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A Survey on Routing Void Detection and Repair Technologies in Underwater Wireless Sensor Networks

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Underwater Wireless Sensor Networks (UWSNs) play a pivotal role in oceanic exploration. However, the stringent characteristics of the underwater acoustic channel, such as high latency and high dynamics, frequently cause routing voids (where data cannot be forwarded). This poses a core challenge to network reliability and efficiency. To systematically tackle this challenge, this paper analyzes 132 relevant studies to present a comprehensive synthesis of void-detection and mitigation techniques in UWSNs. This work proposes a classification framework based on technological evolution, categorizing void-handling techniques into three groups: (1) topology and geometric location-based routing methods, serving as the classical foundation; (2) Autonomous Underwater Vehicle (AUV)-aided approaches, which intervene by introducing external mobile entities; and (3) Artificial Intelligence (AI)-based methods, enabling intelligent avoidance by endowing nodes with learning and decision-making capabilities. This paper offers an in-depth analysis of key technologies, protocols, advantages, and limitations within each category. Furthermore, we systematically elucidate the evolutionary trajectory of void-handling technologies from rule-based passive bypass to predictive proactive intelligence. By establishing this perspective, we provide a strategic roadmap for constructing next-generation, robust, and adaptive underwater communication architectures, while exploring future research directions and challenges to guide subsequent researchers.

KEYWORDS: UWSNs, Void handling, Void detection, Void repair

1. Introduction

Wireless Sensor Networks (UWSNs) are oceanic exploration cornerstones, serving environmental monitoring and national defense [15, 60, 71, 86]. Geographic greedy routing is mainstream for its low overhead and scalability [37]. However, in sparse, dynamic 3D environments, this strategy is susceptible to the routing void problem, causing transmission interruptions and energy wastage [25, 48, 58, 69].

Early research, such as Geographic and Opportunistic Routing with Depth Adjustment for UWSNs (GEDAR) [100], Inherently Void-Avoidance Routing (IVAR) [6], and Hop-by-hop Distance-aware and Energy-efficient Routing Protocol (H2-DAB) [43], utilized depth adjustment or depth-energy metrics to re-establish forwarding. However, these passive strategies rely on easily outdated neighbor tables in dynamic settings, causing high false-positive rates and persistent "repair-re-trap" cycles [43, 44].

Subsequently, research coupled Opportunistic Routing (OR) with Autonomous Underwater Vehicle (AUV) cooperation. OR [92] leverages spatial diversity to bypass lightweight voids via distributed competition. CO-UWSN [86] uses network coding to offset high-noise packet loss. For persistent voids, LETR [115] and EMGGR [66] use AUV mobile sinks, decomposing long transmissions into short segments. Although later studies—such as Energy-efficient Cooperative Opportunistic Routing (ECOR) [41], Fair-Energy [93], and Chain-Based [82]—mitigated energy imbalances and broadcast storms [97], AUV trajectories remain limited by static priors. Facing sudden currents or interference, fixed-path AUVs suffer "timeliness decay," where void topology shifts before vehicle arrival [65].

Recent research treats voids as predictable topological events. "Predict-then-act" approaches use lightweight Long Short-Term Memory (LSTM) or PSO-SVM models to mine traffic and mobility time-series features, predicting void probabilities to trigger proactive power compensation or AUV pre-movement [116, 99].

Alongside predictive methods, topology enhancement mitigates voids. ERR-UWSN [49] constructs virtual Multiple-Input Multiple-Output (MIMO) beams at void edges to enhance penetration. Similarly, Cooperative Energy-Efficient Routing Protocol (CEER) [2] dynamically allocates weights via game theory, while Reinforcement Learning-based Predictive Back-pressure Routing (RE-PBR) [34] adapts AUV paths to real-time traffic.

Specialized protocols like Swarm-IoT [50], Shifted-Energy [35], and Reliable-Clustering [42] reduce void impacts via trajectory optimization and redundant relaying. Despite advancements, challenges remain. Existing models are fragile handling non-linear errors in dynamic environments. Furthermore, AUV schemes' reliance on high-precision positioning and charging infrastructure bottlenecks large-scale, low-cost deployment [28].

