International Journal of Advances in Applied Computational Intelligence

♦ ISSN: 2833-5600 Vol: 08, No. 01, 2026 ♦ PP. 20–32

Article DOI: https://doi.org/10.54216/IJAACI.080104

FULL LENGTH ARTICLE

Green IOT and Sustainable Wireless Sensor Networks: A Deep Reinforcement Learning Approach for Energy Optimization and Qos Enhancement

Surapaneni Phani Praveen[1*] Massila Kamalrudin[2] Sai Srinivas Vellela[3]
Deshinta Arrova Dewi[4] Dedeepya Pulletikurthy[5] Klodian Dhoska[6]

[1] Associate Professor, Department of Computer Science and Engineering, Prasad V. Potluri Siddhartha Institute of Technology, Kanuru, Vijayawada – 520007, Andhra Pradesh, India

[2] Faculty of Information and Communication Technology, Universiti Teknikal Malaysia Melaka (UTeM), Melaka, Malaysia

[3] Associate Professor, Department of CSE – Data Science, Chalapathi Institute of Technology, Guntur – 522016, Andhra Pradesh, India

[4] Professor, Faculty of Data Science and Information Technology (FDSIT), INTI International University, Malaysia

[5] Department of Computer Science & Engineering, SRM university AP, Amaravati, Andhra Pradesh, India

[6] Polytechnic University of Tirana, Tirana, Albania

Emails: phani.0713@gmail.com . massila@utem.edu.my . sais1916@gmail.com . deshinta.ad@newinti.edu.my . dedeepya_pulletikurthy@srmap.edu.in . kdhoska@upt.al

Received: January 18, 2026 Revised: February 12, 2026 Accepted: March 22, 2026 ⋆ Corresponding author

ABSTRACT

Due to the increasing adoption of IoT applications, there is a growing necessity for energy-efficient and sustainable WSN. Yet, traditional routing protocols tend to face problems like energy wastage, congestion, unreliable communication, and shorter network life spans under dynamic network conditions. This study presents the development of a DRL-powered Green IoT framework to enhance efficient communication through WSN while optimizing QoS performance. Specifically, the proposed framework employs the Deep Q-Network, Double Deep Q-Learning, adaptive clustering, and multi-objective optimization in order to enhance both routing and QoS performance.The model makes use of residual energy, congestion levels, throughput, delivery rate, and communication delays during its decision-making processes. Experimentation with the model was performed by making use of Python and NS-3. The simulation results showed that the presented model performed better than traditional routing methods like LEACH, PEGASIS, and HEED when evaluated on factors like energy preservation, enhanced throughput, minimized congestion, reduced delays, and increased network life spans. It can be concluded that DRL-powered communication optimization is a viable solution for the future development of Green IoT communication systems.

Keywords: Green IoT ▪ Wireless Sensor Networks ▪ Deep Reinforcement Learning ▪ Energy Efficiency ▪ QoS Enhancement ▪ Energy Sustainable Communication ▪ Adaptive Routing ▪ Network Lifetime

1. INTRODUCTION

The advent of Internet of Things (IoT) has revolutionized modern communication networks in that it enables automatic information sharing among different smart objects connected in the network. With more deployments, the IoT has produced a lot of communication information that necessitates efficient management solutions for the network (Chen et al., 2014).

Another vital part of the IoT infrastructure includes wireless sensor networks that facilitate healthcare applications, agriculture, industry, transportation, environment monitoring, and smart city applications (Al-Fuqaha et al., 2015; Gubbi et al., 2013). However, wide-scale implementation of WSNs poses challenges such as energy consumption, efficiency of routing, congestion control, scalability, and quality of service.

Sensor nodes operate under low-energy conditions, with low bandwidth and low computation capacities. Since these devices can be installed in distant locations, battery recharges can be both difficult and costly. As such, energy-efficient and sustainable communication is a core area of research in green IoT-driven WSNs (López-Ardao et al., 2021). Green IoT seeks to ensure minimal use of energy, environmental sustainability, effective communication, and prolonged network lifetime while retaining quality of service (Pandiyan et al., 2024).

Routing protocols like LEACH, PEGASIS, TEEN, and HEED have been extensively employed for optimization in WSNs. However, conventional routing protocols have several limitations, such as non-uniform energy consumption, excessive overhead costs, unstable clusters, network congestion, and lack of adaptive capability in dynamic networks (Ding et al., 2021). The advent of Artificial Intelligence (AI), Machine Learning (ML), and Deep Reinforcement Learning (DRL) has enabled communication systems to gain intelligent optimization capabilities. In particular, DRL empowers communication agents to interact with their environments in order to optimize their strategies for resource allocation and routing.

It has been shown that optimizing the communications process via DRL leads to improved energy efficiency, better throughput, congestion management, and overall network lifetime in WSNs utilizing IoT technology (Alsalmi et al., 2024; Dutta et al., 2024). On the other hand, there is an absence of solutions for the simultaneous optimization of various Quality-of-Service (QoS) parameters in IoT-assisted WSNs.

1.1 Background of Green IoT and Sustainable WSNs

The concept of Green IoT has gained importance with the development of a sustainable communication approach that can reduce energy utilization and expenses in networked computer environments. In WSNs, energy from nodes is consumed during communication activities like routing, clustering, packet transfer, and data aggregation. Therefore, an efficient energy-efficient approach is vital for sustainable IoT operations (Adu-Manu et al., 2025).

