

AN EFFICIENT ENERGY-AWARE ROUTING MANAGEMENT TO ENHANCE NODE LIFETIME USING DEEP Q-NETWORK IN WIRELESS SENSOR NETWORKS

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Abstract: Wireless Sensor Networks (WSNs) are used for reliable communication and monitoring, allowing data to be transferred to long-range places. However, because WSNs run on batteries, energy-efficient multi-hop routing is necessary for data transmission. Higher communication delays, increased latency, and a shorter network lifetime are inabilities of traditional WSN routing systems that cannot capture all network information throughout the routing process. In order to overcome these problems, we suggest a routing method that makes use of deep reinforcement learning to send data via multi-hop communication from the origin to the destination. The Deep Q-Network uses Markov Decision Process (MDP) to assist in choosing the best multi-hop path for data transmission. In order to choose the next hop neighbour and provide an ideal path for data packet transmission and network lifetime extension, the DQN takes into account the node's current residual energy, queue capacity, and hop count. Simulations are conducted to analyze the convergence rate, network latency, routing overhead, and network lifetime, the proposed MHRP-DQN protocol performs better random deployment and traditional Q-Learning network. Additionally, it guarantees higher throughput and packet delivery ratio during data transmission in WSNs demonstrating promising performance.

Keywords: Wireless Sensor Networks (WSNs), Deep Q-Network(DQN), Energy-aware multi-hop routing, Network Lifetime.

1. INTRODUCTION

Advancements in networking of devices or objects known as the Internet of Things (IoT) which made possible all recent developments in wireless technology, which allowed items to connect to the internet. The basic technology supporting the development of the Internet of Things is the Wireless Sensor Network [1]. Wireless sensor networks, which are capable of autonomous and intelligent sensing and information exchange, are especially used for continuous monitoring. With multi-hop communication, these sensor devices can gather, arrange, and transmit data to the sink node or base station (BS). WSNs are resilient, distributed, self-organising, scalable, and offer affordable solutions for a variety of applications, including early warning systems, fault tolerance, and location monitoring. Despite these benefits, memory and energy limitations are the challenge of the battery-operated devices. WSNs operate steadily and sustainably over the long term by enable energy efficiency routing and improved network longevity components [2]. The main objective of this research is to employ the Deep Q-Network and energy-efficient routing to increase the network lifetime of WSNs. Consequently, energy-efficient multi-hop routing regulates the total energy consumption of the deployed sensors and enhances network connectivity by extending their lifespan.

An efficient algorithm for choosing a path in WSNs is Q-learning; while sending data packets, the Q-Learning network will constantly engage with the nodes and learn to dynamically adjust to changes in the environment [7]. To learn the proximity of the nodes for choosing the best route, the Q-Learning algorithm needs additional training episodes, which increases convergence time. Specifically, the Q-Learning algorithm must examine the communication channels by studying the search space, which results in an exponential increase in time and cost when the number of nodes increases [8].

In this paper, we present a Deep Q-Network (MHRP-DQN) for multi-hop routing and selecting the best routing path to transmit data in WSNs. The DQN algorithm makes it easier for WSNs to dynamically interact with their surroundings in order to choose a path that uses the least amount of energy, minimizes latency, and efficiently routes data packets from the source to the base station. By dynamically adapting to the environment by modifying learning and updating the Q value, the DQN assists WSNs in choosing the best path for data packet transmission. It also improves energy efficiency and minimizes communication between the source node and base station by selecting relay nodes optimally for efficient data transmission. The performance of the proposed MHRP-DQN algorithm is implemented to analyze the effectiveness of multi-hop routing in terms of Packet delivery ratio, end-to-end latency, routing overhead, network throughput, convergence rate, network lifetime, first node dead, and last node dead. The experiment demonstrates the effectiveness of the proposed MHRP-DQN algorithm, which greatly extended the lifetime of wireless sensor networks by dynamically adjusting to network changes and routing data packets along the best path.

The rest of the paper is structured as Section 2 lists the appropriate papers in the literature for wireless sensor networks. The network's definitions and presumptions along with energy dissipation model for WSNs is presented in Section 3. Section 4 describes the proposed Deep Q-Network. Section 5 provides the simulation parameters, experimental configurations, and performance assessment of the various multi-hop routing algorithms along with a discussion. Section 6 concludes and offers suggestions for additional research.

