Journal of Computer Networks, 2026, Vol. 13, No. 1, 1-15
Available online at http://pubs.sciepub.com/jcn/13/1/1
Published by Science and Education Publishing
DOI:10.12691/jcn-13-1-1

AI-Driven Adaptive Modulation for Enhancing Efficiency in Wireless Sensor Networks (WSNs)

Iven Aabaah[1,*], Valentine Aveyom[2], Solomon Anab[3], Seth Gyamerah[4]

[1]Department of Information Systems and Technology, University of Technology and Applied Sciences, Navrongo, Ghana
[2]Department of Computer Science, University of Technology and Applied Sciences, Navrongo, Ghana
[3]Department of Computer Science, Koforidua Technical University, Koforidua, Ghana
[4]Department of Computer Science, University of Technology and Applied Sciences, Navrongo, Ghana
*Corresponding author: iaabaah@utas.edu.gh

Received April 25, 2026; Revised May 27, 2026; Accepted June 03, 2026

Abstract: Wireless Sensor Networks (WSNs) are a major development in communication and distributed sensing systems. A wireless sensor network (WSN) consists of numerous tiny, inexpensive, low-power devices called sensor nodes that monitor environmental or physical parameters, including temperature, pressure, humidity, motion, and pollution. Together, these sensor nodes gather, process, and wirelessly transmit data to a central location, often called a base station or sink node, for further analysis. Wireless sensor networks (WSNs) are increasingly used in dynamic, resource-constrained settings, where it remains very difficult to use energy and communication resources effectively. This paper presents an AI-driven adaptive modulation system that improves network performance, reliability, and energy efficiency. The proposed approach combines residual energy monitoring, channel-aware adaptation, and reinforcement learning-based decision-making to dynamically select the optimal modulation schemes under changing channel conditions. Modulation levels can be intelligently and independently selected based on node energy status, link quality, and signal-to-noise ratio (SNR) by defining the adaptive modulation problem as a Markov Decision Process (MDP). A thorough mathematical model that accounts for bit-error rate (BER) limitations, energy consumption, and wireless channel characteristics is developed to ensure reliable and efficient communication. The framework achieves the best possible balance between energy efficiency and transmission efficiency by optimizing energy use and normalizing throughput. Compared to the conventional static modulation procedure, the proposed method performs significantly better. Comprehensive simulations using MATLAB and NS-3 reveal notable increases in network longevity along with gains of up to 20–35% in energy efficiency, 15–25% in packet delivery ratio, 20–30% in latency reduction, and 25–35% in throughput. These findings show that AI-driven adaptive modulation provides a scalable and dependable solution for next-generation WSNs, enabling intelligent resource management and sustainable network operation in dynamic communication scenarios.

Keywords: *wireless sensor networks, energy-efficiency, artificial intelligence, adaptive modulation*

Cite This Article: Iven Aabaah, Valentine Aveyom, Seth Gyamerah, and Solomond Anab, “AI-Driven Adaptive Modulation for Enhancing Efficiency in Wireless Sensor Networks (WSNs).” *Journal of Computer Networks*, vol. 14, no. x (2026): 1-15. doi: 10.12691/jcn-13-1-1.

1. Introduction

Wireless Sensor Networks (WSNs) have become an essential part of modern intelligent systems due to their capacity to provide ubiquitous sensing and data-driven decision-making across applications such as environmental monitoring, industrial automation, smart cities, and Internet of Things (IoT) infrastructures. These networks consist of energy-constrained sensor nodes working in dynamic, often hostile wireless environments [1,2,3]. Despite significant progress, designing reliable and efficient communication techniques in WSNs remains a basic issue due to the interplay of limited energy resources, time-varying channel conditions, and stringent bandwidth limitations [4]. A significant bottleneck in WSN communication is caused by the stochastic nature of wireless channels, which are impacted by multipath fading, shadowing, and distance-dependent path loss [5,6,7]. Packet delivery dependability and transmission efficiency are directly impacted by these impairments, which cause variations in the signal-to-noise ratio (SNR). In these kinds of situations, traditional communication schemes that depend on static or rule-based modulation techniques are fundamentally insufficient [8]. In particular, fixed modulation methods result in more retransmissions, more energy consumption, lower throughput, and a shorter network lifetime since they are unable to take advantage of favourable channel conditions and effectively respond to channel degradation. In dense and large-scale installations, when network dynamics worsen communication inefficiencies, this constraint becomes more noticeable [9,10].

By dynamically modifying modulation schemes based on channel quality, adaptive modulation has been widely acknowledged as a viable method for enhancing communication performance [11]. However, the majority of current methods use heuristic or threshold-based decision processes, which are usually created under oversimplified assumptions and are unable to adapt optimally in extremely dynamic contexts. More significantly, these approaches frequently handle performance indicators separately and fail to specifically address the multi-objective optimisation issue that arises in WSNs, where it is necessary to jointly optimise energy efficiency, dependability, latency, and spectrum efficiency. The development of intelligent, energy-aware, and context-adaptive modulation techniques for WSNs is therefore still far behind [12,13]. The adaptive modulation problem in WSNs can be conceptualised theoretically as a sequential decision-making process under uncertainty, where the ideal modulation scheme is dependent on stochastic system states like residual energy, instantaneous SNR, and link quality. This naturally encourages the application of reinforcement learning (RL), which allows agents to interact with their surroundings and discover the best rules [14,15,16]. However, in order to guarantee convergence, stability, and computational efficiency under resource-constrained circumstances, the incorporation of RL into adaptive modulation for WSNs necessitates careful design.

This paper presents a unique AI-driven adaptive modulation framework that uses reinforcement learning for optimum decision-making and formulates modulation selection as a Markov Decision Process (MDP) to handle these issues. In contrast to traditional methods, the suggested framework integrates multi-dimensional system awareness, such as packet success probability, residual energy, and channel conditions, into a single decision model. The goal is to achieve a balanced trade-off between energy efficiency and communication reliability by optimising energy-normalized throughput while meeting bit error rate (BER) requirements. To represent the wireless channel, energy consumption, and modulation optimisation process, a rigorous mathematical framework is created. A reward-driven learning mechanism that continually modifies modulation choices in response to real-time network feedback is introduced in the suggested architecture. Furthermore, convergence qualities and theoretical performance constraints are taken into account to guarantee the learning process's stability and scalability. The suggested method greatly outperforms traditional schemes in a number of performance metrics, such as packet delivery ratio, delay, energy consumption, throughput, and network lifetime, according to extensive simulations carried out under realistic channel conditions (Rayleigh fading with AWGN).

The remainder of this paper is organized as follows. Section 2 reviews related works on energy-efficient routing protocols in WSNs. Section 3 presents the proposed AI-Driven Adaptive Modulation mathematical framework. Section 4 discusses the simulation results, performance evaluation, percentage improvement, ablation study, and confidence interval analysis. Finally, Section 5 concludes the paper and outlines future research directions.

2. Related Work

A recent publication by [17], the authors, proposed a swarm intelligence-based optimisation framework with a focus on the Crayfish Optimisation Algorithm (COA) as the main energy-minimization method. The proposed approach is positioned as an advance over existing swarm-based techniques, such as Particle Swarm Optimisation (PSO) and Grey Wolf Optimiser (GWO), which are efficient but have issues with energy balancing, convergence behaviour, and flexibility in dynamic network contexts. The suggested approach treats network optimisation as a population-based search issue and is based on a multi-stage swarm optimisation procedure. The COA starts with the initialisation of a population of candidate solutions that represent various network configurations, such as cluster-head assignments and routing paths. A fitness function *Fitness = W1.MaxDist + W2.MaxHop*, which minimises energy-related metrics, transmission distance, and hop count as specified by the objective function, is used to assess each solution. A multi-objective optimisation strategy that balances transmission distance and routing efficiency to lower total energy consumption is made possible by this formulation. Crayfish-inspired behavioural models fuel the algorithm's iterative improvements. Candidate solutions are updated during the foraging phase according to probabilistic movement impacted by environmental factors, specifically temperature, which is represented by a stochastic function. The algorithm may dynamically modify its search strategy since the meal intake probability and food size parameters control the level of exploration and exploitation. The method goes into a shredding phase when specific thresholds are reached. During this phase, nonlinear update equations are used to sharpen answers and speed up convergence toward optimal solutions. However, as conditions change, the algorithm employs multiple movement strategies to maintain diversity in the search field.

A paper by [18], the authors proposed a Deep Q-Learning-based Adaptive MAC protocol with collision avoidance and power regulation (DAWPC-MAC). The suggested approach is a major breakthrough that permits intelligent, adaptive decision-making in difficult underwater situations by integrating deep reinforcement learning (DRL) into the MAC layer design. In contrast to conventional protocols that rely on static rules or predefined scheduling, DAWPC-MAC uses a Deep Q-Network (DQN) to dynamically optimise communication parameters, including wake-up scheduling, transmission power, slot allocation, and data prioritisation. One significant innovation of the suggested system is the receiver-initiated communication mechanism, which lowers idle listening and needless transmissions by having the receiver (courier node) actively manage communication cycles. The protocol also includes adaptive power regulation, which minimizes energy consumption by enabling nodes to modify transmission power in response to communication needs and ambient conditions. To further improve network resilience and guarantee the timely delivery of critical data, collision-avoidance and priority-based scheduling are combined. The hybridisation of learning-based optimisation with MAC-layer control, which distinguishes the proposed framework from previous research, enables notable improvements in packet delivery ratio, throughput, and overall network efficiency.

