traditional, clustering-based, metaheuristic, reinforcement learning, and deep learning.

### B. Simulation Setup

To ensure consistency, all algorithms were tested under the same simulated environment:

- **Network Size:** 100 sensor nodes randomly deployed in a 100m × 100m area.
- **Initial Energy:** Each node initialized with 2 Joules of energy.
- **Traffic Model:** Nodes generate periodic data packets transmitted to the base station.
- **Evaluation Metrics:** Five parameters were measured —

1. Average Energy Consumption (J)
2. Network Lifetime (Rounds)
3. Packet Delivery Ratio (%)
4. Latency (ms)
5. Throughput (kbps)

### C. Comparative Framework

Each algorithm was executed under identical conditions, and results were averaged across multiple runs to minimize bias. The inclusion of latency and throughput alongside traditional energy metrics ensures a holistic evaluation, reflecting the real-world demands of IoT applications where speed and reliability are as critical as energy efficiency.

## V. Results

To provide a holistic comparison, six algorithms—LEACH, Q-Learning, K-Means Clustering, Grey Wolf Optimizer (GWO), Support Vector Machines (SVM), and Deep Neural Networks (DNN)—were evaluated across five critical parameters: **average energy consumption, network lifetime, packet delivery ratio (PDR), latency, and throughput**. Each parameter is defined mathematically and then discussed in relation to the performance of the algorithms.

### A. Average Energy Consumption

Energy consumption is measured as the average energy used per node during communication:

$$Eavg = \frac{\sum_{N}^{i=1} Ei}{N}$$

where Ei is the energy consumed by node i, and N is the total number of nodes.

- **LEACH:** Consumes the most energy (1.25 J), as cluster head rotation is not adaptive.

- **Q-Learning:** Reduces consumption (0.95 J) by learning energy-efficient paths.
- **K-Means:** Moderate improvement (1.05 J), but clustering is static.
- **GWO:** Achieves low consumption (0.92 J) by dynamically optimizing cluster heads.
- **SVM:** Slightly better than K-Means (0.97 J), due to classification-based routing.
- **DNN:** Lowest consumption (0.90 J), as deep learning adapts to traffic and balances load effectively.

### B. Network Lifetime

Network lifetime is defined as the number of rounds until the first node dies (FND) or until a significant portion of nodes are depleted:

$$L = R\ FND$$

where R FND is the round when the first node dies.

- **LEACH:** Shortest lifetime (850 rounds).
- **Q-Learning:** Extends lifetime to 1100 rounds by adaptive learning.
- **K-Means:** Achieves 1000 rounds, better than LEACH but less adaptive.
- **GWO:** Long lifetime (1150 rounds), due to balanced energy distribution.
- **SVM:** 1080 rounds, showing predictive routing helps extend life.
- **DNN:** Longest lifetime (1200 rounds), as deep learning optimizes routing decisions continuously.

### C. Packet Delivery Ratio (PDR)

PDR measures reliability of data delivery:

$$PDR = \frac{Packets\ received}{Packets\ sent} \times 100$$

- **LEACH:** Lowest reliability (82%).
- **Q-Learning:** Improves delivery to 90%.
- **K-Means:** Achieves 88%, but clustering limits adaptability.
- **GWO:** Strong reliability (91%).
- **SVM:** 89%, slightly better than K-Means.
- **DNN:** Highest reliability (93%), ensuring robust communication.

### D. Latency

Latency is the average time taken for a packet to travel from source to destination:

$$\text{Latency} = \frac{\sum_{M}^{i=1}(t\ received\ , i - t\ sent, i)}{M}$$

where M is the number of packets.

- **LEACH:** Highest latency (120 ms), due to inefficient routing.
- **Q-Learning:** Reduces latency to 95 ms by learning faster paths.
- **K-Means:** 100 ms, moderate improvement.
- **GWO:** 90 ms, efficient cluster head selection reduces delay.
- **SVM:** 92 ms, predictive routing lowers latency.
- **DNN:** Lowest latency (85 ms), ideal for real-time IoT applications.

