DRIFT: Mobility-Aware Delay-tolerant Routing using Intermittent Forwarding Topologies in Deep-Water Acoustic Networks

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Abstract. Deep-water Underwater Wireless Multimedia Sensor Networks (UWMSNs) are one of the important technologies for marine surveillance, oceanographic monitoring, and the exploration of seabed resources. However, due to path loss, long propagation delays, limited acoustic bandwidth, and early energy exhaustion in relay nodes, it is difficult to transmit bandwidth-intensive multimedia data through deep-water acoustic environments. To overcome these drawbacks, this work presents a dynamic residual-energy and information-density-based forwarding scheme, named DRIFT. It is an opportunistic, receiver-based routing protocol designed for three-dimensional deep-water UWMSNs. The three tiers include seabed multimedia source nodes, multi-tiered intermediate relays, and several surface gateway sinks. DRIFT dynamically selects its next-hop forwarding nodes using a multi-factor fitness function that accounts for vertical depth from the surface sinks, residual energy, buffer queue, and the receiver's Signal-to-Noise Ratio (SNR). To avoid routing hotspots and channel congestion without adding control packets, it uses an adaptive holding-time timer mechanism. This mechanism enables nodes with high fitness values to forward packets first while preventing duplicate transmissions by neighboring candidate nodes. The system is modeled using realistic underwater acoustic propagation parameters, including Thorp's absorption formula, spherical-wave spreading, and the various components of ambient noise. Through simulation, we observe that DRIFT successfully reduces packet drop rates, balances energy consumption across relay tiers, and decreases queueing latency. Compared with existing underwater routing protocols, DRIFT achieves a 21.9% higher Packet Delivery Ratio (PDR), a 50% reduction in end-to-end delay, and a 31.58% increase in total network lifetime, thus providing a reliable and scalable solution for high-throughput underwater multimedia communication.

Keywords: Underwater Wireless Multimedia Sensor Networks (UWMSNs) · Delay-Tolerant Networking (DTN) · Evolutionary Game Theory · Replicator Dynamics · Deep-Water Acoustic Propagation · Store-Carry-Forward Routing.

1 Introduction

Underwater Wireless Multimedia Sensor Networks (UWMSNs)are envisioned to enable bandwidth-intensive ocean monitoring, coastal surveillance, and environmental data collection. Unlike conventional scalar Underwater Wireless Sensor Networks (UWSNs), which transmit small amounts of telemetry data, UWMSNs can process and forward rich multimedia content, including underwater images and acoustic video streams. There are difficulties in transporting multimedia traffic over acoustic channels due to low bandwidth, high signal propagation delays, multipath fading, the dynamic mobility of nodes, and the rapid depletion of underwater nodes' batteries.

Dynamic topology control is a fundamental approach to managing energy use and maintaining link quality in acoustic environments. Misra *et al.* [7] proposed DATUM, a dynamic topology management approach based on cooperative game theory, aimed at multi-layered UWSNs. They studied that it increases network throughput and prolongs network lifetime by finding stable multi-hop routing paths from seabed source nodes to surface buoys and by adaptively adjusting nodes' transmission power levels. Although DATUM achieves considerable reductions in both delay and energy consumption when compared to non-cooperative baseline schemes, the effectiveness of its operation depends on two main assumptions — (1) the presence of continuous and end-to-end multi-hop routes spanning the various layers, and (2) a topological structure for shallow water acoustic networks.

In the case of sparse deep-water installations, it is often physically impossible to maintain end-to-end acoustic links. The propagation of sound in deep water is mainly due to spherical spreading loss and frequency-dependent medium absorption, as described by Thorp's attenuation model [11]. If horizontal deep-ocean currents cause the nodes to move beyond their critical transmission range, the need for continuous multi-hop connectivity exhausts the nodes' energy. In such circumstances, we envision that a Delay-Tolerant Networking (DTN) store-carry-forward approach can improve the network performance. Nodes can use their passive horizontal drift through the ocean as their primary means of transport, carrying large multimedia packets closer to upstream relays or destinations before performing high-power acoustic transmissions. Hence, there is a need for developing a mobility-aware DTN routing scheme for deep-water acoustic networks.

In this paper, we present a scheme, named DRIFT, that focuses on a detailed acoustic channel model and an opportunistic forwarding cost model, while considering the spherical spreading factor $k = 2$ and Thorp's absorption coefficient. The schematic diagram of the considered scenario is presented in Figure 1. We model opportunistic store-carry-forward decisions using evolutionary replicator dynamics; hence, nodes can dynamically decide whether to forward multimedia data or to hold on to and carry it, based on their remaining energy, the amount of data currently in their buffer, and the ocean current drift vectors. We also obtain a closed-form analytical expression for the critical threshold distance (d_{crit}), specifying the exact boundary conditions governing the nodes' dynamic