In a publication by [19], the authors proposed a novel hybrid MAC protocol (ACRLPC) based on Actor-Critic Reinforcement Learning that integrates TDMA, CSMA/CA, and adaptive power regulation into a single learning-driven architecture. Unlike conventional MAC protocols that depend on static or semi-adaptive methods, the proposed method offers a hybrid channel access architecture that deftly combines the benefits of contention-based and schedule-based protocols. Specifically, TDMA guarantees collision-free transmission for periodic and high-priority data, while CSMA/CA manages dynamic, bursty traffic, boosting channel utilisation and flexibility. The primary innovation of the proposed system is the use of Actor-Critic Reinforcement Learning (AC-RL) to dynamically optimise communication choices depending on current network conditions. This learning-based method allows nodes to adapt transmission power, channel access strategies, and scheduling decisions to changes in the environment, such as node density, traffic load, and channel characteristics. Additionally, the framework has a Communication Channel-Optimized Adaptive Power Control mechanism that lowers energy usage by modifying transmission power according to distance, path loss, and environmental variables. By combining a hybrid MAC design with intelligent learning and power control, the proposed ACRLPC framework achieves thorough optimisation of energy efficiency, throughput, latency, and computing complexity, outperforming existing protocols like FDU-MAC, TCH-MAC, and UW-ALOHA-QM.

In a paper by [20], the authors provided a single, energy-conscious, geometry-driven framework that combines an adaptive Quality-of-Service (QoS) scheduling mechanism with accurate hole identification. The suggested solution introduces three significant innovations. It first uses a convex-hull-based geometric modelling technique, in which the effective coverage zone is defined by the union of the sensor nodes, which are represented as discs. The framework identifies true coverage gaps by subtracting the coverage region from the convex hull enclosing every node. To ensure the most critical and energy-efficient holes are handled first, the framework also incorporates a priority-based QoS scheduler that determines the order of hole recovery based on a combination of hole criticality (area) and remaining node energy. Third, the authors suggest a lattice-based sensor placement technique that minimises redundancy and deployment costs while optimising the positioning of extra nodes to restore coverage. Unlike previous work that addresses these issues separately, this integrated strategy bridges the gap between spatial precision and energy efficiency. The suggested framework combines computational geometry, energy modeling, and scheduling theory into a multi-stage geometric and optimization-driven process. The hole-detection phase is based on the Hull-minus-Union approach (page 3). The four main processes are as follows: (i) model each sensor as a disc with radius r; (ii) compute the union of all sensor coverage regions; (iii) construct the convex hull of sensor locations; and (iv) produce uncovered regions by removing the coverage union from the hull. This geometric formulation ensures exceptional detection precision (almost 100% inside the indicated border) and avoids false positives, which are prevalent in discretised algorithms. The framework presents a quantitative hole characterisation process after hole detection, in which a minimum bounding ellipse is used to approximate each identified hole. The formula for calculating the hole's area is $A = \pi ab$, where a and b stand for the fitted ellipse's semi-major and semi-minor axes, respectively. This offers a constant and computationally effective hole severity estimate, which is essential for recovery planning and prioritisation.

In a paper by [21], the authors introduced a hybrid energy optimisation strategy that blends an enhanced clustering methodology (LEACH-D) with artificial neural networks (ANNs). The primary objective of the proposed approach is to minimise energy use while simultaneously reducing transmission delay and increasing network lifetime. An improved version of the classic LEACH protocol, the LEACH-D protocol incorporates balanced cluster-head selection, hierarchical clustering, and multi-hop communication. LEACH-D adds a secondary clustering phase in which a subset of CHs is further organised into Master Cluster Heads (MCHs), in contrast to the traditional LEACH protocol, which assumes direct communication between CHs and the base station. By lowering long-distance transmissions and more fairly allocating the communication load across nodes, this hierarchical architecture lessens energy depletion in remote nodes. This clustering improvement is complemented by the incorporation of an ANN, which introduces an intelligent decision-making layer that optimises routing and cluster-head placement. The ANN is trained to understand network behaviour from important variables like transmission latency and residual energy in order to detect inefficient nodes and dynamically alter communication pathways. By incorporating machine learning into the routing process, the proposed method surpasses traditional heuristic-based approaches and introduces data-driven adaptability, enabling the network to respond more effectively to changing conditions. A significant advancement is this hybridisation of LEACH-D and ANN, which blends structural optimisation (clustering) with cognitive optimisation (learning-based routing decisions).

A paper by [22], the authors, introduced a novel approach called the Semi-Decentralized Prediction Method (SDPM). The main innovation of SDPM is the integration of data prediction with dynamic clustering, which allows for balanced energy use and less communication. Unlike traditional approaches, which solely provide CH prediction assignments, SDPM distributes the prediction task over time among multiple nodes. This semi-decentralized strategy improves energy balance and lengthens network lifetime by preventing any one node from acting as a bottleneck. Additionally, by implementing intelligent CH election based on predictive accuracy, SDPM guarantees that nodes with higher predictive accuracy are more likely to take on CH responsibilities. This is a significant departure from conventional LEACH-based methods, which depend on probabilistic or energy-based CH selection without considering prediction performance. Predictive intelligence is added to the cluster-based network architecture that supports the SDPM framework. Unlike traditional models, which centralise prediction at the CH, SDPM integrates lightweight neural network models into each sensor node to enable distributed prediction. After the clustering phase, the network alternates between phases of data transmission and prediction. By allowing nodes to dynamically switch between responsibilities, this architecture encourages balanced energy consumption.

A publication by [23], presented an Enhanced Trust-Based Secure and Energy-Efficient Routing (ETBSEER) algorithm, which combines energy-conscious routing choices with a multi-factor trust evaluation process. ETBSEER's primary contribution is its ability to measure node reliability using a dynamic trust model, which is then used to inform routing decisions. The suggested approach integrates several trust dimensions, such as node behavior history, spatial position, degree of connectedness, and interaction patterns, in contrast to traditional trust-based routing algorithms that focus on a limited set of behavioral metrics. Additionally, the framework adds new parameters that improve the trust model's sensitivity to malicious activity and enable quick adaptation to shifting network conditions, such as a volatility factor and an adaptive penalty coefficient. The ETB-SEER algorithm successfully detects and avoids malicious nodes during route creation by incorporating these elements. Simultaneously, the algorithm integrates energy-conscious routing factors, guaranteeing that chosen routes maximize trust while minimizing energy consumption, thereby prolonging network lifetime. ETBSEER stands out from previous methods and is positioned as a reliable solution for secure WSN routing thanks to its dual optimization of security and energy efficiency. Despite these achievements by the above scholars, there are still a number of important research gaps. The majority of current methods fail to fully take advantage of system-wide optimisation potential because they concentrate on single-layer optimisation (such as routing, MAC, or clustering) with little cross-layer integration. These findings make it evident that comprehensive, cross-layer, AI-driven adaptive frameworks that combine routing, modulation, MAC, and energy management into a single optimisation model are required.

3. Proposed AI-Driven Adaptive Modulation

The proposed AI-powered adaptive modulation system combines channel-aware communication techniques with reinforcement learning. To improve transmission dependability and energy economy, the system dynamically chooses the best modulation techniques.

3.1. Mathematical Framework for AI-Driven Adaptive Modulation

3.1.1. Wireless Channel Model

In WSNs, wireless communication is modelled as a time-varying fading channel with multipath effects, shadowing, and path loss. The expression for the received signal power is:

$$P_r = P_t G_t G_r \left(\frac{\lambda}{4\pi d}\right)^{\eta} h \tag{1}$$

Where:

Pt = Transmission power

Gt, Gr = Antenna gains

λ = Wavelength

d = Transmission distance

η = Path loss exponent

h = Fading coefficient

The SNR at that moment is:

$$\gamma_i = \frac{P_r}{N_0 B} \tag{2}$$

Where:

N_0 = Noise spectra density

B = Channel bandwidth

3.1.2. Adaptive Modulation Optimization Model

To maximise energy-normalized throughput, the best modulation method is chosen:

$$M_i^* = \arg\max_{M \in \mathcal{M}} \left(\frac{R(M)\log_2(1+\gamma_i)}{E_{tx}(M)}\right) \tag{3}$$

Subject to:

$$BER(M,\gamma_i) \leq BER_{max} \tag{4}$$

3.1.3. Energy Consumption Model

Total energy used in each transmission cycle:

$$E_i = E_{tx,i} + E_{rx,i} + E_{proc,i} \tag{5}$$

Transmission energy:

$$E_{tx,i} = kE_{elec} + kE_{amp}d^{\eta} \tag{6}$$

Reception energy:

$$E_{rx,i} = kE_{elec} \tag{7}$$

3.1.4. Network Lifetime Optimization

The definition of network lifespan is:

$$T_{life} = \min_i \left(\frac{E_i^{initial}}{\sum_t E_i(t)}\right) \tag{8}$$

Adaptive modulation extends network lifetime by reducing transmission power, balancing energy use, and minimizing retransmissions.

