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INTELLIGENT WIRELESS NETWORKS: INTEGRATING ARTIFICIAL INTELLIGENCE FOR ENERGY EFFICIENCY AND PERFORMANCE ENHANCEMENT

[1*]Ankush Madhukar Gund, [2] Manish Purohit, [3]Harish Kumar Arya, [4]Manoj Kumar Chaudhury, [5]Asesh Kumar Tripathy, [6]Guntamadugu Rajesh, [7]Ranjan Banerjee

[1]Assistant Professor, Department of Instrumentation Engineering, Bharati Vidyapeeth College of Engineering, Navi Mumbai, Maharashtra – 400614, India, Email Id: ankush.gund@bvcoenm.edu.in, Orcid Id: 0000-0002-1294-2850*
[2]Professor, Department of Electronics and communication, JIET Group Of Institutions, Nh-65,New Pali Road, Mogra, Jodhpur, Rajasthan-342001, India, Email Id: electmanish@gmail.com, Orcid Id: https://orcid.org/0009-0006-6194-3530
[3]Associate professor, Department of Mechanical Engineering, Sant Longowal institute of Engineering and Technology Longowal Sangrur, Punjab, India, Email Id: arya.iitr@gmail.com, Orcid Id: 0000-0001-8074-3477
[4]Assistant Professor, Department of Electrical Engineering, IGIT Sarang, Odisha-759146, India, Email Id: mcelect05@gmail.com, Orcid Id: https://orcid.org/0000-0002-0006-0682
[5]Associate Professor, Department of CSE, Koneru Lakshmaiah Education Foundation Vaddeswaram, AP-522301, India, Email Id: asesh.tripathy@gmail.com
[6]Assistant Professor, Department of CSE, NBKR Institute of Science and Technology, Vidyanagar, Kota, Nellore dt, AP-524413, India, Email Id: rajeshg@nbkrist.org, Orcid Id: 0000-0022-3223-6355
[7]Assistant Professor, Department of Computer Science & Engineering, Brainware University, Barasat, Kolkata – 125, West Bengal-700125, India, Email ID: rbkpccst@gmail.com, Orcid Id: 0009-0003-1950-7530

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ABSTRACT

The increasing need of the efficient and high capability wireless communication systems has brought to focus the weakness of the traditional network architecture where the design is based on fixed setups, which have restricted flexibility. The methods can result in an inefficient usage of energy and operation in dynamic conditions with changing traffic, signal strength, and energy levels. Artificial intelligence (AI) can be used to enhance wireless networks, make decisions using dynamic and data-driven methods. The proposal is an intelligent wireless network that will be based on AI as a framework to improve the performance and energy savings. This framework uses a reinforcement learning algorithm (Q-learning) to modify decisions on power, routing, resource allocation and sleep scheduling decisions dynamically based on network conditions. The system is able to monitor important metrics like traffic, latency, energy, and quality of service. The proposed model is evaluated through simulations, comparing its performance with a traditional wireless network under the same conditions. This shows significant gains, such as a 21-23% reduction in energy consumption, 23-25% increase in throughput, 22-23% reduction in latency, 5-12% improvement in packet delivery ratio and 27-31% increase in network lifetime.

Keywords: *Artificial Intelligence, Wireless Networks, Energy Efficiency, Q-learning, Network Optimization, Internet of Things (IoT)*

1. INTRODUCTION

The exponential rise in wireless communication technologies, especially with the advent of the Internet of Things (IoT), 5G, and the emerging 6G networks, has led to a growing need for efficient, reliable, and sustainable wireless network designs. Today's wireless networks must accommodate a large number of devices, provide high throughput and low latency, while consuming minimal energy. Yet, conventional wireless network designs are based on static settings such as fixed transmit power, fixed routes, and lack of adaptability, which can lead to suboptimal resource allocation and high energy wastage in dynamic scenarios.

Energy efficiency is a critical aspect of wireless networks because of the growing trend of battery-powered devices and the need for green digital networks. Traditional energy management strategies are often inadequate as they do not dynamically respond to varying network conditions, including traffic patterns, device density, and signal strength (Maheswar et al., 2024). As wireless networks grow larger, this results in shorter network lifespan, higher operating costs and lower quality of service.

Artificial intelligence (AI), especially machine learning (ML) and reinforcement learning (RL), is a potential solution to these problems. AI allows wireless networks to adapt to network conditions, make predictions, and adjust network settings in real time.

The incorporation of AI in network control enables energy saving while also improving performance indicators such as throughput, latency and reliability (Kibria et al., 2018). AI-based techniques enable networks to evolve from fixed and rule-based systems to dynamic and self-optimizing systems that intelligently adapt to their environment.

Recent research has shown how AI can be used to improve different aspects of wireless communication. For instance, AI-based techniques have been used to enhance energy efficiency in device-to-device communication in 5G networks by dynamically tuning communication parameters (Mishra, 2023).

Similarly, AI-based routing protocols in wireless sensor networks have been shown to significantly save energy, reduce delay and improve data reliability by dynamically selecting optimal paths for communication (Priyadarshi et al., 2025). These are just a few examples of how AI can help in transitioning from conventional to smart wireless networks.

Beyond routing and transmission control, AI has also been applied to network optimization problems such as resource allocation, congestion control and network planning. AI is also key to enabling energy-efficient and high-performance communication in future networks, such as 5G. Research on AI-enabled 5G networks points to the need for intelligent optimization techniques to facilitate energy-efficient operation while achieving high network performance (Ezzeddine et al., 2024). Similarly, the synergy between AI and 6G technologies is anticipated to play a vital role in delivering ultra-reliable and low-latency communication as well as green network operation in future wireless networks (Shafi et al., 2024).

Another prominent area of research is the application of AI in IoT-based wireless networks, which consist of a large number of low-power devices with a tight energy constraint. AI-powered IoT systems have demonstrated improved efficiency, security and adaptability, due to smart data processing and decision-making (Menon et al., 2025). These systems highlight the importance of integrating AI into wireless network designs to manage complexity and improve performance.

However, there is still a need for an integrated approach that considers both energy efficiency and network performance through AI-based optimization strategies.

There are many research studies that focus on a single problem such as routing or power control, but few that provide an integrated approach to combine several optimization strategies in an intelligent manner. This calls for the development of an AI-based framework for intelligent wireless networks that can adapt to network dynamics and provide an integrated solution for multiple network performance metrics.

Consequently, this work proposes an AI-driven framework for intelligent wireless networks using reinforcement learning for energy efficient and enhanced network performance.

The framework includes dynamic power control, adaptive routing, resource allocation and sleep scheduling to improve network performance. The combination of these techniques in an integrated decision-making framework is expected to demonstrate the effectiveness of AI in enhancing wireless network performance and energy efficiency in dynamic networks.