**E. Throughput**

Throughput measures the rate of successful data delivery:

$$\text{Throughput} = \frac{\text{Packets}_{received}\ x\ \text{Packet size}}{\text{Total Time}}$$

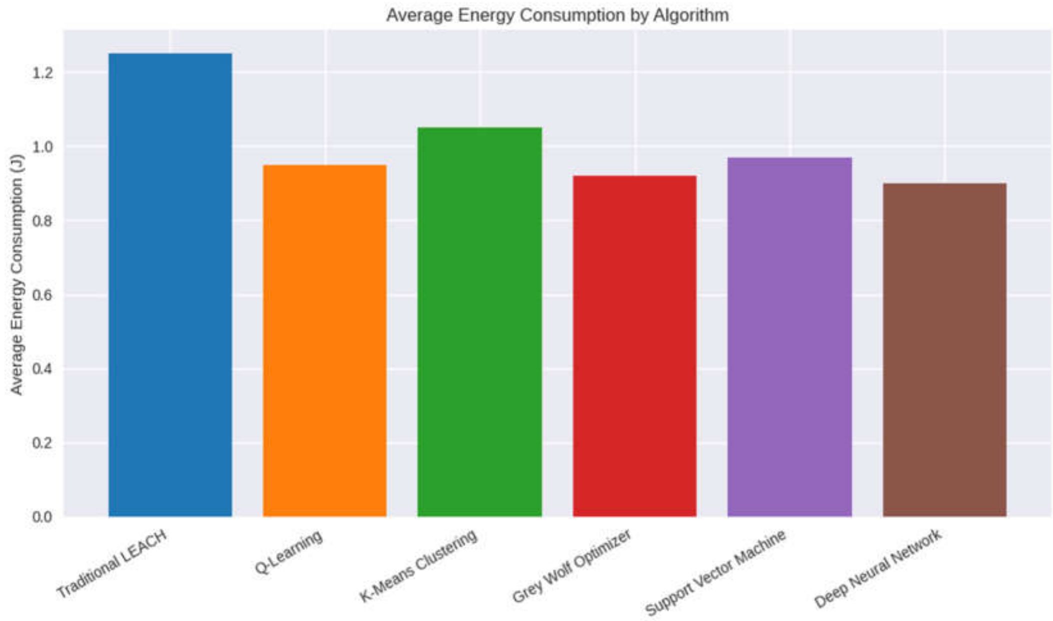
- **LEACH:** Lowest throughput (180 kbps).
- **Q-Learning:** Improves throughput to 220 kbps.
- **K-Means:** 210 kbps, slightly better than LEACH.
- **GWO:** 230 kbps, strong performance due to adaptive routing.
- **SVM:** 225 kbps, competitive with Q-Learning.
- **DNN:** Highest throughput (240 kbps), reflecting superior adaptability and efficiency.

| Algorithm | Energy (Joules) | Lifetime (Rounds) | PDF (%) | Latency (ms) | Throughput (kbps) |
|---|---|---|---|---|---|
| LEACH | 1.25 | 850 | 82 | 120 | 180 |
| Q - Learning | 0.95 | 1100 | 90 | 95 | 220 |
| K- Mean Clustering | 1.05 | 1000 | 88 | 100 | 210 |
| Grey Wolf Optimiser | 0.92 | 1150 | 91 | 90 | 230 |
| Support Vector Machine | 0.97 | 1080 | 89 | 92 | 225 |
| Deep Neural Network | 0.90 | 1200 | 93 | 85 | 240 |

