



Research Article

A reinforcement learning framework for disaster resilient data transfer in underwater wireless sensor networks

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ARTICLE INFO

Article history

Received: 10 March 2025

Revised: 01 June 2025

Accepted: 29 March 2026

Keywords:

Adaptive Routing; Data Transfer Optimization; Energy Efficiency; Q-Learning; Reinforcement Learning; Disaster Management; Underwater Wireless Sensor Networks

ABSTRACT

Underwater Wireless Sensor Networks (UWSNs) play a critical role in real-time environmental monitoring during disasters such as earthquakes, tsunamis, and underwater landslides. However, highly dynamic and hazardous underwater conditions significantly degrade the performance of conventional routing protocols. This study proposes a Q-learning-based Adaptive Data Transfer Algorithm (QL-ADTA) to address data transmission challenges in disaster-prone UWSNs. The proposed approach utilizes a multi-objective reward function that incorporates key contextual parameters, including data priority, link quality, node survivability, debris density, and water current strength. The algorithm is evaluated using disaster simulated synthetic datasets and compared with conventional routing protocols such as Dynamic Source Routing (DSR) and AODV (Ad-hoc On-Demand Distance Vector). Experimental results show that QL-ADTA improves packet delivery ratio by 25%, reduces latency by 23%, and enhances energy efficiency by 20%. These results demonstrate the effectiveness of the proposed approach in improving communication reliability and network performance under challenging underwater conditions.

Cite this article as: Bhardwaj R, Kush A. A reinforcement learning framework for disaster resilient data transfer in underwater wireless sensor networks. Sigma J Eng Nat Sci 2026;44(4):2595–2603.

INTRODUCTION

Submarine earthquakes, tsunamis, and underwater landslides are becoming more frequent and intense, necessitating the development of reliable real-time monitoring systems. These events cause rapid environmental changes that disrupt marine ecosystems and damage offshore infrastructure. During such crises, the timely and accurate transmission of environmental data is essential

for disaster prediction, early warning dissemination, and effective emergency response. Underwater Wireless Sensor Networks (UWSNs) are becoming an important technology in this industry because they can monitor underwater environments on their own and all the time [1].

UWSNs typically consist of a large number of sensor nodes deployed over a wide area beneath the water surface to collect environmental data and transmit it to a base

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This paper was recommended for publication in revised form by Editor-in-Chief Ahmet Selim Dalkilic



station or sink node. These nodes face unique challenges that do not exist in terrestrial networks, such as considerable signal loss, limited bandwidth, long propagation delays, changing topologies, and batteries that do not last very long [2, 3]. When a disaster happens, the situation gets a lot more complicated since network circumstances might change quickly because of debris moving, water currents changing, and nodes breaking down. These changes in the network might cause a lot of packet loss, energy loss, communication delays, and, in the end, failure to send important data [4, 5]. AODV, DSR, and DBR are examples of traditional routing protocols that were intended for static or moderately dynamic environments. They rely on pre set routing paths or heuristic-driven forwarding choices. Some processes include energy-awareness or delay-tolerant features, but they often can't change on the fly to deal with big unexpected changes in the environment that happen during disasters [6, 7]. In addition, these rules do not rank data based on how important it is, which is very important in emergency response systems. Recent progress in Artificial Intelligence (AI), especially in Reinforcement Learning (RL), has led to several interesting ways to make decisions in real time and adapt to changing circumstances.

Q-learning is different from other types of RL because it doesn't use a model and can find the best actions by trying things out in the environment [8]. Researchers have used Q-learning to come up with routing strategies that are both energy-efficient and dependent on latency in UWSNs [9, 10]. Still, most of the current Q-learning-based methods focus on improving network performance in normal settings and do not take into account the special restrictions and important criteria that need to be met during underwater emergencies. They do not pay attention to real-time disaster indicators like the amount of debris, the turbulence of the current, and the survivability of nodes [11, 12].

