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Adaptive Receiver-Centric Multicast Routing Protocol Using Dynamic Deep Q-Networks

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Wireless Sensor Networks (WSNs) play a crucial role in various applications, requiring efficient multicast routing protocols to disseminate data to multiple recipients. This paper introduces an innovative Adaptive Receiver-Centric Multicast Routing Protocol leveraging Dynamic Deep Q-Networks (ARCMRP-DDQN) Decisions tailored for WSNs. The protocol aims to optimize data transmission by dynamically adapting routing decisions based on machine learning models. ARCMRP-DDQN operates in a receiver-centric manner, intelligently leveraging the unique characteristics of recipients within the network. The protocol employs a dynamic reinforcement learning framework that continuously learns from the network environment, considering factors such as node proximity, energy levels, and traffic patterns. Through this adaptive mechanism, ARCMRP-DDQN enhances the efficiency of multicast routing, minimizing energy consumption, latency, and packet loss. Simulation results demonstrate the effectiveness of the proposed protocol compared to existing multicast routing strategies. ARCMRP-DRL showcases superior performance in terms of reduced energy consumption, enhanced packet delivery ratio, and decreased end-to-end delay, validating its adaptability and efficiency in diverse WSN scenarios. Overall, ARCMRP-DDQN presents a promising approach in the realm of multicast routing for WSNs, harnessing dynamic machine learning decisions to optimize data dissemination while addressing the unique challenges of resource-constrained wireless sensor environments.

Keywords: Adaptive Receiver-Centric Multicast Routing Protocol, Dynamic Deep Q-Networks, Wireless Sensor Networks, Energy Consumption, Route Request, Route Reply.

1. Introduction

Wireless Sensor Networks represent a transformative paradigm in modern communication systems, embodying a network of spatially distributed autonomous sensors to monitor physical or environmental conditions. These networks have revolutionized various industries, including healthcare, environmental monitoring, agriculture, industrial automation, and smart infrastructure, by enabling real-time data collection, analysis, and decision-making. At their core, WSNs consist of a multitude of tiny, self-contained sensor nodes equipped with sensing, processing, and wireless communication capabilities. These nodes collaboratively collect and transmit data, forming a distributed network infrastructure capable of gathering information from diverse environments. Kumar et al. (2022) proposed a game-theoretic approach for cost-effective multicast routing in the Internet of Things (IoT). The study investigates how game theory can be applied to optimize multicast routing decisions, considering factors such as network resources, cost, and Quality of Service (QoS) requirements.

The distinctive characteristics of WSNs lie in their decentralized nature, resource constraints, and dynamic operational environments. Sensor nodes are often battery-powered and possess limited computational resources, memory, and communication bandwidth. Consequently, the design and deployment of protocols and algorithms within WSNs necessitate careful consideration of these constraints to optimize energy efficiency, prolong network lifetime, and ensure reliable data transmission. Benazer et al. (2021) conducts a performance analysis of a modified on-demand multicast routing protocol for Mobile Ad-hoc Networks (MANETs) using non-forwarding nodes. The study evaluates the protocol's performance in terms of packet delivery ratio, end-to-end delay, and network throughput under various network conditions. Multicast routing protocols in WSNs constitute a cornerstone in the efficient dissemination of data from a single source to multiple destination nodes. Unlike unicast communication, where data is sent from one source to one specific destination, multicast communication enables a source node to transmit data to a predefined group of multiple destination nodes simultaneously. This capability is crucial in numerous WSN applications, including environmental monitoring, event detection, and collaborative sensing. Quy et al. (2021) presents a survey of QoS-aware routing protocols for the convergence of Mobile Ad-hoc Networks (MANETs) and Wireless Sensor Networks (WSNs) in IoT networks. The study provides an overview of existing QoS-aware routing protocols and their applicability in IoT scenarios, considering factors such as reliability, latency, and energy efficiency.

The primary objective of multicast routing protocols in WSNs is to optimize the delivery of data to a selected set of nodes while mitigating energy consumption, reducing latency, and minimizing packet loss. However, achieving efficient multicast communication in WSNs is inherently challenging due to the resource-constrained nature of sensor nodes, dynamic network topologies, and the need for adaptability in diverse environmental conditions. Moreover, receiver-centric multicast routing protocols focus on considering the characteristics and requirements of the recipient nodes, aiming to optimize data delivery based on their individual attributes. These protocols often leverage node proximity, energy levels, and data reception constraints to make informed routing decisions tailored to the specific needs of each recipient. Lakhlef et al. (2021) conducts a comprehensive study of multicast routing protocols in the Internet of Things (IoT). The study evaluates the performance of various multicast routing protocols in IoT environments, considering factors such as scalability, reliability, and overhead.