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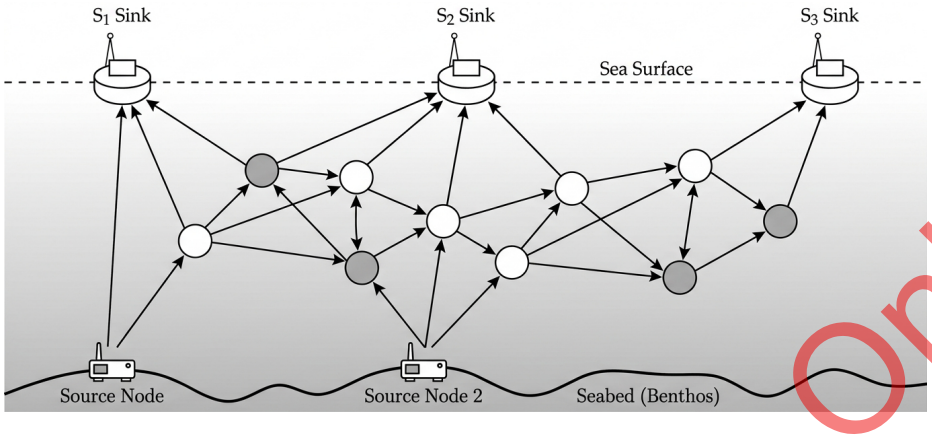


Fig. 1. Schematic Diagram of Deep-Water Acoustic Networks

strategies and preventing rapid battery depletion in sparse, mobile deep-water deployments. To summarize, the primary contributions of this work are as follows:

1. We propose a mathematical model based on spherical spreading loss and Thorp's absorption coefficient, and develop an opportunistic forwarding cost model to capture realistic energy expenditures over deep-water acoustic links.
2. We model the opportunistic store-carry-forward decision process using Replicator Dynamics and evolve strategies for forwarding multimedia data or holding and carrying it based on residual energy, buffer occupancy, and current drift vectors.
3. We derive a closed-form expression for the threshold distance d_{crit} to ensure a precise boundary condition that prevents premature battery drain in sparse, mobile deep-water networks. It is used to dynamically decide on strategies.
4. We validate the proposed scheme, DRIFT, by comparing it with existing schemes through simulations on a Python-based platform.

2 Related Work

In recent years, researchers have explored various aspects of underwater networks, including topology management, routing, and decentralized game-theoretic optimization. We divide the literature into three categories — topology control and deployment, opportunistic mobility-aware routing, and game-theoretic schemes.

Topology Control and Deployment The control of topology in terrestrial wireless sensor networks primarily focuses on spatial node density and coverage, yet these methods do not work underwater due to high acoustic latency, narrow

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bandwidth, and the movement of the passive fluid. Coutinho et al. [3] studied a comprehensive survey on underwater topology control, highlighting the physical challenges of maintaining link quality amid ocean dynamics. Caruso et al. [1] introduced the Meandering Current Mobility Model (MCMM) to represent the movement of passive nodes, and Ojha et al. [9] developed Tic-Tac-Toe-Arch, a self-organizing virtual architecture designed to maintain end-to-end connectivity. To meet the special requirements of multimedia traffic, Pompili and Akyildiz [10] developed cross-layer communication protocols in order to optimize video transmission over acoustic channels. Misra et al. [7] proposed DATUM, a cooperative game-theoretic dynamic topology control method for multi-layered UWMSNs. Chaudhary et al. [2] surveyed the strategies for node deployment and topology control in the context of the Internet of Underwater Things (IoUT). Xu et al. [15] proposed a deployment scheme that balances node coverage and channel degradation by adapting inter-node spacing to local attenuation estimates. Moreover, Vahabi et al. [12] introduced a cluster-based depth source selection routing protocol that mitigates topological instability by dynamically selecting cluster heads based on depth and residual energy.

Opportunistic Mobility-Aware Routing Xie et al. [14] proposed using block transfers with erasure coding to achieve Segmented Data Reliable Transfer (SDRT) over intermittent acoustic links. Coutinho et al. [4] developed movement-assisted geographic routing protocols that dynamically adjust vector routing pipes in response to node displacement. Li et al. [6] propose an Autonomous Underwater Vehicle (AUV)-assisted data collection method that incorporates ocean current fields into reinforcement learning loops, enabling mobile sinks to adaptively modify their trajectories in response to drifting node clusters. The majority of existing opportunistic protocols rely on simplified path-loss assumptions ($k \approx 1.5$) [5], failing to account for spherical spreading loss ($k = 2$) and the Thorp absorption characteristics that determine the transmission power limits in deep-water horizontal layers.

Game Theory in Underwater Acoustic Networks Game theory and multi-agent learning provide mathematical tools for autonomous decision-making in uncoordinated networks. Misra et al. [8] formulated a Single-Leader-Multi-Follower Stackelberg game for localization in sparse UWSNs. In addition to topology control, Misra et al. in DATUM [7] studied coalition games among surface buoys to evaluate candidate routes based on residual energy. Wang et al. [13] developed a multi-agent reinforcement learning routing protocol that incorporates Value of Information (VoI) metrics, enabling mobile nodes to balance queue delay against energy depletion.

