Optimized Routing method for Energy Efficiency in IoT-enabled WSNs

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Abstract—Recently, the Internet of Things (IoT) has garnered significant attention due to its wide-ranging applications, including smart healthcare, home automation, transportation, and smart cities. In these IoT-based systems, Wireless Sensor Networks (WSNs) play a crucial role in gathering the information necessary for smart environments. However, the influx of heterogeneous data from various sensing devices presents challenges such as high communication delays, low throughput, and reduced network lifetime. In this paper, we propose a Deep Reinforcement Learning (DRL)-based intelligent routing scheme for IoT-enabled WSNs that effectively reduces communication delays and enhances network lifetime. The proposed algorithm organizes the entire network into unequal clusters based on the current data load of each sensor node, thereby preventing premature network failure. Extensive experiments are conducted using the ns-3 simulation tool, and the results are compared with state-of-the-art algorithms to demonstrate the effectiveness of the proposed scheme in terms of the number of active nodes, packet delivery rates, energy efficiency, and communication delays within the network.

Keywords: Internet of Things (IoT), Wireless Sensor Networks (WSNs), Multi-objective, Deep Reinforcement Learning, energy efficient

I. INTRODUCTION

Wireless Sensor Networks (WSNs) play a vital role in the Internet of Things (IoT) ecosystem, enabling continuous environmental monitoring and real-time data reporting to a Base Station (BS). These sensor nodes, however, operate on limited power, which necessitates efficient data transmission strategies to mitigate issues such as high communication delays and energy imbalances among deployed nodes [1]. Such challenges are particularly critical in applications like Industrial IoT, home and office automation, healthcare systems, smart city development, and precision agriculture, where reliable and timely data delivery is essential.

To address these challenges, WSNs often employ clustering techniques that partition the network into various clusters, with a designated Cluster Head (CH) responsible for aggregating data from member nodes and relaying it to the BS via multi-hop communication [2]. This clustering mechanism is intended to enhance network longevity by distributing energy consumption more evenly among nodes. However, existing clustering-based routing protocols face significant drawbacks, including high communication delays, low throughput, and the emergence of energy holes, which can lead to premature node failures and reduced network performance [3].

Recent advancements in routing data through experience-based reinforcement learning have shown promise in minimizing communication overhead. Nevertheless, popular techniques such as Feedback Routing for Optimizing Multiple Sinks (FROMS) [4] and role-free clustering with Q-Learning (CLIQUE) [5] often require managing large state-action pairs, leading to complexities known as the curse of dimensionality. In contrast, Deep Reinforcement Learning (DRL) [6] has gained traction for its ability to integrate the strengths of reinforcement learning with deep neural networks, facilitating the design of sophisticated IoT systems.

This paper presents several key contributions aimed at enhancing the efficiency and reliability of IoT-enabled WSNs. Firstly, it introduces an unequal clustering scheme designed to prevent energy holes within the network. Secondly, it proposes a Multi-objective Deep Reinforcement Learning-based intelligent routing algorithm that significantly reduces communication delays and message overhead. Additionally, a novel load balancing scheme is introduced to improve network throughput and extend network lifetime. Finally, extensive simulations are conducted to validate the effectiveness and efficiency of the proposed methodologies, demonstrating their potential to address the challenges faced by current WSN implementations.

II. LITERATURE

J. Boyan et al. [7] introduced the first routing protocol utilizing Q-learning, which selects the optimal route based on the shortest delivery time. However, this method fails to account for the limited battery life of sensor nodes, leading to a reduced network lifespan.

Y. Zhang et al. [8] developed a reinforcement learning-based routing protocol that creates an adaptive spanning tree to balance load and prevent network congestion. Despite this, it experiences low throughput, particularly in large-scale networks due to significant communication delays.

A. Forster et al. [9] proposed the FROMS and E-FROMS protocols, which are reinforcement learning-based multicast routing schemes. FROMS calculates the best path between the source and destination nodes by considering factors such as hop count, distance, latency, and battery power. However, it suffers from a short network lifetime and excessive message overhead. E-FROMS extends FROMS by incorporating energy consumption considerations in WSNs.

T. Hu et al. [10] introduced a routing protocol for underwater sensor networks that identifies forward nodes based on residual energy and energy distribution among nodes, but it has a low packet delivery ratio.

M. Razzaque et al. [11] proposed a routing protocol for adaptive cooperative systems that takes into account reliability and transmission delays.

B. Debowski et al. [12] presented a gradient-based routing protocol that enhances Q-learning by factoring in the energy consumption rate of sensor nodes to improve network longevity, yet it neglects load balancing, which can lead to network segmentation.