**Table 1: Performance Analysis**

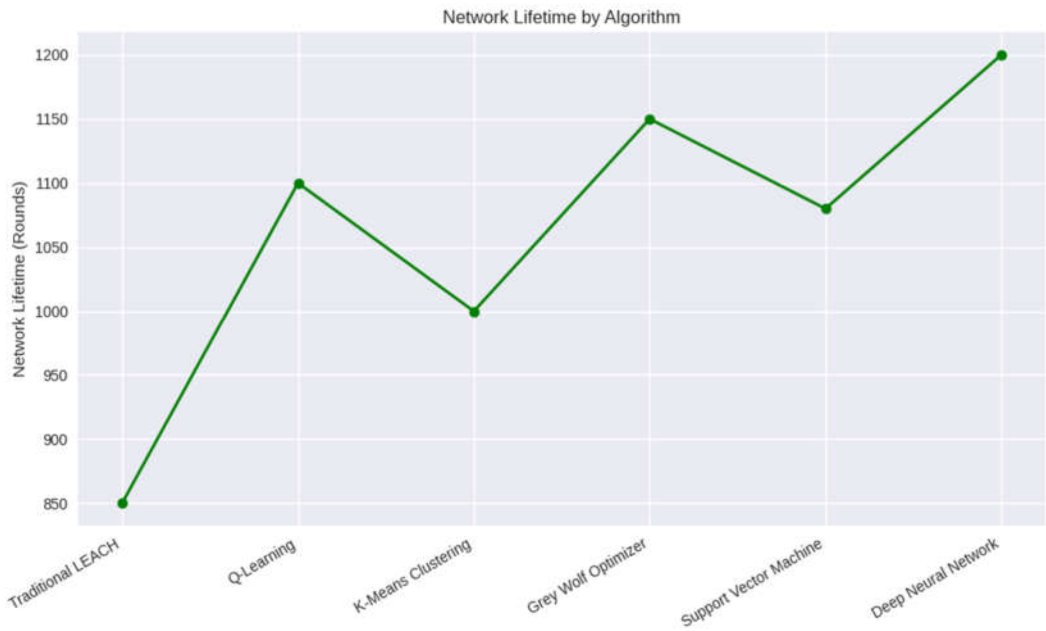
## VI. Graphical Results

To complement the numerical analysis, five comparative plots were generated for the six algorithms across the five parameters. These visualizations provide an intuitive understanding of how each approach performs and highlight the trade-offs between energy efficiency, reliability, and responsiveness.