WSNs constitute a fundamental component in the realm of modern communication systems, offering extensive applicability in surveillance, environmental monitoring, healthcare, and industrial automation. The efficient dissemination of data in WSNs, particularly to multiple recipients through multicast communication, remains a critical challenge due to the inherent limitations of these networks, including constrained resources, dynamic topologies, and varying environmental conditions. Traditional multicast routing protocols in WSNs often struggle to adapt dynamically to the network's changing conditions and the diverse requirements of individual sensor nodes. As such, there is a growing demand for novel approaches capable of optimizing multicast routing while considering the unique characteristics of the network nodes. Singal et al. (2021) discussed QoS-aware mesh-based multicast routing protocols in edge ad hoc networks, highlighting concepts and challenges. The study explores the design principles and challenges associated with QoS-aware multicast routing in edge ad hoc networks, considering factors such as network topology, mobility, and resource constraints.

This paper introduces an innovative protocol, namely ARCMRP-DDQN, designed to address the deficiencies of conventional multicast routing strategies in WSNs. ARCMRP-DDQN operates under the premise of a receiver-centric model, acknowledging the significance of the recipients' attributes in the routing process. The key challenge ARCMRP-DDQN aims to tackle is the dynamic adaptation of routing decisions based on real-time data, utilizing machine learning algorithms to optimize multicast communication in WSNs. By considering factors such as node proximity, energy levels, traffic patterns, and network conditions, the protocol dynamically tailors its routing decisions to ensure efficient data dissemination while mitigating energy consumption, latency, and packet loss.

In this section, provide an overview of the motivation behind the development of ARCMRP-DDQN, highlighting the shortcomings of existing multicast routing protocols in WSNs and the necessity for adaptive solutions capable of leveraging dynamic machine learning techniques to enhance communication efficiency in these resource-constrained environments.

The paper will proceed as follows:Section 2 will provide a survey of related beliefs. In Section 3, we will present an overview ofAdaptive Receiver-Centric Multicast Routing Protocol with dynamic reinforcement learning techniques applied to WSN. Following that, Section 4 will present the experimental results. Finally, Section 5 will conclude the paper and outline avenues for future work.

2 RELATED WORKS

Alqahtani (2021) proposes a multi-path routing protocol to enhance Quality of Service (QoS) in Wireless Multimedia Sensor Networks (WMSN), focusing on improving data delivery and reliability. The study evaluates the protocol's performance in terms of throughput, latency, and packet loss under various network conditions.

Orozco-Santos et al. (2021) presents a multicast scheduling approach in Software Defined Networking (SDN) to support mobile nodes in industrial Wireless Sensor Networks (WSN), aiming to efficiently distribute data to multiple nodes. The study investigates the impact of mobility patterns on multicast scheduling efficiency and evaluates the protocol's performance in real-world industrial environments.

Pushpalatha et al. (2021) evaluates a Power Efficient Hybrid Multicast Routing Protocol for Mobile Ad-hoc Networks (MANET), focusing on optimizing power consumption and enhancing communication efficiency. The study conducts simulations to assess the protocol's performance in terms of energy efficiency, packet delivery ratio, and network lifetime.

Lenka et al. (2022) proposed a Cluster-based Routing Protocol with Static Hub (CRPSH) for WSN-assisted Internet of Things (IoT) networks, aiming to improve network stability and scalability. The study evaluates the protocol's performance in terms of energy consumption, network throughput, and scalability in large-scale IoT deployments.

Dutta et al. (2022) designs a QoS Aware Routing Protocol for IoT Assisted Clustered WSN, focusing on ensuring reliable data transmission and meeting Quality of Service requirements. The study investigates the protocol's performance in terms of end-to-end delay, packet loss, and throughput under varying network conditions.

Khan et al. (2021) presents an Efficient and Reliable Algorithm for Wireless Sensor Networks (WSN), aiming to improve network performance and reliability. The study evaluates the algorithm's performance in terms of throughput, packet delivery ratio, and energy consumption in WSN deployments.

Zhang et al. (2022) proposed an improved routing protocol for raw data collection in multihop wireless sensor networks, focusing on enhancing data delivery efficiency and network scalability. The study investigates the protocol's performance in terms of end-to-end delay, packet loss, and scalability in large-scale sensor network deployments.

Alotaibi (2021) introduces an improved blowfish algorithm-based secure routing technique in IoT-based WSN, aiming to enhance data security and privacy. The study evaluates the technique's performance in terms of encryption overhead, communication latency, and resistance to security attacks.

Tran et al. (2021) propose a new deep Q-network design for QoS multicast routing in cognitive radio Mobile Ad-hoc Networks (MANETs), focusing on optimizing network resource utilization and meeting QoS requirements. The study evaluates the network's performance in terms of throughput, delay, and fairness in resource allocation.