With the adoption of Deep Reinforcement Learning approaches such as Deep Q-Network (DQN), Double Deep Q-Learning (DDQN), and Proximal Policy Optimization (PPO), there have been new possibilities for self-governing communication processes in the framework of Green IoT networks (Schulman et al., 2017; Van Hasselt et al., 2016).

1.2 Motivation of the Study

The motive behind this research comes from the rising need for efficient and intelligent communication networks that can facilitate next-generation IoT applications. Most WSN routing methods do not effectively distribute energy consumption across sensor nodes, causing early failures of nodes, poor communication quality, decreased throughput rate, and limited network lifetime.

Moreover, another crucial motivation for conducting this research is the need for adaptive routing mechanisms and autonomous decision-making ability in IoT environments, where there are changing traffic conditions. Conventional methods of optimizing processes do not have any learning ability; hence, they are unable to adjust to dynamic changes in the network environment.

1.3 Research Objectives

The key aim of this research is to formulate a DRL-based Green IoT paradigm for sustainable wireless sensor networks that minimizes energy usage and improves QoS performance.

Specific aims include:

- To design a DRL-based routing and clustering framework for Green IoT communication.
- To optimize energy utilization and residual energy balancing among sensor nodes.
- To enhance QoS metrics including throughput, packet delivery ratio, latency, and communication reliability.
- To implement adaptive multi-objective optimization using DQN and DDQN techniques.
- To evaluate scalability and performance under heterogeneous IoT environments.
- To compare the proposed framework with conventional routing protocols and reinforcement learning-based approaches.

1.4 Research Contributions

In this work, a sustainable communication approach for Green IoT-based WSNs using DRL technology is proposed, which incorporates intelligent routing algorithm optimization, clustering, energy-efficient communication, and QoS improvement.

The proposed scheme adopts a multi-objective reward optimization approach that takes into account the amount of residual energy, throughput, degree of congestion, delay time, packet delivery ratio, and network lifespan. Through simulations, it is observed that there are improvements in terms of energy efficiency, QoS enhancement, throughput, and sustainability compared to LEACH, PEGASIS, HEED, and reinforcement learning algorithms.

2. RELATED WORK

As a result of the fast growth of the Green IoT and Wireless Sensor Networks (WSN), there has been increasing research on intelligent, efficient, and sustainable communication systems. Deployment of IoT on a large scale for applications such as healthcare, smart cities, agriculture, and industrial automation has posed various issues such as energy consumption, routing efficiency, congestion management, scalability, and Quality of Service (QoS). Therefore, various AI, ML, and DRL approaches have been implemented within WSN architectures.

2.1 Green IoT and Sustainable Wireless Sensor Networks

The concept of Green IoT is concerned with the reduction of energy utilization and minimization of ecological impact along with ensuring effective communication in large-scale IoT systems. As discussed by Al-Fuqaha et al. (2015) and Li et al. (2015), the scalability and intelligence of networking structures in heterogeneous IoT settings was crucial, whereas, Gubbi et al. (2013) pointed out sustainable communication and resource management as key issues for the future.

According to López-Ardao et al. (2021), energy-aware routing and intelligent communication management are required to increase the lifespan of WSNs. In a similar manner, Pandiyan et al. (2024) stated that the AI-based optimization process is highly important in Green IoT systems.

2.2 Machine Learning-Based Energy Optimization in WSNs

The techniques of Machine Learning have been extensively employed in optimizing the routing, energy usage, and communication processes in WSNs. According to Ding et al. (2021), intelligent learning-based routing algorithms have been found more effective than conventional heuristic-based algorithms in conserving energy and adaptation.

Sohail et al. (2019) used the game theory in the context of power management in IoT-based WSNs, whereas Surenther et al. (2023) formulated the deep learning-based grouping process in order to ensure stable communication and reduce the energy consumption. According to Adu-Manu et al. (2025), the framework of Green WSNs using ML techniques is very beneficial.

2.3 Deep Reinforcement Learning in Wireless Sensor Networks

Deep Reinforcement Learning is regarded as one of the successful approaches in optimizing dynamic communication systems. According to Mnih et al. (2015), Deep Q-Network-based reinforcement learning is adopted, while Van Hasselt et al. (2016) suggested Double Deep Q-Learning (DDQN).

Yang et al. (2018) revealed that hierarchical DRL can effectively optimize dynamic communication environments by adjusting the policies of learning. On the other hand, Schulman et al. (2017) presented Proximal Policy Optimization (PPO) to enhance reinforcement learning convergent efficiency.

DRL was employed by Meng et al. (2019) in solving topology optimization problems in WSNs, whereas Hamdi et al. (2021) used DRL in formulating a resource management system in the hybrid energy LoRa network. Khairy et al. (2020) showed that the constraint-based DRL approach enhances energy sustainability and intelligence in resource allocation in IoT communication environments.

2.4 Reinforcement Learning-Based Routing and QoS Enhancement

Emerging studies have been centered around reinforcement learning approaches to support intelligent routing and improve QoS performance in WSNs. Younus et al. (2021) came up with reinforcement learning routing optimization in software-defined WSNs.

On the other hand, Godfrey et al. (2023) presented energy-aware reinforcement learning routing, while Alsalmi et al. (2024) came up with a DRL framework for mobile WSNs. Furthermore, Dutta et al. (2024) suggested context-based DRL approach for flow and energy management. On the other hand, Yuan et al. (2024) showed that DRL-based optimization approach reduces energy consumption and optimizes routing in WSNs.