2. RELATED WORKS

WSNs are employed in a wide range of industries [9], including as the military, healthcare, robotics, environmental monitoring [27], and many daily uses [10]. Smart homes, smart cities, smart grid communication [29], smart agricultural lands, and IoT-enabled appliances [11] are just a few of the cutting-edge domains where WSN applications have expanded its application with the advanced developments in communication and information technologies.

A multi-hop energy model for a cognitive radio network is presented in [12]. By considering factors such as the node's residual energy and network lifetime utilising a multi-hop clustering protocol embedded with imperfect spectrum sensing technique can improve network performance and energy utilization. The study in [13] used dynamic reinforcement learning to implement energy-efficient routing for data transmission in a large-scale network. The presented algorithm increased energy usage by 25% to 30% and increased network lifetime by 11%. In [14], the authors proposed genetic algorithm-based routing optimisation as a way to reconcile energy usage and network longevity.

The study proposed three-stage optimisation approaches for effective path routing, minimal latency, and maximum data transmission throughput in [15]. The work presented in [16] used two-stage optimisation to determine the most effective route between sensor nodes to send data packets in an energy-efficient manner. In order to minimise the search space for choosing the path for data packet transmission, a hierarchical network graph clustering method developed in [17] has carried out comprehensive evaluation that helps in effective data packet delivery using the hierarchical routing system.

Node coverage and energy efficiency, sensor quality, and network lifetime are not balanced by conventional node deployment techniques, such as grid topologies or random node placement [18]. To explore a wide search space and produce optimal or nearly optimal solutions, metaheuristic approaches are used. Various techniques presented in existing literature are Fuzzy Logic System (FIS) [20] [28], Particle Swarm Optimisation (PSO) [21], Genetic Algorithms (GA) [22], and Artificial Rabbits Optimisation (ARO) [23], single metaheuristic algorithms to optimise data transmission routing paths in WSNs. Therefore, researchers introduced hybrid frameworks that combine the capabilities of several computational intelligence algorithms to improve optimization strategies.

Reinforcement learning (RL) uses an agent to maximise the long-term reward in a network that improves the lifetime [24]. Reinforcement learning uses a reward function to determine how much data is transferred in relation to energy usage [25]. To increase the network's energy efficiency, WSNs employ the Deep RL algorithm combined with a Graph Neural Network (GNN) created in [26]. Under ideal circumstances, the devised method increased energy efficiency by 95.8%.

3. WIRELESS SENSOR NETWORK MODEL.

A set of wireless sensor nodes $\{s_1, s_2, s_3 \dots s_N\}$ are randomly placed throughout a 2-D spatial planar area $A \subset R^2$. Each sensor node has a specific communication radius R_c and sensing radius R_s . The base station (BS) is positioned at the center of the coverage area A , are placed strategically on a centre coordinate position of the monitoring area.

Energy Dissipation Model

The network connectivity is crucial for the sink or base station to reliably receive the data gathered by all of the sensor nodes. Consider that during the data transmission, it is assumed that the communication links are reliable and the sensor nodes are trustworthy. When sensor node s_i is within the sensor node s_j sensing range then the distance is computed as given in equation 1

$$G_{i,j} = \begin{cases} 1, & \text{if } \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} < R_s \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

The distance is calculated when sensor node s_i is within sensor node s_j detecting range that ensures network coverage. The quality of communication link is crucial for efficient data gathering, aggregation, and transmission. WSNs transmit data efficiently and extend their network lifetime, which depends on the the initial energy of node. The energy consumed or dissipated by a sensor node is determined by the data packet transmission and reception.

Various channel models are adapted during data transmission based on the transmission distance. A free space model is used by the channels when the distance is less than the threshold distance d_0 , the multipath fading channel is used when the distance is greater than the threshold [12]. The energy used by the sensor node to send l data bits over a distance of d is shown as

$$E_{Tx}(l, d) = \begin{cases} l \cdot E_{elec} + l \cdot \epsilon_{fs} \cdot d^2, & \text{if } d < d_0 \\ l \cdot E_{elec} + l \cdot \epsilon_{mp} \cdot d^4, & \text{if } d \geq d_0 \end{cases} \quad (2)$$

where E_{elec} is the energy consumed for l bits of data, d denotes range between two sensor nodes. ϵ_{fs} and ϵ_{mp} determine free space and multipath fading model used based on the distance, d_0 is the distance which is computed as given in equation 3.