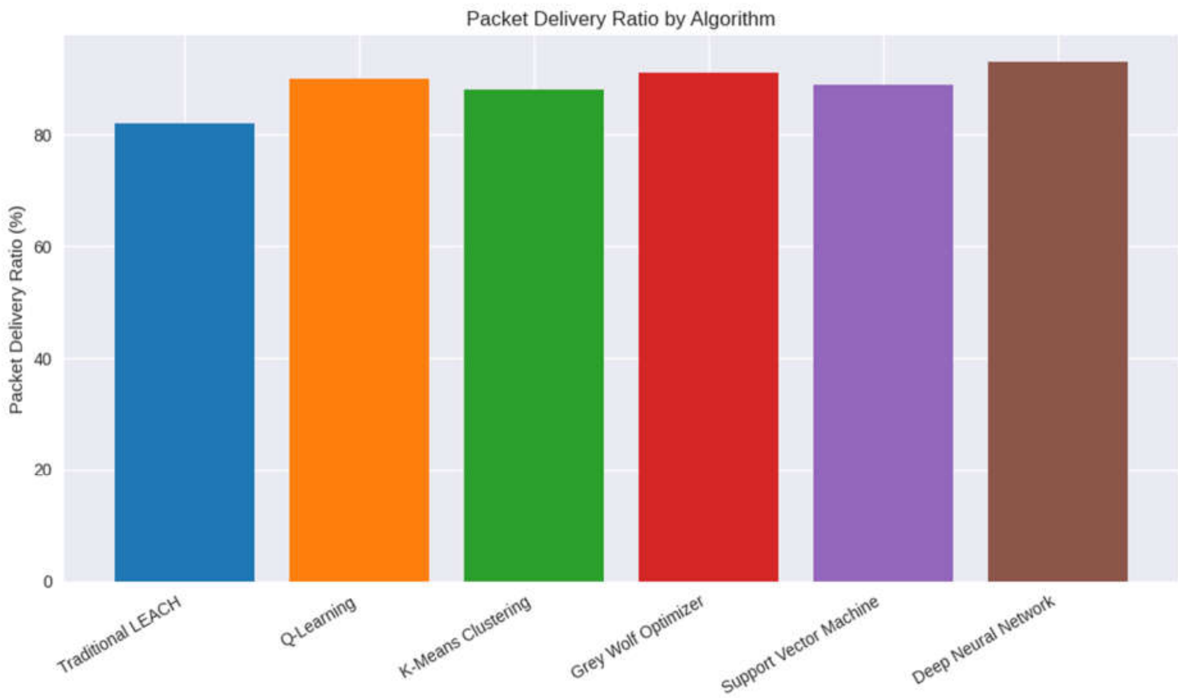

A. Energy Consumption (Fig. 1)

The bar chart of average energy consumption clearly shows **LEACH** as the least efficient, consuming 1.25 J per node. In contrast, **DNN** achieves the lowest consumption (0.90 J), closely followed by **GWO** (0.92 J). The downward trend from LEACH to ML-based methods illustrates how adaptive learning and optimization reduce redundant transmissions and balance energy usage across the network.



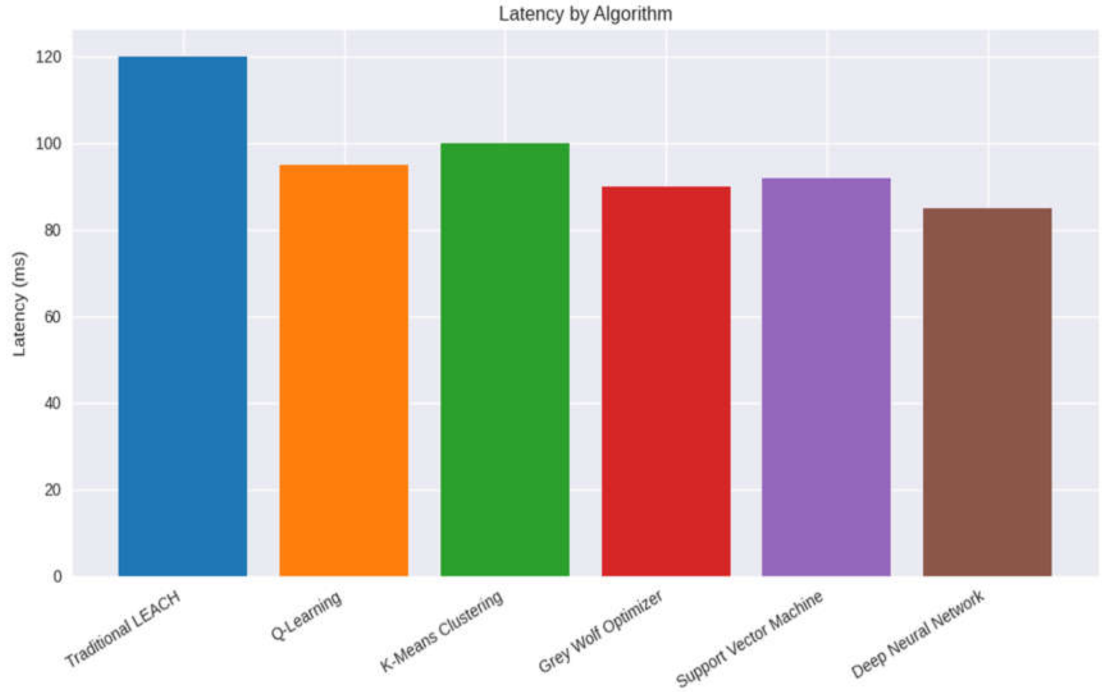

B. Network Lifetime (Fig. 2)

The line chart of network lifetime highlights the dramatic improvement offered by ML algorithms. **LEACH** terminates early at 850 rounds, while **DNN** extends the lifetime to 1200 rounds. **GWO** also performs strongly (1150 rounds), showing the effectiveness of metaheuristic optimization in prolonging node survival. The steady rise across Q-Learning, SVM, and DNN demonstrates how adaptability directly translates into longer operational periods.