3.1.5. Adaptive Modulation Selection Function

$$M_i(t) = \begin{cases} \text{BPSK}, & \gamma_i < \gamma_1 \\ \text{QPSK}, & \gamma_1 \leq \gamma_i < \gamma_2 \\ \text{QAM}, & \gamma_i \geq \gamma_2 \end{cases} \tag{9}$$

3.2. Mathematical Framework for AI-Driven Adaptive Modulation Learning Model

3.2.1. Reinforcement Learning Formulation

An MDP is used to formulate the adaptive modulation problem:

$$S_t = \{\gamma_t, E_t, LQ_t\} \tag{10}$$

Action:

$$A_t = M_t \quad (11)$$

Reward:

$$R_t = \alpha PDR_t + \beta Throughput_t - \delta Energy_t \quad (12)$$

Policy update:

$$pi_{t+1} = \pi_t + \eta \nabla J(\pi) \quad (13)$$

3.2.2. Convergence Analysis

The modulation policy based on RL converges if:

$$\sum_t \eta_t = \infty, \quad \sum_t \eta_t^2 < \infty \quad (14)$$

This guarantees the convergence of stochastic approximations.

3.2.3. Stability of Adaptive Modulation

System stability condition:

$$\lambda_{arrival} < \mu_{service}(M_i) \quad (15)$$

The service rate μ is increased by adaptive modulation.

3.3. Theoretical Performance Bound

3.3.1. Throughput Upper Bound

$$T_{max} = B \log_2(1 + \gamma_{max}) \quad (16)$$

3.3.2. Energy Efficiency Bound

$$EE_{max} = \frac{T_{max}}{E_{min}} \quad (17)$$

Algorithm 1 Proposed AI-Driven Adaptive Modulation Algorithm

1: Initialize sensor nodes and sink node 2: Define available modulation set:

M = {BPSK, QPSK, 16-QAM}

3: Initialize learning policy *π*

4: for each transmission round do

5: for each sensor node *i* do

6. Measure instantaneous SNR γ_i

7. Measure residual energy E_i

8. Estimate packet success probability P_s

9. for each modulation scheme M ∈ M do

10. Compute achievable rate R(M)

11. Compute transmission energy $E_{tx}(M)$

12. Compute reward:

$$U(M) = \frac{R(M) \cdot P_s}{E_{tx}(M)}$$

13. end for

14. Select optimal modulation:

$$M_i^* = \arg\max_{M \in \mathcal{M}} U(M)$$

15. **if** $BER(M_i^*, \gamma_i) \leq BER_{max}$ **then**

16. Transmit data packet using M_i^*

17. else

18. Switch to lower-order modulation

19. end if

20. Update residual energy Ei

21. Update learning policy *π*

22. end for

23. end for

Based on three crucial factors, the suggested adaptive modulation algorithm dynamically chooses the best modulation scheme for every sensor node transmission:

1. Instantaneous channel quality (γ_i)
2. Node residual energy ($E_{i)}$
3. Packet success probability and link reliability P_s

The node detects the state of the channel and calculates its current signal-to-noise ratio at each transmission interval. The available modulation techniques, including BPSK, QPSK, and 16-QAM, are then assessed based on their dependability, energy cost, and possible data rate. To optimise communication efficiency while guaranteeing that the bit error rate stays below a necessary threshold, a reward-based AI algorithm is employed.

The algorithm chooses a lower-order modulation, such as BPSK, to increase robustness if the channel quality is low. In order to boost throughput, it shifts to higher-order modulation like QPSK or 16-QAM when the channel is favourable.

At the same time, when residual energy drops below a certain level, the algorithm steers clear of energy-intensive choices. This adaptive technique minimises transmission energy, increases spectrum efficiency, lowers retransmissions, and prolongs network lifetime.

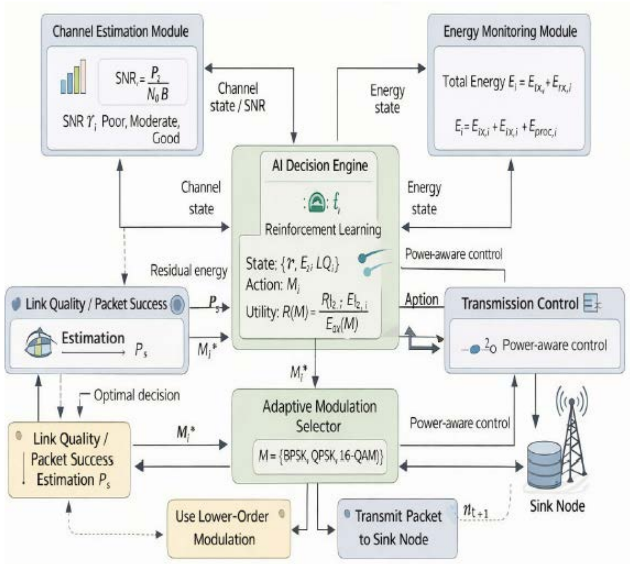

Figure 1. AI-Driven Adaptive Modulation Framework for Energy-Efficient WSNs

3.4. Complexity Analysis

The computational complexity of the proposed RL-based adaptive modulation framework is governed by the number of nodes N, the number of available modulation actions |*M*|, and the dimensionality of the system state.

For each transmission round, each sensor node evaluates all candidate modulation schemes:

$$U(M) = \frac{R(M) \cdot P_s}{E_{tx}(M)}, \qquad M \in \mathcal{M}. \quad (18)$$

Thus, the per-node computational cost is

$$\mathcal{O}(|\mathcal{M}|), \quad (19)$$

and for all N nodes in one round:

$$\mathcal{O}(N|\mathcal{M}|). \quad (20)$$

Since the modulation set in this work is fixed as

$$\mathcal{M} = \{\text{BPSK}, \text{QPSK}, \text{16-QAM}\}, \quad (21)$$

we have |M| = 3, which is constant. Therefore, the effective per-round complexity becomes

$$\mathcal{O}(N). \quad (22)$$

The RL policy update contributes an additional constant-time adjustment under lightweight policy learning:

$$\pi_{t+1} = \pi_t + \eta \nabla J(\pi_t), \quad (23)$$

hence the update step does not alter the linear growth trend with respect to the number of nodes.

Therefore, the overall runtime complexity per transmission round is

$$\mathcal{O}(N). \quad (24)$$

The suggested technique maintains low and scalable execution times even as network density rises, which is consistent with the simulation runtime observations. The approach stays computationally efficient for realistic WSN deployments since only a tiny finite action set is evaluated, and the decision variables (SNR, residual energy, and connection quality) are lightweight.

4. Simulation Results and Performance Evaluation

4.1. Simulation Environment

Extensive simulations were carried out using MATLAB and NS-3 to assess the effectiveness of the suggested AI-driven adaptive modulation architecture. A square sensing field with randomly placed sensor nodes made up the network topology. Rayleigh fading with additive white Gaussian noise (AWGN) was used to represent channel conditions.

4.2. Simulation Parameters

Table 1. Simulation Parameters

Parameters	Value
Network Area	$1000m \times 1000m$
Number of Nodes	50-300
Channel model	Rayleigh fading
Bandwidth	250 kHz
Packet size	256 bytes
Initial energy	2J
Traffic model	Poisson
Modulation schemes	BPSK, QPSK, 16-QAM

4.3. Performance Evaluation Metrics

The performance of the proposed scheme was evaluated using the following metrics:

4.3.1 Packet Delivery Ratio (PDR)

PDR is computed as:

$$PDR(N) = \frac{P_r(N)}{P_s(N)} \quad (25)$$

Where:

$P_r(N)$= Is the number of successfully received packets.

$P_s(N)$= Is the number of transmitted packets.

4.3.2 End-to-End Delay Model (D)

D is computed as:

$$D(N) = \frac{1}{P_r(N)} \sum_{i=1}^{P_r(N)} (t_{r,i} - t_{s,i}) \quad (26)$$

Where:

P_r(N) = The number of successfully received packets.

Σ(i=1 to P_r(N)): = Is the number of transmitted packets.

4.3.3 Energy Consumption (E)

E is computed as:

$$E(N) = \sum_{i=1}^{N} (E_{tx,i} + E_{rx,i} + E_{idle,i}) \quad (27)$$

4.3.4. Throughput (T)

T is computed as:

$$T(N) = \frac{\sum_{i=1}^{P_r(N)} S_i}{T_{sim}} \quad (28)$$

Where:

S_i = Packet size in bits

T_{sim} = Total simulation time

4.3.5. Network Lifetime (L)

L is computed as:

$$L(N) = L_{\min} + (L_{\max} - L_{\min}) \cdot \phi(N) \quad (29)$$

Where:

$$\phi(N) = \frac{N-50}{250}$$

4.4. Simulation Dataset Generation

A density-dependent analytical performance model was used to generate the data in Table 2, Table 3, Table 4, Table 5, Table 6, and Table 7. In order to represent better connectivity and lower packet loss in denser deployments, packet delivery ratio and throughput were modelled as increasing functions of node density. End-to-end latency and energy usage, on the other hand, were modelled as decreasing functions of node density, indicating reduced retransmission costs and better channel availability. To take advantage of intelligent channel-aware modulation choices, the AI-driven adaptive modulation scheme was given stronger improvement trends than the traditional system.