A. Renold et al. [13] developed the Multi-agent Reinforcement Learning Based Self-Configuration and Self-Optimization protocol (MRL-SCSO), which considers residual energy and buffer length for efficient data routing and employs sleep scheduling for energy conservation. However, this protocol is hindered by high latency and poor packet delivery.

W. Guo et al. [14] proposed a Reinforcement Learning Based Routing (RLBR) protocol that selects forwarder nodes based on residual energy, link distance, and hop count, but it faces issues with energy imbalance and high delays.

III. PROPOSED METHOD

The proposed method consists of two main phases: the unequal cluster formation phase and the intelligent data routing phase. The goal is to create unequal clusters that balance energy consumption among sensor nodes and to implement a multi-objective Deep Reinforcement Learning (DRL) approach for efficient data routing, which enhances network throughput and reduces communication delays.

A. Cluster Formation Phase

In this phase, supernodes serve as Cluster Heads (CHs). Initially, the Base Station (BS) sends a HELLO message to the supernodes, which respond with their ID, location, and remaining energy. The BS maintains a list of supernodes sorted by their distance from it. The cluster formation is initiated by the supernodes, with the initial cluster radius set to a predefined value (R). If distances are equal, the cluster radius remains unchanged; otherwise, it is adjusted using the formula:

$$Cr[i + 1] = Cr[i] + R/i + 1 \forall i \in [1,2,\dots m]$$

Each supernode calculates its cluster radius based on its distance from the BS and sends a Cluster Formation Message (CFM) to nearby sensor nodes. These nodes respond with a JOIN message containing their ID and energy information. If a sensor node receives a CFM from multiple supernodes, it selects the nearest one as its CH. This method helps balance the load between clusters near the BS and those farther away.

During this phase, if a sensor node does not receive a CFM, it broadcasts a HELP message to find nearby nodes. Isolated nodes can then join the CH with the highest remaining energy. This mechanism ensures that all sensor nodes are integrated into the network, preventing isolation and enhancing overall connectivity. By allowing free sensor nodes to choose the CH with the maximum remaining energy, the proposed method promotes energy efficiency and prolongs the network's operational lifespan.

B. Intelligent Data Routing Algorithm

The routing process in IoT-enabled WSNs is framed as a multi-objective problem, requiring the identification of optimal paths based on various network parameters. The routing is divided into intra-cluster and inter-cluster phases, utilizing reinforcement learning techniques.

1. **Intra-Cluster Routing**: The state space for each sensor agent includes the destination and information about neighboring nodes. The action space consists of adjacent nodes in the cluster. Rewards are defined based on maximizing node lifetime, minimizing delays, and ensuring energy efficiency.
2. **Inter-Cluster Routing**: The state space for each CH agent includes the destination BS and information about neighboring CHs. The action space consists of adjacent CHs. Rewards focus on minimizing load and communication delays. The inter-cluster routing phase ensures that data is efficiently relayed from CHs to the BS, optimizing the overall data transmission process.

The multi-objective optimization is achieved through a Deep Q-Network (DQN) architecture, which evaluates actions based on a state-action value function. The training process involves updating the network based on experiences stored in memory, optimizing for multiple conflicting objectives to enhance overall network performance. By employing a parallel architecture for the DQN, the proposed method can simultaneously address various objectives, leading to a more robust and efficient routing solution.

In summary, the proposed method leverages unequal clustering and intelligent routing strategies to address the challenges faced by traditional WSNs. By focusing on energy efficiency, load balancing, and reduced communication delays, the framework aims to improve the overall performance and longevity of IoT-enabled WSNs. The integration of DRL further enhances the adaptability of the routing algorithm, allowing it to respond dynamically to changing network conditions and node states. This comprehensive approach not only optimizes data transmission but also ensures the sustainability of the network in the long term.

IV. SIMULATION SETUP

This section provides simulation results for the proposed method. Table 1 shows the simulation parameters used in Network scenario. Figure 1 to figure 5 represent the simulation analysis of output performance compare with existing methods.

Table 1: The experimental parameters

Parameters	***Value***
Nodes	100-150
Super nodes	7-18
Physical Medium	Wireless
MAC Layer	802.11
Traffic Type	CBR, FTP
Propagation radio model	Two ray ground
Position of nodes	Between (0,0) and (100,100)
Sensor nodes energy	0.5J
Super nodes energy	5J
Data packet size	512 bits
Base station	(50,50) and (150,60)