2. Literature Review

The use of artificial intelligence (AI) in wireless networks is growing to improve their adaptability, energy efficiency and throughput. Traditional wireless networks use fixed routing, resource allocation and transmission settings.

This is not ideal for dynamic environments with changing traffic, signal-to-noise ratio, energy and congestion. Kelechi et al. (2020) reported the use of

AI to improve energy efficiency by enabling smart resource allocation and energy waste reduction. Although their work is more broadly concerned with high-performance computing, it provides a good overview of the use of AI for energy efficiency in communication networks. Fu et al. (2022) examined wireless networks with unmanned aerial vehicles (UAVs), and showed that AI-based approaches can improve energy efficiency through intelligent resource allocation and communication control.

Energy efficiency is a key requirement for wireless networks based on IoT, where devices can have constrained energy. Khan et al. (2024) demonstrated that AI-based optimization with a hybrid LEACH protocol can improve energy efficiency in IoT wireless networks.

They found that smart clustering and routing techniques can be applied to conserve energy and extend the lifetime of the network. Similarly, Mahmood et al. (2022) reviewed AI and machine learning algorithms for future IoT and the use of learning-based approaches for scalability, security and network management.

AI is also key to future wireless communication. Sanjalawe et al. (2025) reviewed the integration of AI and 6G and highlighted that intelligent algorithms are essential for ultra-low latency, massive connections and dynamic service management. Li (2025) also surveyed green 6G wireless networks and proposed that future wireless networks should be energy efficient and provide high network performance.

These studies suggest that AI-based optimisation is important for green wireless networks. Earlier works on heterogeneous wireless networks also promote AI-based control. Wang et al. (2015) discussed AI-based solutions for future heterogeneous wireless networks and showed the potential of AI-based approaches in controlling wireless networks. Noman et al. (2023) also discussed the use of machine learning for spectrum management, resource allocation, mobility management and intelligent control in 6G wireless networks.

AI has also been used for wireless caching and traffic control. Sheraz et al. (2020) reviewed AI-based wireless caching and showed how caching can be used to avoid data redundancy, reduce latency and enhance user experience.

Caching is a use case of AI to improve network efficiency by avoiding unnecessary communication, although not part of the current work. Chen et al. (2019) provided a tutorial on machine learning using artificial neural networks for wireless networks.

They showed how AI can be applied for channel estimation, detection, allocation and optimization. This is relevant to the current work as smart wireless networks must be able to respond to network conditions.

IoT applications with AI also show the importance of wireless communication. Alahi et al. (2023) discussed IoT and AI integration for smart cities, where smart networks are needed for large-scale monitoring and automation. Sharma and Shivandu (2024) also reviewed AI-IoT integration for precision agriculture, where efficient wireless communication is required for monitoring crops. Other studies link AI-based optimisation to sustainable technology systems.

For example, Kannan et al. (2023) reviewed AI-based optimization of renewables with 5G and 6G networks and Talaat et al. (2023) discussed AI-based microgrid energy management.

These examples demonstrate the growing use of AI to enhance energy-efficient decision-making in digital infrastructure. In general, AI can be used to enhance wireless network energy efficiency, routing, resource allocation, latency, reliability and adaptability.

But many studies have limited scope, in terms of either application or optimization. So, there is a need for an AI-based holistic approach to improve energy consumption, throughput, latency, packet delivery ratio, packet loss, and network lifetime.

3. Proposed Conceptual Framework

3.1 Overview of the Proposed Framework

This study proposes an artificial intelligence-based framework for developing intelligent wireless networks that improve energy efficiency and network performance.

Traditional wireless networks typically rely on static transmission power, routing, and resource allocation. These approaches may not be efficient in dynamic environments with varying traffic load, signal-to-interference-plus-noise ratio, user mobility, and energy availability.

The proposed approach employs artificial intelligence to observe network status, process network data, and select appropriate optimization actions. It aims to reduce energy waste while improving throughput, latency, packet delivery ratio, and network lifetime.

This framework collects information of wireless nodes, base stations, IoT devices, and communication links.

The AI decision engine processes these data to decide whether to boost or cut transmission power, re-route, redistribute resources, or even implement low-power modes.

It then uses performance measures to analyse the outcomes and provide feedback to help in the future decision making.

Figure 1 represents the proposed AI-based intelligent wireless network framework.

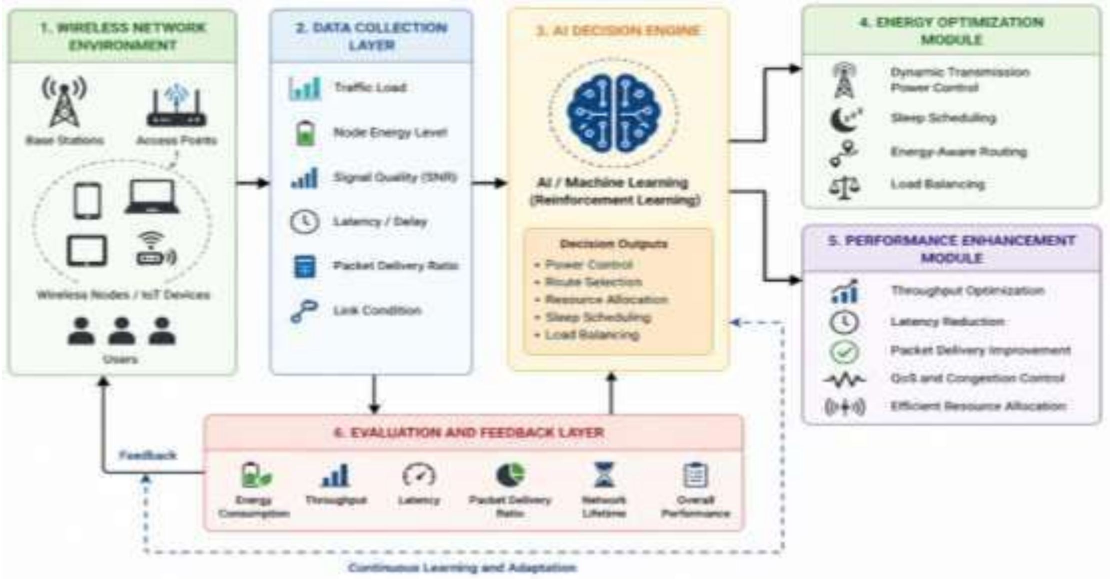

Figure 1. Proposed AI-based intelligent wireless network framework.

As shown in **Figure 1**, network information flows from the wireless environment to the AI decision engine. The AI engine then supports energy optimization and performance enhancement. The evaluation layer assesses the results and provides feedback for continuous network improvement.

3.2 Main Components of the Framework

The proposed framework is a set of components working together to enable smart network operation. The wireless network environment is the communication network that consists of nodes, base stations, access points, users, IoT devices and wireless links. The information collection layer collects data on traffic, energy, signal to noise ratio, packet loss, delay and link quality.