Figure 1 presents the timeline of routing void handling technologies in UWSNs, summarizing the temporal distribution of major protocols from 2015 to the present. As illustrated, the research focus has undergone a significant paradigm shift. Early studies (2015–2018) primarily concentrated on refining geometric and topology-based detour rules to passively bypass void regions. Around 2018, a transition toward active recovery emerged with a surge in AUV-aided mobile relaying protocols. Recently, a burgeoning trend toward Artificial Intelligence (AI) and Reinforcement Learning (RL) reflects a move from rigid, rule-based logic toward highly adaptive and predictive void management frameworks.

Building upon this evolution, this paper categorizes existing void handling strategies into three technical paradigms: (1) network topology and geometric location-based methods, (2) AUV-aided approaches, and (3) artificial intelligence (AI)-based techniques.

The paper is organized as follows: Section 2 examines the core challenges and formation mechanisms of routing voids. Section 3 reviews their principles and representative protocols. Sections 4 and 5 discuss emerging research directions and future challenges, respectively. Finally, Section 6 summarizes findings and concludes the paper.

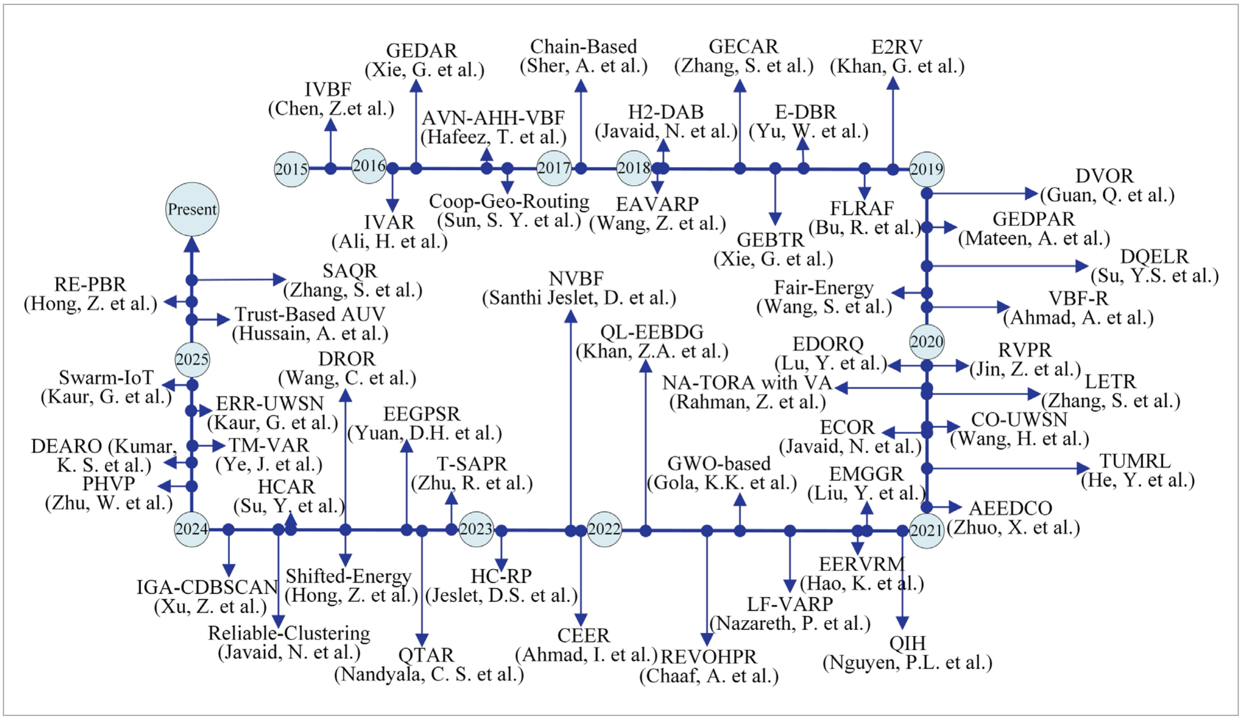
2. Underwater Routing Void: Challenges, Causes, and Detection

2.1. The Core Challenges of UWSNs

UWSN challenges stem from physical environments, acoustic channels, and node constraints.

