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PERFORMANCE ANALYSIS OF UNDERWATER WIRELESS SENSOR NETWORKS USING REINFORCEMENT LEARNING

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ABSTRACT

This article presents a novel routing protocol named DROR, specifically tailored for underwater wireless sensor networks (UWSNs) to tackle the challenge of void regions. DROR integrates Reinforcement Learning (RL) and Opportunistic Routing (OR) in a recipient-oriented approach, considering the energy limitations and the unique underwater setting. It incorporates a mechanism for void rehabilitation, allowing packets to circumvent void nodes and maintain continuous moving for dependable transmission. Furthermore, a dynamic scheduling strategy based on relative Q-values ensures proficient packet forwarding along the most efficient routing path. Simulation outcomes illustrate the efficacy of the suggested protocol concerning delay, PDR, and energy tax in UWSNs with varying Range, Depths, Packet sizes, and moving radius.

Keywords: underwater wireless sensor networks, relative distance-based forwarding protocol, Q-values.

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1. INTRODUCTION

Water covers around 71 % of the Earth's surface, emphasizing the crucial role of underwater communication systems for transmitting data through aquatic environments. UWSNs have become indispensable for a wide array of applications, including oceanic exploration, environmental monitoring, and surveillance beneath the waves. However, devising efficient communication protocols for UWSNs poses considerable challenges due to the harsh underwater conditions, constrained energy reservoirs, and the dynamic nature of underwater settings. Conventional wireless communication methods prove inadequate in such environments, necessitating innovative solutions tailored to their unique characteristics. In this context, the integration of advanced technologies like reinforcement learning and opportunistic routing offers promising avenues for enhancing communication performance and dependability in UWSNs. In UWSNs, the task of replacing batteries is exceptionally challenging due to the submerged and often remote locations of the nodes. Therefore, it is imperative to utilize battery energy efficiently to prolong the lifespan of the network. Overutilization of battery power can lead to premature depletion, resulting in the failure of network nodes. Given the difficulty in deploying nodes in underwater environments, there tends to be a sparse distribution of nodes. Consequently, if nodes fail due to energy depletion, the network's ability to forward packets through multi-hop communication may be compromised. This situation exacerbates the formation of void regions, where data transmission becomes unreliable or impossible due to the lack of functioning nodes. Thus, optimizing energy usage in underwater sensor networks is critical not only for prolonging network lifespan but also for ensuring effective communication by mitigating the risk of void regions and maintaining multi-hop connectivity.

In this paper, we propose a modified RL-based routing protocol using depth information (MDROR). Opportunistic routing plays a crucial role in DROR by providing multiple potential routes from the origin to the destination, ensuring reliable packet delivery. Meanwhile, reinforcement learning empowers nodes to adapt and optimize their routing decisions based on interactions with the underwater environment.

In DROR, each receiver node constructs a candidate forwarding set and evaluates its eligibility based on cumulative rewards calculated through reinforcement learning. This process determines whether the receiver node is qualified to receive packets from the sender, thus ensuring efficient and reliable transmission in UWSNS.

To avert packet loss in void regions, we have incorporated a void recovery mechanism (VRM) within the protocol. This mechanism enables packets to avoid or escape from void nodes encountered during transmission. By doing so, we ensure that packets do not become trapped in areas where communication is unreliable or impossible, thereby preserving the integrity and efficiency of data transmission in the network.

2. RELATED WORK

In this section, our focus is primarily on reviewing the existing literature concerning routing protocols designed specifically for UWSNs. Routing protocols for UWSNs play a pivotal role in ensuring network connectivity, dependable transmission, and energy efficiency. Numerous different strategies have been put forth to overcome the difficulties presented by the submerged environment, which include variable network topology, high propagation delay, and bandwidth constraints.

To give UWSNs dependable and timesaving routing, the EEGNBR protocol presents a localization-free routing technique. EEGNBR maximizes energy efficiency

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and pdr by utilizing a distance-vector mechanism and creating a directing network to decrease network latency and a concurrent working mechanism to minimize forwarding latency.

In the realm of RL based routing, the RL-Based Routing Protocol for UWNs presents a promising approach to adaptively route data in UWSNs. RL algorithms enable nodes to learn and select appropriate relay nodes without prior knowledge of the network infrastructure. While RL-based protocols offer flexibility and adaptability to dynamic underwater environments, research challenges and future directions remain to be addressed [2].

Similarly, the QELAR [3] protocol introduces a Machine Learning based adaptive routing algorithm aimed at extending the lifetime of UWSNs. By considering remaining energy distribution and optimizing routing decisions based on reinforcement learning, QELAR achieves significant improvements in network lifetime and energy efficiency compared to existing protocols.

The QLACO [4] protocol addresses energy efficiency and link instability issues in UWSNs by combining reinforcement learning with an ant colony routing approach. By utilizing a reward function and anti-void mechanism, QLACO enhances pdr and energy consumption efficiency, demonstrating superior performance over existing routing protocols.

Additionally, a cooperative routing strategy [5] using Q-learning to optimize forwarding actions based on received incentives is proposed in the Cooperative Routing Protocol Based on Q-Learning for Underwater Optical-Acoustic Hybrid Wireless Sensor Networks. In terms of packet loss rate, longevity, energy efficiency, network connectivity rate, and latency, this protocol performs better than state of-the-art underwater routing algorithms.