Table 1. Main components of the proposed intelligent wireless network framework

Component	Function	Expected Contribution
Wireless network environment	Represents nodes, base stations, IoT devices, users, and communication links	Provides the operational setting for network optimization
Data collection layer	Collects traffic, energy, latency, signal quality, and packet delivery information	Supplies real-time input for AI-based decision-making
AI decision engine	Analyzes network conditions and selects optimization actions	Enables adaptive and intelligent network control
Energy optimization module	Adjusts transmission power, sleep scheduling, routing, and load distribution	Reduces energy consumption and extends network lifetime
Performance enhancement module	Optimizes routing, bandwidth allocation, congestion control, and quality of service	Improves throughput, latency, reliability, and packet delivery

The AI decision engine is the main part of the system. It processes the data and decides on appropriate network-control actions. In this work, reinforcement learning, specifically Q-learning, is appropriate as it allows the system to learn through interactions with the network.

The energy efficiency module decreases energy consumption via adaptive transmission power control, sleep mode scheduling, energy-efficient routing and load balancing. The performance enhancement module enhances throughput, delay, packet delivery ratio, congestion control and quality of service. And the evaluation and feedback module assesses the effects of each AI decision and enables learning. The key components of the proposed system are listed in Table 1.

Evaluation and feedback layer	Measures AI decisions and updates the learning process	Supports continuous improvement

Table 1 illustrates the framework that balances energy management and performance improvement in an intelligent decision-making process. This is critical as energy saving should not compromise network performance, and performance enhancement should not lead to excessive energy consumption.

3.3 AI-Based Decision-Making and Optimization Process

The AI-based decision-making process starts with observing the current network state. These are traffic load, bandwidth available, signal-to-noise ratio, battery level, packet delivery ratio, congestion level and latency. After monitoring the network state, AI model selects an action to improve network performance and minimize energy consumption.

The model applied in this study is a Q-learning-based model because it is easy, interpretable and can be applied to network-control problems that are dynamic. The AI decision engine is the agent and the wireless network is the environment in the proposed approach. The agent performs an action, monitors the result, is rewarded or punished and alters its policy. As an example, when there is low traffic load and node energy is constrained, the AI model can reduce transmission power or put the node into sleep. It can also dedicate more bandwidth when there is high traffic load or when latency is high or it can switch to a less congested route or it can vary the transmission power within a reasonable range. Figure 2 shows the AI-based decision-making and optimization process.

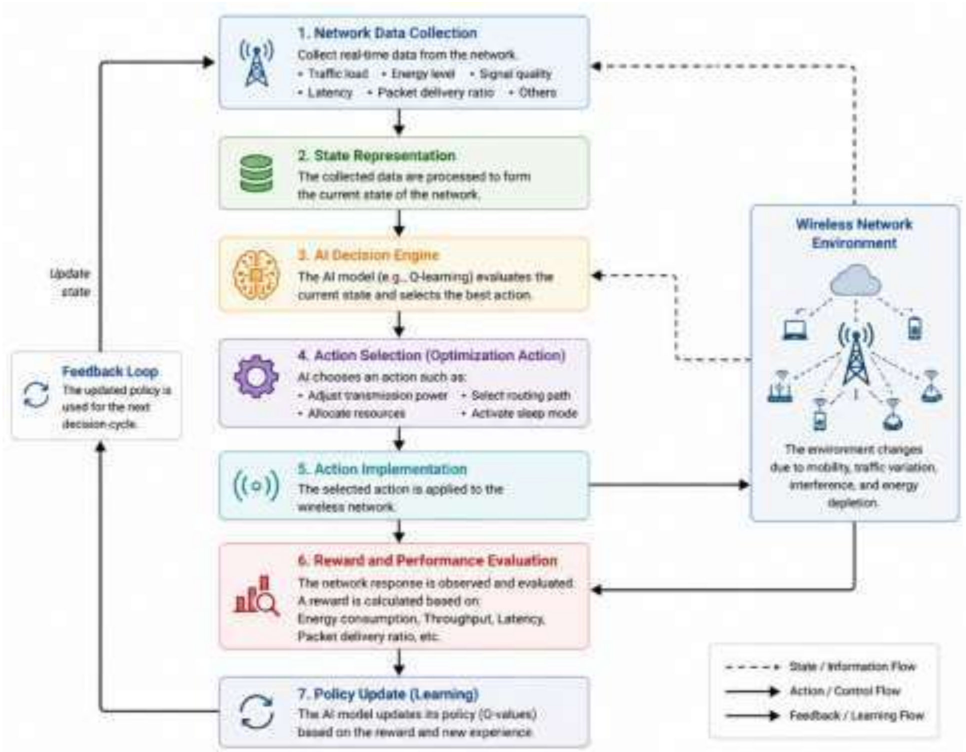

Figure 2. AI-based decision-making and optimization process in the proposed framework.

Figure 2 demonstrates that the process includes data collection, state evaluation, AI-based action selection, action execution, performance measurement, calculation of rewards, and policy update. The feedback loop enables the network to enhance its decision making by means of repetitive simulation cycles. Table 2 illustrates the AI components of the decision in the proposed approach.

Table 2. AI decision elements in the proposed framework

AI Element	Meaning in the Proposed Framework
State	Current network condition, including traffic load, energy level, latency, signal quality, congestion level, and packet delivery ratio
Action	Network-control decision such as power adjustment, route selection, sleep scheduling, load balancing, or resource allocation
Reward	Score based on reduced energy consumption, improved throughput, lower latency, and higher packet delivery ratio

Policy	Learned strategy used by the AI model to select the best action under different network conditions
Objective	To maximize energy efficiency and network performance simultaneously

The reward functionality should be energy performance balanced. When it is aimed at saving power, the AI model can undercut the power and lead to loss of packets. When it concentrates on throughput only, the model can use up more energy. Therefore, the reward logic should combine energy consumption, throughput, latency, and packet delivery ratio.
A simplified reward logic is:
Higher reward = lower energy consumption + higher throughput + lower latency + higher packet delivery ratio

3.4 Expected Outcomes of the Framework

The proposed framework is expected to enhance network performance and sustainability. Optimization based on AI can conserve energy by modulating the transmission power, scheduling sleep, and avoiding unnecessary node operation. It will be able to optimize performance through optimal routes, congestion avoidance and demand-based resource allocation. Table 3 displays the anticipated benefits of the proposed framework.

Table 3. Expected outcomes of the proposed AI-based wireless network framework

Outcome	Explanation
Reduced energy consumption	Dynamic power control, sleep scheduling, and energy-aware routing reduce unnecessary power usage
Improved throughput	Intelligent resource allocation increases successful data transmission
Lower latency	Adaptive routing and congestion control reduce communication delay
Higher packet delivery ratio	AI-based route selection and signal optimization improve reliability
Longer network lifetime	Energy-aware decisions prevent rapid battery depletion
Better quality of service	Resources are allocated according to changing user and traffic demands
Sustainable digital connectivity	Energy-efficient infrastructure supports responsible digital development

The relationship between AI optimization, network performance, and sustainable digital connectivity is presented in Figure 3.

