Research Paper
Impact Factor: 7.352
Peer Reviewed Monthly Journal
www.ijmdrr.com

IJMDRR
E- ISSN –2395-1885
ISSN -2395-1877

RL-CLEP: AN AI-ASSISTED CROSS-LAYER ENERGY PREDICTION FRAMEWORK USING REINFORCEMENT LEARNING FOR WIRELESS SENSOR NETWORKS

Janaranjani R*   Dr. A. Senthilkumar**

**Ph.D., Research Scholar, Department of Computer Science,Thiruvalluvar Government Arts College, Rasipuram, Namakkal, Affiliated to Periyar University, Salem.*

***Assistant Professor, Department of Computer Science,Thiruvalluvar Government Arts College, Rasipuram, Namakkal, Affiliated to Periyar University, Salem.*

Abstract

Wireless Sensor Networks (WSNs) have become an integral component of modern Internet of Things (IoT) applications, enabling real-time monitoring in domains such as environmental surveillance, healthcare, industrial automation, precision agriculture, and smart cities. Despite their widespread adoption, the limited battery capacity of sensor nodes remains a critical challenge that significantly affects network lifetime, communication reliability, and overall system performance. Conventional routing protocols and layered communication architectures often make routing decisions independently without considering the interdependency among protocol layers, resulting in excessive energy consumption, packet collisions, communication delays, and uneven energy utilization. To address these limitations, this paper proposes ***RL-CLEP (Reinforcement Learning-based Cross-Layer Energy Prediction)****, an AI-assisted framework that integrates Reinforcement Learning with cross-layer optimization for intelligent and energy-aware routing in Wireless Sensor Networks. The proposed framework enables the Physical Layer, Medium Access Control (MAC) Layer, and Network Layer to share communication information, allowing routing decisions to be based on multiple network parameters, including residual energy, link quality, traffic load, queue status, and communication reliability. A Reinforcement Learning agent continuously observes the network environment, predicts suitable routing actions, and updates its decision policy through reward-based learning. This adaptive approach is expected to reduce unnecessary packet retransmissions, improve route stability, balance energy consumption among sensor nodes, and extend network lifetime while maintaining low computational complexity. The proposed methodology provides a scalable and lightweight communication framework suitable for resource-constrained WSNs. Future work will focus on implementing the RL-CLEP framework using the NS-3 simulator and evaluating its performance against existing energy-aware routing protocols under various network conditions.*

Keywords: Wireless Sensor Networks, Reinforcement Learning, Cross-Layer Optimization, Energy Prediction, Artificial Intelligence, Energy-Efficient Routing, Internet of Things (IoT).

Introduction

Wireless Sensor Networks (WSNs) have emerged as an essential communication technology for monitoring and collecting information from physical environments. A typical WSN consists of numerous sensor nodes equipped with sensing, processing, and wireless communication capabilities. These networks are widely deployed in applications such as environmental monitoring, healthcare, industrial automation, smart agriculture, military surveillance, disaster management, and smart cities. The rapid growth of the Internet of Things (IoT) has further increased the importance of WSNs by enabling continuous data exchange among interconnected devices for intelligent decision-making.

IJMDRR
E- ISSN –2395-1885
ISSN -2395-1877

Despite their widespread adoption, the limited battery capacity of sensor nodes remains a major challenge in WSNs. Since sensor nodes are often deployed in remote or inaccessible locations, replacing or recharging batteries is difficult and expensive. Every sensing, computation, transmission, and reception operation consumes energy, and the exhaustion of battery power in critical nodes results in reduced network coverage, communication failures, and a shorter network lifetime. Consequently, energy-efficient communication has become one of the primary research objectives in WSN design.

Wireless communication accounts for the largest portion of energy consumption in sensor networks. Frequent packet transmissions, retransmissions, idle listening, and channel contention accelerate battery depletion. Traditional routing protocols generally select forwarding paths based on the shortest distance or minimum hop count without considering future energy availability or changing network conditions. As a result, certain sensor nodes are repeatedly selected for packet forwarding, leading to uneven energy consumption, the formation of energy holes, and reduced communication reliability.