Finally, Singh et al. (2024) came up with a multi-objective QoS enhancement with reinforcement learning techniques, while Ghamry and Shukry (2024) proposed DRL-based clustering and routing approach to improve communication efficiency and cluster-head selection.

2.5 Emerging Intelligent and Federated Learning Approaches

Combining federated learning with mobile edge computing and multi-agent learning systems has resulted in even greater adaptability of WSNs. The impact of mobile edge computing on decreasing communication delay and enhancing the performance of distributed IoT is elaborated by Mao et al. (2017).

A multi-agent DRL framework for effective management of resources was proposed by Li et al. (2023), while a DRL-based resource allocation framework for EH WSNs was suggested by Zhao and Zhao (2021). Hu et al. (2024) underlined the necessity to combine security improvement with intelligent communication optimization.

Khatami et al. (2025) created a QoS-aware fuzzy DRL framework for secure and energy-efficient WSNs, while Sattibabu et al. (2025) proposed a federated reinforcement learning based optimization framework.

2.6 Research Gap and Proposed Research Direction

Based on the review of existing literature, despite the advances made in Green IoT and WSN optimization using DRL techniques, a number of challenges and limitations can be seen. Most of the research papers tend to emphasize on individual optimization goals like energy efficiency and throughput improvements, whereas relatively less attention has been devoted towards optimizing the objectives such as latency, packet delivery rate, congestion, and network life-time.

Apart from that, most of the DRL-based routing algorithms face certain drawbacks such as scalability issues, unstable performance results, inability to perform satisfactorily in heterogeneous environment, and ineffective management of residual energy balance among nodes.

Considering the limitations associated with DRL based solutions, this paper attempts to provide a solution through the implementation of DRL-based Green IoT framework which uses deep Q-network (DQN), double deep Q-learning (DDQN), adaptive clustering, and multi-objective routing approach in WSNs.

3. PROPOSED METHODOLOGY

The section below introduces the designed DRL-based Green IoT framework for WSNs. This approach utilizes intelligent routing, clustering, and optimization by taking advantage of the concepts of DQN and DDQN algorithms within an ever-changing IoT environment.

3.1 Proposed System Architecture

In the suggested architectural design, there are sensors, cluster heads, sink nodes, and an agent of DRL optimization that coordinates the entire process. Sensors collect the information about the environment and forward them using multi-hop intelligent communication to the sink node. The DRL algorithm optimizes the path and selects the best cluster heads considering the following factors: residual energy, communication distance, congestion, traffic load, and delay. The overall design has four levels, which include sensing, clustering, DRL optimization, and sink node communication.

3.2 Network Model

The WSN system comprises Nsensor sensors that are deployed randomly within a two-dimensional sensing region. All nodes have the capability to sense, process, and communicate wirelessly, whereas the sink node lies beyond the sensing region.

The network is represented as:

$$\text{WSN=N,E} \tag{1}$$

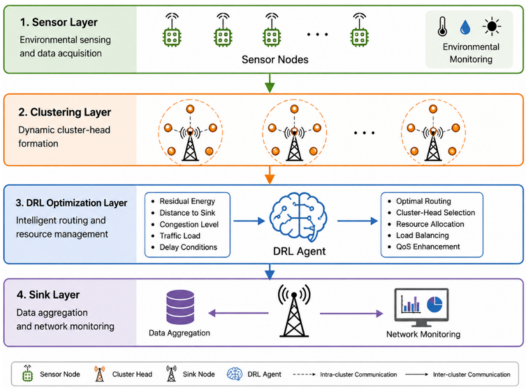

Figure 1. Proposed DRL-Based Green IoT Architecture

Where:

$$\text{N=n1,n2,n3,\ldots,nk denotes sensor nodes.} \tag{2}$$

E represents communication links .

The Euclidean distance between two sensor nodes is calculated as:

$$\text{di,j=xi-xj2+yi-yj2} \tag{3}$$

Where d (i, j) denotes the communication distance between nodes i and j.

The following assumptions have been made:

The sensor nodes do not move once deployed.

All nodes start with the same amount of energy.

Communication channels are symmetric.

Multi-hop routing is used.

Sink node has infinite sources of energy.

3.3 Energy Consumption Model

The proposed framework uses a first-order radio energy model for analyzing the energy consumed during communication.

Transmission energy is calculated as:

$$\text{Etxk,d=Eelec}\times\text{k+}\varepsilon\text{amp}\times\text{k}\times\text{dn (3)} \tag{4}$$

Receiving energy is expressed as:

$$\text{Erx(k)=Eelec}\times\text{k} \tag{5}$$

The residual energy after communication is:

$$\text{Eresidual=Einitial-(Etx+Erx)} \tag{6}$$

Where:

$$\text{E\_tx= Transmission energy} \tag{7}$$

$$\text{E\_rx= Receiving energy} \tag{8}$$

$$\text{E\_elec= Electronic circuit energy} \tag{9}$$

$$\text{k= Packet size} \tag{10}$$

$$\text{d= Communication distance} \tag{11}$$

$$\varepsilon\text{\_amp= Amplifier energy} \tag{12}$$

$$\text{n= Path loss exponent} \tag{13}$$

This model facilitates equitable energy usage and increases the life span of the network.