Figure 1

Evolutionary timeline of routing void handling technologies in UWSNs (2015–Present).



Physical and topological challenges: 3D space complicates routing void morphology [57, 70]. Water-induced mobility causes frequent topology changes, increasing routing difficulty, packet loss [3, 18], and hidden terminal problems.

Acoustic channel challenges: Sound propagation (~1500 m/s) causes extreme delays [90]. Limited bandwidth (< 100 kbps) restricts information-exchange protocols [23, 63]. Severe path loss and noise create highly interfering, lossy channels [33, 35, 96].

Node resource constraints: Nodes face severe energy limitations. Given difficult battery replacement and high communication costs, energy efficiency is paramount for designing hole-handling routing protocols [81, 107].

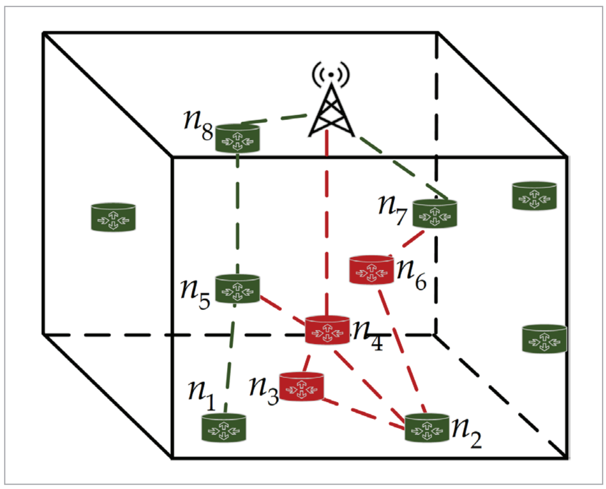
2.2. Formation and Influence of Routing Void

1 Definition and Classification of Void

Figure 2 illustrates the routing void model, where a routing hole occurs when a forwarding node finds no closer neighbor within its communication range [66]. These are called hole or stuck nodes. Without recovery mechanisms, packets drop, causing routing failures despite existing alternative paths [51]. For instance, energy-depleted nodes significantly increase void probabilities [1,119]. Voids are categorized into two types: location-based (no geographically closer neighbors) and depth-based (no shallower neighbors) [44].

Figure 2

Routing void model.



2 **Internal Causes of Voiding**

Routing void causes stem from UWSN physical topology, channel conditions, and node resource challenges [55]. Physically, sparsity from high deployment costs is the primary cause. Furthermore, water-induced mobility creates temporary voids, while underwater obstacles form communication blind areas [24, 87]. At the acoustic channel level, high path loss and complex noise cause unstable links [5], preventing even well-positioned neighbors from communicating. Regarding node limitations, energy depletion or hardware failures cause key nodes to die, resulting in permanent, irreversible energy holes [101].

3 **The Negative Impact of Void on the Network**

Routing voids cause cascading effects on network performance [26]. Directly, packets entering voids are discarded, causing data loss and wasting energy and bandwidth. This loss degrades reliability and quality of service, proving disastrous for time-sensitive applications [30, 55]. In severe cases, large-scale voids block paths, invalidate protocols, and divide networks into isolated islands [20]. Furthermore, bypass mechanisms consume extra time and energy, increasing delay and accelerating new void formation, trapping the network in a vicious circle [8].