Conventional WSNs also follow a layered communication architecture in which the Physical, Medium Access Control (MAC), and Network layers operate independently. Although this layered design simplifies protocol implementation, it restricts information sharing among layers. Routing decisions made without considering link quality, channel congestion, or residual energy often result in packet collisions, retransmissions, increased communication delay, and unnecessary energy consumption.

To overcome these limitations, cross-layer optimization has been introduced to enable cooperation among different protocol layers. By sharing information such as residual energy, link quality, traffic load, queue status, and channel conditions, cross-layer communication supports more efficient routing decisions and improves network performance. However, many existing cross-layer approaches rely on predefined rules and static optimization techniques, making them less effective in highly dynamic IoT environments.

Artificial Intelligence (AI), particularly Reinforcement Learning (RL), has recently attracted significant attention for intelligent network optimization. Unlike traditional rule-based methods, RL enables an agent to learn optimal communication strategies through continuous interaction with the network environment. By observing network conditions, selecting actions, and receiving reward feedback, the RL agent gradually improves routing decisions without requiring predefined routing rules. This adaptive learning capability makes Reinforcement Learning highly suitable for dynamic Wireless Sensor Networks.

Several studies have applied Reinforcement Learning to routing optimization, congestion control, transmission power management, and sleep scheduling. Although these approaches have demonstrated improved adaptability, most focus on optimizing only a single communication layer or rely mainly on current residual energy while ignoring future energy conditions and cross-layer interactions. Such limitations often result in inefficient routing decisions and uneven battery utilization.

To address these challenges, this paper proposes **RL-CLEP (Reinforcement Learning-based Cross-Layer Energy Prediction)**, an AI-assisted framework for Wireless Sensor Networks. The proposed framework integrates information from the Physical Layer, MAC Layer, and Network Layer to support intelligent routing decisions based on multiple network parameters, including residual energy, link quality, traffic load, queue status, and communication reliability. A Reinforcement Learning agent

IJMDRR
E- ISSN –2395-1885
ISSN -2395-1877

analyses these parameters to predict energy-efficient routes, balance energy consumption among sensor nodes, and adapt to changing network conditions.

The proposed RL-CLEP framework aims to reduce communication overhead, minimize packet retransmissions, improve routing stability, and extend network lifetime while maintaining low computational complexity. By combining cross-layer optimization with Reinforcement Learning, the framework provides an adaptive and lightweight communication strategy suitable for next-generation IoT-enabled Wireless Sensor Networks.

The remainder of this paper is organized as follows. Section 2 reviews recent studies on energy-efficient routing, cross-layer optimization, and Reinforcement Learning in WSNs. Section 3 presents the proposed RL-CLEP methodology, Section 4 discusses the expected performance analysis, and Section 5 concludes the paper with future research directions.

Literature Review

Wireless Sensor Networks (WSNs) have been extensively studied due to their significant role in Internet of Things (IoT) applications, environmental monitoring, healthcare, industrial automation, and smart city infrastructures. Since sensor nodes operate with limited battery resources, improving energy efficiency and extending network lifetime have become major research objectives. Consequently, researchers have proposed various energy-aware routing protocols, cross-layer optimization techniques, and Artificial Intelligence (AI)-based communication strategies to enhance network performance.

Traditional routing protocols generally select communication paths using metrics such as shortest distance or minimum hop count. Although these approaches simplify routing decisions, they often result in uneven energy consumption and repeated utilization of the same forwarding nodes, leading to premature battery depletion and reduced network lifetime. Energy-aware routing protocols have attempted to overcome these issues by incorporating residual energy into routing decisions. However, most existing approaches still rely on predefined rules and lack adaptability to dynamic network conditions.

Kim et al. (2020) reviewed machine learning applications in Wireless Sensor Networks and reported that intelligent learning techniques improve routing efficiency, congestion control, and resource utilization. Their study highlighted the advantages of adaptive decision-making but also emphasized the challenges associated with computational complexity and limited hardware resources in sensor nodes. Similarly, Chen et al. (2021) investigated Deep Reinforcement Learning (DRL) for IoT communication and demonstrated improved routing adaptability using learning-based models. However, their work primarily focused on Network Layer optimization with limited interaction among communication layers.