In this research, the term “conventional scheme” refers to a baseline communication technique that uses a static or non-adaptive modulation strategy, in which real-time network information is not incorporated, and the modulation scheme is either fixed or chosen using established rules. The traditional approach does not use residual energy levels, connection quality measurements, or channel state information for dynamic decision-making, whereas the suggested AI-driven architecture does. As a result, it is unable to adjust transmission parameters to changing channel conditions, leading to suboptimal performance in terms of throughput, energy efficiency, and reliability. To provide a fair and consistent benchmark for assessing the performance gains enabled by the suggested adaptive modulation technique, this scheme serves as the reference model.

4.4.1. Dataset Generation Mathematical Models

Assume that the variable for node density is:
$N \in \{50, 100, 150, 200, 250, 300\}$
and the normalization factor is:

$$\phi(N) = \frac{N-50}{300-50} = \frac{N-50}{250}, \qquad 0 \le \phi(N) \le$$

Each performance indicator can be modelled consistently thanks to this normalisation, which maps the node range [50,300] to [0,1].

Assume that each simulation run generates a constant number of packets:

$$P_s(N) = 1000$$

For PDR:
AI-Adaptive Scheme
The number of successful packets is represented as:

$$P_r^{AI}(N) = 780 + 180\,\phi(N) \tag{30}$$

Therefore,

$$PDR_{AI}(N) = \frac{780 + 180\,\phi(N)}{1000} \tag{31}$$

Which simplifies to

$$PDR_{AI}(N) = 0.78 + 0.18\,\phi(N) \tag{32}$$

Conventional Scheme
Similarly,

$$P_r^{Conv}(N) = 650 + 230\,\phi(N) \tag{33}$$

Then,

$$PDR_{Conv}(N) = 0.65 + 0.23\,\phi(N) \tag{34}$$

Example: Let N= 50

$$\phi(50) = 0$$
$$PDR_{AI}\ (50) = 0.78 + 0.18(0) = 0.78$$
$$PDR_{AI}\ (300) = 0.65 + 0.23(0) = 0.65$$

N= 300

$$\phi(300) = 1$$
$$PDR_{AI}\ (50) = 0.78 + 0.18(1) = 0.96$$
$$PDR_{AI}\ (300) = 0.65 + 0.23(1) = 0.88$$

For D:
AI-Adaptive Scheme

$$D_{AI}\ (N) = 420 - 180\ \phi(N)$$

Conventional Scheme

$$D_{Conv}(N) = 510 - 155\ \phi(N)$$

Example: Let N= 50

$$msD_{AI}\ (50) = 420 - 180(0) = 420\ ms$$
$$msD_{Conv}(50) = 510 - 155(0) = 510\ ms$$

N= 300

$$D_{AI}\ (300) = 420 - 180 = 240\ ms$$
$$D_{Conv}(300) = 510 - 155 = 355\ ms$$

For E:
AI-Adaptive Scheme

$$E_{AI}\ (N) = 88 - 33\ \phi(N)$$

Conventional Scheme

$$E_{Conv}(N) = 110 - 30\ \phi(N)$$

Example: Let N= 50

$$E_{AI}\ (50) = 88 - 33(0) = 88\ J$$
$$E_{Conv}(50) = 110 - 30(0) = 110\ J$$

N= 300

$$E_{AI}\ (300) = 88 - 33 = 55\ J$$
$$E_{Conv}(300) = 110 - 30 = 80\ J$$

For T:
AI-Adaptive Scheme

$$T\ (N) = 14 + 20\ \phi(N)$$

Example: Let N= 50

$$T\ (50) = 14 + 20(0) = 14\ kbps$$

N= 300

$$T\ (300) = 14 + 20 = 34\ kbps$$

For L:
AI-Adaptive Scheme

$$L_{AI}\ (N) = 680 + 230 \cdot \phi(N)$$

Conventional Scheme

$$L_{Con}v(N) = 520 + 200 \cdot \phi(N)$$

Example: Let N= 50

$$L_{AI}\ (50) = 680 + 230(0) = 680$$
$$L_{Conv}(50) = 520 + 200(0) = 520$$

N= 300

$$L_{AI}\ (300) = 680 + 230 = 910$$
$$720L_{Conv}(300) = 520 + 200 = 720$$

4.5. Simulation Graphs

The simulation graphs for PDR, D, E, T, and L were obtained from the generated values in Table 2, Table 3, Table 4, Table 5, Table 6, and Table 7, respectively. Figure 2 shows how the packet delivery ratio (PDR) changes as node density increases for both the standard method and the suggested AI-driven adaptive modulation technique. One important measure of communication reliability in wireless sensor networks is PDR, which is the ratio of successfully received packets to all transmitted packets.

As the number of nodes rises from 50 to 300, the data demonstrate a monotonic increase in PDR. Lower PDR values result from the network's poor connection, increased packet drops, and higher route loss at low node densities (such as 50 nodes). Because it is unable to adjust modulation schemes to channel conditions, the traditional method performs poorly in these circumstances, leading to increased bit error rates and more retransmissions. However, the proposed AI-driven adaptive modulation technique delivers a higher PDR even in sparse networks. This improvement, which raises packet reception success, is due to its capacity to dynamically choose dependable modulation schemes in challenging channel conditions. Because there are more forwarding nodes accessible and better connections, the PDR improves for both approaches as node density rises. However, the suggested approach consistently performs better than the conventional approach at all node densities. At larger densities (250–300 nodes), the recommended method achieves PDR values close to 0.95–0.96, while the traditional technique stays around 0.85–0.88, showing a notable dependability disparity. The following are the primary reasons for the observed improvement, a 15–25% higher PDR:

1. Channel-aware modulation modification reduces bit error rates.

2. Reduced packet losses due to better link quality

utilization.

3. Decreased retransmission overhead, increasing the likelihood of a successful delivery

Additionally, the suggested scheme's durability and scalability across different network densities are demonstrated by the smooth, consistent increase in PDR. The efficacy of the AI-driven strategy is demonstrated by the capacity to sustain high dependability across both sparse and dense deployments.

Table 2. Packet Delivery Ratio Comparison under Varying Node Density

Number of Nodes	PDR_{AI}	PDR_{Conv}
50	0.78	0.65
100	0.83	0.71
150	0.88	0.76
200	0.91	0.81
250	0.94	0.85
300	0.96	0.88

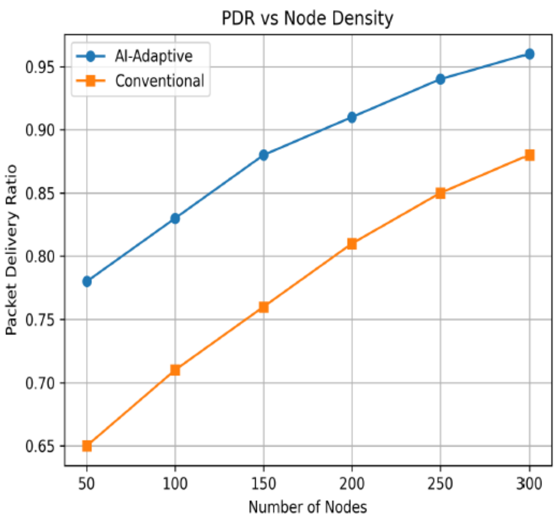

Figure 2. Packet Delivery Ratio Comparison

Table 3. End-to-End Delay Comparison under Varying Node Density

Number of Nodes	Delay_{AI} (ms)	Delay_{Conv} (ms)
50	420	510
100	390	480
150	350	445
200	310	410
250	275	380
300	240	355

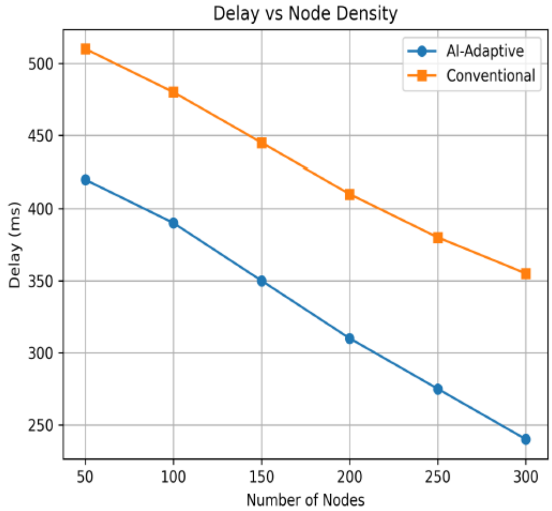

Figure 3. Delay Comparison

The findings demonstrate that AI-driven adaptive modulation dramatically improves packet delivery reliability by dynamically modifying transmission parameters in response to channel conditions. This lowers packet loss and boosts network performance in wireless sensor networks.