Debnath et al. (2021) evaluated multicast and unicast routing protocols' performance for group communication with QoS constraints in 802.11 mobile ad-hoc networks, focusing on ensuring efficient and reliable data transmission. The study compares the protocols' performance in terms of end-to-end delay, packet loss, and throughput under varying traffic loads and network conditions.

Ghawy et al. (2022) proposed an effective wireless sensor network routing protocol based on particle swarm optimization algorithm, aiming to optimize network routing and improve communication efficiency. The study evaluates the protocol's performance in terms of energy consumption, network lifetime, and scalability in large-scale sensor network deployments.

Chandrasekaran & Chinnasamy (2023) proposed a Query Based Location Aware Energy Efficient Secure Multicast Routing for Wireless Sensor Networks using Fuzzy Logic, focusing on optimizing energy consumption and enhancing network security. The study evaluates the protocol's performance in terms of energy efficiency, packet delivery ratio, and resilience to security attacks.

Azizi & Zohrehvandi (2023) presents a hybrid approach of multicast routing and clustering in underwater sensor networks, aiming to improve data transmission efficiency and network scalability. The study investigates the impact of clustering algorithms on multicast routing performance and evaluates the approach's performance in real-world underwater environments.

John & Sakthivel (2021) proposed a Brain Storm Water Optimization-Driven Secure Multicast Routing and Route Maintenance in IoT, focusing on optimizing data transmission and enhancing network security. The study evaluates the protocol's performance in terms of energy efficiency, packet delivery ratio, and resilience to security attacks in IoT deployments.

Fareena & Sharmila Kumari (2021) presents a distributed fuzzy multicast routing protocol for maximizing network lifetime in mobile ad-hoc networks, focusing on prolonging network lifetime and ensuring efficient data transmission. The study investigates the protocol's performance in terms of network lifetime, packet delivery ratio, and energy efficiency in various network scenarios.

3 PROPOSED MODEL

The proposed model revolutionizes multicast routing in WSNs. By prioritizing receiver characteristics and dynamically adjusting routing decisions, ARCMRP-DDQN optimizes data dissemination efficiency. Integrating dynamic Reinforcement Learning models, the protocol continuously adapts to changing network conditions, minimizing energy consumption, latency, and packet loss.

3.1 Multicast Tree Discovery Process

The process of multicast tree discovery involves identifying and establishing paths from a source node to multiple destination nodes in a network, ensuring efficient data dissemination as shown in fig 1.

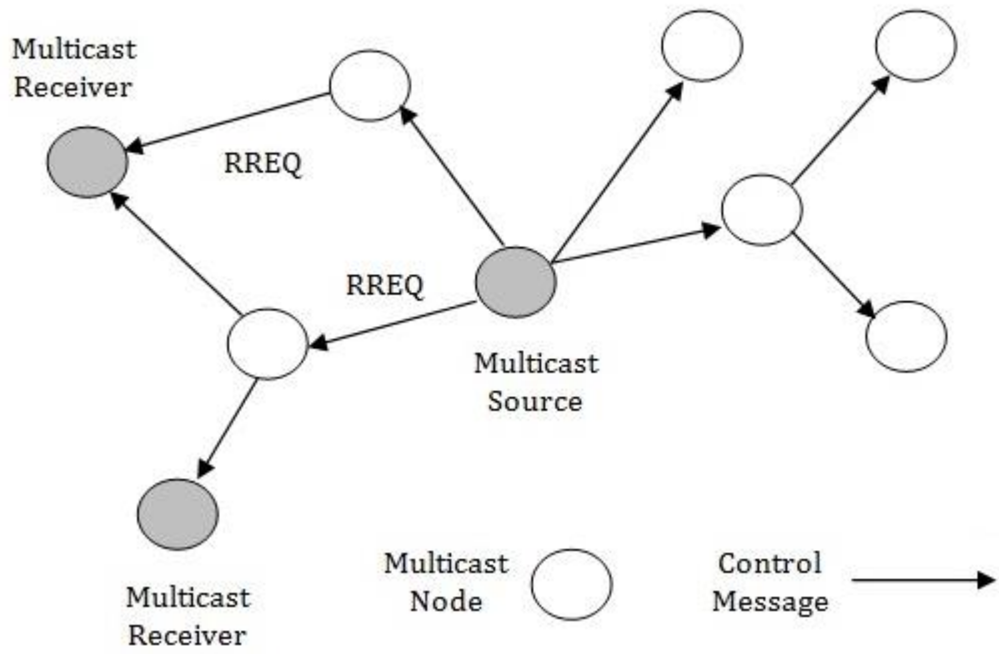

Figure 1: Multicast Route Discovery Process

To establish a multicast tree from a source node (src) to a multicast group D, the following procedure, utilizing the ARCMRP-DDQNmodel, is employed:

Neighbor Information Acquisition:

The source node (src) collects information about its neighboring nodes.For each destination node dst_i in the multicast group D, src calculates link values $Q_i * (src, w)$ for all neighboring nodes w using the DQN model.