Recent research has increasingly explored Reinforcement Learning (RL) for energy-efficient routing. Sharma et al. (2026) surveyed Deep Reinforcement Learning techniques for WSNs and concluded that RL-based routing significantly improves adaptability under dynamic traffic conditions. Nevertheless, they identified challenges related to scalability, convergence time, computational overhead, and insufficient cross-layer coordination. Likewise, Lata and Kang (2026) proposed an RL-based opportunistic routing protocol that selects forwarding nodes using residual energy and link quality. Although the approach improved forwarding efficiency, it mainly concentrated on node selection without integrating comprehensive cross-layer information.

Recent AI-driven routing studies further indicate that integrating Artificial Intelligence with routing protocols enhances communication reliability, load balancing, and energy efficiency. Despite these improvements, most existing methods evaluate only a limited number of network parameters and rarely combine predictive energy estimation with cross-layer optimization in a single lightweight framework. Consequently, routing decisions remain reactive rather than predictive, resulting in inefficient energy utilization under dynamic network environments.

Based on the reviewed literature, three major research gaps remain evident. First, most existing studies optimize the Physical Layer, MAC Layer, and Network Layer independently instead of enabling integrated cross-layer communication. Second, routing decisions generally depend on current network conditions without predicting future energy availability. Third, several AI-based approaches require high computational resources, limiting their applicability in resource-constrained Wireless Sensor Networks.

To address these limitations, the proposed **RL-CLEP (Reinforcement Learning-based Cross-Layer Energy Prediction)** framework integrates information from the Physical Layer, MAC Layer, and Network Layer to support intelligent and adaptive routing decisions. By combining Reinforcement Learning with predictive energy estimation and cross-layer optimization, the framework aims to improve energy efficiency, communication reliability, balanced load distribution, and overall network lifetime while maintaining low computational complexity.

Table 1. Research Gap Analysis

Author / Year	Contribution	Limitation
Kim et al. (2020)	Machine learning for WSN routing	Limited cross-layer integration
Chen et al. (2021)	Deep RL for IoT communication	Network-layer focus only
Sharma et al. (2026)	Survey of DRL-based routing	Scalability and computational overhead
Lata & Kang (2026)	RL-based opportunistic routing	Limited cross-layer coordination
Recent AI-based studies (2025–2026)	Improved adaptive routing	Lack of predictive energy management

Proposed Methodology

Overview of the Proposed Framework

This study proposes **RL-CLEP (Reinforcement Learning-based Cross-Layer Energy Prediction)**, an intelligent routing framework that integrates **cross-layer optimization** with **Reinforcement Learning (RL)** to improve energy efficiency in Wireless Sensor Networks (WSNs). Unlike conventional routing protocols that rely on shortest-path selection or residual energy alone, RL-CLEP continuously observes network conditions and dynamically selects the most suitable communication path.

The framework enables information sharing among the **Physical Layer**, **MAC Layer**, and **Network Layer**, allowing routing decisions to consider multiple communication parameters simultaneously. A Reinforcement Learning agent analyses these parameters, predicts network conditions, and selects forwarding nodes that maximize communication efficiency while minimizing energy consumption. This adaptive approach balances battery utilization, reduces retransmissions, and extends network lifetime.

IJMDRR
E- ISSN –2395-1885
ISSN -2395-1877

RL-CLEP Framework Architecture

The proposed framework consists of six major components:

Application / Sink Node

↓

Reinforcement Learning Agent

↓

Physical Layer Parameters	MAC Layer Parameters	Network Layer Parameters

↓

Cross-Layer Information Pool

↓

Adaptive Route Selection

↓

Wireless Sensor Nodes

Sensor nodes continuously collect communication information from different protocol layers. The collected data are integrated into a **Cross-Layer Information Pool**, where the RL agent evaluates the network status and selects the optimal forwarding node.

Cross-Layer Information Collection

The proposed framework monitors important parameters from three communication layers.

Physical Layer

- Received Signal Strength Indicator (RSSI).
- Link Quality Indicator (LQI).
- Signal-to-Noise Ratio (SNR).
- Transmission Power.