The energy efficient guiding network based routing [6] for UWSNs, introduces a novel approach to routing by leveraging a localization-free scheme. By establishing a directing network and employing a simultaneous operation mechanism, this protocol reduces forwarding delay and improves energy efficiency, making it suitable for intermittent connectivity applications.

In contrast, the Reinforcement Learning-Based Routing Protocol for UWSNs explores the use of reinforcement learning algorithms to adaptively route data in dynamic underwater environments. By learning from interactions with the environment, RL-based protocols enable nodes to make informed routing decisions without prior knowledge of the network infrastructure, thus improving adaptability and overall network performance.

Periodic beaconing is used by the GCORP Protocol [7] to distribute location and energy information among nodes, making it possible to choose the best relay nodes for data forwarding.

Similarly, the Relative Distance-Based Forwarding Protocol (RDBF) [8] employs a fitness factor to restrict the pool of potential forwarders, ensuring the selection of suitable relays for packet transmission based on appropriateness.

The GEDAR Protocol [9] leverages node positions to greedily forward packets and employs a Depth adjustment related topology control algorithm to maintain network connectivity.

In contrast, the Vector-Based Routing Protocol [10] dynamically adjusts pipe radius based on network dimensions, range, and node count to manage energy consumption effectively.

3. METHODOLOGY

A. Network Scenario

The underwater sensor network architecture is shown in Figure-1.

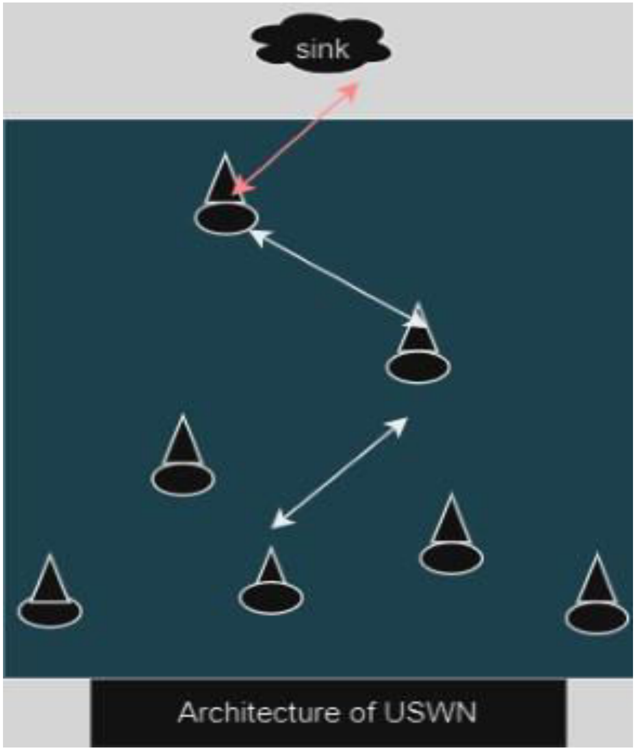

Figure-1. Architecture of UWSN.

We envision a multihop UWSN comprising several sensor nodes and a central hub. These sensor nodes come equipped with pressure gauges, acoustic modems, and various Sensors. They are placed underwater at varying depths, securely fastened to the seabed, and assigned the duty of data collection. Meanwhile, the central hub equipped with both acoustic and radio frequency modems, is located at the surface of the water to gather and streamline the sensory data for forwarding.

Each node possesses a distinct identifier and can ascertain its depth using a pressure sensor. All sensor nodes have identical forwarding radii and restricted initial energy resources, while the central hub benefits from inexhaustible energy reserves. Given the finite transmission range of sensor nodes and the suitability of acoustic waves for Underwater Communication, sensory data are relayed to the central hub in a step-by-step manner, utilizing the acoustic channel. Subsequently, the sink relays this data to onshore facilities via a radio channel.

In addition, because of the complicated underwater environment and the impact of water currents, irregular mobility, and sporadic link disconnections cause changes in the network architecture.

B. Packet Delivery Probability Model

Packet delivery probability is a statistic we use to evaluate nodes' successful transmission within a single hop. Bit number n, signal frequency Fr, and forwarding distance (a) an are examples of characteristics that may be used to describe the Probability (Pb). This probability is formulated as follows:

$$Pb(a,n,Fr) = (1 - P_r(a,Fr))^n \qquad (1)$$

Where $P_r(a,Fr)$ is the bit error probability and is calculated as

$$p_b(a,f) = \int_0^{\infty} p_e(y) f_{SNR}(a,f,y)\,dy \qquad (2)$$

Where $p_e(y)$ is the likelihood of an error when the selected modulation scheme's average signal-tonoise ratio is y. The function $f_{SNR}(a,f,y)$ denotes the probability density given specific parameters a, f, and y, which may differ based on the selected fading models.