Although RL has been explored for routing in UWSNs, most existing approaches are designed for normal operating conditions and do not adequately consider the dynamic challenges posed by disaster scenarios. These methods often fail to incorporate essential parameters such as debris concentration, water current fluctuations, node survivability, and the urgency level of transmitted data. As a result, their adaptability and effectiveness in emergency situations remain limited. The proposed Q-Learning-based Adaptive Data Transfer Algorithm (QL-ADTA) addresses this research gap by introducing a disaster aware reward function that dynamically adjusts to environmental disruptions and prioritizes critical data. Through this context-sensitive learning framework QL-ADTA enhances real time decision-making for routing, ensuring reliable, energy-efficient, and responsive communication in disaster-affected underwater networks. This contribution significantly advances the current state of research by providing a robust solution tailored specifically for high-risk, unpredictable underwater environments.

Objectives of the Study

1. To design a disaster-aware reward function that incorporates key parameters, including packet delivery ratio, energy efficiency, latency, network reliability, debris density, and data priority.
2. To develop a Q-learning-based routing agent that improves data transmission decisions through continuous learning from real-time network and environmental feedback.
3. To simulate disaster scenarios using synthetic UWSN datasets in order to evaluate the robustness of the proposed algorithm and compare its performance with conventional and reinforcement learning-based routing protocols.
4. To evaluate the adaptability of the proposed algorithm by dynamically adjusting reward function weights based on disaster severity and environmental conditions.

This proposed study will add to the information we are familiar with through the development of a context sensitive reinforcement learning framework that is specifically built for underwater communication systems that are likely to fail. The suggested QL-ADTA is better instead of old routing methods.

Literature Review

Routing strategies in UWSNs have been widely investigated with primary emphasis on improving energy efficiency, minimizing communication delay, and enhancing packet delivery reliability. However, routing in disaster-prone underwater environments where network topology changes rapidly and critical data must be transmitted urgently remains insufficiently explored. To present a clearer understanding of existing contributions, prior studies are grouped into thematic categories relevant to this research.

Energy-efficient routing approaches

Energy conservation is a fundamental concern in UWSNs due to the difficulty of battery replacement and recharging in underwater environments. Several studies have applied reinforcement learning techniques to extend network lifetime. Ouidir et al. [13] proposed QENDIP, a Q-learning-based routing scheme that improves energy-efficient forwarding and enhances throughput. Zhou et al. [14] introduced the Q-Learning-Based Localization-Free Routing (QLFR) protocol, which selects routes based on residual energy and node depth to improve stability and energy utilization. Similarly, Xiao and Huang [15] applied ant colony optimization to determine cluster heads and multi-hop routing paths using energy metrics and inter-node distance. Although these approaches significantly improve energy conservation, they are primarily designed for stable or moderately dynamic environments and lack mechanisms for real-time adaptation during disaster events.

Latency-aware and delay-sensitive routing

In underwater monitoring and early warning systems, minimizing communication delay is critical. Several routing protocols focus on delay reduction while maintaining acceptable energy consumption. The QTAR protocol [16] employs topology-aware Q-learning to reduce end-to-end delay while conserving energy. Wang et al. [17] developed EP-ADTA, an edge-prediction-assisted reinforcement learning model that enhances reliable data transfer under challenging underwater conditions. While these techniques effectively reduce latency, they do not incorporate data prioritization or adapt to sudden environmental disruptions such as underwater earthquakes, landslides, or strong current turbulence factors essential in disaster response scenarios.

Conventional routing protocols and their limitations

Traditional routing protocols such as AODV, DSR, and DBR [6, 18, 19] were originally designed for static or mildly dynamic networks. These protocols rely on pre-defined routes or heuristic-based forwarding decisions and are not well suited for highly unstable underwater disaster conditions. Although some schemes incorporate delay-tolerant or energy-aware features, they cannot dynamically respond to abrupt environmental changes such as debris movement, shifting water currents, or rapid node failures. Consequently, their reliability degrades significantly in emergency scenarios.