3.4 Deep Reinforcement Learning Framework

The proposed routing framework models the routing process as an MDP which consists of state space, action space, reward function, and policy learning.

3.4.1 State Space Representation

The routing agent takes into account residual energy, node density, network congestion, delay, queuing length, and link quality before taking action.

$$St=Er,Ds,Cl,Nd,Ql,Lq \tag{14}$$

Where:

$$E\_r= \text{Residual energy} \tag{15}$$

$$D\_s= \text{Distance to sink} \tag{16}$$

$$C\_l= \text{Congestion level} \tag{17}$$

$$N\_d= \text{Node density} \tag{18}$$

$$Q\_l= \text{Queue length} \tag{19}$$

$$L\_q= \text{Link quality} \tag{20}$$

3.4.2 Action Space

The action space represents next-hop routing decisions:

$$At=a1,a2,a3,\ldots,an \tag{21}$$

Where a_n denotes a routing action within the network environment.

3.4.3 Reward Function Design

The reward function jointly optimizes energy efficiency and QoS performance:

$$R=\alpha PDR+\beta TH-\gamma Delay-\delta Energy \tag{22}$$

Where:

$$PDR= \text{Packet Delivery Ratio} \tag{23}$$

$$TH= \text{Throughput} \tag{24}$$

$$Delay= \text{End-to-End Delay} \tag{25}$$

$$Energy= \text{Energy Consumption} \tag{26}$$

$$\alpha, \beta, \gamma, \delta= \text{Weight coefficients} \tag{27}$$

3.5 Deep Q-Network Optimization

DQN algorithm is employed by the model for estimation of the optimal routing process in dynamically changing communication conditions. The update formula for Q-values is presented below:

$$Q(s,a)=Q(s,a)+\eta[r+\lambda \max Q(s',a')-Q(s,a)] \tag{28}$$

Where:

$$Qs,a= \text{Q-value of state-action pair} \tag{29}$$

$$\eta= \text{Learning rate} \tag{30}$$

$$r= \text{Immediate reward} \tag{31}$$

$$\lambda= \text{Discount factor} \tag{32}$$

$$s'= \text{Next state} \tag{33}$$

DDQN is applied for improving the convergence and solving the problem of overestimations (Van Hasselt et al., 2016).

3.6 Adaptive Clustering Mechanism

Adaptive clustering technique is applied for optimizing energy consumption and communications process. Cluster-head selection depends on the following parameters: energy level, quality of links, degree of congestion, and proximity to the sink.

The fitness function of a cluster-head is:

$$FCH=w1Er+w2Lq-w3Ds-w4Cl \tag{34}$$

Where:

$$F\_CH= \text{Cluster-head fitness value} \tag{35}$$

$$E\_r= \text{Residual energy} \tag{36}$$

$$L\_q= \text{Link quality} \tag{37}$$

$$D\_s= \text{Distance to sink} \tag{38}$$

$$C\_l= \text{Congestion level} \tag{39}$$

$$w\_1,w\_2,w\_3,w\_4= \text{Weight coefficients} \tag{40}$$

3.7 Proposed DRL-Based Routing Algorithm

The proposed algorithm for DRL based routing involves monitoring network environment, making optimal forwarding decisions, determining reward values, and updating routing policies through optimization of DQN/DDQN learning processes. This algorithm facilitates adaptive and energy-aware communication with quality-of-service support.

Table 1. DRL-Based Energy-Efficient Routing Algorithm

Algorithm 1: DRL-Based Energy-Efficient Routing Algorithm

Input: Sensor Nodes N; Initial Energy E; Network Topology T; Learning Rate η; Discount Factor λ.
Output: Optimal Energy-Efficient Routing Paths.

Begin

1. Initialize wireless sensor network $WSN(N,E,T)$.
2. Deploy sensor nodes randomly within sensing area.
3. Initialize residual energy and network parameters.
4. Form clusters dynamically using adaptive clustering.
5. Select cluster heads based on residual energy, distance to sink, link quality, and congestion level.
6. Initialize DRL agent with DQN/DDQN model.
7. Repeat until convergence condition is satisfied:
   (a) Observe current network state S_t.
   (b) Select routing action A_t using DRL policy.
   (c) Forward packets through selected next-hop node.
   (d) Measure energy consumption, throughput, packet delivery ratio, communication delay, and congestion level.
   (e) Compute reward R_t using the reward function.
   (f) Update Q-values: $Q(s,a) \leftarrow Q(s,a) + \eta[r + \lambda \max Q(s',a') - Q(s,a)]$.
   (g) Update routing policy.
   (h) Update residual energy of sensor nodes.
8. End repeat.
9. Select optimal routing path.
10. Transmit aggregated data to sink node.

End

3.8 Simulation Environment and Parameters

The framework is realized using Python and NS-3 simulation tools. The DRL and network optimization in the proposed model utilize TensorFlow and PyTorch library, respectively.

Table 2. Simulation Parameters

Parameter	Value
Simulation Area	1000 m × 1000 m
Number of Sensor Nodes	100–500
Initial Node Energy	2 Joules
Packet Size	512 Bytes
Transmission Range	100 m
Simulation Time	1000 s
Learning Rate	0.001
Discount Factor	0.95
Replay Memory Size	10,000
Compared Protocols	LEACH, PEGASIS, HEED, DRL

3.9 Performance Evaluation Metrics

The proposed framework is analyzed based on various QoS and energy-based evaluation metrics.