The Signal to Noise ratio at the receiver is modeled by taking into consideration both path loss gain and losses as shown below:

$$S.N.R = \frac{Eb_n}{P.L(a,Fr)\cdot N_0} \qquad (3)$$

Where Eb_n stands for the energy required for each piece of transmission, $P.L(a,Fr)$ shows Path Loss for frequency Fr and distance a and N_0 shows the noise power density in the context of a white Gaussian additive noise channel.
One way to formulate the path loss is as

$$P.L(a,Fr) = (a^k)\cdot \alpha(Fr)^a \qquad (4)$$

Where k∈[1,2] represents the spreading loss factor which relates to the geometry of propagation, while $\alpha(Fr)$ denotes the absorption coefficient which can be formulated as:

$$10\log\alpha(Fr) = 0.16\times\frac{Fr^2}{1+Fr^2} + 43\times\frac{Fr^2}{4111+Fr^2} + 3\times10^{-5}Fr^2 + 0.004 \qquad (5)$$

C. Reinforcement Learning Based Framework

RL offers a decision-making framework devoid of the necessity for prior knowledge, achieving the global optimal policy through continual interaction. Given that nodes within distributed networks typically possess localized and restricted information, RL facilitates learning from the surroundings to increase overall objectives, rendering it particularly apt for underwater routing to determine optimal paths. Given the widespread utilization of Q-learning as a value-based and prominent R.L method in addressing routing issues, we establish the routing framework for UWSNs under an RLbased system model. The pertinent definitions of *St, Ac, Pr, Rw* within the Markov decision processes model are elaborated as shown below:

- **STATE:** we establish St={St_1,St_2,St_3,....} to denote the state, where St_i signifies that the packet is on node i. The status changes from St_i to St_j when the packet is relayed from node I to node J.
- **Action:** We designate the action as Ac={ Ac_1,Ac_2,Ac_3,....} and the selection of node i as relay node is represented asAc_i.
- **Transition probability:** we denote transition probability as the likelihood that node i will complete action Ac_j from state St_i to St_j. The chance of a failed transition is described as

$$Pb_{St_iSt_j}^{\ \ Ac_j} = 1 - Pb_{St_iSt_j}^{\ \ Ac_j}$$

- **Reward:** The immediate benefit received by node i upon taking action aj to transition from state si to state sj is referred to as a reward $Rw_{Ac_{ij}}^{St_iSt_j}$. The relay node selection process is directly impacted by the reward function design, which is dependent on network needs.

By leveraging environmental feedback, RL empowers UWSN to choose the node with the greatest state value SV as the optimal node for packet forwarding from the outset, achieving the global optimum policy by using environmental input. The Q-value is used in Q-learning to evaluate an action's efficacy in a certain condition. For a given state-action pair, it is formulated as shown below:

Qπ(Sti,Acj) = dri(Acj) + γ PSj∈St(PbAcStijStj · SV π(Stj)) (6)

Here, the value of the joint consideration comprises the Direct Reward, denoted by the former term, and the Discounted Long Term reward, represented by the later term. The discount Factor γ $(0 \le \gamma < 1)$ is employed to regulate the influence of the Long Term Reward on decisionmaking. The direct reward function is formulated as:

$$dr_i(Ac_j) = \sum_{S_j\in St}(Pb_{St_iSt_j}^{Ac_j}\cdot Rw_{St_iSt_j}^{Ac_j}) \qquad (7)$$

The Bellman optimality equation formulates the Optimal Q-value as

Q(Sti,Acj) = dri(Acj) + γ PSj∈St(PbAcStijStj·
$SV\,(St_j)$) (8)

$$SV\,(St_j) = \max_{Ac} Q^{*}(St_j, Ac) \quad (9)$$

D. DROR

MDROR blends RL and OR inside an M-DBR protocol, taking into account the dynamic nature of the topology owing to limited energy and the underwater environment. This integration preserves the energy economy while guaranteeing data transfer performance in real-time. Decentralized routing choices are made at the receiver end in DROR. Nodes analyze information from the packet header when they receive a packet and decide whether to add themselves to the candidate forwarding set depending on predetermined standards. The RL-based paradigm states that a node is more likely to forward packets if it has a higher Q-value in the CFS. To address situations where packets get stuck in void regions, a void recovery mechanism is activated, enabling packets to circumvent these regions and continue toward the sink. To further maximize energy-efficient packet transmission, DROR incorporates a multipath suppression system and a dynamic holding time mechanism. The following details are included in the packet header and are relevant to routing:

a) **Packet identifier:** The distinct I.D is its Identifier.

b) **Source node I.D:** The unique node I.D assigned to the source.

c) **Sender node I.D:** The unique node I.D assigned to the sender.

d) **Remaining energy:** The current node's remaining energy data.

e) **Depth:** The current node's depth data.

f) **Q:** The sender's and the current node's Q value in the state-action pair. vii) SV: The current node's SV value.

g) **Q-last:** The Q-Value of the sender's ideal optimal node during the most recent transmission. ix) recovflag: recovflag: The permitted forwarding direction of a packet may be determined by using this information, which is either zero or one, and is used in the void recovery process.

The structure of the packet header is shown in Figure-2.

E. Selection of Candidate Forwording Set

To determine the candidate forwarding set, we utilize the depth values of nodes as input. Initially, we gather the depth information of neighboring nodes for the node under consideration. If the recovery flag is zero, indicating that the node is not in a void space, we proceed with our algorithm. However, if the recovery flag is 1, indicating that the node is in a void space, we initiate the void recovery mechanism.