2.3. Overview of Mainstream Void Detection Methods

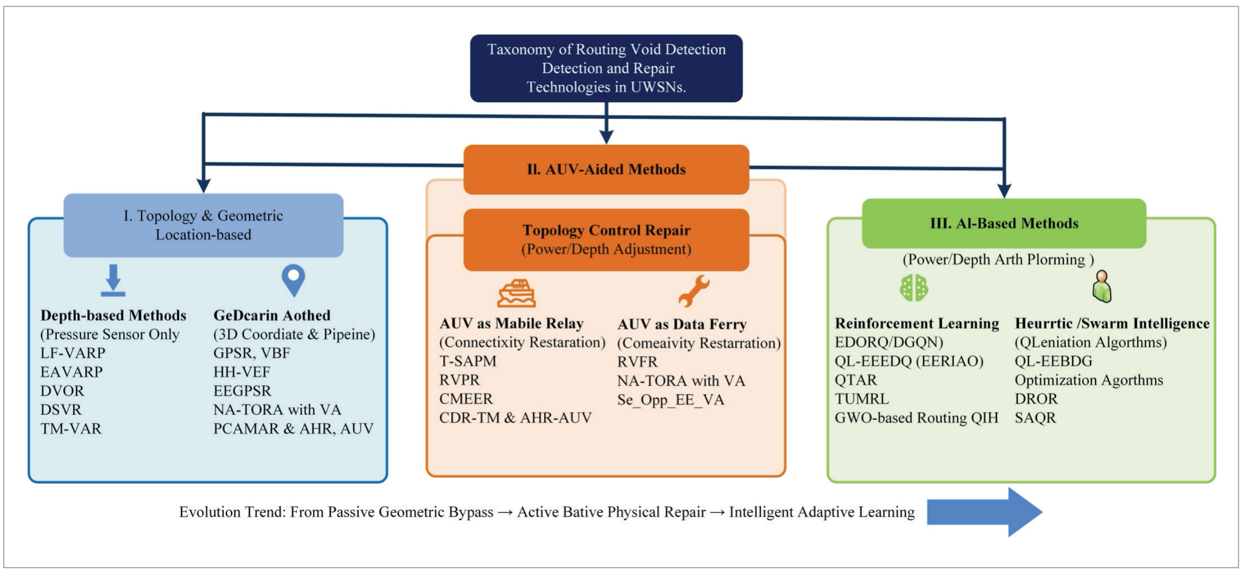
Having analyzed the causes, classifications, and effects of underwater routing voids, we transition to solutions. Void handling techniques demonstrate a clear evolutionary context: from traditional passive bypass using local geometric information, to active repair via external units like AUVs, and recently, AI-driven intelligent adaptive path planning. Subsequent sections categorize existing void treatment schemes into these three evolutionary stages, systematically analyzing their core ideas, representative protocols, advantages, and limitations to provide a deeper understanding of advancements.

3. Key Technologies and Research Advances

This study analyzes UWSN routing void technologies, categorizing them based on the evolutionary stages in Figure 1: from passive geometric bypass to active AUV recovery, and highly adaptive AI strategies. Accordingly, we discuss three primary categories: (1) Topology and Geometric Location-based, (2) AUV-Aided, and (3) AI-Based methods. Figure 3

Figure 3

Classification of routing void detection and repair technologies in UWSNs.



visually presents this comprehensive taxonomy and representative protocols.

3.1. Routing Methods Based on Network Topology and Geometric Location

1 **Core Ideas and Technical Principles**

Figure 4 summarizes classical topology and geometry-based routing methods for UWSN voids. Utilizing local physical and geometric properties, they enable greedy forwarding without global information. Primary metrics are depth-based (selecting shallower nodes) and location-based forwarding (selecting neighbors offering greatest geographic progress, like VBF). Voids occur when nodes hit a "local optimum" lacking suitable next hops. Recovery mechanisms mitigate this by circumnavigating boundaries until greedy forwarding resumes. Despite local information and dynamic topology constraints, this distributed solution underpins advanced routing technologies.

2 **Key Technologies and Representative Protocol Analysis**

While classical Deep Routing (DBR) is simple, "hot node" energy depletion and sparsity frequently cause routing voids. Recent energy-aware research [65] addresses this, exemplified by EAVARP [96]. EAVARP constructs a minimum-hop concentric-shell model around the sink (Figure 5), forwarding exclusively to closer shells. Its void-avoidance mechanism uses a 2-bit code to flag and bypass hole nodes lacking capable parent or sibling forwarders. EAVARP's stratification avoids voids and balances energy, but static topology restricts it to stable networks. Alternatively, E2RV [51] actively avoids voids using residual energy and two-hop depth variance, increasing communication overhead. LF-VARP [73] mitigates this passively, reducing overhead via a local fitness function combining depth, energy, and distance. However, its adaptability in highly dynamic underwater environments remains constrained.

Building on EAVARP, fitness-based selection evaluates depth, energy, and distance. Though balancing energy, manual weights lack adaptability, merely detouring voids. Conversely, "no-hole" routing completely avoids them. The Distance Vector-based Opportunistic Routing (DVOR)

Figure 5
Concentric shell network model of EAVARP protocol.