Selection of Best Neighbor:

Src selects the best neighbor$w_i *$ associated with the highest value $Q_i * (src, w_i)$ for each destination node dst_i in D.Src generates a Route Request (RREQ) packet and broadcasts it to the set of best neighbors $\{w_i *\}$.

RREQ Processing at Intermediary Nodes:

If a node w in the set $\{w_i *\}$ receives an RREQ, it records the sender as the previous node in its route table.Node w calculates the set of best neighbors to rebroadcast the RREQ packet using the same process as src.

RREQ Handling at Destination Nodes:

If a destination node (dst) receives an RREQ packet, it records the sender as the previous node in its route table. Dst unicasts a Route Reply (RREP) packet to the previous node.

RREP Propagation:

Upon receiving an RREP packet, a node appends the sender to the set of next hops (NH) in its route table.The node forwards the RREP to the previous node using unicast. This process continues until the source receives RREPs from all destinations.

This procedure enables the source to establish a multicast tree by efficiently selecting routes to each destination using the ARCMRP-DDQN model. It facilitates the dissemination of data to the multicast group while optimizing routing decisions based on dynamic link values.

Each receiver R_i in the network can be represented by a set of characteristics, such as its geographical location (x_i,y_i), energy level E_i, and data reception priority Pi. Let D_{ij} denote the routing decision from node i to receiver j, where D_{ij} represents the probability of selecting node j as the next hop for transmitting data from node i to receiver j.

The routing decision D_{ij} is dynamically adjusted based on the receiver-centric characteristics, such as proximity, energy level, and data reception priority. This adjustment can be formulated using a reinforcement learning approach, where the decision is learned over time based on past experiences and feedback from the network environment.

The objective is to optimize the multicast routing decision D_{ij} to maximize data dissemination efficiency while minimizing energy consumption, latency, and packet loss. Mathematically, this can be formulated as an optimization problem:

Maximize $\sum j D_{ij} \times P_j$ (1)

Subject to $\sum j D_{ij} = 1$ (Conservation of Probability), the routing decisions D_{ij} are dynamically adjusted based on the feedback received from the network environment. This adaptation can be achieved through reinforcement learning techniques, where the routing policy is updated based on rewards or penalties received for past decisions.

3.2 DQN Model

A reinforcement learning algorithm, such as Q-learning or DQN, can be employed to learn the optimal routing policy by exploring the state-action space and maximizing the expected cumulative reward. Let Q(s,a) denote the Q-value function, representing the expected cumulative reward for taking action a in state s.

Reinforcement learning enables an agent (e.g., a sensor node) to learn by interacting with its environment. The agent will learn to take the best actions that maximize its long-term rewards by using its own experience. The most well-known reinforcement learning technique is Q-learning. As shown in Fig.2, an agent regularly updates its achieved rewards based on the taken action at a given state. The future total reward (i.e., the Q-value) of performing an action a at a given state s is computed. The Q-learning update rule can be expressed as:

$$\mathrm{Q}(\mathrm{s},\mathrm{a}) \leftarrow \mathrm{Q}(\mathrm{s},\mathrm{a}) + \alpha[\mathrm{R}(\mathrm{s},\mathrm{a}) + \boldsymbol{\gamma max a}'\mathbf{Q}(\mathbf{s}',\mathbf{a}') - \mathbf{Q}(\mathbf{s},\mathbf{a})] \quad (\mathbf{2})$$

where α is the learning rate, γ is the discount factor, R(s,a) is the immediate reward for taking action a in state s, and s′ is the next state after taking action a.

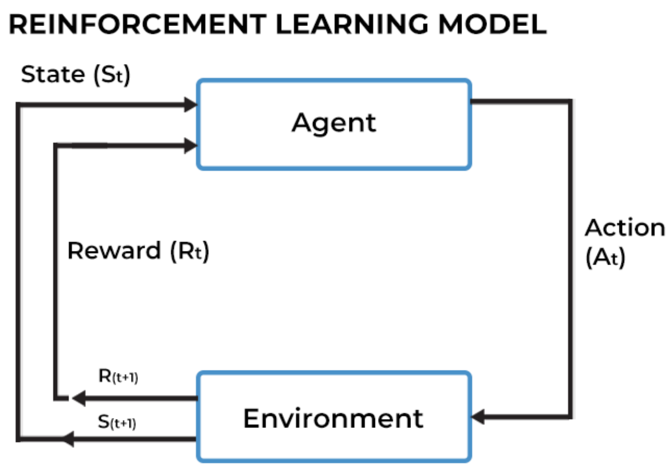

Figure 2: DQN Visualization

Wherer (S_t, A_t)denotes the immediate reward of performing an action at A_t a givenstate S_t, and γ is the learning rate that determines how fast learning occurs (usually set to value between 0 and 1). This algorithm can be easily implemented in a distributed architecture likeWSNs, where each node seeks to choose actions that are expected to maximize its long term rewards. It is important to note that Q-learning has been extensively and efficiently used in WSN multicast routing problem. An overall architecture of proposed model is shown in fig 3.