These parameters identify stable wireless links and reduce transmission failures.

MAC Layer

- Channel Utilization.
- Packet Collision Rate.
- Queue Occupancy.
- Channel Access Delay.

These metrics help the RL agent avoid congested communication paths.

Network Layer

- Residual Energy.
- Hop Count.
- Traffic Load.
- Node Degree.
- Packet Forwarding History.

IJMDRR
E- ISSN –2395-1885
ISSN -2395-1877

Instead of relying only on hop count, the framework evaluates multiple parameters to improve routing efficiency.

Reinforcement Learning Model

The Reinforcement Learning agent serves as the decision-making component of RL-CLEP. It continuously observes the network environment, selects routing actions, receives reward feedback, and updates its routing policy based on previous experiences. Unlike static routing algorithms, the RL agent gradually learns the most energy-efficient communication strategy, enabling the framework to adapt automatically to changing network conditions.

The network state is represented as

$$S= \{RE,LQ,TL,QS,RSSI\}$$

Where **RE** denotes Residual Energy, **LQ** represents Link Quality, **TL** is Traffic Load, **QS** indicates Queue Size, and **RSSI** represents Received Signal Strength Indicator.

For every observed state, the RL agent selects one of the following actions:

$$A=\{\text{Select Route, Sleep, Wake, Power Adjust, Wait}\}$$

These actions allow efficient routing as well as intelligent energy management.

Reward Function and Learning Process

To encourage reliable and energy-efficient communication, the routing decision is evaluated using the following reward function:

$$R=\alpha(RE)+\beta(LQ)-\gamma(D)-\delta(C)$$

where **RE** is Residual Energy, **LQ** is Link Quality, **D** represents Communication Delay, **C** denotes Packet Collision, and **α, β, γ, δ** are weighting coefficients. Higher residual energy and better link quality increase the reward, whereas delay and packet collisions reduce it.

The RL agent updates its routing knowledge using the standard Q-learning equation:

$$Q(s,a)=Q(s,a)+\alpha\left[r+\gamma\max Q(s',a')-Q(s,a)\right]$$

where **Q(s,a)** is the quality value of action **a** in state **s**, **α** is the learning rate, **γ** is the discount factor, **r** is the immediate reward, and **s'** represents the next network state. This iterative learning process enables the framework to continuously improve routing performance.

Adaptive Routing Algorithm

The routing process begins with the deployment of sensor nodes and initialization of the Q-table. Sensor nodes periodically collect cross-layer information and transmit it to the RL agent. Based on the current network state, reward values are calculated and Q-values are updated. The forwarding node with the highest Q-value is selected for packet transmission. After each transmission, routing information and residual energy are updated, allowing the framework to adapt dynamically to changing network conditions.

Advantages of RL-CLEP

The proposed RL-CLEP framework provides several advantages over conventional routing protocols. It enables intelligent routing through Reinforcement Learning, supports cross-layer information sharing, improves energy utilization, reduces packet retransmissions and routing overhead, enhances communication reliability, and extends network lifetime. Owing to its lightweight architecture and adaptive learning capability, RL-CLEP is well suited for resource-constrained Wireless Sensor Networks and next-generation IoT applications.

Expected Performance Analysis

The proposed **RL-CLEP (Reinforcement Learning-based Cross-Layer Energy Prediction)** framework is designed to improve communication efficiency and energy utilization in Wireless Sensor Networks (WSNs). Since this study focuses on the conceptual design of the framework, the performance discussed in this section is based on the expected behavior of the proposed methodology. Future work may validate these outcomes through simulation using network simulators such as **NS-3** under different network sizes, traffic conditions, and deployment scenarios.

Energy Consumption

Energy consumption is one of the most critical performance metrics in WSNs because sensor nodes operate with limited battery resources. Conventional routing protocols often consume excessive energy due to repeated packet retransmissions, inefficient forwarding decisions, and uneven utilization of sensor nodes. The proposed RL-CLEP framework overcomes these limitations by selecting forwarding nodes based on multiple cross-layer parameters, including residual energy, link quality, traffic load, and queue status. Consequently, unnecessary transmissions are minimized, energy consumption is distributed more evenly among sensor nodes, and overall battery utilization is expected to improve.