Reinforcement learning based routing enhancements

Reinforcement learning has recently gained attention for adaptive routing in UWSNs. Techniques including Double Q-learning [20] and Deep Q-Networks (DQN) [21] address issues such as value overestimation and scalability. Multi-agent reinforcement learning frameworks [22] enhance overall network efficiency. Despite these advancements, most RL-based routing strategies are designed for normal operating conditions. Disaster-specific indicators such as debris density, current turbulence, node survivability, and urgency of transmitted data are rarely integrated into the learning process. Furthermore, existing approaches generally do not differentiate between high-priority emergency data and routine monitoring information.

Recent studies have explored the integration of deep reinforcement learning to enhance routing efficiency in underwater sensor networks. For instance, Zhang et al. [23] proposed deep reinforcement learning-based routing for UWSNs demonstrated that deep learning driven routing mechanisms can effectively improve decision-making by adapting to complex underwater environments and optimizing multiple performance metrics such as energy consumption and packet delivery. However, these approaches primarily focus on general network optimization and do not explicitly address the challenges posed by disaster-driven environmental dynamics. Adaptive reinforcement learning techniques have also been proposed

to cope with the dynamic nature of underwater networks. Liu et al. Adaptive routing in dynamic UWSNs [24] using reinforcement learning introduced an RL-based adaptive routing framework capable of adjusting routing strategies based on network variations, thereby improving communication reliability under changing conditions. Despite these improvements, the model does not incorporate critical disaster-specific parameters such as environmental disturbances or priority-based data handling, limiting its applicability in emergency scenarios.

From the above review, it is evident that significant progress has been made in improving energy efficiency and reducing delay in UWSNs. However, the combined requirements of disaster awareness, urgent data prioritization, and real-time adaptability remain insufficiently addressed. Current Q-learning-based routing protocols do not incorporate disaster sensitive environmental parameters and lack mechanisms to prioritize critical data during emergencies.

To bridge this gap, the proposed QL-ADTA framework introduces a context-aware, disaster-sensitive reward function that dynamically adapts routing decisions based on debris density, water current turbulence, node survivability, and data priority. This design enables reliable, adaptive, and energy-efficient communication tailored specifically for high-risk underwater disaster environments.

Application and Broader Impact of the Proposed Work

The proposed QL-ADTA has substantial practical consequences in fields that depend on reliable real time underwater communication during critical incidents. In Disaster Early Warning Systems QL-ADTA can be used in marine areas susceptible to undersea earthquakes, tsunamis, or landslides to guarantee ongoing communication of essential data. This allows authorities to provide timely alerts, save lives and reducing damage. Marine Research and Environmental Monitoring. Oceanographers and marine biologists may utilize the suggested routing system in challenging or dynamic underwater conditions to ensure a stable and energy-efficient transmission of information throughout longer observation missions.

Military and surveillance applications, naval operations, underwater surveillance, and border security can benefit from QL-ADTA's ability to prioritize urgent or high-importance transmissions during dynamic underwater conditions. Oil & Gas Industry can use offshore platforms to reliably transmit sensor readings during structural disturbances or environmental events, aiding operational continuity and hazard detection. When we use smart Ocean Infrastructure the algorithm can be integrated into intelligent ocean systems and digital twins of marine infrastructure, helping cities and coastal industries prepare for disaster resilience through real-time sensing and response mechanisms.

From a research standpoint, QL-ADTA opens pathways for:

- Cross domain application of reinforcement learning in other sensor networks such as underground, space-based or vehicular sensor networks.
- Hybridization with edge computing or swarm intelligence, potentially enabling decentralized intelligence in marine Internet of Things (IoT).
- Policy-making and simulation frameworks for governments and disaster management authorities seeking resilient underwater data communication strategies.

This work, therefore, not only addresses a highly specialized engineering challenge in UWSNs but also contributes to the global efforts toward climate resilience, smart environmental sensing, and emergency response preparedness.