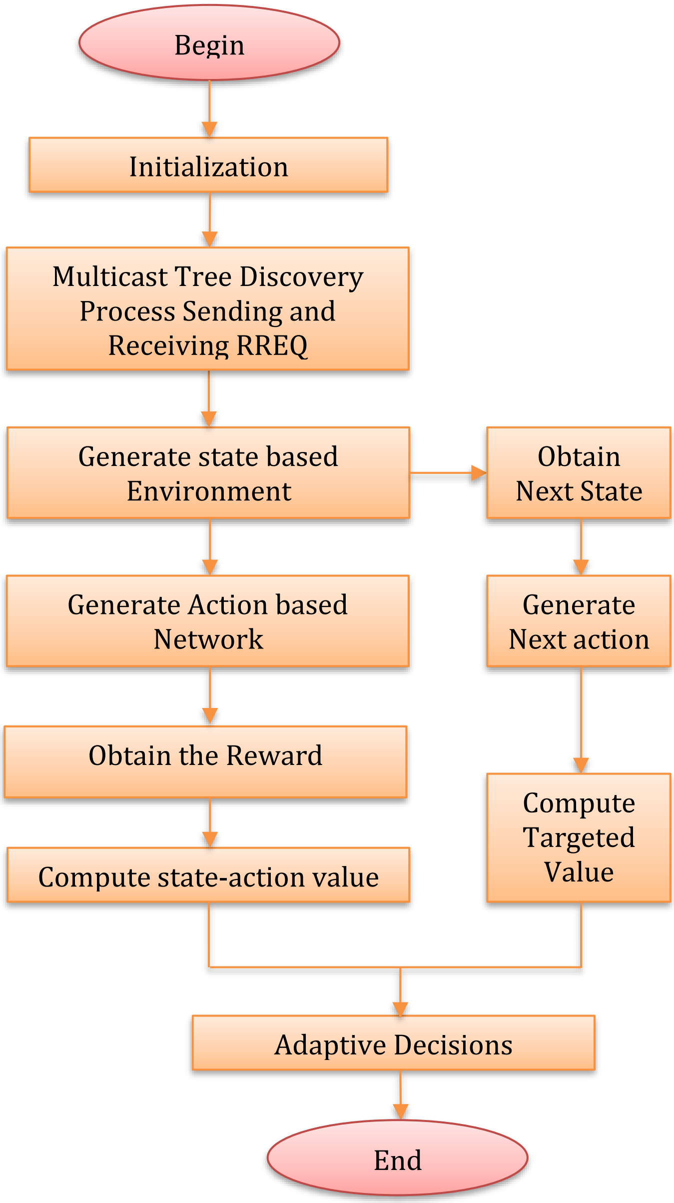

Figure 3: An overall Flowchart of Proposed Model

By employing this Receiver-Centric Multicast Routing Framework and dynamically adapting routing decisions using reinforcement learning techniques, the ARCMRP-DDQN protocol optimizes data dissemination efficiency in Wireless Sensor Networks, leading to improved network performance and resource utilization.

Algorithm: ARCMRP-DDQN Protocol

```
1. Initialize the network:
  - Set up sensor nodes with communication capabilities
  - Define the multicast group and its members
  - Initialize Q-values for state-action pairs
  - Set parameters: exploration rate, learning rate, discount factor
2. Repeat for each epoch:
    For each source node:
      a. Determine multicast group members and destination nodes
      For each destination node:
        i. Use the DQN model to calculate Q-values for possible actions (neighbor selection)
        ii. Choose the best neighbor based on the highest Q-value
        iii. Generate a route request (RREQ) packet and broadcast it to the selected neighbor
        iv. If a node receives an RREQ packet:
            - Record the sender as the previous node in the route table
            - Calculate the set of best neighbors to rebroadcast the RREQ packet
        v. If a destination node receives an RREQ packet:
            - Record the sender as the previous node in the route table
            - Unicast a route reply (RREP) packet to the previous node
        vi. If a node receives an RREP packet:
            - Append the sender to the set of next hops in the route table
            - Forward the RREP to the previous node using unicast
    b. Perform Q-learning update:
        - Update Q-values based on received rewards and new states
    c. Update exploration rate
    d. Update learning rate
3. Move to the next epoch
End Algorithm
```