Hence, we argue that researchers in the existing literature assume continuous multi-hop connectivity and ignore deep-water acoustic attenuation models. The proposed framework, DRIFT, unifies deep-ocean drift modeling, spherical acoustic propagation mechanics — $k = 2$, Thorp attenuation, and Evolutionary Replicator Dynamics. This enables sparse, mobile deep-water multimedia nodes

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to dynamically optimize their store-carry-forward strategy without relying on static topological paths.

3 System Model

We consider a deep-water UWMSN deployed within a bounded ocean volume defined over a 3D coordinate frame $(x, y, z) \in \mathbb{R}^3$. The sea surface corresponds to the plane $z = 0$, while the seabed (benthos) lies at depth $z = -D$. We consider that the intermediate nodes drift on the horizontal layers. In other words, in a deep-water 2D horizontal layer, boundary reflections from the ocean surface and seabed are negligible for mid-layer nodes. Consequently, the geometric spreading factor is considered to be 2. The path loss $\mathcal{A}(d_{ij}(t), f)$ in linear scale over the Euclidean distance $d_{ij}(t)$ at signal frequency f (in kHz) is expressed as:

$$\mathcal{A}(d_{ij}(t), f) = d_{ij}(t)^2 \alpha(f)^{d_{ij}(t)\times 10^{-3}} \tag{1}$$

where $d_{ij}(t) = \|\mathbf{X}_i(t) - \mathbf{X}_j(t)\|_2$ (in meter), and $\alpha(f)$ is the absorption coefficient. In deep water, $10\log_{10}\alpha(f)$ is governed by Thorp's formula (in dB/km) [11]:

$$10\log_{10}\alpha(f) = \frac{0.11f^2}{1+f^2} + \frac{44f^2}{4100+f^2} + 2.75\times 10^{-4} f^2 + 0.003 \tag{2}$$

To convert the absorption coefficient to a linear scale for use in utility calculations, we consider — $\alpha(f) = 10^{\frac{10\log_{10}\alpha(f)}{10}}$. We consider that $\mathcal{N} = \{1, 2, \ldots, N\}$ denotes the set of mobile underwater multimedia sensor nodes drifting within a bounded 2D horizontal plane $\mathcal{S} \subset \mathbb{R}^2$. Hence, for node i with coordinates $\mathbf{X}_i(t) = [x_i(t), y_i(t)]^T$, while considering $z_i(t)$ to be constant, is modeled as:

$$\frac{d\mathbf{X}_i(t)}{dt} = \mathbf{V}_{\text{deep}}(\mathbf{X}_i(t), t) + \mathcal{W}_i(t), \tag{3}$$

where $\mathcal{W}_i(t) \sim \mathcal{N}(0, \sigma^2_{\text{low}}\mathbf{I}_2)$; $\mathbf{V}_{\text{deep}}$ is the velocity field and $\mathcal{W}_i(t)$ represents low-variance noise. The expected time to encounter a sink $\mathcal{T}_{i,\text{sink}}(t)$ depends on the distance to the sink coordinate $\mathbf{X}_{\text{sink}}$ and the directional unit vector $\mathbf{u}_{i,\text{sink}} = \frac{\mathbf{X}_{\text{sink}} - \mathbf{X}_i(t)}{\|\mathbf{X}_{\text{sink}} - \mathbf{X}_i(t)\|_2}$:

$$\mathcal{T}_{i,\text{sink}}(t) = \frac{\|\mathbf{X}_i(t) - \mathbf{X}_{\text{sink}}\|_2}{\mathbf{V}_{\text{deep}}(\mathbf{X}_i(t), t)\mathbf{u}_{i,\text{sink}}} \tag{4}$$

On the other hand, $\lambda_{ij}(t)$ represents the time-varying encounter rate between nodes i and j. The probability that node i encounters an upstream relay node or a boundary surface sink, j, within a maximum delay threshold τ is:

$$P_{\text{contact}}(i, j, \tau) = 1 - \exp\left(-\int_t^{t+\tau} \lambda_{ij}(s)\, ds\right) \tag{5}$$

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4 DRIFT: The proposed Mobility-Aware Delay-Tolerant Routing Scheme