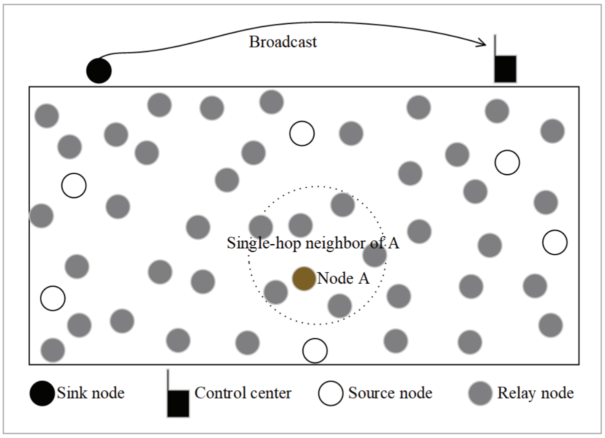


Figure 4
Summary of routing methods based on network topology and geometric position.

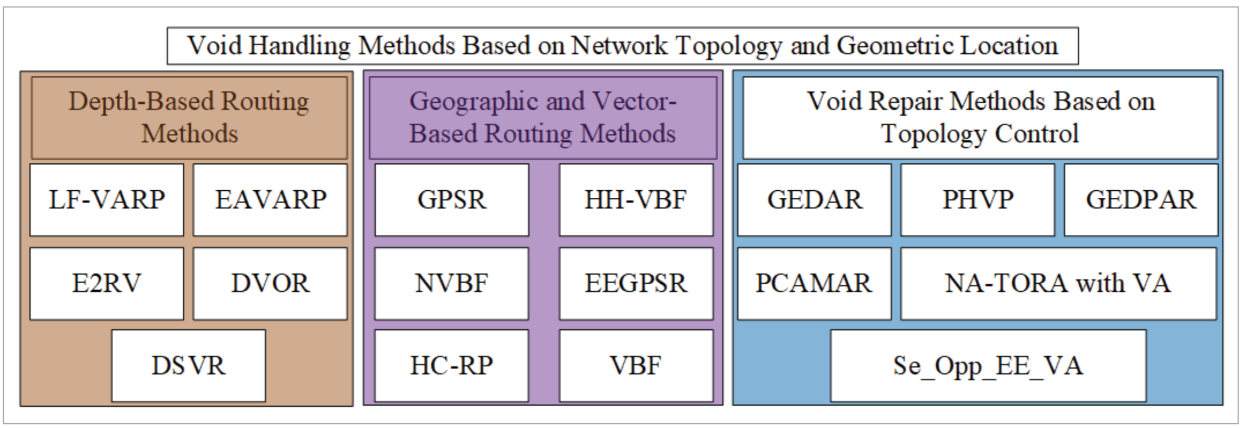
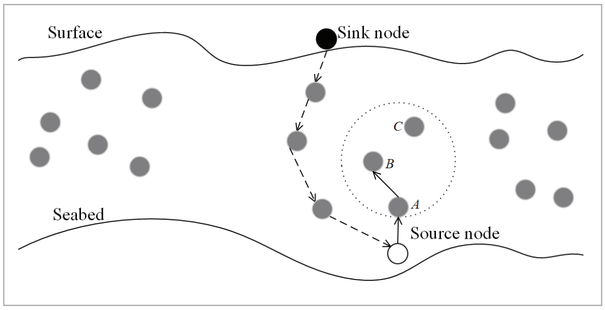


Figure 6

Schematic diagram of candidate forwarding set selection based on hop count in DVOR protocol.



builds a logical gradient via periodic sink broadcasts, assigning minimum hop counts [28]. Excluding infinite-count nodes achieves high PDR [68] and low delay despite overhead.

Figure 6 illustrates DVOR. Broadcasting only to lower hop-count neighbors (e.g., A and B, excluding C) prevents entering holes. However, its strictly decreasing hop-count rule frequently yields null candidate sets, suspending sparse-topology forwarding. Lacking priority suppression, rebroadcasts cause packet redundancy and channel contention. Finally, hop-count-only routing ignores link quality, energy, and mobility, funneling traffic into error-prone links, degrading reliability and lifetime.