Subsequently, if the recovery flag is neither zero nor one, we calculate the difference between the depth of our node and its neighboring nodes. If the depth difference is less than zero, signifying that the neighboring node is at a shallower depth or closer to the surface compared to our node, we include that node in the CFS. This process is repeated for all neighboring nodes, thereby determining the potential candidates for forwarding. Once we have our candidate forwarding set we move forward to a selection of optimal node.

Below is the algorithm for selecting the Candidate forwarding set.

F. Selection of Relay Node

To increase the dependability of UWSNs, DROR uses OR to choose optimal nodes from the CFS, which is made up of a portion of the sender's nearby nodes. Because it directly influences the choice of relay node and protocol performance, the CFS selection is thus very crucial in DROR. The receiver, not the sender, decides the suggested protocol, and the receiver is shallower than the sender's. Because the design considers the sink's objective location, it makes it possible.

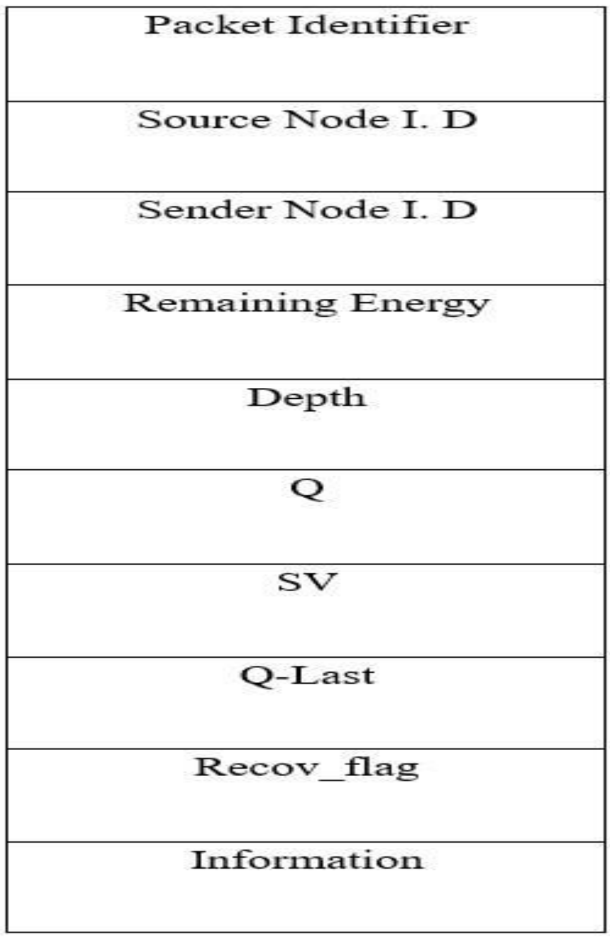

Figure-2. Packet Header.

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For us to understand the global transmission direction and minimize energy waste from pointless transmission. Data might be sent first in the OR by the best node in the CFS. However, owing to a lack of learning capability, this strategy may cause data transmission to follow a local optimum routing route rather than the global optimal one. RL gives networks the capacity to learn, remember, and adapt to changes in their surroundings. To choose the best relay node, we thus include Q-learning into OR in this journal.

Algorithm 1: The Selection of Candidate

```
for each neighbour node of node k denoted by node l do
  Extract depth and recov_flag of node l from packet
  if recov_flag=0 then
    if d(l) − d(k) < 0 then
        CS(k)=CS(k)∩ l
    end if
  end if
end for
if CS(k)! = ∅ then
  Switch to Algorithm 2
else
  Switch to Algorithm 3
end if
```

The reward function is used in the RL framework to transfer tasks' global goals into a Q-learning model, and it is essential to obtaining the best possible solution to an optimization issue. To achieve low end-to-end latency, energy efficiency, and reliability for UWSNs, we formulate reward function as

$$R_{s_i s_j}{}^{a_j} = -g - w*(E_i + E_j) - (1-w)*\left|recov\_flag - D_{ji}\right| - c*coid\_flag$$

Where g denotes a constant cost parameter that's used to describe how much energy and bandwidth are used during packet delivery. Functions about depth and remaining energy are represented by DE_{ji} and RE_i, respectively The weight coefficient w, constrained within the range of (0,1), facilitates a trade-off between remaining energy and depth considerations. The void flag serves as a local indicator distinguishing void nodes, while C denotes a penalty coefficient regulating the penalty associated with selecting void nodes.

By integrating remaining energy into the Reward function, UWSNs prioritize nodes with higher residual energy for forwarding, mitigating premature node depletion and extending network lifetime. Incorporating Depth into the reward function encourages UWSNs to choose nodes with significant depth differences for forwarding, thereby reducing jump count, energy use, and latency.

The parameter recovflag - DEji guides packet transmission. When recovflag=1, indicating packet transmission from a void node requiring void region bypassing, recovflag - Dji= 1- Dji. This prompts void recovery mechanism activation, with preference given to nodes with minimal depth differences from the void node, yielding higher immediate rewards with larger 1 - Dji values. Conversely, when recovflag=0, allowing upward packet transmission to the sink, recovflag- Dji= Dji. Nodes with significant depth differences from the sender are preferred, yielding higher rewards with larger Dji values. This utilization of recovflag - Dji facilitates more efficient and reliable packet forwarding.