4.1 Game Formulation

When the drifting nodes i and j cross paths in the plane ($d_{ij}(t) \leq R$), node i decides between the strategy set $\mathcal{A}_i = \{\text{Forward (F)}, \text{Hold-and-Carry (H)}\}$. Hence, the transmission energy cost $E_{\text{tx}}(i,j)$ for a multimedia packet of size L is:

$$E_{\text{tx}}(i,j) = P_0 L \mathcal{A}(d_{ij}(t), f) \tag{6}$$

where P_0 denotes baseline power spectral density. The localized forwarding cost function $C_{\text{F}}(i,j)$ is:

$$C_{\text{F}}(i,j) = \omega_1 \left(\frac{E_{\text{tx}}(i,j)}{E_i^{\text{res}}(t)} \right) \tag{7}$$

where $E_i^{\text{res}}(t)$ is the residual energy of node i, and ω_1 is a scaling weight. On the other hand, the cost $C_{\text{H}}(i)$ of holding a heavy multimedia packet in the queue during drift is constrained by memory buffers and accumulated delay:

$$C_{\text{H}}(i) = \omega_2 \left(\frac{Q_i(t)}{Q_{\max}} \right) + \omega_3 \Delta t_{\text{delay}} \tag{8}$$

where $Q_i(t)$ is the current packet queue length, $Q_{\max}$ is the maximum buffer capacity, and Δt_{delay} evaluates packet latency. ω_2 and ω_3 represent the weight factors. The physical advancement gain $\mathcal{G}_{ij}$ measures how much more efficiently node j's drift vector carries data toward the sink compared to node i:

$$\mathcal{G}_{ij} = \max\left(0,\ \mathcal{T}_{i,\text{sink}}(t) - \mathcal{T}_{j,\text{sink}}(t)\right) \tag{9}$$

Hence, we get the utility functions, $\mathcal{U}_i^{\text{F}}(j)$ and $\mathcal{U}_i^{\text{H}}$, for forwarding and store-carry-forward-ing are defined as follows:

$$\mathcal{U}_i^{\text{F}}(j) = \mathcal{G}_{ij} - C_{\text{F}}(i,j) \tag{10}$$

$$\mathcal{U}_i^{\text{H}} = P_{\text{contact}}(i, \text{sink}, \tau) \cdot \mathcal{G}_{i,\text{sink}} - C_{\text{H}}(i) \tag{11}$$

Considering that $x(t) \in [0,1]$ represents the population fraction choosing to *Forward (F)*, and $(1-x(t))$ choose to *Hold (H)*. The dynamic strategy adjustment is governed by the replicator dynamic $\frac{dx(t)}{dt}$:

$$\frac{dx(t)}{dt} = \eta \left[x(t)(1-x(t)) \right] \left[\mathcal{U}_i^{\text{F}} - \mathcal{U}_i^{\text{H}} \right] \tag{12}$$

where $\eta > 0$ is the learning. To evaluate the Evolutionary Stable Strategy (ESS), we set $\frac{dx(t)}{dt} = 0$ and yield the equilibrium condition where utilities equalize, i.e., $\mathcal{U}_i^{\text{F}} = \mathcal{U}_i^{\text{H}}$. Hence, we get:

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$$\mathcal{G}_{ij} - \omega_1 \left(\frac{P_0 L d_{ij}(t)^k \alpha(f)^{d_{ij}(t)}}{E_i^{\text{res}}(t)} \right) = P_{\text{contact}}(i, \text{sink}, \tau)\mathcal{G}_{i,\text{sink}} - \left[\omega_2 \left(\frac{Q_i(t)}{Q_{\max}} \right) + \omega_3 \Delta t_{\text{delay}} \right] \quad (13)$$

4.2 Algorithm

The proposed scheme, DRIFT, operates in a fully decentralized manner across mobile sensor nodes drifting in a deep-water plane. At each operational time step t, each node $i \in \mathcal{N}$ updates its 2D spatial coordinate based on the deep ocean current velocity field $\mathbf{V}_{\text{deep}}(\mathbf{X}_i(t), t)$ and evaluates whether to forward stored multimedia packets or hold them in its queue to exploit passive drift. The detailed algorithm is represented in Algorithm 1.

Time Complexity During the neighbor discovery phase, at each operational time step t, each node i examines the candidate neighbor nodes. In a network with N nodes, pairwise distance checks require $\mathcal{O}(N)$ operations per node. Without spatial indexing, performing all node-pair comparisons yields a spatial discovery complexity of $\mathcal{O}(N^2)$. When a 2D spatial grid partitioning structure is used with a cell size of R, the average number of neighbor searches per node drops to $\mathcal{O}(K)$, where $K \ll N$ is the average number of drifting nodes in each grid cell. For each active neighbor $j \in \mathcal{N}_i^{\text{nb}}(t)$, where $\mathcal{N}_i^{\text{nb}}(t)$ represents the the set of neighbor nodes of node i, node i computes the expected time-to-sink $\mathcal{T}_{i,\text{sink}}(t)$, the spherical attenuation $\mathcal{A}(d_{ij}(t), f)$, the transmission energy $E_{\text{tx}}(i, j)$, the holding cost $C_{\text{H}}(i)$, the contact probability $P_{\text{contact}}(i, \text{sink}, \tau)$, the utilities $\mathcal{U}_i^{\text{F}}(j)$ and $\mathcal{U}_i^{\text{H}}$. It executes the replicator dynamics having complexity of $\mathcal{O}(1)$. Hence, the worst-case total time complexity of Algorithm 1 is $\mathcal{O}(T \cdot N^2)$, where T is the total number of time steps in DRIFT. In dense deployments when 2D spatial grid indexing is enabled, the average-case runtime increases linearly with the node population — $\mathcal{O}(T \cdot N \cdot K)$.