$$d_0 = \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}} \quad (3)$$

The reception of data packet by a sensor incurs certain amount of energy which is represented as in equation 4.

$$E_{Rx}(l) = l \cdot E_{elec} \quad (4)$$

4. PROPOSED DEEP Q-NETWORK FOR TRANSMISSION OF DATA IN WSNs

The proposed multi-hop routing algorithm based on the Deep Q-learning Network for energy-aware data transmission between the sensor nodes and the sink or Base Station (BS) is described. It uses multi-hop route selection, which is modelled as a Markov Decision Process (MDP) that finds the best way between the sensor node and the base station. The DQN is utilized to choose a possible path that is steady for data transmission.

4.1 DEEP Q-NETWORK

Q-learning is a reinforcement learning that calculates the expected long-term benefit of performing a specific activity in a specific state. These values can be kept in a Q-table for comparatively modest situations. However, a tabular representation is impractical since real-world settings could have millions or even an infinite number of potential states. Deep Q-Networks solve this issue by substituting a deep neural network for the Q-table. The network can learn valuable representations from high-dimensional inputs and approximates the action-value function. A Markov Decision Process (MDP), which is widely used in Q-learning is also used by DQN. The MDP is described as a 5-tuple representation (S, A, P, R, γ) , where S represents the finite number of states, A relates to the current actions, P is the probability matrix used in state transmission to move from state S_t to another state $S_{(t+1)}$ at time t when an agent takes action $A(t)$ based on the policy, and R stands for the immediate reward as $R(t)$, and γ denotes the discount factor.

Q-learning does not require a model to calculate the action-value function that will be acting in state s and based on the course of action transfer it to $s+1$.

The update rule for Q-learning is given in equation 5

$$Q(s, a) = Q(s, a) + \alpha [r + \gamma \max_{a'} Q(s', a') - Q(s, a)] \quad (5)$$

where the learning rate is given by α . Deep Q-Network will approximate the Q-function using a neural network as given in equation 6

$$Q((s, a, \theta) \approx Q^*(s, a) \quad (6)$$

where θ is the DQN network's trainable parameters.

The neural network generates Q-values for every possible action for a given state. Then, employing an ϵ -greedy strategy, the agent chooses an action depending on these values.

The reward function r_t is defined as in equation 7

$$r_t = \left(\frac{Egy_{ct}}{Egy_{init}} \right) - \left(\frac{dist}{2 \times dist_A} \right) \quad (7)$$

The reward function considers the current energy of the node and the distance to transfer the data to the BS to reward the intermediate nodes during the data transmission.

4.2 REPLAY THE EXPERIENCE

Experience replay is one of DQN's key breakthroughs. The agent records its interactions with the environment in a replay buffer is represented in equation 8

$$D = \{(s_t, a_t, r_t, s_{t+1}, done_t)\} \quad (8)$$

DQN randomly selects mini-batches from the replay buffer rather than upgrading the network using successive experiences.

The target Q-values are computed using the target network, which is defined as in equation 9

$$Y_t = \begin{cases} r_t & \text{on termination} \\ r_t + \gamma \max_{a'} Q(s_{t+1}, a'; \theta^-) & \text{otherwise} \end{cases} \quad (9)$$

The target network's parameters are represented by θ^- . The online network's parameters are used to update the target network on a regular basis.

4.3 GREEDY EXPLORATION

The Q-Network calculates the stable target network $Q_{\text{target}}(S_t, a_t, \theta^-)$ and policy $Q_{\text{policy}}(S_t, a_t, \theta)$. The agent then chooses an action a_t from the Action Space A and uses the ϵ -greedy function to choose the next hop neighbouring node from the set of neighbouring nodes $M \subset s$ based on the network environment's constraints using the policy π , which is defined in equation 10.

$$\pi(s) = \begin{cases} \arg\max_j Q(s_t, a; \theta) & \text{with pr}(1-\epsilon) \\ \text{random Action} & \text{otherwise} \end{cases} \quad (10)$$

4.4 TRAINING OF DQN

The goal of the DQN network's training is to reduce the inconsistency between the target and predicted Q-values. The squared loss function of DQN is defined in equation 11

$$L(\theta) = E(s, a, r, s') \sim D[(Y_t - Q(s, a; \theta))^2] \quad (11)$$

where the parameter y is defined as $Y_t = r + \gamma \max_{a'} Q(s', a'; \theta^-)$ for non-terminal transitions.