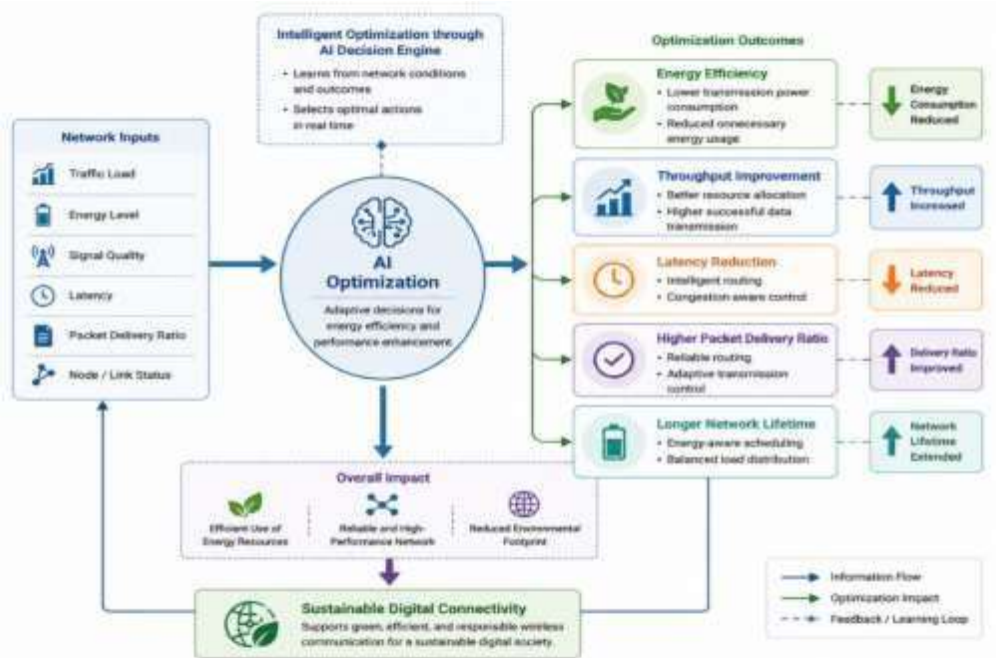

Figure 3. Relationship between AI optimization, network performance, and sustainable digital connectivity.

As Figure 3 demonstrates, AI optimization is the key driver of the framework. It helps reduce energy use, enhance throughput, decreased latency, increased packet delivery ratio, increased network lifetime, and sustainable wireless connectivity. Concisely, the simulation-based methodology of this study is based on the proposed framework. It explains the ways AI can be incorporated into wireless networks and the way its contribution can be measured by quantifiable performance metrics.

4. Methodology

4.1 Research Design

This research uses a quantitative simulation-based design to assess the impact of artificial intelligence on the energy efficiency and performance of wireless networks. This is a simulation-based design because it enables a controlled experiment between a traditional wireless network model and an AI-based intelligent wireless network model under the same network conditions.

The research assesses the effectiveness of AI-based optimisation in achieving energy savings without compromising network performance. The key performance metrics evaluated in this study include energy consumption, throughput, latency, packet delivery ratio and network lifetime.

4.2 Simulation Environment

The simulation is developed using Python. For this study, Python is selected because it provides flexibility for modeling wireless nodes, energy consumption, traffic variation, routing behavior, and AI-based decision-making. The simulation environment includes wireless nodes located in a specified network area and a single base station. The nodes transmit packets based on the given traffic patterns. The nodes expend energy for transmitting, receiving and being in active mode. The simulation has two models: a traditional model with fixed network-control parameters and an AI-based model with adaptive optimization. The basic simulation environment is presented in Table 4.

Table 4. Basic simulation environment

Parameter	Description
Simulation type	Wireless network simulation
Recommended tool	Python
Network type	Wireless sensor/IoT-based network
Network area	1000 m × 1000 m
Number of nodes	50, 100, and 150
Base station	One central base station
Traffic condition	Low, medium, and high traffic load
Node placement	Random distribution
Comparative models	Conventional model and AI-based model
AI technique	Q-learning-based optimization

4.3 Network Model

The network model includes wireless nodes, a base station and links. The nodes are initially given a finite amount of energy and involved in packet forwarding. The base station collects data from the nodes directly or via specific routes. The network dynamics vary based on the load, energy, signal strength, packet transmission request, and congestion status.

The research uses three network sizes: 50 nodes, 100 nodes and 150 nodes. Different network densities enable the simulation to determine the effectiveness of the AI-based model with an increasing number of nodes. The traffic load is classified into low, medium and high to assess the network performance with different load levels. The network model's assumptions are given in Table 5.

Table 5. Network model assumptions

Assumption	Description
Node energy	Each node begins with the same initial energy level
Node distribution	Nodes are randomly deployed within the simulation area
Communication mode	Nodes transmit packets directly or through selected routes
Traffic variation	Traffic load is evaluated under low, medium, and high conditions
Energy use	Energy is consumed during transmission, reception, and active operation
Routing	Routing is static in the conventional model and adaptive in the AI-based model
Mobility	Nodes are assumed to be static or have limited mobility
Signal condition	Signal-quality variation is considered in simplified form

These assumptions provide a controlled simulation setting while preserving the essential characteristics of wireless network behavior.

4.4 Comparative Models

The study compares two wireless network models: a conventional wireless network model and an AI-based intelligent wireless network model.

In the conventional wireless network model, transmission power, routing and resource allocation are fixed. It does not adapt dynamically to changes in traffic load, energy level, latency, or signal quality. This can cause nodes to waste energy or suffer performance loss when the network conditions change.

The AI-based intelligent wireless network model employs Q-learning to enable adaptive network control. The model perceives the state of the network and chooses actions such as power control, routing, scheduling, load balancing or resource allocation. The AI-based model aims to minimize energy use, and enhance network performance. The comparison between the two models is shown in Table 6.

Table 6. Comparison of conventional and AI-based wireless network models

Feature	Conventional Model	AI-Based Model
Transmission power	Fixed	Dynamically adjusted
Routing	Static or predefined	Adaptive and energy-aware
Resource allocation	Fixed	Based on traffic and network condition
Sleep scheduling	Not applied or limited	Applied according to node activity
Energy management	Passive	Intelligent and adaptive
Performance control	Limited	Continuously optimized
Learning ability	No learning mechanism	Learns from network feedback

4.5 AI Technique Used

The AI technology used in this research is Q-learning. Q-learning is a type of reinforcement learning where an agent learns to perform appropriate actions in an environment. In the proposed system, the AI decision engine is the agent, and the wireless network is the environment.