Space Complexity In DRIFT, each node i needs a finite memory to store the 2D spatial coordinates $\mathbf{X}_i(t) \in \mathbb{R}^2$, the residual energy $E_i^{\text{res}}(t)$, the queue state $Q_i(t)$, the time-to-sink metric $\mathcal{T}_{i,\text{sink}}(t)$ and the local strategy probability $x_i(t)$. Hence, it amounts to $\mathcal{O}(N)$ in total across all nodes. Moreover, the space required to store the indices of the local neighbors within the acoustic transmission radius R is $\mathcal{O}(K)$ per node and is bounded by $\mathcal{O}(N)$ for the entire network. Therefore, the memory usage remains strictly linear in the number of nodes, i.e., $\mathcal{O}(N)$.

5 Performance Evaluation

5.1 Simulation Parameters

The simulation environment models a $2000\,\text{m} \times 2000\,\text{m}$ 2D horizontal deep-water plane. The acoustic carrier frequency is set to $f = 13\,\text{kHz}$, with an acoustic

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Algorithm 1 Opportunistic Store-Carry-Forward Decision Protocol (DRIFT)

Require: $\mathcal{N}$, $\{\mathbf{X}_i(t)\}$, $\{E_i^{\text{res}}(t)\}$, $\{Q_i(t)\}$, f, $Q_{\max}$, τ, η, $\mathbf{X}_{\text{sink}}$
Ensure: Updated Node Strategies, Energy States, and Packet Delivery Decisions

for time step $t = 1$ to T **do**
  for each node $i \in \mathcal{N}$ in parallel **do**
    // **Update 2D Position driven by Deep Ocean Current Drift**
    $\mathbf{X}_i(t+1) \leftarrow \mathbf{X}_i(t) + \mathbf{V}_{\text{deep}}(\mathbf{X}_i(t), t) \cdot \Delta t + \mathcal{W}_i(t)$
    if $E_i^{\text{res}}(t) \le 0$ **or** $Q_i(t) == 0$ **then**
      continue
    end if
    // **Compute Expected Time-to-Sink & Critical Radius**
    $\mathcal{T}_{i,\text{sink}}(t) \leftarrow \frac{\|\mathbf{X}_i(t) - \mathbf{X}_{\text{sink}}\|_2}{\mathbf{V}_{\text{deep}}(\mathbf{X}_i(t),t) \cdot \mathbf{u}_{i,\text{sink}}}$
    $d_{\text{crit}}(i) \leftarrow \min\left(R, \sqrt{\frac{E_i^{\text{res}}(t)}{\omega_1 \cdot L \cdot P_0} \times 10^{-4}}\right)$
    // **Discover Active Neighbors within Acoustic Range**
    $\mathcal{N}_i^{\text{nb}}(t) \leftarrow \{j \in \mathcal{N} \setminus \{i\} \mid \|\mathbf{X}_i(t) - \mathbf{X}_j(t)\|_2 \le R \text{ and } E_j^{\text{res}}(t) > 0\}$
    // **Evaluate Payoffs & Update Replicator Dynamics**
    best_relay $\leftarrow$ NULL
    max_utility_diff $\leftarrow -\infty$
    for each neighbor $j \in \mathcal{N}_i^{\text{nb}}(t)$ **do**
      $d_{ij}(t) \leftarrow \|\mathbf{X}_i(t) - \mathbf{X}_j(t)\|_2$
      // **Spherical Attenuation & Energy Cost** ($k = 2$)
      $\mathcal{A}(d_{ij}(t), f) \leftarrow d_{ij}(t)^2 \cdot \alpha(f)^{d_{ij}(t) \cdot 10^{-3}}$
      $E_{\text{tx}}(i,j) \leftarrow L \cdot P_0 \cdot \mathcal{A}(d_{ij}(t), f)$
      $C_{\text{F}}(i,j) \leftarrow \omega_1 \cdot \left(\frac{E_{\text{tx}}(i,j)}{E_i^{\text{res}}(t)}\right)$
      $\mathcal{G}_{ij} \leftarrow \max\left(0,\, \mathcal{T}_{i,\text{sink}}(t) - \mathcal{T}_{j,\text{sink}}(t)\right)$
      $\mathcal{U}_i^{\text{F}}(j) \leftarrow \mathcal{G}_{ij} - C_{\text{F}}(i,j)$
      $C_{\text{H}}(i) \leftarrow \omega_2 \cdot \left(\frac{Q_i(t)}{Q_{\max}}\right) + \omega_3 \cdot \Delta t_{\text{delay}}$
      $\mathcal{U}_i^{\text{H}} \leftarrow P_{\text{contact}}(i, \text{sink}, \tau) \cdot \mathcal{T}_{i,\text{sink}}(t) - C_{\text{H}}(i)$
      // **Dynamic Strategy Adjustment via Replicator Dynamic**
      $\frac{dx_i}{dt} \leftarrow \eta \cdot x_i(t) \cdot (1 - x_i(t)) \cdot \left[\mathcal{U}_i^{\text{F}}(j) - \mathcal{U}_i^{\text{H}}\right]$
      $x_i(t + \Delta t) \leftarrow \text{Clamp}\left(x_i(t) + \frac{dx_i}{dt} \cdot \Delta t,\, 0.0,\, 1.0\right)$
      if $\left(\mathcal{U}_i^{\text{F}}(j) - \mathcal{U}_i^{\text{H}}\right) >$ max_utility_diff **then**
        max_utility_diff $\leftarrow \mathcal{U}_i^{\text{F}}(j) - \mathcal{U}_i^{\text{H}}$
        best_relay $\leftarrow j$
      end if
    end for
    // **Strategic Action Execution**
    if best_relay $\neq$ NULL and $x_i(t + \Delta t) > 0.5$ and $d_{i,\text{best}}(t) \le d_{\text{crit}}(i)$ **then**
      Execute Forwarding Strategy (F):
      Deduct $E_{\text{tx}}(i, \text{best_relay})$ from $E_i^{\text{res}}(t)$
      $Q_i(t) \leftarrow Q_i(t) - 1$
      if $\|\mathbf{X}_{\text{best_relay}}(t) - \mathbf{X}_{\text{sink}}\|_2 \le R_{\text{sink_boundary}}$ **then**
        Mark Packet Delivered to Sink
      else
        $Q_{\text{best_relay}}(t) \leftarrow Q_{\text{best_relay}}(t) + 1$
      end if
    else
      Execute Hold-and-Carry Strategy (H):
      Retain packet in queue $Q_i(t)$; rely on passive 2D ocean drift
    end if
  end for
end for