Additionally, a penalty term C * voidflag is introduced for void nodes to deter them from packet forwarding. Voidflag serves as a local indicator, with nodes setting it to 1 when they have not overheard packets forwarded from shallower neighbor nodes for a period, signifying void node status. Conversely, void nodes reset voidflag to 0 upon overhearing packets from shallower neighbors. Nodes with voidflag = 1 are penalized and prevented from forwarding packets, reducing end-to-end latency and energy use by ensuring the selection of non-void nodes for packet forwarding. In our protocol, nodes determine candidacy for packet forwarding based on Algorithm 1 upon packet reception. If deemed a candidate, nodes calculate the Q value using equations discussed before and set the holding time. Otherwise, nodes discard the packet. Packet data is updated with local information, and nodes forward packets upon the expiry of the holding time. Upon packet reception, the sink discontinues forwarding and broadcasts information to neighbor nodes, as depicted in algorithm 2.

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Algorithm 2: Choosing Relay node

```
for each node k ∈CS(l) do
  Calculate Q value using Eq. (6)
  Set Thold
end for
Start timing for the timer
for each node k ∈CS(l) do
  if Time< Thold (k) then
    Wait
  else
    Switch to Algorithm 4
  end if
if the packet is not delivered to the Sink then
  k = l
  Switch to Algorithm 1
else
  The sink broadcasts to inform it's neighbours
end if
end for
```

G. Void Recovery Mechanism

During data transmission, the remaining energy and Packet Delivery Ratio (PDR) of UWSNs decrease when packets encounter void regions, leading to dropped packets. To address this issue, a void recovery mechanism is devised to facilitate packet bypassing of void nodes and forwarding to the sink. This mechanism leverages the voidflag at nodes and the recovflag in packet headers to navigate void zones. Initially, when a node, say k, has a packet to send, both the voidflag and recovflag are set to 0, and the packet is broadcasted. If the packet remains unheard even after some time, node k identifies itself as a void node and sets both voidflag and recovflag to 1 before rebroadcasting the packet. Upon packet reception, nodes extract the recovflag. If recovflag = 0, nodes engage in candidate forwarding set selection per Algorithm 1.

Conversely, if recovflag = 1, indicating that the node is in a void state and triggering the VRM, nodes not included in the sender's CFS are allowed to transmit packets. These nodes then select relay nodes using algorithm 2. The illustration of packet transmission in void regions is depicted in Figure-3.

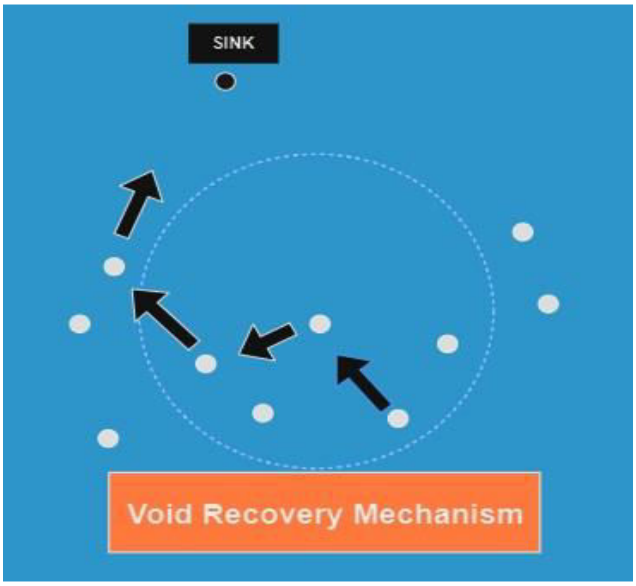

Figure-3. Diagram of the recovery mechanism for void spaces.

H. Redundant Packet Suppression Mechanism

In underwater wireless sensor networks ($UWSN$), nodes often have multiple neighbors, leading to redundant packet transmissions that can significantly increase energy use and end-to-end latency. Given the limited energy resources in UWSNs, it's crucial to minimize unnecessary transmissions. To address this, we propose a mechanism to suppress redundant packet transmissions by leveraging node overhearing and packet ID recording.

When a node sends out a packet with a recovflag set to 0, neighboring nodes will reject the packet if they overhear it during the holding period. Alternatively, after the holding period has passed, they will send the package. Additionally, every node maintains a record of the IDs of the packets it has sent to stop nodes from continuously sending the same packet and wasting energy. Nodes initially verify the ID when they receive a packet to see whether they have previously forwarded it. This approach efficiently reduces redundant transmissions in both sender and receiver nodes, enhancing energy and transmission efficiency in UWSNs. Additionally, it facilitates the efficient forwarding of packets trapped in void zones to the sink.

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Algorithm 3: Void Recovery Mechanism

```
if CS(k)=∅ then
   void_flag(k)=1
   Node k calculates V value
   recov_flag=1
   Node k updates local information into the
   packet and forward
   for each neighbour of node k denoted by node l do
        Extract recov_flag in the packet
        if recov_flag=1 then
           CS(k)=CS(k)∪l
        end if
    end for
Switch to Algorithm 2
end if
```

Algorithm 4: Packet de-duplication system

```
for node k do
   extract the recov_flag and ID of the packet
   if packet ID∈ SID(k) then
     if recov_flag=1 then
        node k updates and forwards the packet
     else
     node k drops the packet
     end if
  else
     node k updates and forwards the packet
  end if
end for
```

4. PERFORMANCE COMPARISON

We assess the DROR protocol's performance in this section. To illustrate DROR's good performance; we compare it with three additional routing protocols: EBER2, QBOR, and QLFR. In conclusion, we showcase the parameter analysis to demonstrate the impact of various factors on the suggested approach.