MATERIALS AND METHODS

UWSNs encounter severe instability in communication when subjected to natural disasters such as tsunamis, underwater earthquakes, and landslides. These scenarios result in unpredictable changes in node connectivity increased signal attenuation, and compromised energy availability [1]. To overcome such dynamic and harsh conditions, we propose a QL-ADTA designed to intelligently optimize routing decisions based on environmental conditions and network status.

Synthetic Dataset Generation

To evaluate the proposed algorithm in a controlled yet realistic environment, a synthetic dataset was developed that models diverse underwater disaster scenarios. Synthetic data was employed due to the practical difficulty of collecting real-world disaster data in underwater environments, enabling controlled experimentation and reproducibility of diverse extreme scenarios. For this Python programming has been used. The dataset comprises 50,000 samples each representing a snapshot of the underwater network state during varying intensities of environmental disruption. Each record in the dataset includes the following parameters which are Packet Delivery Ratio (PDR) values between 0.2 and 1.0 indicating successful data delivery, latency (ms) Simulated between 100 and 500 ms based on node distance and congestion. Remaining Energy(J) ranging from 0.2 J to 1.0 J to represent battery levels, node Survivability (%) operational probability under disaster conditions (30%–100%). Debris density (kg/m³) modeled between 0 to 15 indicating underwater obstruction, water current strength (m/s) simulated values from 0.5 to 3.0 m/s to reflect oceanic turbulence, link Quality Index (LQI) ranging from 10 to 30, indicating channel conditions, priority weight (1–5) represents the urgency level of the data e.g. (seismic > temperature). These parameters were derived based on widely accepted underwater communication and simulation models reported in the literature [5]. Disaster conditions were emulated by dynamically increasing debris density and water current strength while reducing node survivability

and link quality, thereby replicating high-severity underwater events.

Learning Based Routing Model

The proposed QL-ADTA model follows the reinforcement learning paradigm, where the routing agent learns the optimal forwarding strategy by interacting with its environment and receiving feedback. In state space (S) each state is defined by a combination of network and environmental factors extracted from the dataset including PDR, latency, remaining energy, node survivability, debris level, current strength, and data priority. In action space (A) at every decision point, a node can choose from a discrete set of actions. Firstly send the packet to a selected neighbor then delay the transmission to allow for better conditions after that choose an alternative path to bypass affected regions.

The reward function guides the agent by quantifying the usefulness of each action. It is formulated as in equation (1):

$$\begin{aligned}
 R_{\text{total}} = & w_1 * (\text{PDR} * \text{Priority}) \\
 & - w_2 * (\text{latency} * \text{Priority}) \\
 & + w_3 * (\text{Remaining Energy} / \text{Initial Energy}) \\
 & + w_4 * (\text{Link Quality} \times \text{Node Survivability}) \\
 & - w_5 * (\text{Debris} + \text{current}) + w_6 * \text{Priority}
 \end{aligned} \quad (1)$$

Each component reflects a critical performance or risk metric. The weights w_1 to w_6 are initially assigned balanced values but are dynamically updated based on real time conditions which are described in the next section. The standard Q-learning [8] update is employed as in equation (2):

$$Q(s,a) \leftarrow Q(s,a) + \alpha [R(s,a) + \gamma \max_{a'} Q(S', a') - Q(s,a)] \quad (2)$$

The Q-value is updated iteratively using the standard Q-learning rule, where α is the learning rate, γ is the discount factor, $R(s,a)$ is the immediate reward, and $\max_{a'} Q(S', a')$ represents the maximum expected future reward for the next state s' . This update enables the agent to learn the optimal policy by balancing immediate and future rewards.