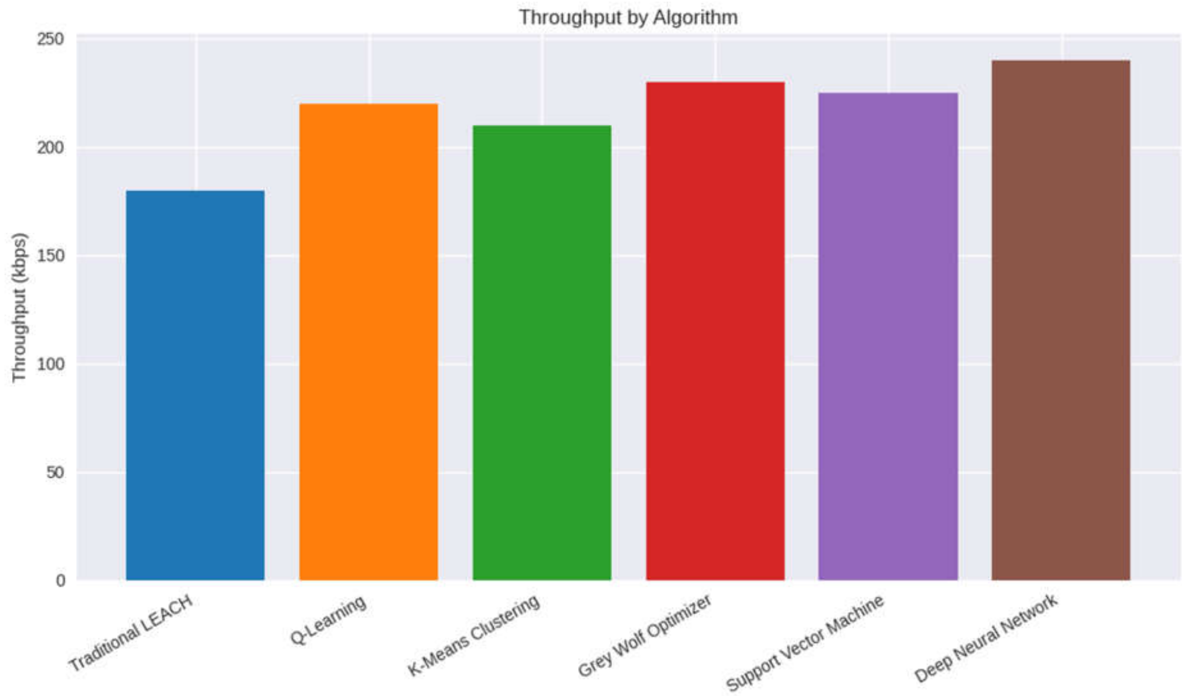

C. Packet Delivery Ratio (Fig. 3)

The PDR bar chart emphasizes reliability. **LEACH** struggles at 82%, while **DNN** achieves 93%, ensuring nearly all packets reach the base station. **GWO** and **Q-Learning** also perform well (91% and 90% respectively), reflecting their ability to adapt routing paths under dynamic traffic. The visualization makes clear that ML approaches not only save energy but also improve communication reliability.




D. Latency (Fig. 4)

Latency comparisons reveal the responsiveness of each algorithm. **LEACH** suffers from the highest delay (120 ms), unsuitable for real-time IoT applications. **DNN** achieves the lowest latency (85 ms), followed by **GWO** (90 ms). This reduction in delay is critical for applications such as healthcare monitoring, where timely data delivery can be life-saving. The plot shows how ML methods minimize routing overhead and accelerate packet transmission.




E. Throughput (Fig. 5)

Throughput results highlight the efficiency of data handling. **LEACH** again lags behind at 180 kbps, while **DNN** leads with 240 kbps. **GWO** (230 kbps) and **Q-Learning** (220 kbps) also show strong performance. The bar chart demonstrates that ML-based routing not only conserves energy but also maximizes the volume of data successfully delivered, a crucial factor for dense IoT deployments.