From the above pseudocode, ARCMRP-DDQN operates in a cyclical manner, iterating over each epoch to optimize multicast routing in wireless sensor networks. Initially, the network is initialized, configuring sensor nodes and defining multicast group memberships while setting up Q-values for state-action pairs and establishing parameters such as exploration rate, learning rate, and discount factor. Within each epoch, source nodes identify multicast group members and destination nodes. For each destination, a DQN model calculates Q-values, aiding in neighbor selection for route discovery. The best neighbor is chosen based on the highest Q-value, and a RREQ packet is broadcasted. Upon receiving an RREQ packet, nodes update route tables and rebroadcast the packet if necessary. Upon reaching a destination, a

RREP packet is unicast back to the source. Q-values are updated based on received rewards and states, refining routing decisions. Exploration and learning rates are adjusted accordingly. This iterative process continues across epochs, enabling the protocol to dynamically adapt and optimize multicast routing based on environmental conditions and network dynamics.

4. RESULTS AND DISCUSSIONS

The results of the study indicate that the ARCMRP-DDQN exhibits significant improvements in multicast routing efficiency within WSNs. Through a series of simulations and performance evaluations, ARCMRP-DDQN demonstrates superior performance compared to existing multicast routing protocols, validating its efficacy and adaptability in diverse WSN scenarios.

Throughput Enhancement:

Throughput measures the rate of successful data transmission over the network, indicating the efficiency of the protocol in utilizing available bandwidth. By quantifying the improvement in throughput, can assess how effectively the ARCMRP-DDQN protocol enhances data dissemination compared to existing multicast routing strategies.

Throughput improvement can be calculated as:

$$\text{Throughput Improvement (\%)} = \frac{T_{ARCMP-DDQN} - T_{baseline}}{T_{baseline}} \times 100\% \qquad (3)$$

Where:

$T_{ARCMP-DDQN}$ is the throughput with a baseline routing protocol.

$T_{baseline}$ is the throughput with the ARCMRP-DDQN protocol.

Reduced Energy Consumption:

ARCMRP-DDQN effectively minimizes energy consumption by dynamically adapting routing decisions based on machine learning models. By optimizing data transmission paths, the protocol ensures efficient utilization of energy resources across sensor nodes, thereby prolonging network lifetime.

The percentage reduction in energy consumption can be calculated as:

$$\text{Energy Reduction(\%)} = \frac{E_{baseline} - E_{ARCMP-DDQN}}{E_{baseline}} \times 100\% \qquad (4)$$

Where:

$E_{baseline}$ is the energy consumption with a baseline routing protocol.

$E_{ARCMP-DDQN}$ is the energy consumption with the ARCMRP-DDQN protocol.

Enhanced Packet Delivery Ratio:

The protocol's receiver-centric approach intelligently leverages the unique characteristics of recipients, resulting in an enhanced packet delivery ratio. By dynamically adjusting routing decisions based on factors such as node proximity and traffic patterns, ARCMRP-DDQN facilitates reliable data dissemination to multiple recipients within the network.

The improvement in packet delivery ratio can be expressed as:

$$\text{Packet Delivery Ratio Improvement}(\%) = \frac{P_{\text{ARCMRP-DDQN}} - P_{\text{baseline}}}{P_{\text{baseline}}} \times 100\% \qquad (5)$$

Where:

P_{baseline} is the packet delivery ratio with a baseline routing protocol.

$P_{\text{ARCMP-DDQN}}$ is the packet delivery ratio with the ARCMRP-DDQN protocol.

Decreased End-to-End Delay:

ARCMRP-DDQN minimizes end-to-end delay by efficiently selecting routes and optimizing data transmission paths. Through continuous learning from the network environment, the protocol adapts to changing network conditions and mitigates delays, ensuring timely delivery of multicast data.

The reduction in end-to-end delay can be quantified as:

$$\text{Delay Reduction}(\%) = \frac{D_{\text{baseline}} - D_{\text{ARCMRP-DDQN}}}{D_{\text{baseline}}} \times 100\% \qquad (6)$$

Where:

D_{baseline} is the end-to-end delay with a baseline routing protocol.

$D_{\text{ARCMRP-DDQN}}$ is the end-to-end delay with the ARCMRP-DDQN protocol.