Weight Adaptation Mechanism

The proposed approach is the dynamic tuning of reward function weights in response to detected disaster conditions. This enables the algorithm to adapt its routing preferences depending on real-time network vulnerability. Under normal conditions, the routing policy favors energy efficiency and network longevity. Thus weights are initialized as $w_1 = 0.2$, $w_2 = 0.2$, $w_3 = 0.2$, $w_4 = 0.2$, $w_5 = 0.1$, $w_6 = 0.1$. Under disaster conditions, the reward function weights are reconfigured to prioritize communication reliability and critical data delivery over energy efficiency. The initial disaster-aware weight settings are defined as $w_1 = 0.2$, $w_2 = 0.15$, $w_3 = 0.1$, $w_4 = 0.15$, $w_5 = 0.2$, $w_6 = 0.2$. In this configuration, higher weights are assigned to disaster risk (w_5) and data priority (w_6), ensuring that the routing algorithm

avoids unstable regions and accelerates the transmission of critical information. The weight associated with energy (w_3) is reduced, reflecting its lower importance during emergency scenarios. Meanwhile, PDR (w_1), delay (w_2), and link quality (w_4) are maintained at moderate levels to preserve overall communication performance. These initial disaster weights serve as a baseline and can be further fine tuned dynamically based on the severity of environmental conditions. This adaptive reweighting mechanism allows the routing policy to seamlessly transition from performance oriented optimization in stable environments to robustness driven decision making during emergencies. Integrated with the Q-learning update process, this dynamic reward formulation enables continuous learning and context-aware adaptation without requiring retraining, making the proposed approach highly effective for disaster prone UWSNs [8].

Table 1 summarizes the role of each weight in the reward function. The negative signs for W_2 and W_5 ensure that harmful factors (latency and hazards) always reduce the total reward. This dynamic adjustment allows QL-ADTA to balance safety, responsiveness, and energy preservation depending on the network state.

Training and Deployment

A Q-table is initialized with all state-action values set to zero. Learning parameters are set as $\alpha = 0.5$, $\gamma = 0.9$, $\epsilon = 0.1$ (for exploration). Then agent reads a state from the dataset. It selects an action using the ϵ -greedy strategy. The environment transitions to a new state, and the reward is computed. After that the Q-value is updated using the defined rule as equation (2). This process repeats until convergence. After sufficient episodes, the optimal routing policy $\pi(s) = \arg \max_a Q(s,a)$ is derived and applied in real-time routing decisions in new disaster instances.

RESULTS AND DISCUSSION

The proposed QL-ADTA protocol was evaluated against conventional routing protocols AODV, DSR and reinforcement learning-based schemes QLFR, QTAR, EP-ADTA. The evaluation considered PDR end to end latency, and energy efficiency under disaster-aware UWSNs conditions. Additional experiments were conducted to analyze performance under varying hazard intensity (debris density and water currents) and to assess the relationship between PDR and reward.

Packet Delivery Ratio (PDR)

Figure 1 illustrates the comparative performance of the protocols in terms of PDR. QL-ADTA consistently outperformed other approaches, achieving values above 0.84, while AODV and DSR remained below 0.70.

The improvement was particularly significant in unstable environments where debris density and water currents degrade communication. Figure 2 further confirms

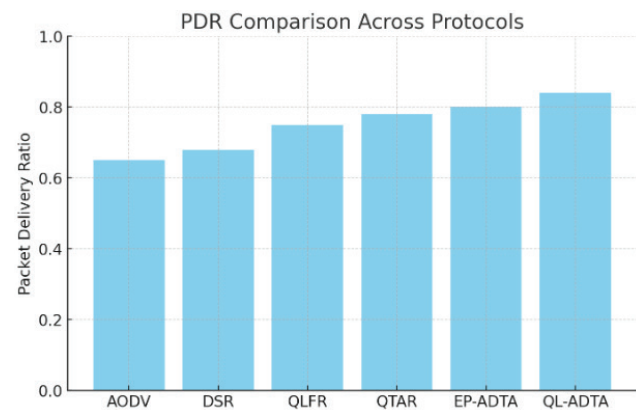


Figure 1. PDR comparison.