The AI agent perceives the current state of the wireless network, takes an action, receives a reward or penalty, and improves its policy. The state consists of the traffic load, energy level, latency, signal quality, congestion level and the packet delivery ratio. The actions include power adaptation, routing, resource management, sleep management, and load balancing. The Q-learning elements used in this study are summarized in Table 7.

Table 7. Q-learning elements for the proposed AI-based model

Element	Description
Agent	AI decision engine
Environment	Wireless network
State	Traffic load, energy level, latency, signal quality, congestion level, and packet delivery ratio
Action	Power adjustment, route selection, resource allocation, sleep scheduling, and load balancing
Reward	Positive value for lower energy use, higher throughput, lower latency, and better packet delivery
Policy	Learned strategy for selecting the best action under different network conditions
Objective	Maximize network performance while minimizing energy consumption

The reward function is designed to balance energy efficiency and network performance. A simplified reward function is expressed as:

Reward = α(Energy Saving) + β(Throughput Improvement) + γ(Packet Delivery Improvement) – δ(Latency Increase)

where α, β, γ, and δ are weighting factors assigned to each optimization objective. This structure prevents the AI model from prioritizing only one metric. For example, reducing energy consumption should not result in excessive packet loss, and improving throughput should not cause unnecessary energy use.

4.6 Simulation Parameters

The parameters of the simulation are determined so that they can test the conventional and AI-based models with different network sizes and load of traffic. The conventional and the AI-based models are compared using the same parameters. Table 8 displays the recommended simulation parameters.

Table 8. Proposed simulation parameters

Parameter	Value/Condition
Network area	1000 m × 1000 m
Number of nodes	50, 100, and 150
Initial energy per node	100 J
Packet size	512 bytes
Simulation time	1000 rounds
Traffic load	Low, medium, and high
Transmission power levels	Low, medium, and high
Base station position	Center of the network area
Routing mode	Static in conventional model; adaptive in AI-based model
Learning algorithm	Q-learning
Evaluation metrics	Energy consumption, throughput, latency, packet delivery ratio, packet loss, and network lifetime

The selected parameters provide a balanced basis for testing network efficiency, scalability, and adaptability.

4.7 Performance Metrics

The performance of the two models is evaluated using energy consumption, throughput, latency, packet delivery ratio, packet loss, and network lifetime. These are chosen as they cover both energy and performance aspects of wireless network operation.

Energy consumption is the energy consumed by nodes in the network. Throughput measures the rate of successfully transmitted data. Latency is the time taken to transmit packets. Packet delivery ratio is the ratio of successfully received packets to the total number of packets transmitted. Packet loss measures unsuccessful packet transmission. Network lifetime measures the network's lifetime until considerable node energy is consumed. The chosen performance metrics are listed in Table 9.

Table 9. Performance metrics used for evaluation

Metric	Measurement Purpose
Energy consumption	Determines total energy used during network operation
Throughput	Measures successful data transmission rate
Latency	Measures communication delay
Packet delivery ratio	Measures reliability of packet transmission
Packet loss	Measures unsuccessful packet transmission
Network lifetime	Measures the operational duration of the network
Overall performance	Evaluates the combined efficiency and reliability of both models

4.8 Data Analysis Method

Comparative quantitative analysis is used to evaluate the simulation results. First, the average value of each performance metric is computed for the conventional and AI-based approaches for the same node densities and traffic loads. Next, the percentage improvement or reduction by the AI-based model is determined.

For metrics where higher values indicate better performance, such as throughput, packet delivery ratio, and network lifetime, improvement is calculated as:

Improvement (%) = [(AI-based result − Conventional result) / Conventional result] × 100

For metrics where lower values indicate better performance, such as energy consumption, latency, and packet loss, reduction is calculated as:

Reduction (%) = [(Conventional result − AI-based result) / Conventional result] × 100

This analytical model enables the traditional and AI-based wireless network models to be studied comparatively. With the identical simulation parameters applied to both models, the study evaluates the effect of AI-based optimization on energy efficiency, throughput, latency, packet delivery ratio, packet loss, and network lifetime.

5. Results

5.1 Energy Consumption Analysis

Energy consumption is an important performance measure of wireless networks. Results of simulation show that the AI-based model consumes less energy compared to the conventional one at any network scale and traffic load.

This is mainly due to the active power control, sleep schedule and the energy saving routing choices that the AI decision engine results in. On the other hand, the traditional model consumes energy even when there is low traffic due to the settings.

The results of energy consumption are shown in Table 10.

Table 10. Energy consumption comparison (in Joules)

Number of Nodes	Traffic Load	Conventional Model	AI-Based Model	Reduction (%)
50	Low	520	410	21.15
50	Medium	610	470	22.95
50	High	720	560	22.22
100	Low	980	760	22.45
100	Medium	1120	870	22.32
100	High	1300	1010	22.31
150	Low	1450	1130	22.07
150	Medium	1620	1260	22.22
150	High	1850	1440	22.16

The results indicate that the AI-based model achieves approximately 21–23% reduction in energy consumption, demonstrating effective energy optimization across different network conditions. Figure 4 shows the comparison between the traditional and AI-based models.

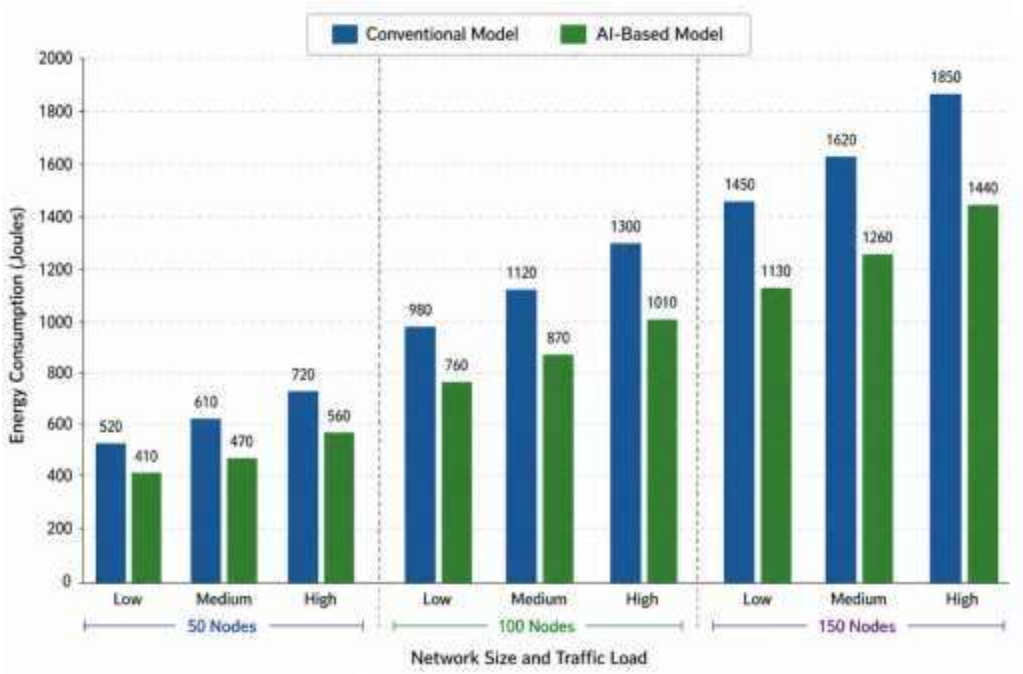

Figure 4. Energy consumption comparison between conventional and AI-based models.