5. RESULTS AND DISCUSSION

The experiments are conduction and findings assess the performance of the proposed MHRP- DQN algorithm for optimal routing in WSNs are described in this section. The experimental trial studies the effectiveness of the MHRP- DQN in establishing a steady data transmission and reception to the destination by altering the number of sensor nodes deployed in the environment. We evaluate the effectiveness of the proposed MHRP-DQN technique against the multi-hop routing protocol with random node deployment, classical reinforcement algorithm-based Q-Network. By changing the number of sensor nodes in the WSNs, the effectiveness of the proposed MHRP-DQN efficacy in routing and node deployment is compared with other algorithms is evaluated in the given simulation environment.

5.1 EXPERIMENTAL SETUP

The performance of the proposed multi-hop routing with Deep Q-Network technique is evaluated experimentally using a 2.40GHz core i5 processor with 16GB RAM running a 64-bit Windows operating

system. The simulation network is made up of 20, 30, 40, 50, and 60 nodes that are dispersed throughout a 100 m x 100 m area. The BS or sink node is positioned in the middle of the monitoring area at 50 m x 50 m. During the routing process, all of the sensor nodes transmit data using the common IEEE 802.15.4 protocol. Python 3.11 and the Pytorch framework's libraries are used to carry out the experimental tests.

5.2 PERFORMANCE EVALUATION

The proposed MHRP-DQN performance is evaluated in our simulation by considering the packet delivery ratio, routing overhead, network lifetime, end-to-end delay, first and last node dead, and convergence rate. On successful delivery of the data packet to the base station, the above-mentioned performance metrics are calculated. Network lifespan and packet delivery ratio are two of these parameters that are crucial for extending communication in network to achieve the primary goal of efficient communication in WSNs. The average of ten simulation trials is presented as the outcome for each algorithm after the experimental trials using the same simulation parameter settings. To examine the effects of changing the number of sensor nodes placed in the environment, we assess the proposed MHRP-DQN algorithm's performance with other developed algorithms.

Packet Delivery Ratio (PDR)

The packet delivery ratio (PDR) of the three algorithms is shown in Figure 1. From the Figure, it can be visioned that the proposed MHRP-DQN method achieved better PDR for different number of deployed sensor nodes and reached a maximum of 93.2% for 60 nodes. Effective data transfer without retransmission without packet dropping is the reason for the escalation in PDR. The likelihood of a data packet becoming stuck in a node dead zone is reduced due to the nodes' dense deployment. When compared to other algorithms, MHRP-DQN protocol has the highest PDR since it uses algorithms to detect changes in the environment, such as congestion or node death.

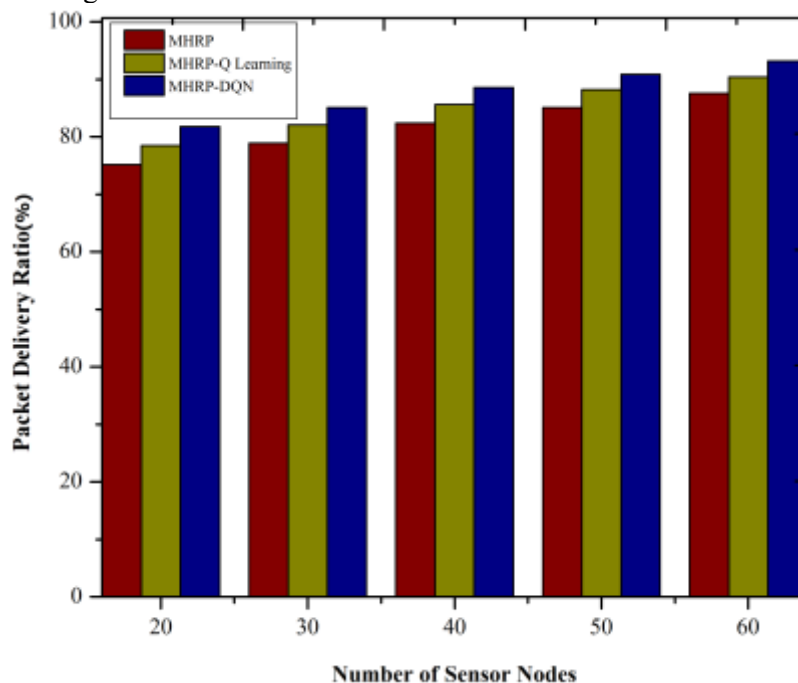


Figure 1: Packet Delivery Ratio of three algorithms for different number of sensors

The throughput of the network increases as the number of nodes deployed in the network increases. Figure 2 illustrates how MHRP-DQN outperforms other algorithms in terms of network throughput efficiency. As seen in Figure 2, the throughput of the sensor nodes increases correspondingly with the PDR as PDR and throughput are directly proportional and depends on the successful transmission of data packets.