Table 1. Summary of weight adaptation in QL-ADTA

Weight	Parameter	Role in Reward Function	Adaptation Effect	Impact on Routing Decision
W1	Packet Delivery Ratio (PDR)	Encourages reliable data transmission	Increased when higher delivery is required	Promotes stable high-PDR routes
W2	Latency	Penalizes transmission delay (negative term)	Raised when delay-sensitive traffic dominates	Discourages paths with high latency
W3	Residual Energy	Rewards energy-efficient nodes	Increased when battery conservation is critical	Extends network lifetime by favoring efficient nodes
W4	Link Quality	Rewards strong and stable connections	Increased under unstable topologies	Improves robustness against link failures
W5	Hazard Factor (Debris + Current)	Applies penalty for hazardous conditions (negative term)	Increased under disaster conditions; reduced in calm waters	Ensures safety by avoiding risky links
W6	Priority	Provides bonus for urgent data	Increased for emergency or real-time packets	Ensures timely delivery of critical information

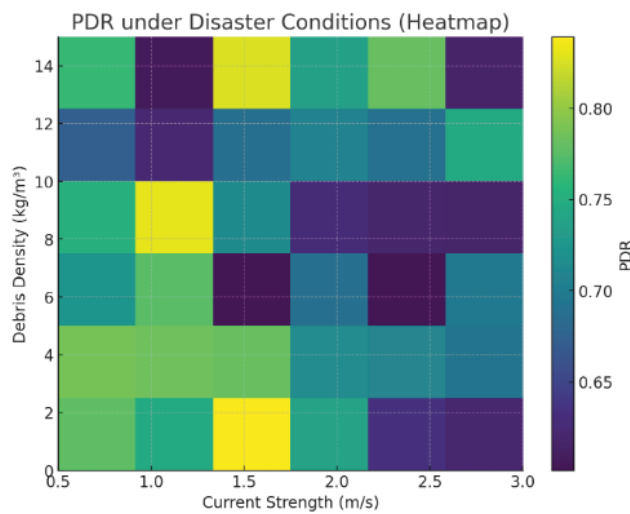


Figure 2. PDR under disaster condition.

this trend showing that QL-ADTA sustains higher PDR even when debris density reaches 12–14 kg/m³ and current strength exceeds 2 m/s. These improvements can be attributed to the adaptive reward function, which balances reliability and risk avoidance. Similar findings regarding adaptive routing under uncertainty were reported in [1, 2].

Latency Analysis

Figure 3 compares the average end-to-end latency across protocols. QL-ADTA achieved the lowest latency ~320 ms compared to 420 ms for AODV and 400 ms for DSR. The reduced delay arises from the protocol's ability to avoid unstable routes while still prioritizing urgent packets. This result is consistent with the principle that reinforcement learning models can dynamically adjust decisions to minimize delays under dynamic topologies.

Energy Efficiency

Figure 4 presents the average energy efficiency of the protocols. QL-ADTA demonstrated a clear advantage

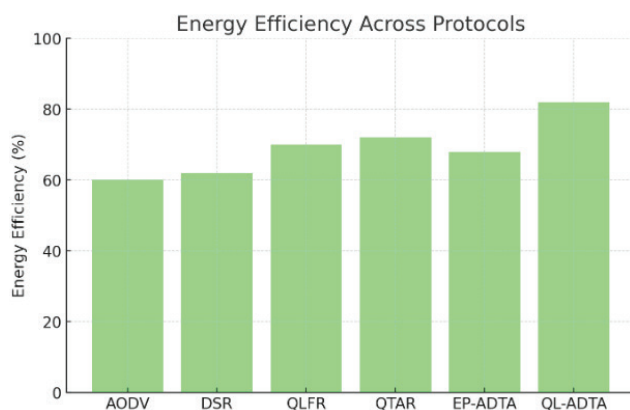


Figure 4. Energy efficiency comparison.