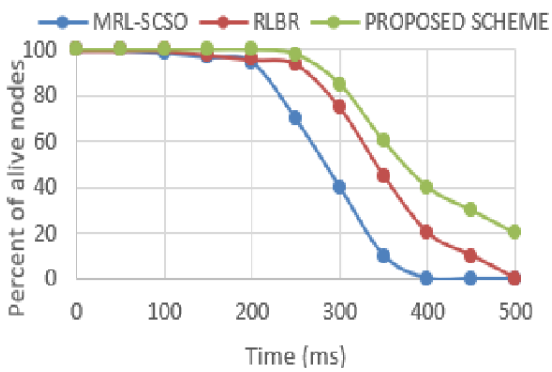


Figure 1: Alive Nodes (100 Sensor nodes)

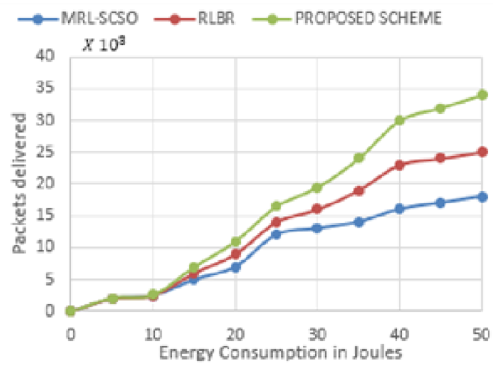


Figure 2: Energy Consumption (100 Sensor nodes)

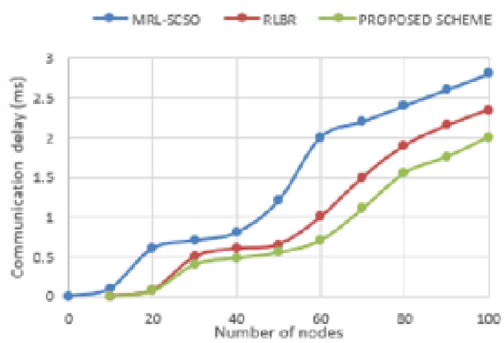


Figure 3: Communication Delay (100 Sensor nodes)

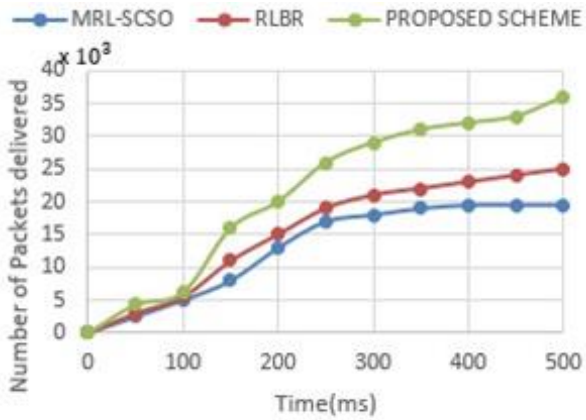
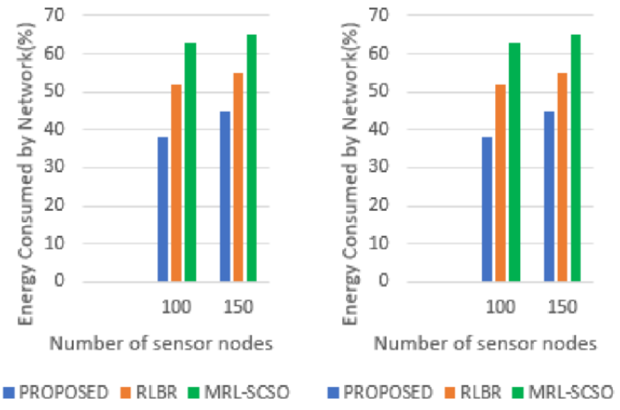


Figure 4: Packet delivery time (100 Sensor nodes)



(a) Equal Load (b) Unequal Load

Figure 5: Energy Consumption of Network

V. CONCLUSION

In this paper, we propose an energy-efficient intelligent routing scheme for IoT-enabled Wireless Sensor Networks (WSNs) that features a novel unequal clustering strategy, where super nodes serve as cluster heads to effectively manage deployed sensor nodes and prevent premature network failure. The approach incorporates load balancing to mitigate issues such as energy holes and network partitioning, while addressing multiple objectives, including lifetime, throughput, and delay for intra-cluster routing, and load, throughput, and delay for inter-cluster routing. This comprehensive strategy significantly enhances both network lifetime and performance. Various simulation results demonstrate that our algorithm outperforms state-of-the-art methods, specifically MRL-SCSO and RLBR, in key metrics such as packet delivery, energy efficiency, communication delay, and the number of active nodes. Additionally, we analyze the message and time complexity of the proposed algorithm. Future work will focus on improving the reliability of the scheme through a fault tolerance mechanism and addressing congestion and interference during data scheduling at intermediate nodes, with potential applications in smart cities, precision agriculture, healthcare, and home automation.

VI. REFERENCES

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