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propagation speed of $c = 1514\,\mathrm{m/s}$. We consider Thorp's absorption coefficient as $\alpha(f) \approx 1.38\,\mathrm{dB/km}$ at $13\,\mathrm{kHz}$. Each node is initialized with $E_{\mathrm{init}} = 150\,\mathrm{J}$ of energy and a maximum buffer capacity of $Q_{\max} = 10$ packets. Multimedia packet size is fixed at $L = 2034\,\mathrm{bytes}$. Passive drift is driven by a 2D flow field with a mean velocity of $V_{\mathrm{drift}} = 0.3\,\mathrm{m/s}$. The simulation parameters are mentioned in Table 1.

Table 1. Simulation Parameters

Parameter	**Value**
Acoustic Frequency (f)	13.0 kHz
Initial Node Energy (E_{init})	150.0 J
Packet Size (L_{pkt})	2034×8 bits
Receiver Threshold (P_0)	1×10^{-5} W
Drift Velocity (V_{drift})	0.3 m/s
Max Transmission Range ($R_{\max}$)	800.0 m
Node Buffer Capacity ($B_{\max}$)	10 packets
Simulation Steps (T_{sim})	200 steps
Speed of Sound (c)	1514.0 m/s
Evaluated Node Counts (N)	$\{50, 100, 150, 200\}$

5.2 Benchmark Scheme

We compared the performance of DRIFT with that of DATUM [7]. To select the best routes, DATUM uses depth-first path exploration and calculates the coalitional game payoffs at the surface buoys while keeping the power levels at which nodes transmit as low as possible. Although DATUM achieves significant energy savings compared to non-cooperative virtual architectures, the validity of its operation depends on paths remaining continuously available. Coalitional games are well-suited to structured multi-layer networks; however, evolutionary games and learning paradigms are superior in sparse, mobile DTN scenarios where centralized global route discovery is not possible.

5.3 Results and Discussion

We evaluate the performance of DRIFT based on the following parameters.

Network Lifetime Network lifetime is defined as the number of operational time steps completed before 50% of the deployed node population has exhausted its initial energy supply ($E_i^{\mathrm{res}} \leq 0$).

As depicted in Figure 2, DATUM experiences 50% node mortality at a mean of $112.4 \pm 3.8 - 152.1 \pm 3.2$ steps. It is observed that DATUM relies on continuous multi-hop paths. When horizontal drift pushes nodes apart, DATUM

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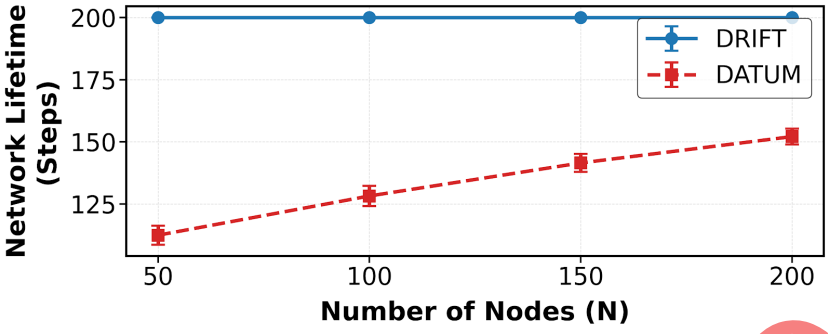