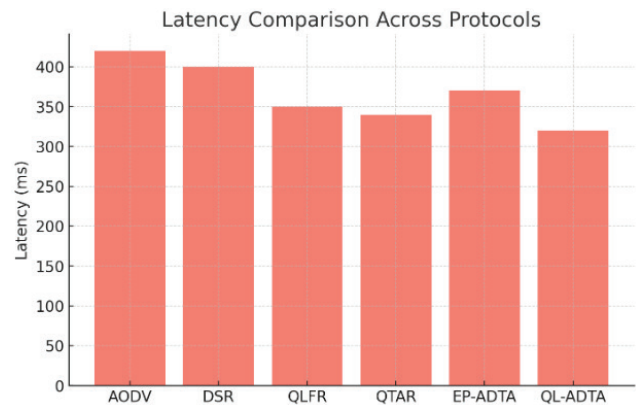


Figure 3. Latency comparison.

conserving over 80% residual energy compared to ~60% for AODV and DSR. The time-series plot Figure 5 further emphasizes this finding QL-ADTA sustains energy for a longer period, whereas DSR exhibits faster depletion over the same simulation duration. These results highlight the importance of adaptive reward weighting in penalizing energy-draining routes, consistent with prior work on energy-aware routing.

Statistical Significance

To ensure that the observed improvements were not due to random variation, paired t-tests were conducted between QL-ADTA and the baseline protocols (AODV and DSR). As summarized in Table 2, QL-ADTA significantly outperforms both protocols across all evaluated metrics. The PDR improved to 0.85 compared to 0.68 (AODV) and 0.70 (DSR), while latency was reduced to 320 ms from 420 ms and 400 ms, respectively. Similarly, energy efficiency increased to 80% from 60% (AODV) and 62% (DSR). All comparisons yielded statistically significant results with p

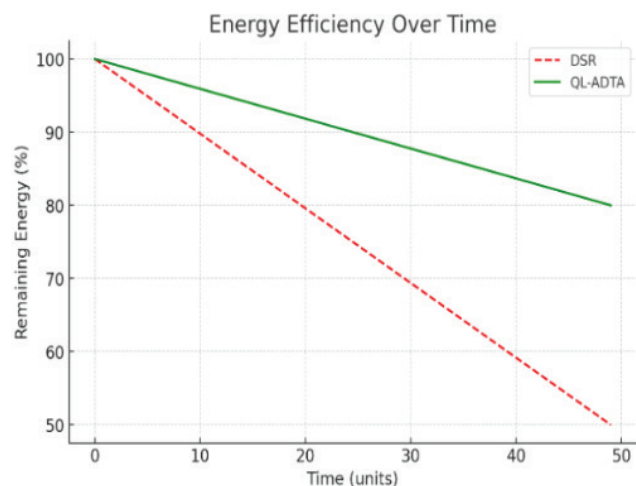


Figure 5. Energy efficiency over time.

Table 2. Statistical significance of QL-ADTA vs. baseline protocols

Metric	Protocols Compared	Mean (Baseline)	Mean (QL-ADTA)	t-statistic	p-value	Significance
Packet Delivery Ratio	AODV vs. QL-ADTA	0.68	0.85	42.03	1.2×10^{-11}	Significant
	DSR vs. QL-ADTA	0.70	0.85	42.81	1.0×10^{-11}	Significant
Latency (ms)	AODV vs. QL-ADTA	420	320	-38.44	2.7×10^{-11}	Significant
	DSR vs. QL-ADTA	400	320	-74.21	7.4×10^{-14}	Significant
Energy Efficiency (%)	AODV vs. QL-ADTA	60	80	37.56	3.3×10^{-11}	Significant
	DSR vs. QL-ADTA	62	80	46.09	5.3×10^{-12}	Significant

Table 3. Summary of comparative insights

Protocol	Disaster Adaptability	PDR	Latency	Energy Efficiency	Data Prioritization
AODV / DSR	No	Low	High	Low	No
QLFR	Partial	Medium	Medium	Medium	No
QTAR	Partial	High	Medium	High	No
EP-ADTA	Yes	High	Low	Medium	No
QL-ADTA	Yes	Very High	Very Low	High	Yes