Packet Delivery Ratio (PDR):

$$\text{PDR=Packets ReceivedPackets Sent} \times 100(11)\ \text{Throughput:} \tag{41}$$

$$\text{Throughput=Total Data ReceivedSimulation Time}(12)\ \text{End-to-End Delay:} \tag{42}$$

$$\text{Delay=Receive Time-Send Time}(13)\ \text{Additional metrics include:} \tag{43}$$

- Network Lifetime
- Energy Efficiency

Overall, these metrics analyze the performance related to routing efficiency, improvement of QoS, reliability of communication, scalability, and sustainability of the WSN networks in the presence of the Green IoT framework.

4. RESULTS AND PERFORMANCE ANALYSIS

In this section, we provide simulation results and comparative study among the proposed DRL-based Green IoT framework, LEACH, PEGASIS, and HEED under different scenarios. The analysis involved energy efficiency, QoS, throughput, delay, congestion, scalability, and lifetime of the network via Python and NS-3 simulations. It is found that the proposed DRL-based Green IoT framework performs much better than existing routing protocols.

4.1 Residual Energy Analysis

Residual energy is an indicator of the sustainability and stability of the network. Table 2 below shows the residual energy performance of both methods at various rounds of simulations.

Table 3. Comparative Residual Energy Analysis

Simulation Rounds	LEACH (J)	PEGASIS (J)	HEED (J)	Proposed DRL Model (J)
200	1.62	1.71	1.76	1.89
400	1.31	1.45	1.53	1.72
600	0.98	1.14	1.28	1.56
800	0.67	0.89	1.02	1.37
1000	0.42	0.65	0.81	1.18

The proposed DRL method had better performance with respect to residual energy than the traditional models. The proposed technique was able to maintain 1.18 J as residual energy when there were 1000 rounds compared to 0.42 J maintained by LEACH.

The performance of residual energy in different rounds of simulations can be seen from Figure 2 below.

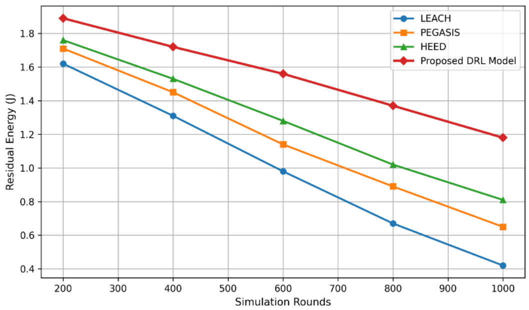

Figure 2. Residual Energy Comparison Under Different Simulation Rounds

Graphical analysis verifies slow energy consumption rate in the model; this proves its appropriateness for sustainable Green IoT communication systems.

4.2 Packet Delivery Ratio Analysis

Packet Delivery Ratio (PDR) measures routing stability and reliable communication. Table 3 shows comparative PDR results with an increase in nodes density.

Table 4. Packet Delivery Ratio Comparison

Number of Nodes	LEACH (%)	PEGASIS (%)	HEED (%)	Proposed DRL Model (%)
100	89.4	91.8	93.1	97.2
200	87.1	89.9	91.5	96.3
300	84.7	87.5	89.2	95.1
400	81.5	84.6	87.4	93.7
500	78.9	82.1	85.6	92.4

The proposed DRL model provided the highest PDR among all node densities, staying stable at 92.4%, even at 500 nodes. It is evident that better congestion-aware routing and communication are now possible.

Figure 3 shows comparative PDR performances under increasing node density.

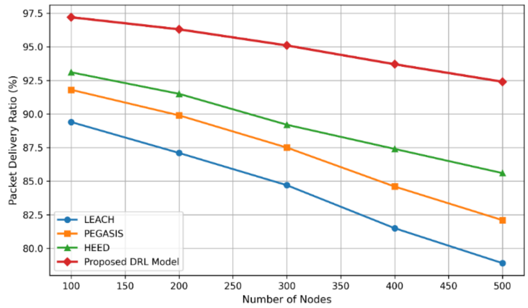

Figure 3. Packet Delivery Ratio Performance Under Increasing Node Density

The graphical representation indicates that the PDR of standard procedures drops considerably with respect to an increase in node density, but the PDR of the new approach remains almost constant in terms of communication efficiency.

4.3 Throughput Performance Analysis

Throughput refers to the total data transmission rate achieved in the network. Comparison of throughput is demonstrated in Table 4.

Table 5. Throughput Performance Comparison

Simulation Time (s)	LEACH (kbps)	PEGASIS (kbps)	HEED (kbps)	Proposed DRL Model (kbps)
200	214	238	251	298
400	228	249	267	324
600	243	261	281	347
800	251	274	296	368
1000	267	289	311	392

The proposed framework maintained higher throughput for all simulated periods of time. Specifically, at 1000s the throughput was 392 kbps against 267 kbps for LEACH. This improvement is due to adaptive routing and congestion management in the proposed system.

Figure 4 illustrates the throughput for various routing protocols.