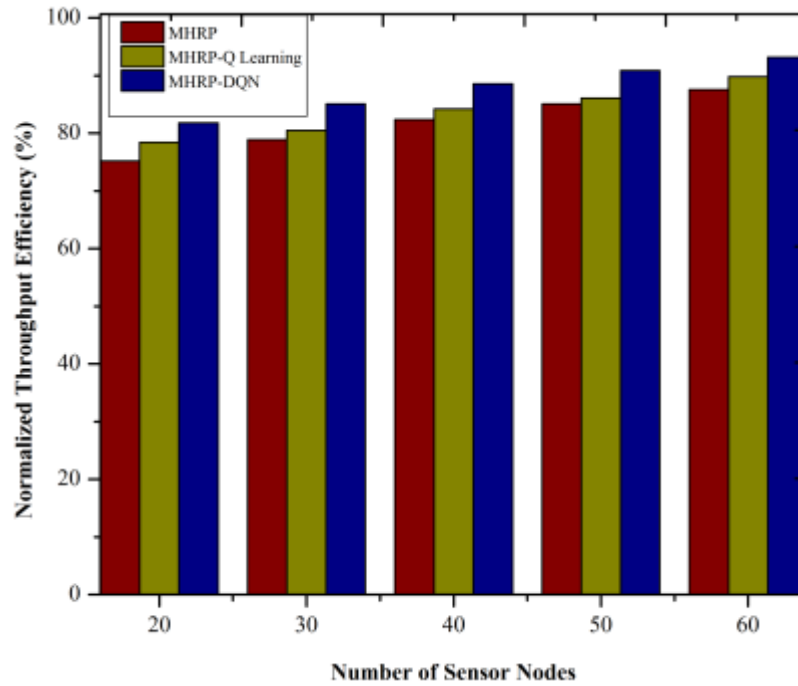


Figure 2: Throughput of three algorithms for different number of sensors

Routing overhead

As seen in Table 1, increasing the deployment of sensor node number of nodes from 20 to 60 has an effect on the network's routing overhead. As the number of deployed sensor nodes rose from 20 to 60, it is evident from Figure 8 that the suggested MHRP-Duel DQN routing overhead increased from 25.90% to 44.86%. This increase could be caused by an increase in the number of control packets, buffer overflow, retransmission brought on by network congestion, or an increase in the number of hops as the distance between the source sensor node and the base station grows, possibly as a result of an energy hole or to avoid a congested path.

Table 1: Routing overhead of three algorithms for different number of sensors

Sensor Density (N)	MHRP	MHRP- Q Learning	MHRP-DQN
20	30.50%	28.20%	25.90%
30	35.40%	32.80%	30.20%
40	41.50%	38.20%	35.00%
50	47.10%	43.40%	39.60%
60	53.10%	48.90%	44.80%

Network Lifetime

Figure 9 shows the network lifetime of the developed algorithms for varying the number of nodes in the environment. It is the most important statistical measure that depends on the quality of services considered like energy and distance for improving performance and routing in multi-hop scenarios of WSNs. The impact of changing the number of nodes distributed in the network is evaluated for the three routing protocols for transmitting data over multi-hop communication using the defined protocols. With 20 nodes, MHRP-DQN obtains 31.80% lifetime; with 60 nodes, the algorithm gets 100% lifetime. The network lifetime of the proposed MHRP-DQN considerably increases as the number of nodes increases from 20 to 60 which is mainly due to denser deployment of node which provides more connectivity to the sensor nodes to transfer data to the BS without any interruption in the network.