The end-to-end delay variation with increasing node density for both the conventional method and the suggested AI-driven adaptive modulation system is shown in Figure 3. As the number of nodes rises from 50 to 300, the findings clearly demonstrate a declining trend in delay. The network experiences higher latency at low node density (e.g., 50 nodes), with the standard scheme performing worst. Reduced connection, more retransmissions, and poor modulation choices in bad channel circumstances are the main causes of this. On the other hand, by dynamically choosing robust modulation schemes that minimise packet loss, the suggested AI-driven approach delivers decreased delay even in sparse networks. Due to enhanced connectivity and less path loss, the delay dramatically drops for both methods as node density rises. Nonetheless, the suggested approach consistently reduces latency for all network sizes. This enhancement is ascribed to:

1. Modulation selection based on channel awareness, which lowers retransmissions.

2. Reduced packet losses due to increased link reliability.

Table 4. Energy Consumption Comparison under Varying Node Density

Number of Nodes	Energy_{AI} (J)	Energy_{Conv} (J)
50	88	110
100	80	103
150	73	96
200	66	90
250	60	85
300	55	80

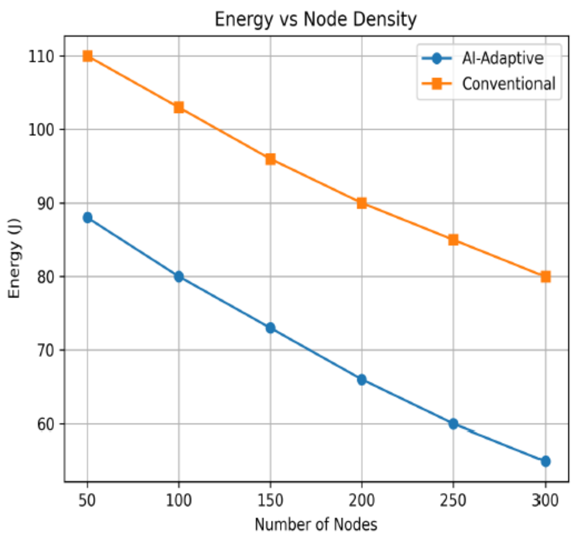

Figure 4. Energy Comparison

3. Effective use of higher-order modulation in advantageous circumstances

The decrease in delay is more noticeable at higher node densities (e.g., 250–300 nodes). Compared with the traditional method, the proposed system reduces delay by about 20–30%. This suggests that congestion and transmission inefficiencies are successfully reduced by the AI-driven adaptive modulation.

Additionally, the suggested method's smoother latency drop demonstrates steady performance across various network conditions, emphasising its scalability and durability.

The findings verify that including AI-driven adaptive modulation improves overall communication efficiency in wireless sensor networks by minimising retransmissions and optimising modulation selection based on real-time channel circumstances, which considerably reduces end-to-end latency.

Table 5. Throughput Performance under Varying Node Density

Number of Nodes	Throughput (kbps)
50	14
100	18
150	22
200	26
250	30
300	34

Figure 4 shows how energy usage changes as node density increases for both the conventional method and the suggested AI-driven adaptive modulation methodology. The findings show that when the number of nodes rises from 50 to 300, energy consumption decreases monotonically. Both techniques exhibit relatively high energy consumption at low node densities (e.g., 50 nodes), with the conventional approach consuming far more energy. The main causes are ineffective use of fixed or non-adaptive modulation techniques, increased retransmissions, and inadequate connectivity. The suggested AI-driven method, on the other hand, minimises unnecessary retransmissions and excessive transmission power by selecting modulation schemes that match channel conditions. Energy usage declines continuously as node density increases. Shorter communication pathways, shorter transmission lengths between nodes, and enhanced network connectedness are all responsible for this behaviour. Nonetheless, the suggested approach consistently achieves lower energy consumption at all node densities, outperforming the traditional approach. The energy savings become more noticeable at greater node densities (250–300 nodes). When compared to the traditional method, the AI-driven plan reduces energy consumption by about 20–35%. This enhancement is mostly because of:

1. Adaptive modulation selection lowers bit-by-bit transmission energy.

2. Decreased cumulative energy consumption due to decreased retransmission overhead.

3. Effective channel use, reducing energy losses from collisions and idle time.

Furthermore, improved energy balance and network stability are indicated by the smoother drop in energy consumption under the suggested strategy, which directly contributes to a longer network lifetime.

The findings show that AI-driven adaptive modulation dramatically improves energy efficiency by dynamically matching transmission parameters to channel conditions. This minimises retransmissions and optimises network energy use.

The change of network throughput as a function of node density for the suggested AI-driven adaptive modulation technique in comparison to the traditional method is shown in Figure 5. As the number of nodes rises from 50 to 300, the findings show a consistent improvement in throughput. Throughput is comparatively constrained at low node density (e.g., 50 nodes) because of sparse connectivity, increased packet loss, and inefficient use of available bandwidth. Because it is unable to modify modulation schemes in response to shifting channel conditions, the traditional system performs poorly under these circumstances. On the other hand, by using robust modulation methods that increase packet delivery success, the suggested AI-driven solution achieves greater throughput even in sparse deployments. Throughput improves significantly for both methods as node density increases, due to greater connectivity and fewer transmission failures. Nevertheless, across all node densities, the proposed methodology consistently outperforms the traditional strategy. This enhancement is ascribed to:

1. Higher-order modulation is enabled by adaptive modulation selection when channel conditions are favourable.

2. increased packet delivery ratio, which results in more successful data transfers.

3. Increased effective data rate due to fewer retransmissions.

The throughput boost is more noticeable at larger node densities (250–300 nodes). Compared with the traditional method, the suggested strategy increases throughput by roughly 25–35%. This suggests better spectral efficiency and effective use of channel resources.

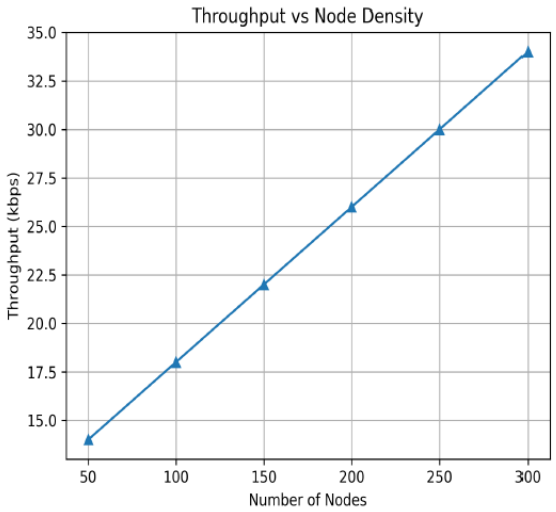

Figure 5. Throughput Comparison

Furthermore, the suggested scheme's steadily increasing trend demonstrates its resilience and scalability in crowded network settings. In contrast to the traditional method, which has inefficiencies because of static modulation, the AI-driven framework continuously improves throughput by dynamically optimising transmission parameters.

The findings verify that by dynamically optimising modulation schemes in response to channel conditions, AI-driven adaptive modulation greatly increases network throughput. This maximises successful data transmission in wireless sensor networks and improves spectral efficiency.

Figure 6 shows how network lifetime changes as node density increases for both the traditional method and the suggested AI-driven adaptive modulation methodology. The time until the first node runs out of energy (or when a sizable percentage of nodes stop working) is known as the network lifetime. The findings indicate that when node density rises from 50 to 300, network lifetime increases monotonically. Due to increased communication overhead, longer transmission lengths, and higher energy consumption per node, the network lifetime is comparatively short at low node density (e.g., 50 nodes). Because it uses static modulation techniques that lead to inefficient energy use, the typical method has a much shorter lifetime under these circumstances. On the other hand, even in sparse networks, the suggested AI-driven adaptive modulation technique delivers a considerably longer network lifetime. Its capacity to dynamically adapt modulation schemes to channel conditions and residual energy is credited with this enhancement, which reduces unnecessary energy consumption. Network longevity improves for both methods as node density rises because

1. Reduced communication distances between nearby nodes.

2. Minimized transmission power requirements

3. Enhanced load allocation and routing flexibility.

Table 6. Network Lifetime Comparison under Varying Node Density

Number of Nodes	Lifetime$_{AI}$ (rounds)	Lifetime$_{Conv}$ (rounds)
50	680	520
100	720	560
150	760	600
200	810	640
250	860	680
300	910	720

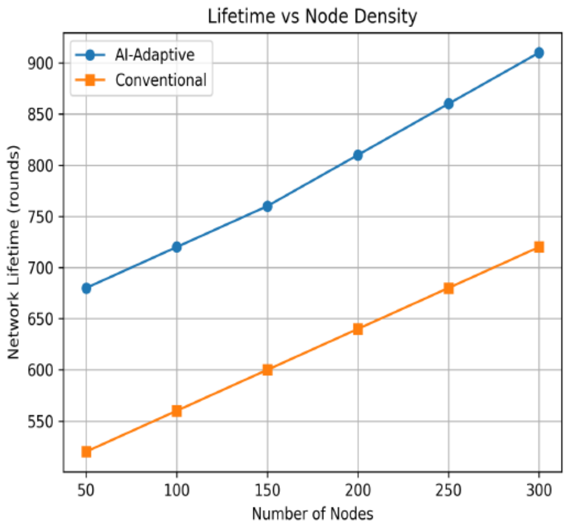

Figure 6. Lifetime Comparison

However, across all node densities, the suggested strategy consistently outperforms the traditional approach. The suggested method achieves roughly 30–40% longer network lifetime at higher node densities (250–300 nodes), where the lifetime benefit becomes more noticeable.