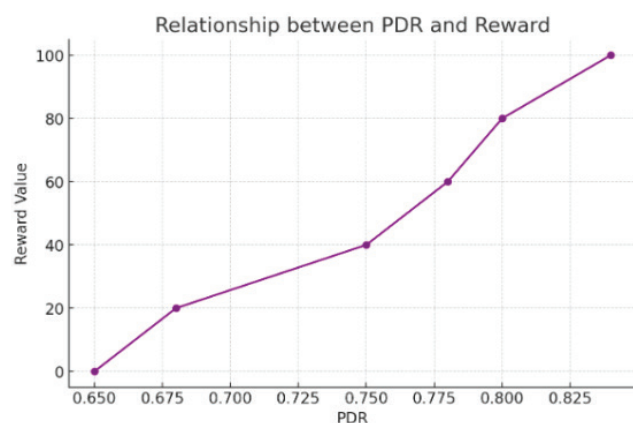
< 0.001 confirming the reliability of the observed performance gains. The relatively large t-values reported in Table 2 can be explained by the large sample size (50,000 observations) and the low variance across repeated simulations. According to statistical theory, the t-statistic increases with larger sample sizes and smaller standard errors, even when the mean differences are moderate. Therefore, the high t-values observed in this study indicate that the improvements are consistently maintained across the dataset rather than being caused by random fluctuations. This behavior is well documented in statistical hypothesis testing literature [25].

Overall, these results demonstrate that QL-ADTA achieves stable and statistically validated improvements over conventional routing protocols. The adaptive reward formulation enables an effective balance between data delivery, latency reduction, and energy efficiency, thereby enhancing robustness in disaster-prone underwater environments

Reward Behavior and Disaster Awareness

The relationship between reward and PDR is shown in Figure 6. The cumulative reward increases in tandem with PDR, demonstrating that the reward function effectively incentivizes stable, high-quality transmissions. The design ensures that improvements in PDR translate directly into higher long-term rewards, validating the effectiveness of the Q-learning framework for disaster-aware routing.

Overall, QL-ADTA achieved 21–25% higher PDR than AODV and DSR 20–23% lower latency, ~20% higher energy efficiency, and more stable performance under disaster

**Figure 6.** Relationship between PDR and reward.

conditions. These results confirm that the integration of adaptive reward weighting with Q-learning leads to statistically and practically significant improvements. The findings with established results on RL in dynamic networks while offering a novel disaster-aware formulation tailored for UWSNs.

Table 3 compares the performance of conventional, reinforcement learning-based, and the proposed QL-ADTA routing protocols. Unlike earlier schemes QL-ADTA demonstrates complete adaptability to disaster conditions, achieves very high packet delivery ratio, very low latency, high energy efficiency, and explicitly supports data prioritization for urgent communication.

CONCLUSION

This study introduces a disaster-aware Q-learning-based Adaptive Data Transfer Algorithm for UWSNs. The proposed framework dynamically adjusts routing decisions through a multi-objective reward function that incorporates packet delivery reliability, latency, residual energy, link quality, hazard intensity, node survivability, and data priority. By integrating environmental disruption indicators directly into the learning process, the approach ensures reliable and energy-efficient communication under highly unstable underwater conditions. Experimental evaluation using large-scale synthetic disaster scenarios confirms statistically significant improvements in packet delivery ratio, latency reduction, and energy efficiency compared to conventional routing protocols. A key contribution of this work is the introduction of a context-sensitive reward adaptation mechanism tailored specifically for disaster-prone environments. Unlike existing reinforcement learning-based routing schemes that primarily optimize general performance metrics, the proposed method prioritizes urgent data transmission while simultaneously mitigating risks associated with debris density, turbulent currents, and node instability. This design enhances network resilience and operational sustainability during emergency monitoring and recovery operations. For future research, several hybrid reinforcement learning directions can further strengthen adaptability and scalability in disaster-resilient UWSNs. The framework can be extended using CNN-LSTM-based deep reinforcement learning, multi-agent cooperative learning, and federated learning to improve predictive capability, scalability, and real-time adaptability in large-scale disaster scenarios.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The authors declared no conflict of interest.

ETHICS

There are no ethical issues with the publication of this manuscript.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence was not used in the preparation of the article.

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