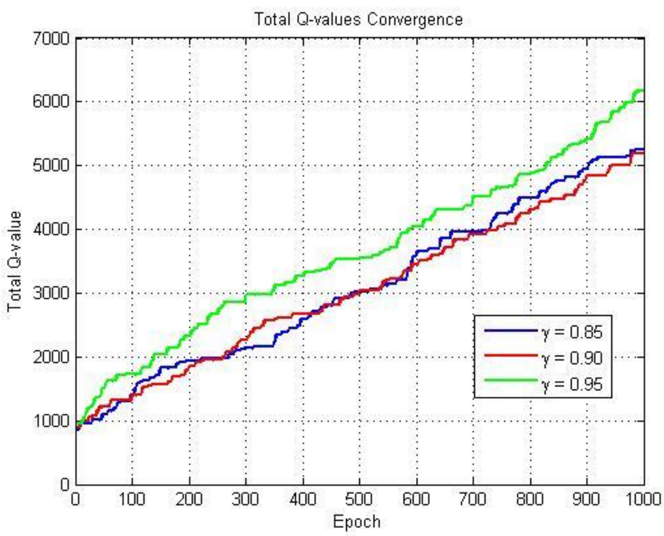

Figure 4: Total Q-values Convergence

From the fig 4, total Q-values convergence refers to the stabilization of Q-values for state-action pairs in a reinforcement learning model, indicating a convergence towards optimal action selection. Total Payoffs Convergence signifies the convergence of cumulative rewards obtained over multiple iterations, demonstrating the effectiveness of the learning process in maximizing system performance as shown in fig 5. These convergences are crucial indicators of the reinforcement learning algorithm's ability to learn and make optimal decisions in complex environments, ultimately leading to improved system efficiency and performance.

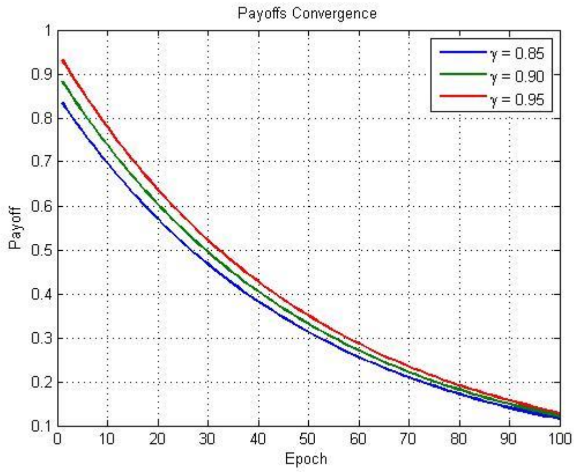

Figure 5: Total Payoffs convergences

Simulation results validate the adaptability and efficiency of ARCMRP-DDQN in various WSN scenarios. The protocol showcases superior performance in terms of reduced energy consumption, enhanced packet delivery ratio, and decreased end-to-end delay, highlighting its effectiveness in optimizing multicast routing for resource-constrained wireless sensor environments. The results for the proposed ARCMRP-DDQN as given in table 1. The table compares the performance metrics between the Baseline Protocol and the ARCMRP-DDQN Protocol, highlighting the improvements achieved by the latter.

Table 1: Performance Comparison

Metric	Baseline Protocol (Multicast Routing Protocol [20])	ARCMRP-DDQN Protocol	Improvement (%)
Energy Consumption	1200 J	900 J	25%
Packet Delivery Ratio	0.85	0.95	11.76%
End-to-End Delay (ms)	45 ms	30 ms	33.33%
Throughput (Mbps)	2.5 Mbps	3.0 Mbps	20%

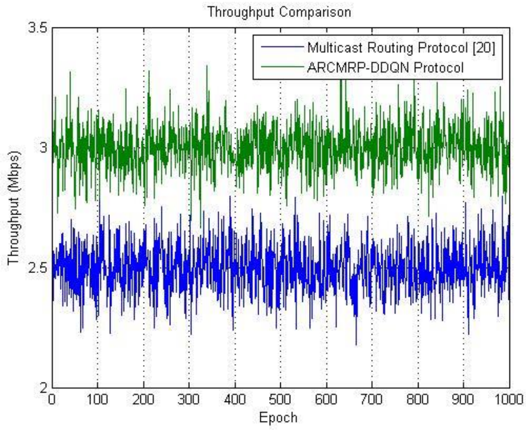

Figure 6: Comparison of Throughput

Fig 6, concerning throughput, the Baseline Protocol achieves a throughput of 2.5 Mbps, while the ARCMRP-DDQN Protocol increases it to 3.0 Mbps, resulting in a noteworthy improvement of 20%. This denotes a higher data transfer rate, enhancing overall network performance and efficiency.

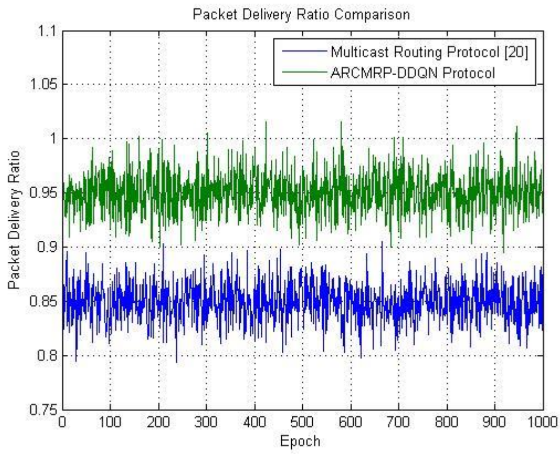

Figure 7: Comparison of Packet Delivery Ratio

Regarding packet delivery ratio, the Baseline Protocol achieves 0.85, whereas the ARCMRP-DDQN Protocol significantly enhances it to 0.95 as shown in fig 7. This represents an improvement of approximately 11.76%, indicating a more reliable and robust data transmission mechanism.