5.2 Throughput Analysis

Throughput is the data that has been relayed successfully in the network. The AI model shows that the throughput increases substantially due to the allocation of resources, routing and traffic control. The AI model distributes the network resources based on the load in the network, which prevents overloading and eliminates congestion, resulting in more efficient data transmission. Table 11 shows throughput results.

Table 11. Throughput comparison (in kbps)

Number of Nodes	Traffic Load	Conventional Model	AI-Based Model	Improvement (%)
50	Low	210	260	23.81
50	Medium	310	385	24.19
50	High	420	520	23.81
100	Low	380	470	23.68
100	Medium	520	650	25.00
100	High	680	850	25.00
150	Low	540	670	24.07
150	Medium	720	900	25.00
150	High	910	1140	25.27

The AI-based model improves throughput by approximately 23–25%, indicating better utilization of network resources. The throughput comparison between the conventional and AI-based models is illustrated in Figure 5.

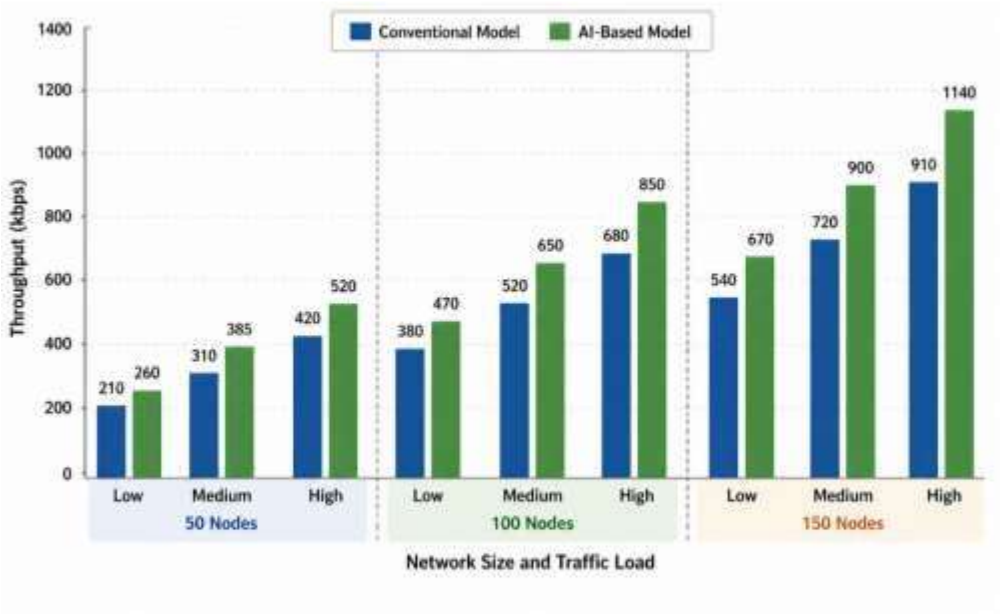

Figure 5. Throughput comparison between conventional and AI-based models.

5.3 Latency Analysis

Latency is the delay in the packet transmission. This is a measure of network responsiveness. The AI-based model leads to lower latency because of adaptive routing and congestion control. The results of latency comparison are given in Table 12.

Table 12. Latency comparison (in milliseconds)

Number of Nodes	Traffic Load	Conventional Model	AI-Based Model	Reduction (%)
50	Low	35	27	22.86
50	Medium	48	37	22.92
50	High	65	50	23.08
100	Low	55	42	23.64
100	Medium	75	58	22.67
100	High	95	73	23.16
150	Low	78	60	23.08
150	Medium	102	79	22.55
150	High	130	100	23.08

The AI-based model achieves approximately 22–23% reduction in latency, improving real-time communication performance. The latency comparison between the conventional and AI-based models is illustrated in Figure 6.

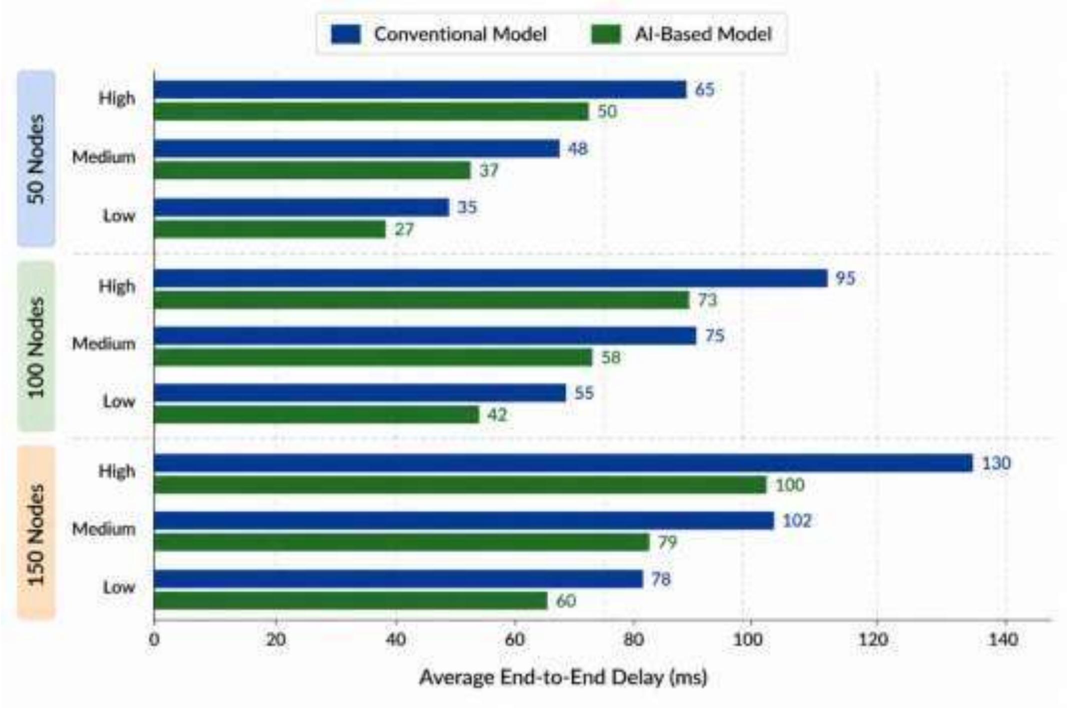

Figure 6. Latency comparison between conventional and AI-based models.