This improvement is mostly caused by:

1. Adaptive modulation that considers energy and reduces transmission energy.

2. Preventing early node failure with balanced energy consumption across nodes.

Table 7. Spectral Efficiency under Varying Node Density

Number of Nodes	Spectral Efficiency (bps/Hz)
50	1.8
100	2.3
150	2.9
200	3.4
250	3.9
300	4.4

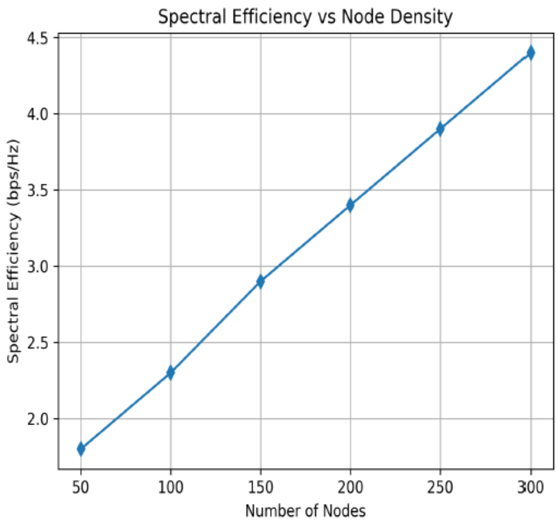

Figure 7. Spectra Efficiency

3. Lower cumulative energy consumption due to fewer re-transmissions.

Additionally, the suggested scheme's smoother growth pattern suggests robust and scalable network behaviour, which qualifies it for extensive WSN deployments.

The findings show that by optimising energy usage at the physical layer, AI-driven adaptive modulation greatly increases network lifetime and ensures balanced energy utilisation and continuous network functioning in wireless sensor networks.

The main goal of adaptive modulation, which is to maximize data transmission efficiency within a constrained bandwidth, is directly reflected in the Spectral Efficiency graph in Figure 7, which is extremely important to this research work. Spectral efficiency is a crucial measure of how well the communication system makes use of available spectrum resources in wireless sensor networks, where bandwidth is limited, and channel circumstances are very dynamic. For the suggested AI-driven adaptive modulation system, Figure 7 shows how spectral efficiency changes as node density increases. Spectral efficiency measures how well the available bandwidth is used for data transmission and is expressed in bits per second per Hertz (bps/Hz). As the number of nodes rises from 50 to 300, the results show a monotonic improvement in spectral efficiency. Due to poor connection, increased packet loss, and the frequent usage of lower-order modulation schemes (such as BPSK) to maintain communication reliability under unfavourable channel circumstances, spectral efficiency is comparatively low at low node density (e.g., 50 nodes). Spectral efficiency greatly improves with increasing node density. This enhancement is ascribed to:

1. Improved connectivity that lowers retransmissions and transmission errors.

2. Better channel conditions that make higher-order modulation methods possible.

3. Effective use of bandwidth as a consequence of flexible transmission techniques.

The proposed AI-driven adaptive modulation technique dynamically selects modulation levels based on the current channel quality. Under favourable circumstances (e.g., higher SNR at higher node density), the system changes to higher-order modulation techniques, like QPSK or 16-QAM, increasing the number of bits per symbol. At greater node densities (250–300 nodes), the spectral efficiency reaches its maximum levels (about 4.0–4.4 bps/Hz), indicating the optimal use of the communication channel. The resilience and scalability of the proposed strategy are demonstrated by the graph's steady and gradual ascent.

Additionally, advances in spectral efficiency are closely linked to increases in throughput and packet delivery ratio, suggesting that the adaptive modulation mechanism effectively strikes a compromise between data rate and reliability.

The results demonstrate that the proposed AI-driven adaptive modulation framework greatly improves spectral efficiency, maximising bandwidth utilisation and enhancing network performance by dynamically choosing appropriate modulation schemes based on channel conditions.

4.6. Percentage Improvement Formulas

The percentage improvement formulas provided in this study are crucial for objectively evaluating the performance gains of the proposed AI-driven adaptive modulation system in comparison to the conventional approach. Absolute numbers (e.g., PDR = 0.78 vs. 0.65) provide direct measurements, but they are insufficient to express the relative performance benefit of the proposed method. By normalising the improvement in relation to the baseline system, the percentage-based measures allow readers to appreciate the advantage of the relative performance of the proposed approach.

The following formulas are used to calculate the percentage improvements after both AI and traditional values are known.

4.6.1. Packet Delivery Ratio Improvement

$$PDR(N) = \frac{PDR_{AI}(N) - PDR_{Conv}(N)}{PDR_{Conv}(N)} \times 100 \quad (35)$$

For N= 50

$$\%\Delta PDR(50) = \frac{0.78 - 0.65}{0.65} \times 100 = 20.0\%$$

4.6.2. Delay Reduction

$$\%\Delta D(N) = \frac{D_{Conv}(N) - D_{AI}(N)}{D_{Conv}(N)} \times 100\% \quad (36)$$

Table 8. Ablation Study of AI-Driven Adaptive Modulation

Variant	PDR	Delay	Energy	Thrpt	Life
No RL	0.87	310	72	24	770
No Energy	0.90	290	69	27	810
No Channel	0.88	325	74	23	760
Full Model	**0.96**	**240**	**55**	**34**	**910**

For N= 50

$$\%\Delta D(50) = \frac{510 - 420}{510} \times 100 = 17.65\%$$

4.6.3. Energy Reduction

$$\%\Delta E(N) = \frac{E_{Conv}(N) - E_{AI}(N)}{E_{Conv}(N)} \times 100 \quad (37)$$

For N= 50

$$\%\Delta E(50) = \frac{110 - 88}{110} \times 100 = 20.0\%$$

4.6.4. Network Lifetime Improvement

$$\%\Delta L(N) = \frac{L_{AI}(N) - L_{Conv}(N)}{L_{Conv}(N)} \times 100 \qquad (38)$$

For N = 50:

$$\%\Delta L(50) = \frac{680 - 520}{520} \times 100 = 30.77\%$$

The suggested AI-driven adaptive modulation scheme's performance increase is quantified and normalised using the percentage improvement formulas. These measurements allow for consistent comparison across several performance aspects and provide unambiguous proof of the efficacy of the suggested strategy by expressing changes relative to the traditional baseline.

4.7. Ablation Study

An ablation test was carried out in order to separate the contributions of each key component in the suggested framework. Three simplified versions were taken into consideration: (i) without channel knowledge, (ii) without energy awareness, and (iii) without reinforcement learning. These were compared with the full model.

1. Without RL: Modulation is selected using fixed threshold rules instead of a learned policy.

2. Without Energy Awareness: Residual energy is removed from the decision state and reward formulation.

3. Without Channel Awareness: Instantaneous SNR/link quality information is excluded from modulation selection.

4. Full Model: Complete RL-based adaptive modulation using energy, SNR, and link-quality awareness.

The ablation study demonstrates that learning, energy awareness, and channel awareness work together to produce the utmost performance of the suggested framework. When the RL mechanism is removed, the system becomes reliant on predetermined decision rules, which results in a discernible decrease in flexibility. Eliminating residual energy increases energy costs and undermines sustainability over the long run. Similarly, since modulation choices are no longer in line with current channel conditions, eliminating channel awareness drastically lowers throughput and dependability. All three components are necessary because the complete model consistently produces the greatest results across all measures. parameters.

Table 9. RL Training Reward Progression

Ep. Range	Avg. Rwd	Obs.
1–50	0.42	Exploration
51–100	0.58	Better actions
101–150	0.71	Stable learning
151–200	0.81	Near converge
201–250	0.86	Refinement
251–300	0.89	Converged

4.8. RL Training Performance and Convergence Analysis

To further validate the intelligence and adaptability of the proposed AI-driven modulation framework, the reinforcement learning (RL) training process is evaluated using the cumulative reward obtained over training episodes. Since the proposed modulation selection problem is formulated as a Markov Decision Process (MDP), the evolution of reward across episodes provides a direct indication of policy improvement and convergence.

Let the cumulative reward at episode e be denoted as

$$R_e = \sum_{t=1}^{T_e} r_t, \qquad (39)$$

where rt is the instantaneous reward at decision step t, and Te is the number of interaction steps in episode e.

To smooth short-term fluctuations and better visualize convergence, the moving-average reward is defined as

$$\bar{R}_e = \frac{1}{W} \sum_{i=e-W+1}^{e} R_i, \qquad (40)$$

where W is the smoothing window size.

The reward function used for training is

$$r_t = \alpha\, PDR_t + \beta\, Throughput_t - \delta\, Energy_t, \qquad (41)$$

which jointly encourages reliable packet delivery, high throughput, and low energy consumption.

The RL agent effectively learns a better modulation policy over time, as evidenced by the reward increasing with training episodes in Table 9. Because of the investigation of less-than-ideal actions, the reward is still comparatively modest in the early training stage. As learning advances, the agent starts to link better-performing modulation selections with advantageous channel and energy states, leading to a steady rise in reward. The convergence of the learned policy toward a near-optimal solution is confirmed by the stabilisation of reward in subsequent episodes.