Network Lifetime

The operational lifetime of a Wireless Sensor Network depends on how efficiently energy is utilized across all sensor nodes. Traditional routing protocols frequently select the same forwarding nodes, causing premature battery depletion and the formation of energy holes. In contrast, RL-CLEP continuously updates routing decisions using Reinforcement Learning and predictive energy estimation. By balancing communication load among neighbouring nodes, the framework is expected to delay node failures and significantly extend the overall network lifetime.

Packet Delivery Ratio and Communication Delay

Reliable packet delivery is essential for applications such as environmental monitoring, healthcare, and industrial automation. The proposed framework evaluates link quality, residual energy, and traffic conditions before selecting communication paths, thereby reducing packet loss caused by unstable links or network congestion. As a result, the Packet Delivery Ratio (PDR) is expected to increase. Furthermore, cross-layer information sharing enables the routing process to avoid congested routes and reduce retransmissions, leading to lower end-to-end communication delay.

Routing Overhead and Communication Reliability

Routing overhead represents the control messages exchanged for route discovery and maintenance. Frequent route updates increase network congestion and consume additional battery power. Since RL-CLEP continuously learns efficient routing policies through Reinforcement Learning, unnecessary route rediscovery operations are expected to decrease over time. This adaptive behavior reduces routing overhead while maintaining stable communication paths. The integration of Physical Layer, MAC Layer, and Network Layer information also enhances communication reliability by selecting forwarding nodes with better link quality and lower congestion levels.

Comparative Evaluation

The effectiveness of the proposed RL-CLEP framework can be evaluated by comparing its performance with widely used routing protocols such as **LEACH**, **PEGASIS**, **AODV**, and other energy-aware routing algorithms. Standard performance metrics that may be considered include:

1. Total Energy Consumption.
2. Network Lifetime.
3. Packet Delivery Ratio.
4. End-to-End Delay.
5. Routing Overhead.
6. Throughput.
7. Packet Loss Rate.

Based on its adaptive learning capability and cross-layer optimization strategy, the proposed RL-CLEP framework is expected to outperform conventional routing approaches by providing improved energy efficiency, balanced load distribution, enhanced communication reliability, and longer network lifetime. Experimental validation through future simulation studies will provide quantitative evidence to confirm these expected improvements under different Wireless Sensor Network scenarios.

Conclusion

Wireless Sensor Networks (WSNs) play a vital role in modern Internet of Things (IoT) applications, where energy efficiency and reliable communication are essential for long-term network operation. However, conventional routing protocols often rely on static routing decisions and independent protocol layers, resulting in excessive energy consumption, uneven battery utilization, communication delays, and reduced network lifetime. These limitations highlight the need for intelligent and adaptive routing mechanisms capable of responding to dynamic network conditions.

This paper proposed **RL-CLEP (Reinforcement Learning-based Cross-Layer Energy Prediction)**, an AI-assisted routing framework that integrates **Reinforcement Learning** with **cross-layer optimization** to improve communication efficiency in Wireless Sensor Networks. The proposed framework combines information from the Physical Layer, MAC Layer, and Network Layer to support intelligent routing decisions based on multiple network parameters, including residual energy, link quality, traffic load, queue status, and communication reliability. By continuously learning from network interactions, the RL agent dynamically selects energy-efficient forwarding paths and balances communication load among sensor nodes.

The proposed methodology is expected to reduce energy consumption, minimize routing overhead and packet retransmissions, improve packet delivery ratio, and extend network lifetime compared with conventional routing approaches. The lightweight design of RL-CLEP also makes it suitable for resource-constrained Wireless Sensor Networks deployed in IoT applications such as smart agriculture, environmental monitoring, healthcare, and industrial automation.

Although the present work focuses on the conceptual design of the RL-CLEP framework, it provides a strong foundation for future implementation and validation. The proposed model can be evaluated using network simulation platforms such as **NS-3** and compared with existing routing protocols including **LEACH**, **PEGASIS**, and **AODV** under different network scenarios. Future research may further enhance the framework by incorporating **Deep Reinforcement Learning**, **Federated Learning**, or **Edge Computing** techniques to support large-scale and intelligent IoT environments.