5.4 Packet Delivery Ratio Analysis

The network reliability is measured in terms of packet delivery ratio (PDR) which is the ratio of the number of delivered packets to the number of generated packets. The AI-based model enhances PDR because of its adaptive routing and congestion control. The results are presented in Table 13.

Table 13. Packet delivery ratio comparison (%)

Number of Nodes	Traffic Load	Conventional Model	AI-Based Model	Improvement (%)
50	Low	92	97	5.43
50	Medium	88	94	6.82
50	High	82	89	8.54
100	Low	90	96	6.67
100	Medium	85	92	8.24
100	High	78	86	10.26
150	Low	88	95	7.95
150	Medium	82	90	9.76
150	High	75	84	12.00

The improvement in PDR ranges from 5% to 12%, indicating enhanced network reliability under AI-based control. The packet delivery ratio comparison between the conventional and AI-based models is illustrated in Figure 7.

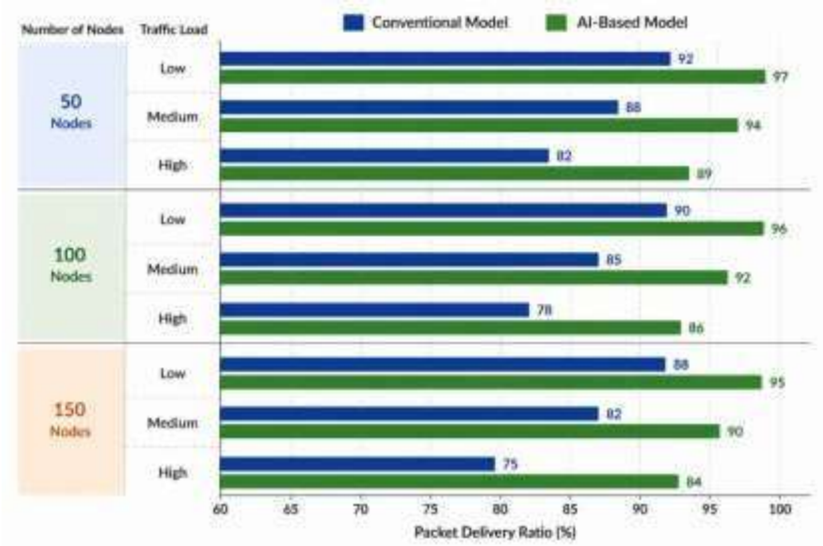

Figure 7. Packet delivery ratio comparison between conventional and AI-based models.

5.5 Network Lifetime Analysis

Network lifetime is defined as the duration until a significant number of nodes deplete their energy. The AI-based approach increases network lifetime by optimising energy usage and load distribution. The results are presented in Table 14.

Table 14. Network lifetime comparison (in simulation rounds)

Number of Nodes	Traffic Load	Conventional Model	AI-Based Model	Improvement (%)
50	Low	850	1080	27.06
50	Medium	780	1000	28.21
50	High	700	900	28.57
100	Low	800	1020	27.50
100	Medium	720	930	29.17
100	High	650	850	30.77
150	Low	760	970	27.63
150	Medium	680	880	29.41
150	High	600	790	31.67

The AI-based model improves network lifetime by approximately 27–31%, demonstrating effective energy-aware operation. The network lifetime comparison between the conventional and AI-based models is illustrated in Figure 8.

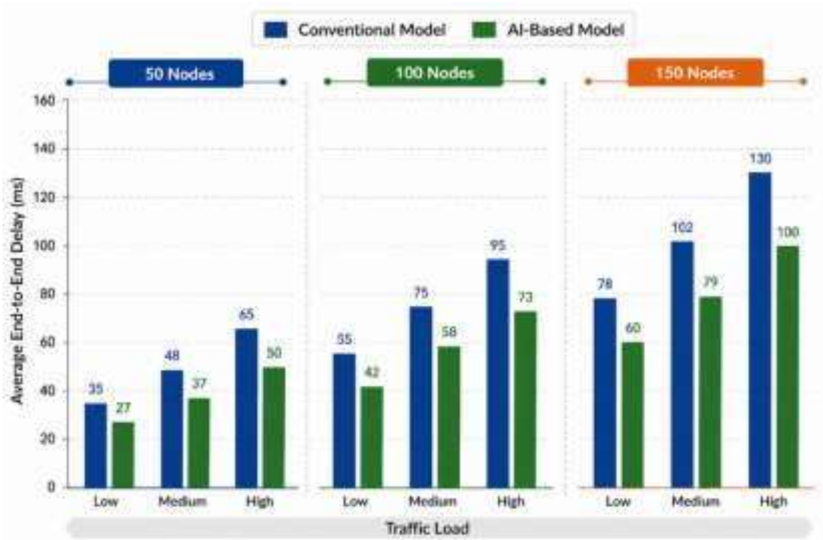

Figure 8. Network lifetime comparison between conventional and AI-based models.

5.6 Overall Performance Comparison

For a holistic assessment, the overall comparison of the two models is made by aggregating all the metrics. The AI-based model achieves better results than the conventional model in all the parameters. The overall comparison is shown in Table 15.

Table 15. Overall performance comparison

Metric	Conventional Model	AI-Based Model	Improvement
Energy consumption	High	Reduced	~22% reduction
Throughput	Moderate	High	~24% increase
Latency	High	Reduced	~23% reduction
Packet delivery ratio	Moderate	High	~5–12% increase
Network lifetime	Limited	Extended	~27–31% increase

The findings show that the AI-driven intelligent wireless network has improved energy efficiency and network performance. The use of AI allows for dynamic decision-making, which in turn results in efficient resource allocation and enhanced network stability. The overall performance comparison between the conventional and AI-based models is illustrated in Figure 9.