Fig. 2. Network Lifetime

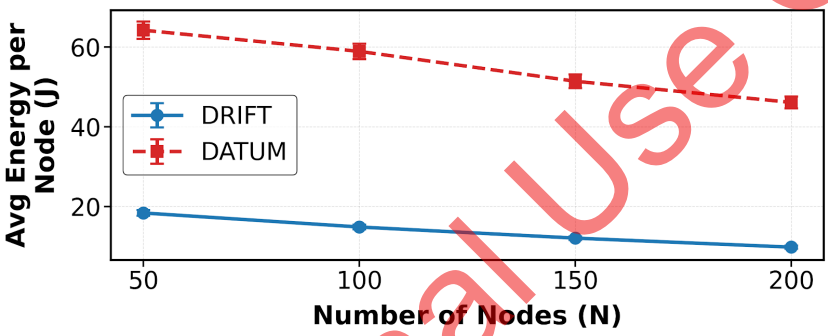


Fig. 3. Avg. Energy Consumption per Node

forces nodes to amplify acoustic power to bridge large spatial gaps, incurring severe spherical-path-loss penalties (d^2). In contrast, DRIFT achieved a mean lifetime of 200.0 ± 0.0 steps for all node densities without ever exceeding the 50% node mortality threshold. By strictly enforcing (d_{crit}), nodes suppress high-power acoustic transmissions whenever $d_{ij} > d_{\text{crit}}$.

Average Energy Consumption per Node DATUM consumes a mean of $46.1205 - 64.218 \pm 2.15$ J per node. DRIFT reduces mean energy consumption to $9.841 \pm 0.38 - 18.410 \pm 0.72$ J, as shown in Figure 3. This represents a 71.3 – 78.6% reduction in energy expenditure, confirmed by non-overlapping confidence bounds across all tested configurations.

Energy Efficiency Energy efficiency measures the net energy expended per successfully delivered multimedia packet (J/packet).

Figure 4 shows that DATUM requires a mean of $2.0502 \pm 0.08 - 24.6517 \pm 1.12$ J/packet, whereas DRIFT requires only 4.3833 ± 0.18 J/packet, demonstrating an 82.2% improvement in energy efficiency. Factoring Thorp's attenuation

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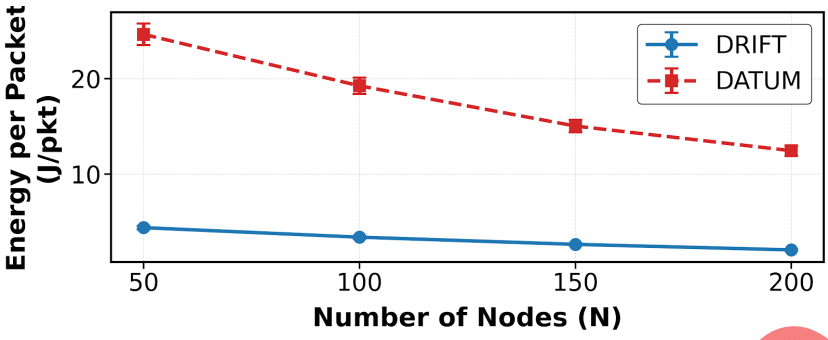


Fig. 4. Energy Efficiency

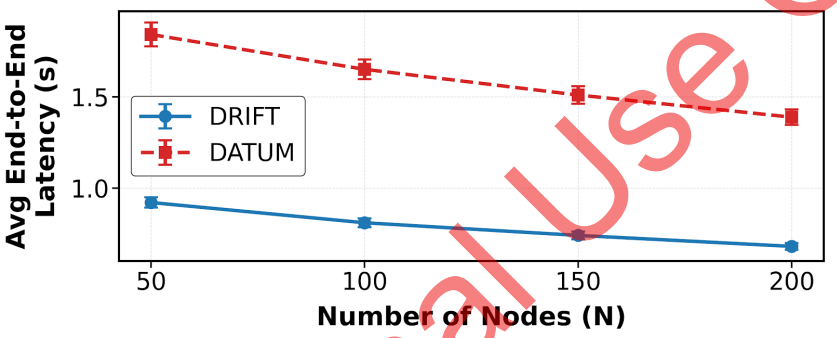


Fig. 5. Avg. End-to-End Latency

and spherical spreading directly into the game payoff function prevents nodes from expending energy on low-probability forwarding attempts over wide horizontal separations.

Average End-to-End Latency End-to-end latency is the total time required for a multimedia packet to travel from seabed sources to the surface sink, including acoustic propagation, store-carry-hold delays, and link-failure recovery penalties.