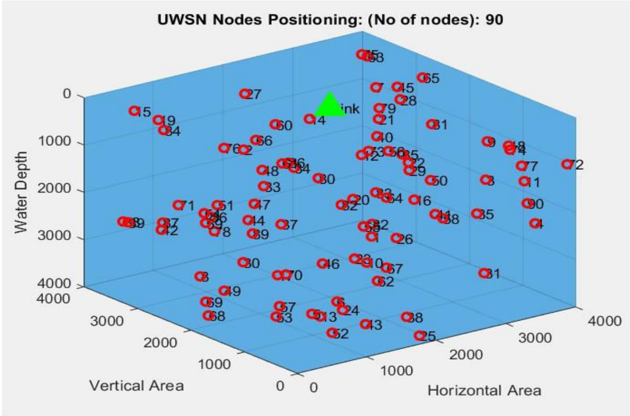

Figure-4. Deployment of nodes.

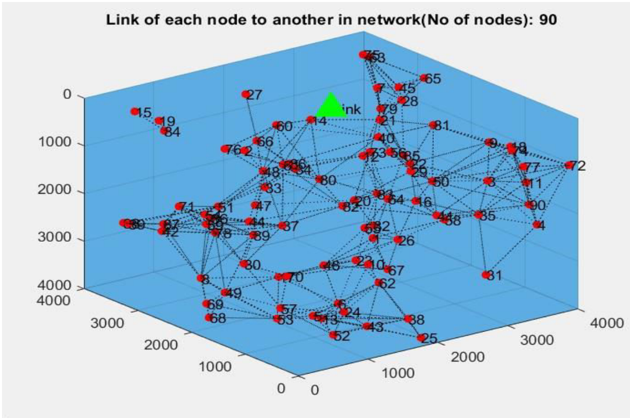

Figure-5. Communication links between Nodes.

5. PERFORMANCE ASSESSMENT

In this section, we will compare our protocol with different parameters such as communication range, moving radii, packet size, and depths. First let's see the performance of our protocol with different ranges such as R=900m, R=1000m and R=1100m. In Fig [9] we can observe that as the communication range increases, there is a gradual decrease in the latency of communication. This reduction occurs because the larger communication range results in fewer hops to reach the sink, thereby reducing both transmission and processing latency at relay nodes. Additionally, a larger communication range encompasses more nodes, providing a greater selection of suitable relay nodes. Furthermore, transitioning from limited to hefty node deployment introduces better relay nodes for packet forwarding, contributing to further reductions in latency.

In Figure-10 we can observe that the progressive expansion of the communication range leads to a gradual increase in the PDR. This phenomenon occurs because the enlarged communication range encompasses more neighbor nodes capable of forwarding packets from the sender. Consequently, the broader routing path enhances dependability during the transfer. With the proliferation of deployed nodes, a greater number of eligible nodes can participate in packet forwarding, further contributing to the improved PDR. Moreover, as the number of void

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regions diminishes with the increasing node deployment, the PDR experiences additional enhancements.

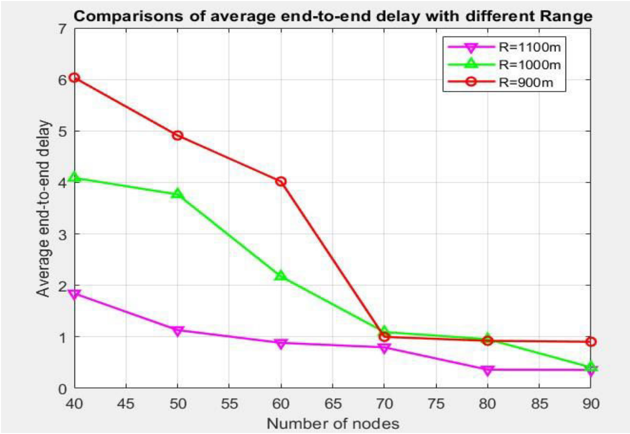

Figure-6. Comparative assessment of average end-to-end delay across different ranges.

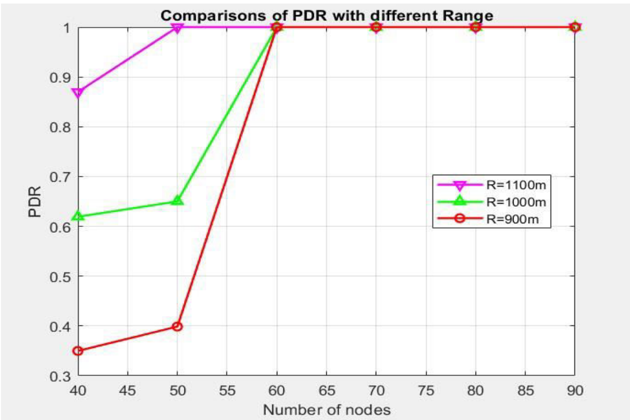

Figure-7. Comparative assessment of PDR across different communication ranges.