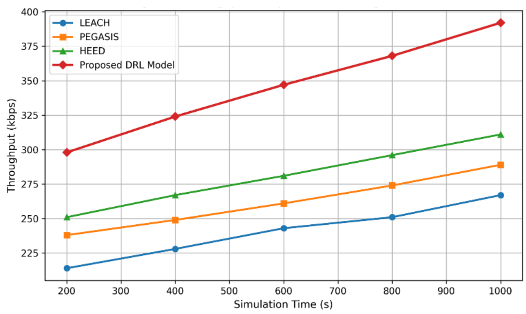

Figure 4. Throughput Comparison of Routing Protocols

Figure 4 proves that the presented framework for DRL is able to deliver stable throughput in dynamically changing communication scenarios.

4.4 End-to-End Delay Analysis

Delay of communication is a crucial QoS parameter for an IoT network. Analysis of end-to-end delay is provided in Table 5.

Table 6. End-to-End Delay Comparison

Number of Nodes	LEACH (ms)	PEGASIS (ms)	HEED (ms)	Proposed DRL Model (ms)
100	94	82	76	48
200	112	96	88	57
300	129	107	96	64
400	146	118	104	72
500	163	132	117	81

The delay attained by the model remained the lowest irrespective of the number of nodes involved. For instance, at 500 nodes, the DRL model exhibited 81 ms delay while LEACH exhibited 163 ms delay.The graphical depiction of delay performance is shown in figure 5.

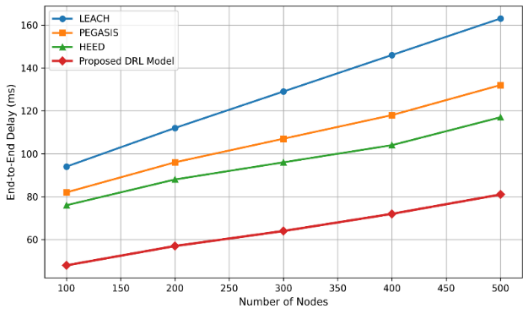

Figure 5. End-to-End Delay Under Different Node Densities

These results have shown that adaptive congestion-aware routing helps increase communication response time.

4.5 Network Lifetime Evaluation

Lifetime of the network is measured in terms of energy efficiency. The table below shows the comparative analysis of network lifetime.

Table 7. Comparative Network Lifetime Analysis

Routing Protocol	First Node Death	Half Node Death	Last Node Death
LEACH	512	781	1024
PEGASIS	648	923	1288
HEED	731	1054	1412
Proposed DRL Model	1026	1463	1895

The above-proposed DRL-based framework led to an extended network lifetime of 1895 rounds before the last node dies. This is because of efficient utilization of energy and optimized routing path selection.

Graphical comparison of network lifetime is presented in Figure 6.

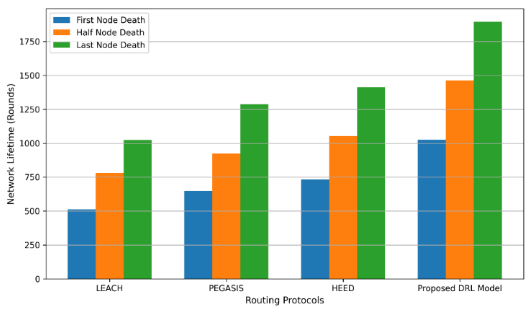

Figure 6. Comparative Network Lifetime Analysis

This is confirmed by Figure 6 below where the suggested framework proves more effective in delaying node exhaustion compared to traditional routing techniques.

4.6 Congestion Analysis

Congestion is a critical factor in causing losses and poor stability in communication. Congestion ratios are presented in table 7.

The congestion ratio for the proposed DRL network is constantly lowest as the communication complexity increases.

Figure 7 presents the congestion ratio performance under different node densities.

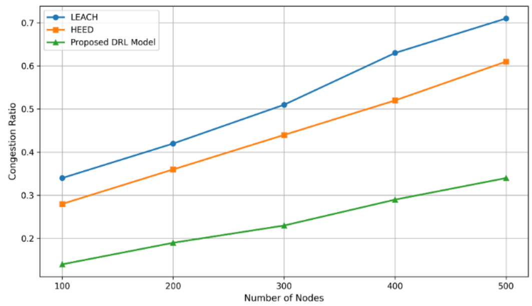

Figure 7. Congestion Ratio Under Increasing Node Density

The above graphical representation shows that the DRL algorithm successfully strikes a balance between communication and reduces routing congestion.

4.7 Energy Consumption Analysis

Energy consumption analysis measures the efficiency of using communication resources. Table 8 shows energy consumption results.

Table 8. Average Energy Consumption Analysis

Number of Nodes	LEACH (J)	PEGASIS (J)	HEED (J)	Proposed DRL Model (J)
100	0.82	0.74	0.69	0.51
200	1.14	1.03	0.96	0.73
300	1.48	1.29	1.16	0.88
400	1.86	1.61	1.42	1.03
500	2.17	1.92	1.74	1.24

Energy consumption by the proposed framework was considerably less compared to conventional systems. The energy utilized by the proposed scheme at 500 nodes was 1.24 J, whereas it was 2.17 J in case of LEACH.

Energy utilization graphically shown in figure 8.

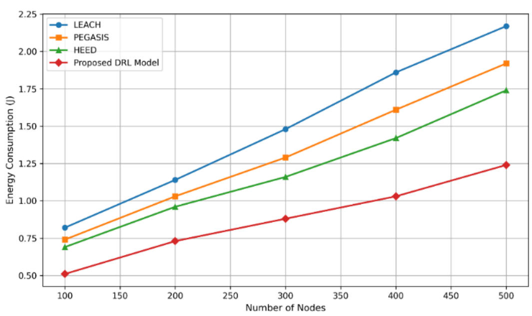

Figure 8. Average Energy Consumption Comparison

Results confirm the efficacy of Adaptive Clustering and Intelligent Routing Optimization for sustainable communication in Green IoT.