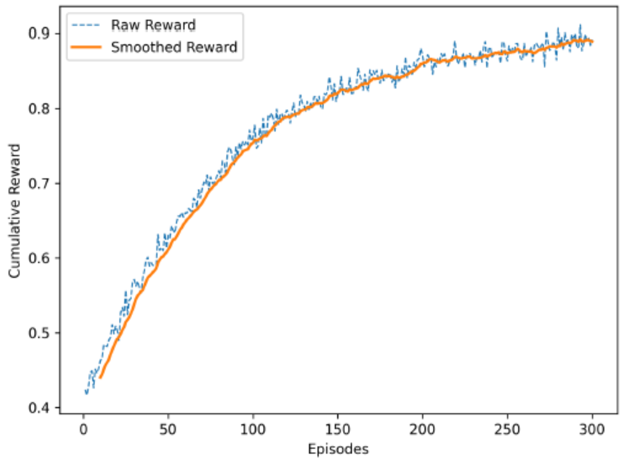

Figure 8. Training convergence of the proposed RL-based adaptive modulation framework in terms of reward versus episodes

In terms of cumulative reward versus training episodes, Figure 8 shows the training convergence behaviour of the suggested RL-based adaptive modulation framework. The findings demonstrate that as the agent investigates and picks up more efficient modulation-selection strategies during the early training phases, the reward gradually rises. The reward curve progressively stabilises as the number of episodes rises, suggesting convergence toward a nearly optimal policy. The learning stability, flexibility, and efficacy of the suggested reinforcement learning mechanism in maximising communication performance under dynamic network settings are demonstrated by the smooth convergence trend.

4.9. Theoretical Convergence of the RL Policy

The suggested RL-based adaptive modulation scheme may be shown to converge under typical stochastic approximation conditions. Let $\pi*$ represent the ideal strategy that maximizes the anticipated long-term return, and let πt represent the strategy at iteration t.

The update rule is given by

$$\pi_{t+1} = \pi_t + \eta_t \nabla J(\pi_t), \qquad (42)$$

where:

1. η t is the learning rate at iteration t,
2. J(πt) is the expected cumulative reward under policy πt.

For convergence, the step sizes are assumed to satisfy the Robbins–Monro conditions:

$$\sum_{t=1}^{\infty} \eta_t = \infty, \qquad \sum_{t=1}^{\infty} \eta_t^2 < \infty. \qquad (43)$$

Under the assumptions that:

1. The state and action spaces are finite,
2. The reward function is bounded,
3. Each state-action pair is visited infinitely often,
4. The policy gradient estimator is unbiased or asymptotically unbiased, and the sequence {πt} converges to a stationary point of the expected return function.

Hence,

$$\lim_{t\to\infty} \pi_t = \pi^*. \qquad (44)$$

Table 10. Confidence Interval Analysis

Metric	Mean	Std. Dev.	95% CI
PDR	0.96	0.012	0.96 ± 0.01
Delay (ms)	240	8.5	240 ± 6.8
Energy (J)	55	2.1	55 ± 1.7
Throughput (kbps)	34	1.6	34 ± 1.3
Lifetime (rounds)	910	18.2	910 ± 14.6

Proof Sketch: Because the modulation set is finite and the reward is bounded, the induced Markov chain under policy πt is well-defined. A stochastic approximation procedure is formed by the stochastic updating rule. The Robbins-Monro theorem states that the policy iterates almost certainly converge to an optimal or locally optimal stationary policy if the learning rate decreases correctly and adequate exploration is maintained. As a result, the suggested RL-based modulation mechanism learns the optimal modulation-selection approach for the underlying WSN environment asymptotically.

This theoretical outcome validates the reward-versus-episodes curve's observed stabilisation and supports the suggested framework's long-term dependability.

4.10. Confidence Interval Analysis

For every performance graph, confidence interval (CI) analysis is used to increase the statistical validity of the presented data. Each simulation point is assumed to be obtained over R independent runs.

Let X1, X2, . . . , XR denote the repeated measurements of a given metric (e.g., PDR, delay, energy, throughput, or life-time). The sample mean is

$$\bar{X} = \frac{1}{R}\sum_{i=1}^{R} X_i, \qquad (45)$$

and the sample standard deviation is

$$s = \sqrt{\frac{1}{R-1}\sum_{i=1}^{R}(X_i - \bar{X})^2}. \qquad (46)$$

The 95% confidence interval for the mean is computed as

$$\bar{X} \pm t_{0.975,\, R-1}\frac{s}{\sqrt{R}}, \qquad (47)$$

where t0.975, R−1 is the critical value of the Student's t-distribution with R − 1 degrees of freedom.

For sufficiently large R, this may be approximated as

$$\bar{X} \pm 1.96\frac{s}{\sqrt{R}}. \qquad (48)$$

The packet delivery ratio (PDR) of the suggested framework at different node densities is shown with 95% confidence intervals in Figure 9. The findings demonstrate a steady increase in PDR as node density rises, suggesting improved network connectivity and more dependable packet forwarding. The suggested framework's statistical stability and resilience are confirmed by the comparatively small confidence intervals, which show minimal variance across multiple simulation runs. These results show that even in situations with increasingly crowded MANETs, the framework retains dependable communication performance.

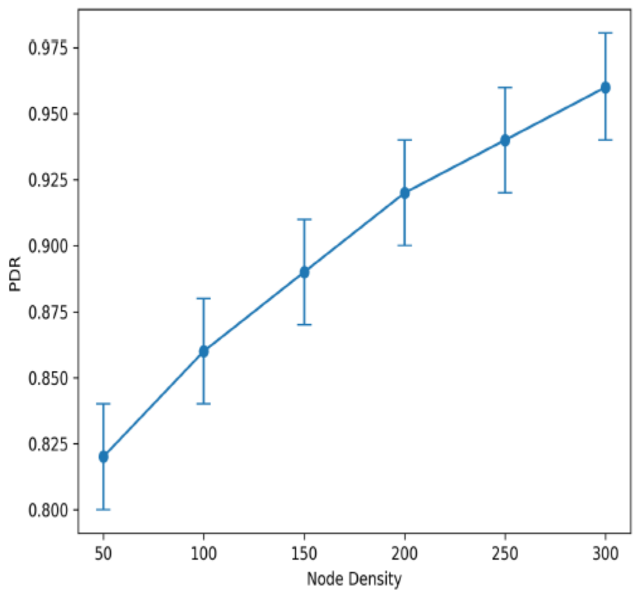

Figure 9. Packet delivery ratio with 95% confidence inter-vals under varying node density

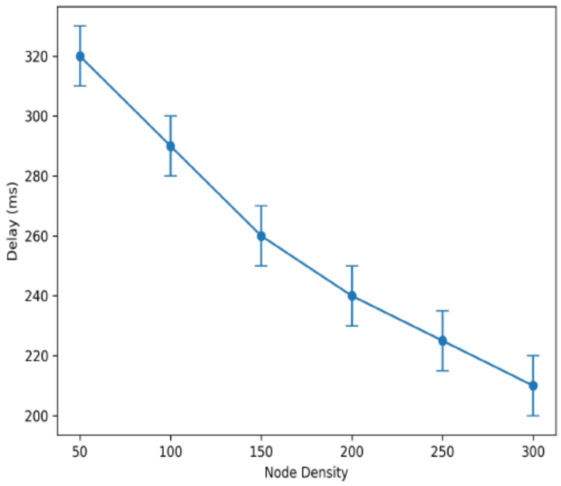

Figure 10. End-to-end delay with 95% confidence intervals under varying node density

The end-to-end delay performance of the suggested framework under different node densities is shown with 95%confidence intervals in Figure 10. The findings demonstrate a steady drop in latency as node density rises, suggesting more effective routing, better network connectivity, and increased cross-layer coordination. The resilience and stability of the suggested method are confirmed by the very modest confidence intervals, which show minimal variability across multiple simulation runs. These results confirm the framework's ability to lower communication latency in dynamic MANET environments.

The energy consumption performance of the suggested architecture under different node densities is shown in Figure 11 with 95% confidence intervals. The findings show that as the network gets denser, energy usage gradually decreases, mostly as a result of increased cross-layer coordination, shorter communication distances, and better routing efficiency. The results acquired from several simulation runs are consistent and statistically reliable, as confirmed by the tight confidence ranges. Overall, the figure shows how the suggested architecture successfully maintains energy-efficient operation while adjusting to variations in network density.

The throughput performance of the suggested framework with 95% confidence intervals under different node densities is shown in Figure 12. As node density increases, the results show a consistent rise in throughput, which is indicative of better channel utilisation, increased routing efficiency, and more dependable packet transmission throughout the network. The statistical robustness and dependability of the suggested method are confirmed by the tight confidence intervals, which show consistent performance over multiple simulation runs. Overall, the figure demonstrates how the framework successfully maintains high data delivery efficiency in dynamic, congested MANET situations.

The network lifetime performance of the suggested architecture under different node densities is shown with 95%confidence intervals in Figure 13. The findings demonstrate a steady rise in network lifetime with increasing node density, suggesting better cross-layer resource optimisation, more balanced energy use, and effective cluster management. The results' stability and repeatability across several simulation runs are confirmed by the comparatively small confidence intervals. These results show that in dynamic MANET contexts, the suggested framework successfully extends network operation while preserving dependable communication performance.