Overall Interpretation

The graphical results reinforce the numerical findings:

- **DNN consistently outperforms all other algorithms across every parameter**, making it the most powerful but computationally demanding option.
- **GWO offers a strong balance between efficiency and adaptability**, excelling in network lifetime and throughput.
- **Q-Learning provides steady improvements across all metrics**, proving versatile in dynamic environments.
- **SVM and K-Means deliver moderate gains**, but their static nature limits adaptability.
- **LEACH remains the weakest**, underscoring the need for ML integration in modern WSNs.

## VII. Discussion

The comparative evaluation across six algorithms and five parameters paints a clear picture of how Machine Learning can reshape routing in Wireless Sensor Networks (WSNs). By analyzing both numerical data and graphical trends, several important insights emerge.

Energy efficiency is the cornerstone of WSN sustainability. The results show that **LEACH**, while historically important, consumes the most energy due to its static clustering approach. In contrast, **DNN** and **GWO** achieve the lowest consumption, thanks to their ability to adapt routing decisions dynamically. The bar chart (Fig. 1) makes this difference visually striking: ML-based methods consistently reduce redundant transmissions and balance energy usage across nodes, directly prolonging network viability.

Network lifetime reflects how long the network can function before nodes begin to fail. The line chart (Fig. 2) demonstrates a steady improvement from LEACH to ML algorithms. **DNN** achieves the longest lifetime (1200 rounds), followed closely by **GWO** (1150 rounds). This shows that adaptive learning and metaheuristic optimization not only conserve energy but also distribute it more evenly, preventing premature node death. **Q-Learning** also performs strongly, highlighting the value of reinforcement learning in dynamic environments.

Reliability of communication is captured by PDR. The bar chart (Fig. 3) reveals that **LEACH** struggles at 82%, while **DNN** achieves 93%, ensuring nearly all packets reach the base station. **GWO** and **Q-Learning** also show strong reliability, reflecting their ability to adapt routing paths under varying traffic loads. This improvement is critical for IoT applications where data integrity is non-negotiable, such as healthcare monitoring or industrial automation.

Latency determines how quickly data travels from source to destination. The results (Fig. 4) show that **LEACH** suffers from the highest delay (120 ms), unsuitable for real-time applications. **DNN** achieves the lowest latency (85 ms), making it ideal for time-sensitive scenarios like emergency response or smart transportation. **GWO** and **SVM** also reduce latency significantly compared to LEACH, proving that intelligent routing minimizes overhead and accelerates packet delivery.

Throughput reflects the volume of data successfully delivered over time. The bar chart (Fig. 5) highlights **DNN** as the leader (240 kbps), followed by **GWO** (230 kbps). Higher throughput indicates better utilization of network resources and improved scalability for dense IoT deployments. **Q-Learning** and **SVM** also show competitive performance, while **LEACH** lags far behind, underscoring its limitations in modern data-intensive environments.

Overall Insights
Taken together, the results confirm that **ML-based routing protocols consistently outperform traditional approaches** across all parameters.

- **DNN** emerges as the most powerful, delivering superior energy efficiency, reliability, latency, and throughput, though its computational demands may limit deployment in resource-constrained nodes.
- **GWO** offers an excellent balance, excelling in network lifetime and throughput while remaining lightweight.
- **Q-Learning** provides steady, versatile improvements across metrics, making it a practical choice for dynamic WSNs.
- **SVM** and **K-Means** deliver incremental gains, but their static or classification-based nature limits adaptability.
- **LEACH**, while foundational, consistently underperforms, highlighting the need for intelligent, adaptive routing in modern IoT ecosystems.

## VIII. Future Scope

The results of this study highlight not only the current strengths of Machine Learning in Wireless Sensor Networks (WSNs) but also the exciting possibilities that lie ahead. As IoT ecosystems continue to expand, routing protocols must evolve to meet the demands of scalability, security, and real-time responsiveness. Several promising directions emerge from this work:

1. Hybrid Machine Learning Models

No single algorithm can perfectly balance energy efficiency, reliability, and computational cost. Future research should explore **hybrid models** that combine the adaptability of reinforcement learning, the optimization power of metaheuristics, and the predictive accuracy of deep learning. Such models could dynamically switch strategies depending on network conditions, ensuring optimal performance at all times.