In Figure-11 we can observe that the energy expenditure associated with increasing the communication range exhibits a gradual increase. This trend arises due to the expanding communication range, which results in a reduction in the count of hops required from the source node to the sink. Consequently, there is a decrease in the number of packets forwarded and the corresponding energy consumption for transmission. However, as the number of nodes increases, more eligible nodes become involved in packet forwarding, resulting in increased energy use for packet transmission and reception.

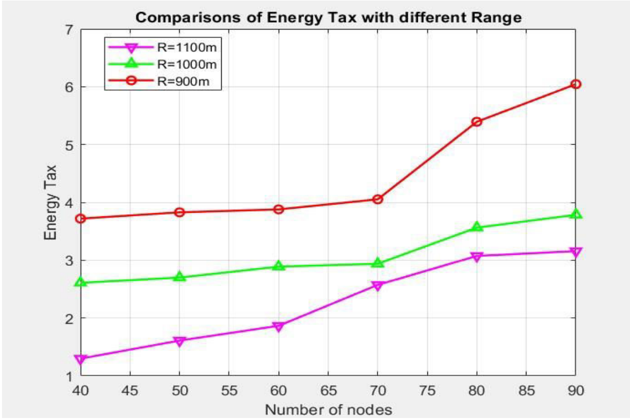

Figure-8. Comparative assessment of energy tax across different communication ranges.

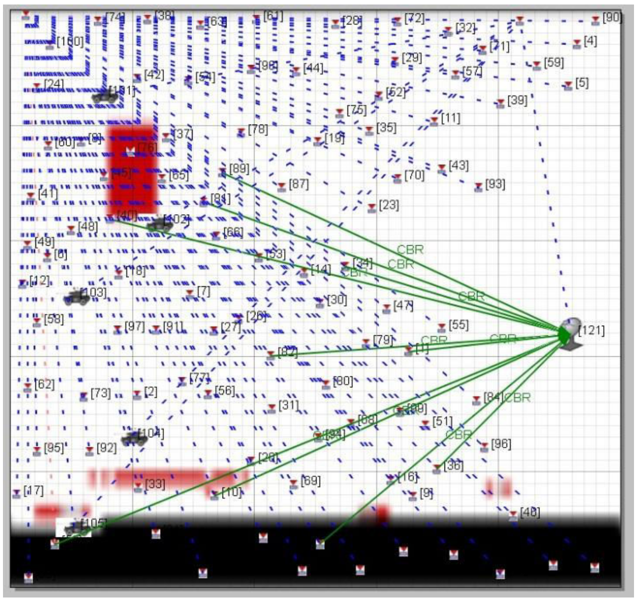

Figure-9. System configuration.

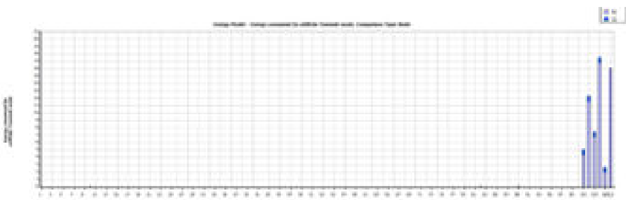

Figure-10. Energy consumed (in mWh) in transmit mode, comparison type: Node

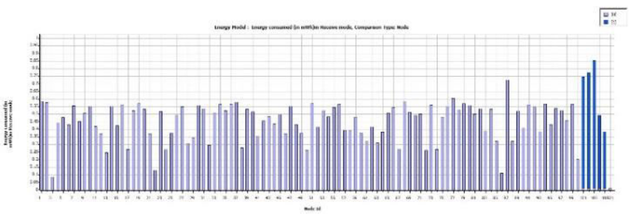

Figure-11. Energy consumed (in mWh) in receiver mode, comparison type: Node.

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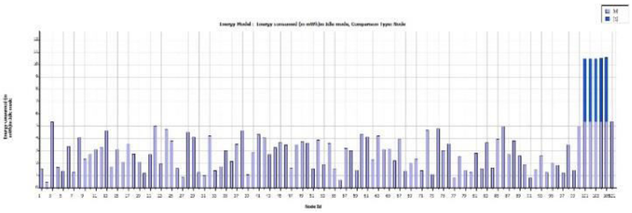

Figure-12. Energy consumed (in mWh) in idle mode, comparison type: Node.