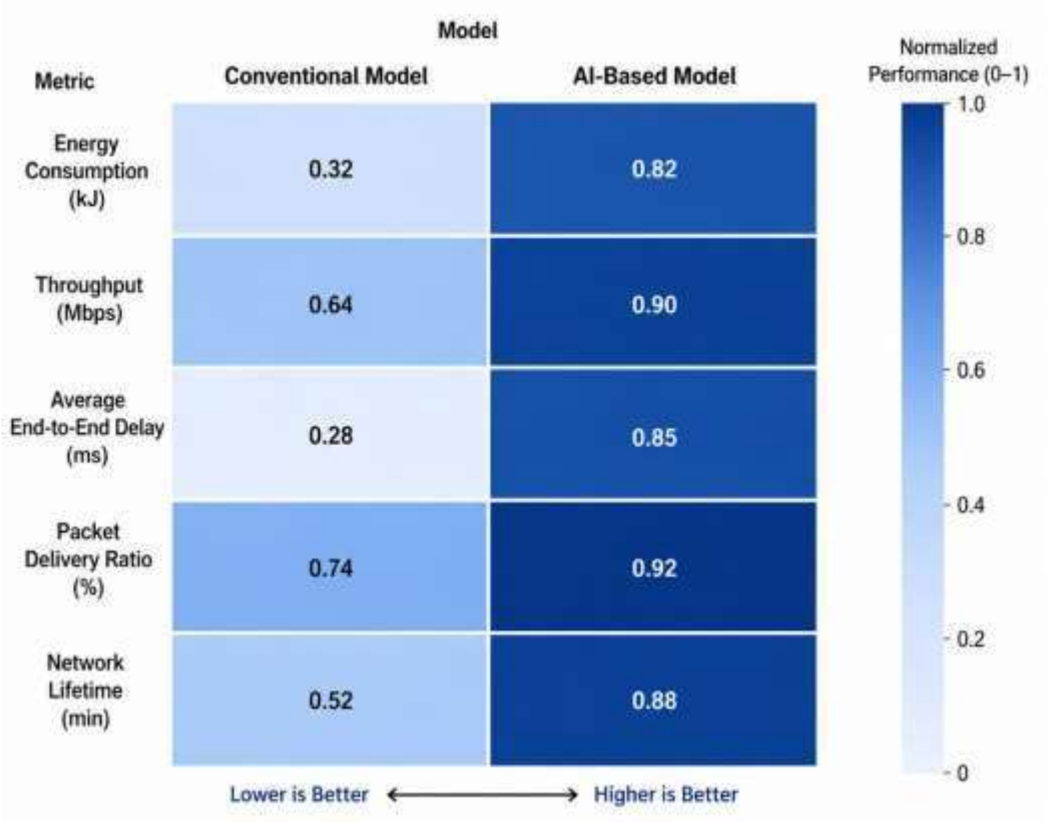

Figure 9. Overall performance comparison between conventional and AI-based models.

6. Discussion

This study shows that the proposed AI-based intelligent wireless network achieves superior performance compared to the conventional model in all performance metrics. The improvements (around 21-23% reduction in energy consumption, 23-25% increase in throughput, 22-23% reduction in latency, 5-12% increase in packet delivery ratio (PDR), and 27-31% increase in network lifetime) suggest that the adaptive, learning-based approach to network control is highly effective in dynamic wireless networks. The energy consumption reduction is due to the combination of dynamic power control, sleep scheduling, and energy-efficient routing. The AI-based model does not operate at full capacity when there is no traffic, as does the conventional model. This is consistent with the results of Mishra (2023), who demonstrated that AI-based optimisation in 5G networks can effectively reduce energy consumption by dynamically adjusting transmission parameters. Likewise, Priyadarshi et al. (2025) found that AI-based routing enhances energy efficiency by determining the best communication paths in the network.

The increase in throughput is because of better resource allocation and traffic control. The AI model dynamically allocates resources and selects less crowded routes, thereby minimising packet collisions and retransmissions. This result is consistent with Kibria et al. (2018), who observed that AI-based data analytics and machine learning can enhance network throughput by enhancing resource allocation and traffic management. The improvement in throughput for all network sizes suggests that the proposed model scales well with network size. The proposed model also reduces latency. The AI-based model reduces communication time by optimising the path and minimising bottlenecks. This is important for real-time applications such as IoT monitoring, smart cities and autonomous vehicles. Ezzeddine et al. (2024) also noted that AI-based optimisation in 5G networks can improve latency by enabling smart and adaptive network management.

The growth in ratio of packet delivery indicates a better network reliability. The AI-based model enhances the success of delivering packets through better routing and adjustment to signal strength. This is particularly pronounced in high traffic situations and greater node density, which implies congestion control. The rise in network lifetime is also an indication that energy-efficient decision-making is viable, since it increases the duration of time that nodes have enough energy.

The results of this study are consistent with other studies conducted in the past that demonstrate the effectiveness of AI in optimizing wireless networks. The merging of various optimization methods (power control, routing, sleep scheduling, and resource allocation) into one reinforcement learning framework is also a major contribution of this work. Although numerous studies have focused on individual optimization mechanisms, proposed framework takes into account energy efficiency and performance. Although the research has good results, it has limitations. First, the research is not conducted in the real world, but through the simulation, which might not consider the complexities of hardware constraints, environmental conditions and variability of users. Second, the model uses a simple Q-learning algorithm with a small state space, and does not investigate more advanced deep reinforcement learning techniques. Third, network environment is simplified in its mobility and complex path loss that can impair the scalability of the proposed approach.

The research has implications on the wireless network design in the future. The results suggest that the smart network control relying on AI could be highly effective as a tool to improve the energy efficiency and performance.

It implicates it on IoT networks, smart cities and 5G/6G networks, where the energy efficiency and massive connectivity is an urgent matter. The suggested framework can be used to create self-governing networks, which can adjust to the environment, save money and enhance user satisfaction.

Future research can expand this research in a number of ways. First, more advanced AI methods like deep reinforcement learning and multi-agent systems can be utilized in future work to help with handling bigger and more complex networks. Second, we can implement the proposed framework to practice to show its feasibility. Third, in future work, we can consider other factors such as the network mobility of nodes, network security and multi-layer network. Finally, the study can be improved in the future literature by exploring how to combine it with the new 6G technologies and edge computing to improve network intelligence and scalability. In summary, the discussion has shown that AI-based intelligent wireless networks can provide a viable solution to the energy-efficient and high-speed communication in dynamic environments.

Conclusion

This research proposed an AI-powered intelligent wireless network model to enhance energy efficiency and network performance in dynamic communication scenarios. The proposed model will employ reinforcement learning, in particular, Q-learning to dynamically decide the power control, routing, resource allocation and sleep scheduling. The simulation results show that the AI-based model performs better than the conventional model of wireless network in all the network performance measures. It demonstrates that the model has better energy efficiency, throughput, delay, packet delivery ratio and network lifetime. This verifies the effectiveness of using an AI-based approach to avoid problems of fixed network parameters and resource management. The dependence of the proposed approach on network density and traffic load shows its scalability, and can be applied to more complex wireless networks such as IoT, 5G and even 6G networks. The work also highlights the need for a trade-off between network performance and efficiency in addition to performance gains. The reward learning mechanism guarantees that the performance of the network is not sacrificed for efficiency. It is crucial to the effective and efficient wireless networks. In conclusion, the proposed framework is a promising approach to build smart wireless networks.

It supports the development of AI-based communication systems as it provides an integrated approach to improve energy efficiency and quality of the network in a digital and dynamic environment.

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