4.8 Scalability Analysis

Scalability Analysis examines adaptability to growing numbers of nodes. Table 9 below illustrates the results of scalability analysis.

Table 9. Scalability Performance Analysis

Number of Nodes	Routing Success Rate (%)	Average Link Stability (%)	Proposed DRL Scalability Index
100	96.8	94.2	0.92
200	95.6	92.5	0.89
300	94.1	90.7	0.86
400	92.7	88.6	0.83
500	91.3	86.4	0.79

The framework performed well in achieving consistent routing success and communication performance even when applied in dense IoT networks.

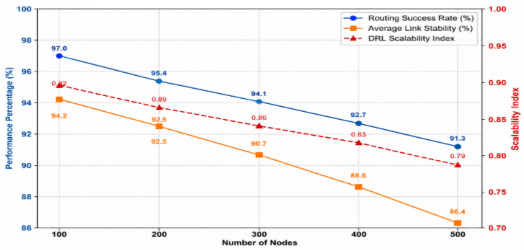

Figure 9. Scalability Performance Under Increasing Node Density

Graphical representation of scalability analysis is shown in Figure 9.

It can be seen that there is high scalability and adaptability of the framework in large-scale Green IoT deployment cases.

4.9 QoS Improvement Analysis

For QoS analysis, parameters such as throughput, packet delivery ratio, delay, congestion, and network lifetime are considered. The results are compared in Table 10.

However, the DRL QoS framework suggested in this research proved to be remarkably effective in enhancing QoS measures without compromising energy sustainability.

The normalized comparison of QoS improvements is shown in Figure 10.

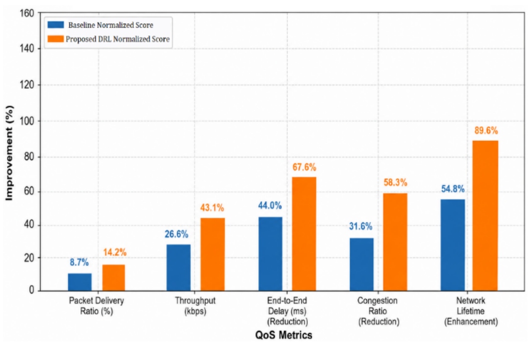

Figure 10. Overall QoS Performance Enhancement

(Normalized Improvement)

Normalized performance results show that the proposed protocol consistently performs better than conventional routing protocols in terms of throughput, delay reduction, congestion avoidance, packet reliability, and extended network lifetime.

4.10 Summary of Experimental Findings

The experimental simulation findings prove that the suggested DRL-enabled Green IoT framework performs much better than the LEACH, PEGASIS, and HEED frameworks when considering residual energy conservation, packet delivery rate, throughput, delay reduction, congestion management, energy efficiency, scalability, and network longevity. All of this is made possible by the incorporation of clustering techniques, congestion-aware routing, dynamic residual energy balancing, and DQN/DDQN based multiple objective optimization techniques.

In summary, the suggested approach can effectively support reliable and energy efficient QoS-aware communication in next-generation Green IoT systems, which include smart cities, healthcare, industrial automation, environment monitoring, and intelligent transport systems.

5. DISCUSSION

It can be seen from the study that the suggested Deep Reinforcement Learning (DRL) based Green IoT framework offers an intelligent and sustainable approach for communicating in the Wireless Sensor Network (WSN) within heterogeneous IoT networks. Application of Deep Q-Network (DQN), Double Deep Q-Learning (DDQN), adaptive clustering and reward-based learning contributed in improving the Quality of Service (QoS), energy efficiency and increased network sustainability.

The suggested approach contrasts the typical routing methods where routing is based on fixed routing paths, as here, dynamic changes in communication policies based on the current situation of congestion, traffic intensity, available energy and communication efficiency are adopted. The experiment findings reveal that the reinforcement learning based approach outperforms the traditional heuristic approaches for routing.

5.1 Interpretation of Energy Optimization Behavior

The suggested methodology greatly enhanced residual energy saving as well as balancing energy consumption between sensor nodes. Lower rate of energy depletion was possible due to:

- Adaptive cluster-head rotation
- Residual energy-aware routing
- Traffic-sensitive communication management
- Intelligent multi-hop path selection

The dynamic resource allocation of DRL minimized excessive data forwarding and communication overhead. This is similar to the findings from López-Ardao et al. (2021) and Godfrey et al. (2023). The significance of smart routing towards building green IoT systems was emphasized in both studies. What sets our framework apart from previous ones is the concurrent optimization of all four parameters mentioned in a single learning process.

5.2 QoS Enhancement and Communication Reliability

The proposed framework using DRL successfully achieved high communication reliability despite an increase in the number of nodes due to its ability to detect the levels of congestion, link quality, remaining energy, and communication delays. This was achieved through the ability of the DRL algorithm to adapt the routing process based on the prevailing network conditions.

The results agree with Singh et al. (2024) and Younus et al. (2021), which indicate that reinforcement learning leads to improved QoS and adaptability of the routing process. The advantage of the proposed framework compared to other QoS schemes is that it did not use up more energy.