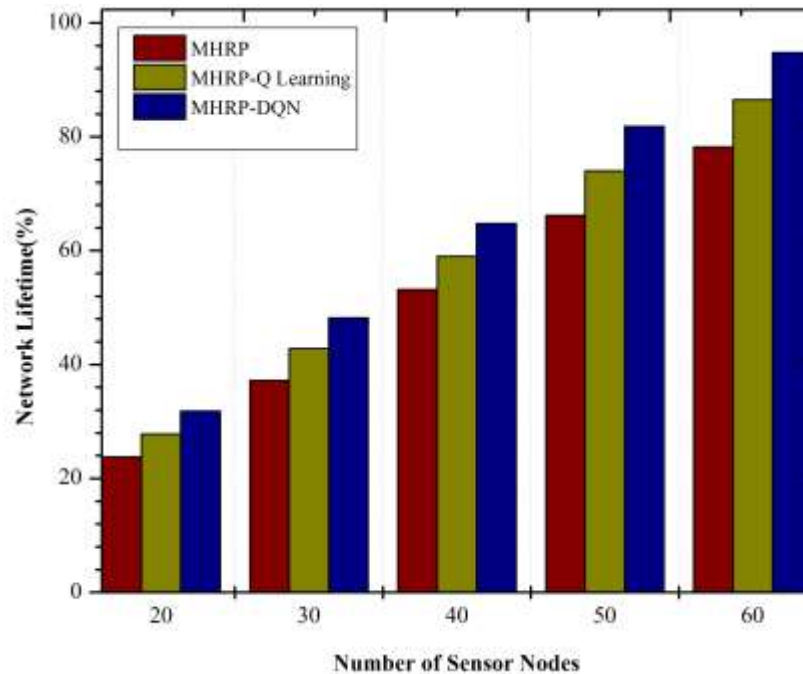


Figure 3: Network lifetime of three algorithms for different number of sensors

First node dead

The first-node death time is given in Table 2 that verify the extended network lifetime of the sensor nodes. When we examine the performance of the proposed MHRP-DQN algorithm, Table 2 shows that, for 20 sensor nodes, the first node dies at round 318; when the number of nodes rises to 50, the first node dies at round 818 and it rises to 948 rounds for 60 nodes. It can be evidently seen that the performance of the proposed MHRP-DQN increases with increase in the number of sensor nodes due to dense deployment of nodes make it to optimally choose the path for data transmission. The results show that the proposed MHRP-DQN has promising performance when compared with other models.

Table 2: First Node Dead of three algorithms for different number of sensors

Sensor Density (N)	MHRP	MHRP- Q Learning	MHRP-DQN
20	238	278	318
30	372	428	482
40	532	590	648
50	662	740	818
60	782	865	948

Last node dead

Table 3 informs about the death of the last node in the network for the three algorithms with sensors nodes deployed in the environment. The proposed MHRP-DQN has good network lifetime with nodes transmitting upto 832 iterations for 20 nodes and for 50 and 60 nodes, the last node died at rounds 1312 and 1402, respectively. Since the first node dies at round 948, for 60 nodes, we can clearly observe from the results that MHRP-DQN achieves 100% network lifespan for 60 nodes, even though we have set the maximum simulation as 1000 rounds. With a maximum network lifetime of the network, the proposed MHRP-DQN protocol is able to perform successful data transmission for a longer time when compared with other algorithms

Table 3: Last Node Dead of three algorithms for different number of sensors

Sensor Density (N)	MHRP	MHRP-Q Learning	MHRP-DQN
20	752	792	832
30	895	958	1,022
40	1,092	1,132	1,172
50	1,222	1,268	1,312
60	1,312	1,358	1,402

6. CONCLUSION

This study presents multi-hop routing protocol employing Deep Q-Network (MHRP-DQN) for transmitting data using multi-path transmission to the destination. The proposed MHRP-DQN considers three crucial factors namely the node's buffering capability, hop distance, and remaining energy in routing. By continuously learning the changes in the environment, the DQN transmits the data packets via the best possible path which ensuring selecting nodes with high energy levels to minimizes communication latency and distance, extending network lifetime and lowering node energy usage. In order to assess the effectiveness of the proposed energy-aware MHRP-DQN, we evaluated the performance through simulations and compared the outcomes with random deployment, classical Q-Network. The simulation results demonstrate that the proposed MHRP-DQN greatly enhances the network performance and strength of WSNs and performs better than the other algorithms in terms of packet delivery rate, node energy, throughput, routing overhead, and latency. To improve learning and intelligence in routing of data packets in WSNs, meta-heuristic-based optimisation approach for data packet routing combined with numerous agent-based deep learning techniques can be extended as future work.

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