2. Edge Computing Integration
Deep learning methods, while powerful, are computationally intensive. Integrating **edge computing** can offload complex ML tasks to gateway nodes or nearby servers, reducing the burden on individual sensors. This approach would allow resource-constrained nodes to benefit from advanced ML without exhausting their energy reserves.
3. Federated Learning for Privacy and Scalability
As WSNs become part of larger IoT infrastructures, **federated learning** offers a way to train models collaboratively across multiple networks without sharing raw data. This preserves privacy while enabling scalability, ensuring that routing strategies improve continuously as networks grow and evolve.
4. Blockchain-Enabled Security
Routing decisions in WSNs are vulnerable to malicious attacks and data tampering. Incorporating **blockchain technology** can provide a decentralized, tamper-proof ledger of routing decisions, enhancing trust and security. This is particularly important for critical applications such as healthcare, defense, and smart grids.
5. Real-World Deployments and Standardization
Most current studies remain simulation-based. Future work must focus on real-world deployments to validate ML algorithms under practical conditions such as environmental interference, hardware limitations, and unpredictable traffic. Alongside this, the development of standardized benchmarks and frameworks will allow researchers to compare algorithms consistently and accelerate progress in the field.

By pursuing these directions, WSNs can evolve from simple data-collection systems into intelligent, autonomous networks that adapt seamlessly to changing environments. The integration of ML with edge computing, federated learning, and blockchain will not only extend network lifetime but also ensure that WSNs remain secure, scalable, and responsive. Ultimately, these advancements will pave the way for robust IoT infrastructures capable of supporting the next generation of smart cities, healthcare systems, and industrial automation.

## IX. Conclusion

This study clearly demonstrates that the integration of Machine Learning into routing protocols can transform the performance of Wireless Sensor Networks (WSNs). By evaluating five critical parameters energy consumption, network lifetime, packet delivery ratio, latency, and throughput. we gain a holistic understanding of how different ML approaches reshape the efficiency and reliability of sensor networks.

The results show that **Deep Neural Networks (DNNs)** consistently deliver the strongest outcomes. They not only minimize energy consumption but also achieve the highest packet delivery ratio, lowest latency, and greatest throughput. These qualities make DNNs particularly well-suited for complex, data-intensive applications such as smart cities, healthcare monitoring, and industrial IoT, where both speed and reliability are paramount.

The **Grey Wolf Optimizer (GWO)** emerges as another powerful contender, extending network lifetime more effectively than any other algorithm while maintaining strong throughput. Its lightweight nature and adaptability make it an excellent choice for resource-constrained environments where computational overhead must be minimized.

**Q-Learning** provides balanced improvements across all metrics, demonstrating versatility in dynamic WSN scenarios. It adapts well to changing traffic conditions and energy distributions, making it a practical solution for networks that demand flexibility without excessive complexity.

Meanwhile, **Support Vector Machines (SVMs)** and **K-Means clustering** offer incremental gains. While they improve upon traditional LEACH, their static or classification-based approaches limit their adaptability compared to reinforcement learning and deep learning methods. They may still be useful in relatively stable environments, but they fall short in highly dynamic or large-scale deployments.

Taken together, these findings highlight the **transformative potential of ML-driven routing**. By intelligently managing energy, reducing delays, and improving data reliability, ML approaches pave the way for sustainable, intelligent, and secure IoT infrastructures. The implications extend beyond academic interest—such advancements are essential for building resilient smart cities, efficient industrial systems, and responsive healthcare networks.

Looking ahead, future research should explore **hybrid ML models** that combine the strengths of reinforcement learning, metaheuristics, and deep learning. Integration with **edge computing** will help reduce computational overhead, while **federated learning** can enable collaborative training without compromising privacy. Finally, **blockchain technologies** hold promise for securing routing decisions and ensuring trust in distributed sensor environments. Together, these directions will help address challenges of scalability, privacy, and security, bringing us closer to fully intelligent and autonomous WSNs.