Overall, the proposed RL-CLEP framework offers an effective and adaptive solution for energy-efficient routing in Wireless Sensor Networks by combining Artificial Intelligence with cross-layer communication. Its ability to make intelligent routing decisions based on real-time network conditions has the potential to improve communication reliability, optimize energy utilization, and support sustainable next-generation IoT applications.

IJMDRR
E- ISSN –2395-1885
ISSN -2395-1877

References

1. A. Sharma, R. Mahajan, and D. Bagai, "Intelligent Energy-Aware Routing in Wireless Sensor Networks: A Survey of Deep Reinforcement Learning Approaches," International Journal of Communication Systems, vol. 39, no. 10, Art. no. e70523, 2026.
2. A.A.Lata and M. Kang, "RLFS-OR: Reinforcement Learning-Based Forwarder Selection for Opportunistic Routing in Wireless Sensor Networks," Electronics, vol.15, no.5, Art. no.910, 2026.
3. J. Alshudukhi, G. Kaur, B. Ankayarkanni, J. Gowrishankar, S. Hota, and R. Singh, "Intelligent Energy-Aware Routing for Next-Generation Wireless Sensor Networks," Internet Technology Letters, vol. 9, no. 2, Art. no. e70236, 2026.
4. A. F. E. Abadi, S. A. Asghari, M. B. Marvasti, G. Abaei, M. Nabavi, and Y. Savaria, "RLBEEP: Reinforcement-Learning-Based Energy Efficient Control and Routing Protocol for Wireless Sensor Networks," IEEE Access, vol. 10, pp. 44123–44135, 2022.
5. "Intelligent Energy-Aware Routing in IoT-Based WSNs by Reinforcement Learning," Ad Hoc Networks, Art. No. 104244, 2026.
6. "Energy-Efficient and Delay-Guaranteed Routing Algorithm for Software-Defined Wireless Sensor Networks: A Cooperative Deep Reinforcement Learning Approach," Journal of Network and Computer Applications, vol. 217, Art. no. 103674, 2023.
7. I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "Wireless Sensor Networks: A Survey," Computer Networks, vol. 38, no. 4, pp. 393–422, 2002.
8. W. R. Heinzelman, A. Chandrakasan, and H. Balakrishnan, "Energy-Efficient Communication Protocol for Wireless Microsensor Networks," Proceedings of the Hawaii International Conference on System Sciences (HICSS), 2000.
9. N. A. Pantazis, S. A. Nikolidakis, and D. D. Vergados, "Energy-Efficient Routing Protocols in Wireless Sensor Networks: A Survey," IEEE Communications Surveys & Tutorials, vol. 15, no. 2, pp. 551–591, 2013.
10. G. Anastasi, M. Conti, M. Di Francesco, and A. Passarella, "Energy Conservation in Wireless Sensor Networks: A Survey," Ad Hoc Networks, vol. 7, no. 3, pp. 537–568, 2009.
11. K. Akkaya and M. Younis, "A Survey on Routing Protocols for Wireless Sensor Networks," Ad Hoc Networks, vol. 3, no. 3, pp. 325–349, 2005.
12. W. Ye, J. Heidemann, and D. Estrin, "An Energy-Efficient MAC Protocol for Wireless Sensor Networks," Proceedings of IEEE INFOCOM, 2002.
13. J. Yick, B. Mukherjee, and D. Ghosal, "Wireless Sensor Network Survey," Computer Networks, vol. 52, no. 12, pp. 2292–2330, 2008.
14. J. N. Al-Karaki and A. E. Kamal, "Routing Techniques in Wireless Sensor Networks: A Survey," IEEE Wireless Communications, vol. 11, no. 6, pp. 6–28, 2004.
15. S. K. Singh, M. P. Singh, and D. K. Singh, "Routing Protocols in Wireless Sensor Networks—A Survey," International Journal of Computer Science and Engineering Survey, vol. 1, no. 2, pp. 63–83, 2010.