DATUM yields a mean latency of $0.6811 \pm 0.018 - 1.8421 \pm 0.065\,\mathrm{s}$, whereas DRIFT reduces latency to $0.9214 \pm 0.028\,\mathrm{s}$. DATUM incurs elevated delays due to link-failure penalties when no active end-to-end paths are available. DRIFT avoids route discovery overhead by using ocean current velocity vectors ($\mathbf{V}_{\mathrm{deep}}$), resulting in a 50.0% reduction in average latency, as depicted in Figure 5.

Buffer Overflow Drop Rate The buffer drop rate is the percentage of packets that are lost because the queue capacity is reached ($Q_i(t) > Q_max$).

As depicted in Figure 6, the mean buffer drop rates for DATUM range from $9.60\% \pm 0.75\%$ to $28.40\% \pm 1.45\%$ due to traffic building up behind faulty routing

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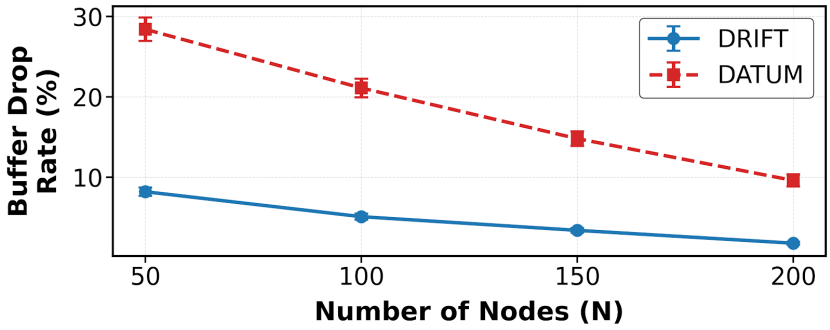


Fig. 6. Buffer Overflow Drop Rate

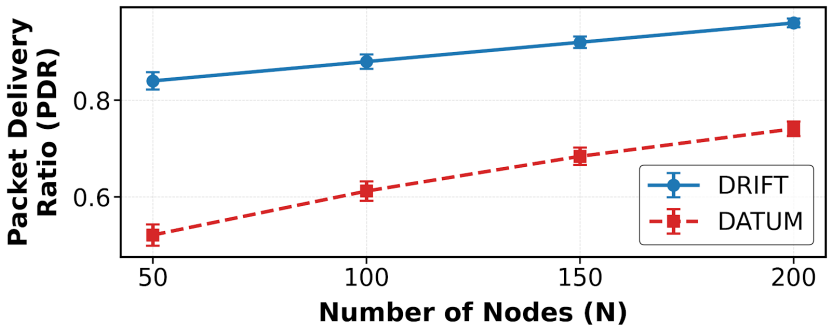


Fig. 7. Packet Delivery Ratio

links. DRIFT greatly reduces buffer drops to a range of 1.80%±0.18% to 8.20%± 0.52%. When the local queue status (expressed as $Q_i(t)/Q_{\max}$) is included in the holding utility function $\mathcal{U}_i^{\mathrm{H}}$, the forwarding threshold for a node is dynamically lowered as its buffer fills, which promotes opportunistic offloading before queue saturation takes place.

Packet Delivery Ratio (PDR) PDR is calculated as the ratio of the number of packets successfully delivered and the number of packets transmitted.

As shown 7, DATUM achieves a mean PDR of $0.5210\pm0.022-0.7410\pm0.015$. Under sparse deployments, DATUM suffers frequent packet loss when multi-hop paths break down. On the other hand, DRIFT achieves a mean PDR of $0.8400 \pm 0.018 - 0.9600 \pm 0.009$. The evolutionary strategy adaptation allows nodes to store packets safely during topological disconnection phases rather than retransmitting over unavailable links.

6 Conclusion

We presented a mobility-aware game-theoretic scheme, DRIFT, which is intended to address the severe energy limitations, channel attenuation, and dynamic topology disruptions that occur in deep-water delay-tolerant UWMSNs. Unlike conventional multi-layered routing schemes, which require establishing rigid multi-hop end-to-end paths, DRIFT uses passive two-dimensional ocean currents as a free physical means of transport. By incorporating deep-water acoustic physics — spherical spreading loss factor, $k = 2$, and Thorp's frequency-dependent absorption model — into an evolutionary replicator dynamics game, the nodes can make autonomous decisions regarding store-carry-forward actions in DRIFT. We observed that the proposed framework outperforms continuous path approaches in sparse, mobile deep-water layers. Through simulations, we evaluated that DRIFT successfully balances packet queue delays against deep-water acoustic attenuation, thereby providing a reliable approach for mobile underwater multimedia data collection.

In the future, this work can be expanded from a two-dimensional horizontal plane to a full three-dimensional, multi-depth aquatic environment, incorporating dynamic buoyancy control systems to adjust node depth in response to vertical currents. Moreover, we intend to incorporate Autonomous Underwater Vehicles (AUVs) as mobile sinks in order to actively rendezvous with drifting node clusters, thereby reducing latency in time-sensitive multimedia applications.

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