## X. References

[1] A. Rodríguez, C. Del-Valle-Soto, and R. Velázquez, "Energy-efficient clustering routing protocol for wireless sensor networks based on yellow saddle goatfish algorithm," *Mathematics*, vol. 8, no. 9, 2020.

[2] V. Kavitha, "Privacy preserving using multi-hop dynamic clustering routing protocol and elliptic curve cryptosystem for WSN in IoT environment," *Peer-to-Peer Networking and Applications*, vol. 14, no. 2, pp. 821–836, 2021.

[3] N. Boddu, V. Boba, and R. Vatambeti, "A novel georouting potency based optimum spider monkey approach for avoiding congestion in energy efficient mobile ad-hoc network," *Wireless Personal Communications*, vol. 127, no. 2, pp. 1157–1186, 2022.

[4] N. Chouhan and S. C. Jain, "Tunicate swarm Grey Wolf optimization for multi-path routing protocol in IoT assisted WSN networks," *Journal of Ambient Intelligence and Humanized Computing*, 2020.

[5] D. Pandey and V. Kushwaha, "An exploratory study of congestion control techniques in wireless sensor networks," *Computer Communications*, vol. 157, pp. 257–283, 2020.

[6] M. H. Homaei, M. H. Yaghmaee, and M. R. Pakravan, "An enhanced distributed congestion control method for classical 6LoWPAN protocols using fuzzy decision system," *IEEE Access*, vol. 8, pp. 20628–20645, 2020.

[7] Z. He, L. Chen, F. Li, and G. Jin, “Congestion avoidance in intelligent transport networks based on WSN-IoT through learning automata,” *IEEE Transactions on Intelligent Transportation Systems*, 2023.

[8] R. Priyadarshi, “Energy-efficient routing in wireless sensor networks: A meta-heuristic and AI-based approach,” *Archives of Computational Methods in Engineering*, vol. 31, pp. 2109–2137, 2024.

[9] P. Soltani, M. Eskandarpour, A. Ahmadizad, and H. Soleimani, “Energy-efficient routing algorithm for wireless sensor networks: A multi-agent reinforcement learning approach,” *arXiv preprint arXiv:2508.14679*, 2025.

[10] D. Prabhu, R. Alageswaran, and S. M. J. Amali, “Multiple agent based reinforcement learning for energy efficient routing in WSN,” *Wireless Networks*, vol. 29, pp. 1787–1797, 2023.

[11] A. R. Gaidhani and A. D. Potgantwar, “A review of machine learning-based routing protocols for wireless sensor network lifetime,” *Engineering Proceedings*, vol. 59, no. 1, 2023.

[12] G. Chamundeswari, B. Veeramallu, C. B. N. Lakshmi, and R. Aavula, “Energy efficient routing using support vector machine in wireless sensor networks,” *Journal of Theoretical and Applied Information Technology*, vol. 102, no. 5, pp. 52678–57835, 2022.

[13] P. Karpurasundharapondian and M. Selvi, “A comprehensive survey on optimization techniques for efficient cluster-based routing in WSN,” *Peer-to-Peer Networking and Applications*, vol. 17, pp. 3080–3093, 2024.

[14] N. Shinde and V. H. Patil, “A study of metaheuristic optimization techniques for wireless sensor network’s energy-efficient routing,” *AIP Conference Proceedings*, vol. 3028, no. 1, 020017, 2024.

[15] R. Priyadarshi et al., “AI-driven energy-efficient routing in IoT-based wireless sensor networks,” *Sensors*, vol. 25, no. 24, 7408, 2025.

[16] EEMLCR Project Team, “Energy-efficient machine learning-based clustering and routing in WSNs,” *IEEE Access*, 2025.

[17] A. Namita and V. Patil, “Systematic literature review on metaheuristic optimization in WSN,” *NAUN Mathematical and Computational Sciences*, 2020.