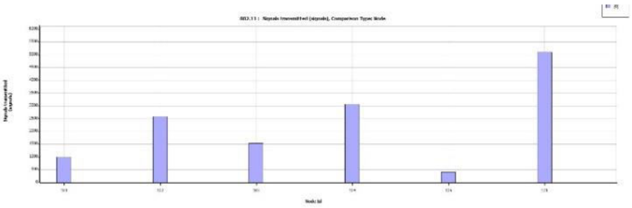

Figure-13. Signals Transmitted, comparison type: Node

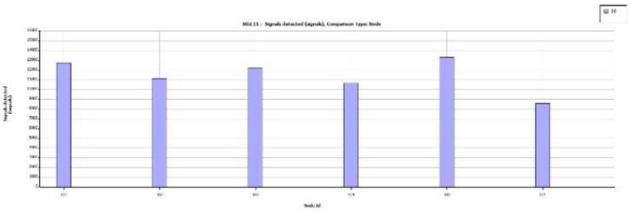

Figure-14. Signals detected, comparison type: Node

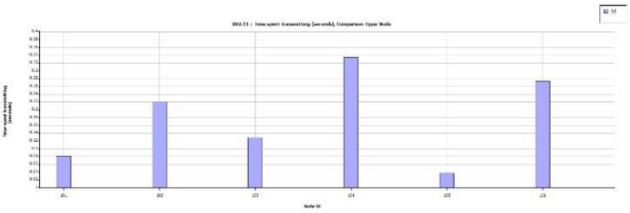

Figure-15. Time spent transmitting, comparison type: Node

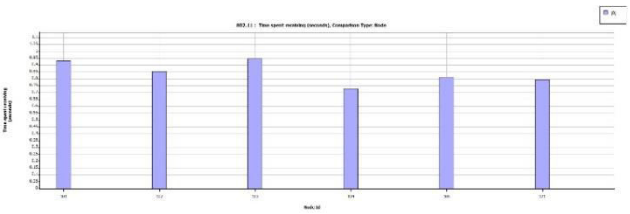

Figure-16. Time spent receiving, comparison type: Node

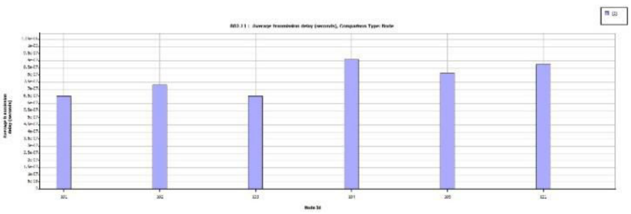

Figure-17. Average transmission delay (seconds), comparison type: Node

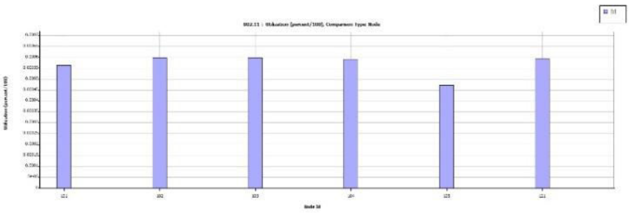

Figure-18. Utilization (percentage/100), comparison type: Node

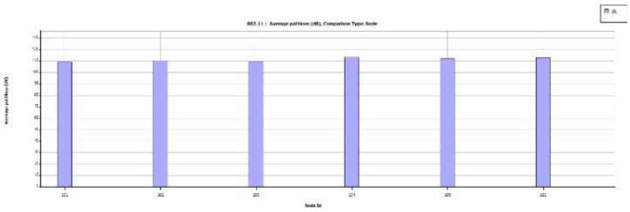

Figure-19. Average Path loss (dB), comparison type: Node

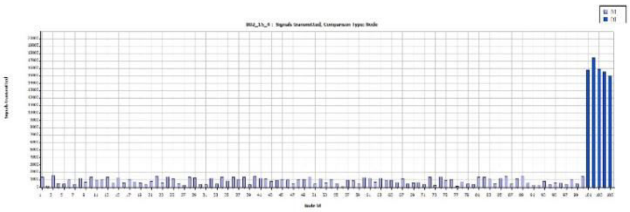

Figure-20. Signals transmitted, comparison type: Node

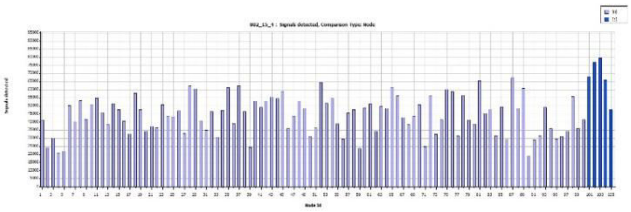

Figure-21. Signals detected, comparison type: Node

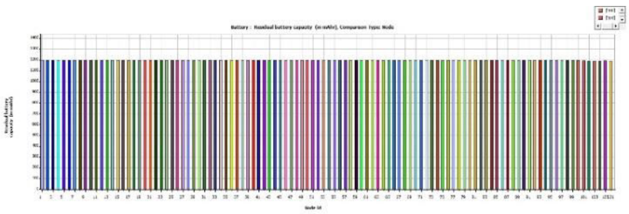

Figure-22. Residual Battery capacity (in mAhr), comparison type: Node

6. CONCLUSIONS

This paper introduces an Opportunistic Routing (OR) protocol for $USWNs$, leveraging Reinforcement Learning (RL) techniques and depth information to address void regions efficiently. The proposed protocol establishes an RL-based framework, combining RL for optimal routing path selection and OR for reliable data delivery. It takes into account depth, remaining energy, and void nodes to ensure swift and energy-efficient data transfer. Furthermore, a void recovery mechanism is devised to steer packets away from void nodes during transmission, thereby enhancing Packet Delivery Ratio (PDR). Additionally, to mitigate end-to-end delay and enhance network reliability, a dynamic scheduling strategy based on relative Q-values is introduced. Simulation outcomes demonstrate the protocol's effectiveness in improving latency, PDR, and energy efficiency in UWSNs.

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