5.3 Throughput Stability and Communication Continuity

The proposed model retained consistent throughput, since routing was optimized on-the-go based on network characteristics rather than set routing paths. The DRL model minimized routing instability and retransmission, thus resulting in continuous communication during highly congested networks.

This corroborates the findings by Alsalmi et al. (2024) and Dutta et al. (2024), who found that through DRL-based communication management, both throughput and routing flexibility in IoT-based WSNs are improved. The proposed framework was able to retain throughput, energy efficiency, congestion control, and QoS stability.

5.4 Delay Reduction and Congestion-Aware Communication

This approach resulted in reduced communication delay and congestion because of traffic management. The DRL agent kept redistributing the communication traffic without having too much of it accumulate at some particular forwarding nodes.

The better congestion management could be attributed to:

- Environment-aware communication learning
- Congestion-sensitive reward optimization
- Adaptive next-hop routing
- Dynamic traffic redistribution

These results are in agreement with those reported by Hamdi et al. (2021) and Hu et al. (2024), who stressed that intelligent communication optimization enhances routing efficiency and reliability in WSN environments.

5.5 Network Lifetime and Sustainable Operation

The presented framework significantly increased the network lifetime by ensuring load balance while limiting imbalance in energy consumption. The significant improvement is largely attributed to:

- Balanced residual energy utilization
- Intelligent cluster-head rotation
- Reduced communication overhead
- Adaptive multi-hop forwarding
- Congestion-aware routing

The results confirm those of Surenther et al. (2023) and Ghamry and Shukry (2024). Intelligent clustering and routing facilitate sustainable communication in wireless sensor networks. The proposed framework additionally incorporates the benefits of scalability, QoS improvement, congestion control, and energy balancing into Green IoT technology.

5.6 Comparative Analysis with Existing Research

The comparative analysis reveals that most of the current researches related to DRL for WSN consider separate aspects like throughput maximization, clustering, and power saving. However, the framework proposed here achieves all these goals at once, along with addressing QoS, scalability, traffic management, routing, and network lifetime.

Table 10. Comparative Discussion with Existing Research

Study	Primary Contribution	Major Limitation	Advantage of Proposed Framework
Godfrey et al. (2023)	RL-based energy-efficient routing	Limited QoS integration	Simultaneous QoS and energy optimization
Alsalmi et al. (2024)	Throughput-oriented DRL routing	Limited congestion adaptability	Congestion-aware autonomous routing
Dutta et al. (2024)	Contextual flow management	Limited scalability analysis	Enhanced scalability evaluation
Ghamry and Shukry (2024)	DRL-based clustering optimization	Limited residual energy balancing	Improved energy preservation
Singh et al. (2024)	QoS-aware reinforcement learning	Limited network lifetime optimization	Integrated lifetime and QoS enhancement
Proposed Study	Multi-objective DRL-enabled Green IoT optimization	Increased computational complexity under ultra-dense deployment	Unified optimization of energy, QoS, congestion, scalability, and sustainability

5.7 Practical Implications of the Proposed Framework

This proposed framework exhibits high applicability in practical applications of IoT-based communication networks where autonomous, scalable, and energy-efficient network management is needed. The possible domains of application include:

- Smart cities
- Environmental monitoring
- Industrial IoT systems
- Intelligent transportation
- Healthcare monitoring
- Precision agriculture

The capability of simultaneously optimizing communication efficiency and energy consumption renders this framework particularly suitable for sustainability-oriented next-generation IoT environments.

5.8 Limitations and Future Research Scope

Despite the promising results, some limitations still exist in the current study. The process of DRL training might become more complex when applied to ultra-dense network settings, while the existing framework concentrates mostly on static deployment strategies. Additionally, the concepts of security-aware communication intelligence and collaborative learning have not been considered.

The recent research carried out by Khatami et al. (2025) and Hu et al. (2024) further stresses the significance of ensuring security and intelligence through robust communication protocols in Wireless Sensor Networks. Hence, potential enhancements may utilize security-aware and distributed reinforcement learning methods to support next-generation Green IoT systems.

In future studies, one can concentrate on:

- Multi-agent DRL-based communication optimization
- Federated reinforcement learning integration
- Mobility-aware adaptive routing
- Security-aware and privacy-preserving DRL architectures
- Edge-assisted intelligent communication management
- Lightweight and explainable DRL optimization models

6. CONCLUSION

This research work presented the Green IoT Framework through DRL in order to achieve energy efficient, reliable, and Quality of Service-oriented wireless sensor networks. This Green IoT Framework was based on DQN, DDQN, adaptive clustering, and multi-objective optimization techniques to perform intelligent communication management.

The experimental results revealed that the proposed system outperforms LEACH, PEGASIS, and HEED systems regarding residual energy efficiency, packet delivery ratio, throughput improvement, delay minimization, congestion control, scalability, and network lifetime. Due to adaptive clustering, congestion control, and energy balance management, the sustainability of communication has been improved significantly.

One of the significant contributions of this paper lies in the concurrent optimization of energy efficiency and Quality of Service using the DRL system approach. In comparison to conventional systems where researchers have considered individual optimization problems, the proposed system has achieved the optimization goals concurrently.

Hence, it can be concluded from this research work that the proposed system based on DRL is quite effective and sustainable for future green wireless sensor networks.

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