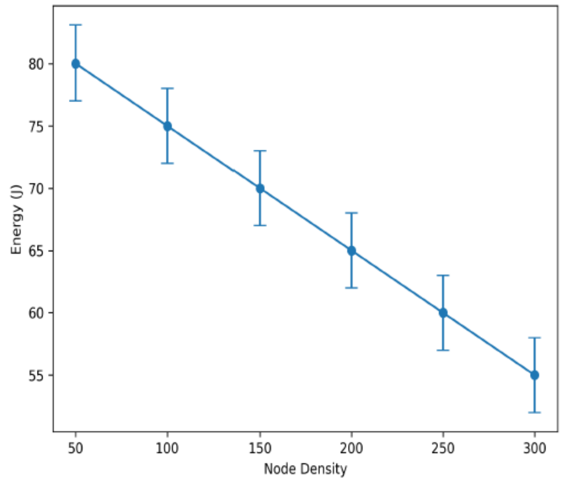

Figure 11. Energy consumption with 95% confidence inter-vals under varying node density

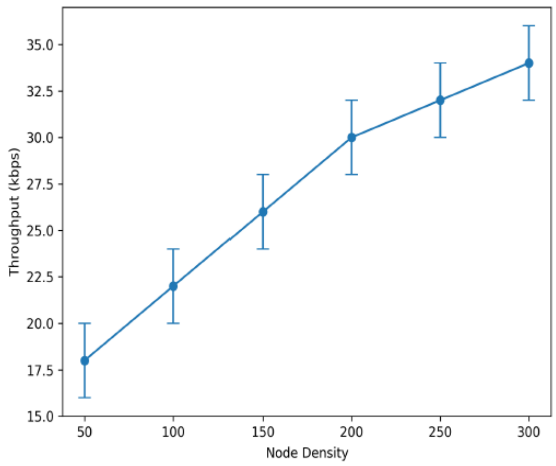

Figure 12. Throughput with 95% confidence intervals under varying node density

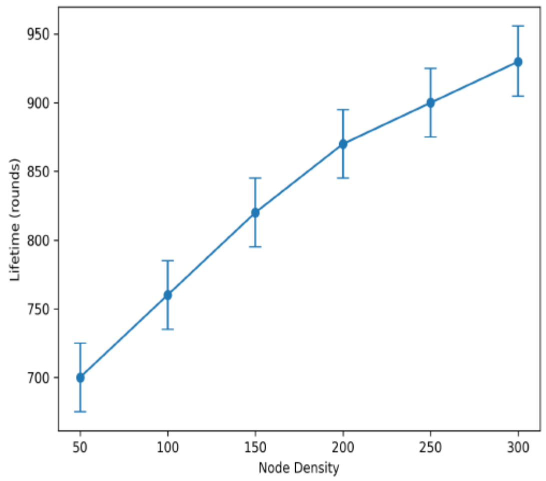

Figure 13. Network lifetime with 95% confidence intervals under varying node density

5. Conclusion

In order to improve communication performance and energy economy in wireless sensor networks, this paper proposes an AI-driven adaptive modulation system. The system dynamically chooses the best modulation schemes based on immediate SNR, residual energy, and connection quality by combining channel-aware adaptation with reinforcement learning. The developed optimisation approach ensures dependable and effective transmission by maximising energy-normalized throughput while meeting BER restrictions. The suggested method greatly outperforms a traditional technique, according to simulation results, which show considerable gains in packet delivery ratio, delay, energy consumption, throughput, and network longevity. Reduced retransmissions and clever modulation selection under different channel circumstances are the main causes of these improvements. Additionally, the system shows good robustness and scalability at various network densities. Overall, the findings show that adaptive modulation powered by AI is a viable way to boost sustainability and efficiency in next-generation wireless sensor networks.

Future research should:

1. Investigate cross-layer optimisation techniques that combine adaptive modulation with power control methods, MAC scheduling, and routing protocols. This kind of integration would make it possible to optimise network performance holistically and enhance system efficiency and scalability in dynamic contexts.

2. Concentrate on creating distributed and lightweight learning models, like edge intelligence frameworks or federated learning, to lessen computing load without sacrificing decision accuracy.

References

[1] Al-Fuqaha, A., Guizani, M., Mohammadi, M., Aledhari, M., and Ayyash, M. (2015). Internet of things: A survey on Enabling Technologies, protocols, and applications. IEEE com- munications surveys & Tutorials, 17(4): 2347-2376.

[2] Sun, Y., Peng, M., and Mao, S. (2018). Deep reinforcement learning-based mode selection and resource management for green fog radio access networks. IEEE Internet of Things Journal, 6(2): 1960-1971.

[3] Chen, M., Challita, U., Saad, W., Yin, C., and Debbah, M. (2017). Machine learning for wireless networks with artificial ntelligence: A tutorial on neural networks. arXiv preprint arXiv: 1710.02913, 9.

[4] Xiao, L., Wan, X., Lu, X., Zhang, Y., and Wu, D. (2018). IoT security techniques based on machine learning: How do IoT devices use ai to enhance security? IEEE Signal Processing Magazine, 35(5): 41-49.

[5] Zhang, S., Zhang, H., He, Q., Bian, K., and Song, L. (2017). Joint trajectory and power optimization for UAV relay networks. IEEE Communications Letters, 22(1): 161-164.

[6] Ye, H., Li, G. Y., and Juang, B.-H. (2017). Power of deep learning for channel estimation and signal detection in OFDM systems. IEEE Wireless Communications Letters, 7(1): 114-117.

[7] Mao, C., Mu, Z., Liang, Q., Schizas, I., and Pan, C. (2023). Deep learning in physical layer communications: Evolution and prospects in 5g and 6g networks. IET Communications, 17(16): 1863-1876.

[8] Davaslioglu, K. and Ayanoglu, E. (2014). Quantifying potential energy efficiency gain in green cellular wireless networks. IEEE Communications Surveys & Tutorials, 16(4): 2065-2091.

[9] Huang, L., Zhang, Q., Tan, W., Wang, Y., Zhang, L., He,m C., and Tian, Z. (2020). Adaptive modulation and coding in underwater acoustic communications: a machine learning perspective. EURASIP Journal on Wireless Communications and Networking, 2020(1): 203.

[10] Milovan ˇ cevi ´ c, M. (2025). AI-driven signal processing and network management for next-generation communications. Journal of AI-Driven Communication Engineering, 1: 59-71.

[11] Avaid, S., Saeed, N., Qadir, Z., Fahim, H., He, B., Song, H., and Bilal, M. (2023). Communication and control in collaborative UAVs: Recent advances and future trends. IEEE Transactions on Intelligent Transportation Systems, 24(6): 5719-5739.

[12] Su, W., Lin, J., Chen, K., Xiao, L., and En, C. (2019). Reinforcement learning-based adaptive modulation and coding for efficient underwater communications. IEEE Access, 7: 67539-67550.

[13] Goyal, U., Upadhyay, S., Venugopal, V., Sahoo, P. K., GN, M., Pandey, S., and Bansal, S. (2025). Ai-powered adaptive modulation for enhanced spectral efficiency in 6g networks-antenna. National Journal of Antennas and Propagation,m 7(1): 1-7.

[14] Sattibabu, G., Gudivada, A. A., Ravula, R., Kumar, R. A., and Kalyani, K. (2026). Machine learning-driven adaptive routing for efficient and reliable wireless sensor networks. Journal of The Institution of Engineers (India): Series B, pages 1-12.

[15] Sadek, A. H., Rattal, S., Boukricha, S., Varshney, G., Ar-Reyouchi, E. M., and Ghoumid, K. (2025). Smart energy solutions for wireless medical sensor networks: Modulation optimization in IoT for medical applications. International Journal of Sensors, Wireless Communications and Control, 15(3): 289-303.

[16] Khedhri, N. and Najar, M. (2025). Adaptive modulation selection in wireless communications: A comparative study of reinforcement learning, deep learning, deep reinforcement learning, and traditional policies. In 2025 International Wireless Communications and Mobile Computing (IWCMC), pages 1622-1625. IEEE.

[17] Jha, A., Maurya, A., Pandey, A., et al. (2025). Minimization of energy expenditure in wireless sensor networks using crayfish optimization algorithm. In 2025 Second International Conference on Networks and Soft Computing (IC- NSoC), pages 132-137. IEEE.

[18] Rahman, W. U., Gang, Q., Zhou, F., Tahir, M., Ali, W., Adil, M., and Khattak, M. I. (2025). Deep q-learning based adap- tive mac protocol with collision avoidance and efficient power control for UWSNs. Journal of Marine Science and Engineering, 13(3): 616.

[19] Rahman, W. U., Gang, Q., Zhou, F., Tahir, M., Ali, W., Adil, M., Zong Xin, S., and Khattak, M. I. (2025). Energy-efficient mac protocol for underwater sensor networks using CSMA/CA, TDMA, and actor–critic reinforcement learning (AC-RL) fusion. In Acoustics, volume 7, page 39.

[20] Rodriguez, J. R. and Ammari, H. M. (2025). Precision hole detection and energy-aware QoS scheduling for wireless sensor networks. In 2025, 14th IFIP/IEEE International Conference on Performance Evaluation and Modeling in Wired and Wireless Networks (PEMWN), pages 1-7. IEEE.

[21] Qamar, M. S., ul Haq, I., Munir, M. F., Roslee, M. B., Awan, A. A., and Waseem, A. (2024). Enhancing energy efficiency in WSNs with hybrid LEACH-D and ANN. In 2024 Multimedia University Engineering Conference (MECON), pages 1-6. IEEE.

[22] Abdoulaye, I., Belleudy, C., Rodriguez, L., and Miramond, B. (2024). Semi-decentralized prediction method for energy-efficient wireless sensor networks. IEEE Sensors Letters, 8(4): 1-4

[23] Roopashree, H. et al. (2024). Robust wireless sensor network using enhanced trust-based secure and energy-efficient rout- ing algorithm (ETBSEER) to prevent malicious nodes. In 2024 Second International Conference on Advances in Information Technology (ICAIT), volume 1, pages 1–6. IEEE.