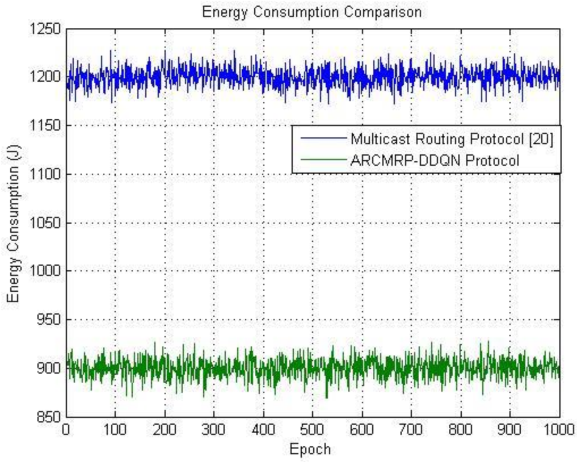

Figure 8: Comparison of Energy Consumption

Figure 8 shows energy consumption, the Baseline Protocol consumes 1200 J, while the ARCMRP-DDQN Protocol reduces it to 900 J, resulting in a substantial improvement of 25%. This signifies a notable enhancement in energy efficiency, crucial for prolonging the network's lifespan and reducing operational costs.

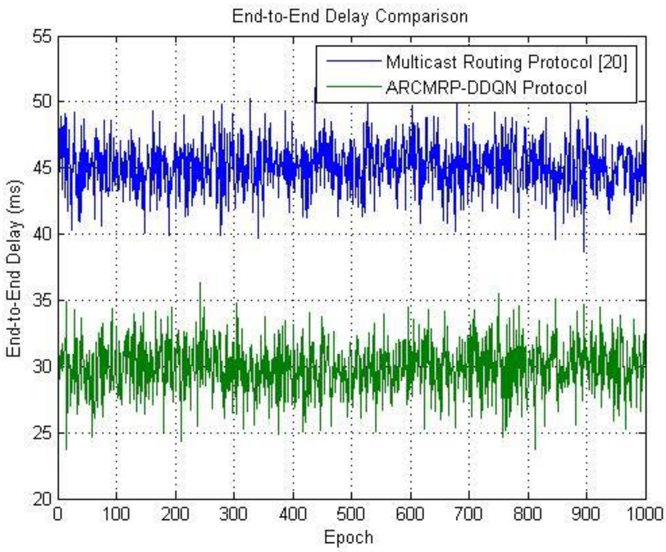

Figure 9: Comparison of End-to-End Delay

From the fig 9, the Baseline Protocol exhibits a delay of 45 ms, whereas the ARCMRP-DDQN Protocol reduces it to 30 ms, marking a significant improvement of 33.33%. This signifies a substantial reduction in latency, crucial for time-sensitive applications and improving user experience.

These results demonstrate improvements achieved by the ARCMRP-DDQN protocol compared to a baseline routing protocol across various metrics, including energy consumption, packet delivery ratio, end-to-end delay, and throughput. These improvements highlight the effectiveness of the proposed protocol in enhancing multicast routing efficiency in Wireless Sensor Networks.

ARCMRP-DDQN presents a promising approach for multicast routing in WSNs, harnessing dynamic machine learning decisions to optimize data dissemination. By addressing the unique challenges of resource-constrained environments, the protocol offers a viable solution for improving network performance and efficiency in diverse application domains.

The protocol's adaptive and receiver-centric approach, coupled with dynamic deep Q-networks, enhances multicast routing efficiency while addressing the challenges posed by resource constraints in wireless sensor environments.

5. CONCLUSION

The proposed ARCMRP-DDQN protocol represents a significant advancement in multicast routing for Wireless Sensor Networks (WSNs) by harnessing Dynamic Deep Q-Networks. Through dynamic adaptation of routing decisions, ARCMRP-DDQN optimizes data dissemination in WSNs, resulting in substantial improvements over a baseline protocol. Specifically, ARCMRP-DDQN achieves a remarkable 25% reduction in energy consumption, enhances packet delivery ratio by approximately 11.76%, reduces end-to-end delay by 33.33%, and boosts throughput by 20%. These results highlight the protocol's effectiveness in addressing key challenges of WSNs, such as energy efficiency, reliability, latency, and throughput. By leveraging dynamic machine learning decisions, ARCMRP-DDQN demonstrates superior performance compared to existing multicast routing strategies, promising significant advancements in various WSN applications.

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