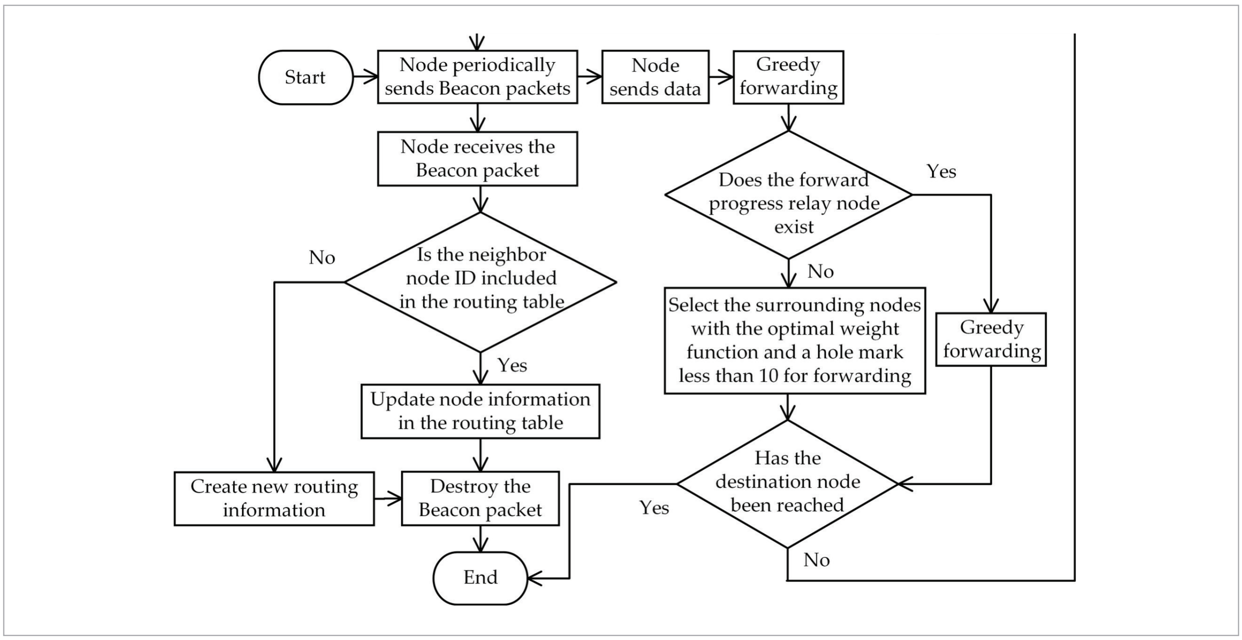
To repair physical voids, GEDPAR [47] employs staged recovery, attempting ″soft″ power increases to connect, then ″hard″ depth adjustment if unsuccessful. This energy-efficient approach suits mobile nodes due to mobility overheads. Geolocation-based methods like GPSR [48] and VBF use 3D coordinates, relying on boundary bypassing and virtual pipelines. GPSR's rigid ″right-hand rule″ creates long, inefficient detours. Conversely, EEGPSR [112] calculates a weight—combining neighbor direction and relative distance—to intelligently select the optimal next hop. Although sacrificing global optimality, EEGPSR shortens detour paths, reducing latency and energy consumption for mobile underwater networks.

Figure 7 visualizes this: while GPSR rigidly detours along boundaries, EEGPSR uses its weight function to dynamically identify a shorter bypass route.

Classical VBF protocol's fixed pipes cause routing interruptions in sparse networks [100]. NVBF protocol [80] integrates forward distance and residual energy to enhance robustness. A Hybrid Cooperation-Based Routing Protocol [45] uses

Figure 7

Schematic diagram of comparison between EEGPSR and GPSR void bypass paths.



two-hop neighbors for early void detection, despite overhead. To eliminate voids from physical partitioning, topology control-based methods reconfigure networks [29, 38, 88]. First, physical location adjustment [27, 37, 84] moves void nodes vertically, though high energy limits this to highly mobile nodes. Second, staged recovery strategies like GEDPAR [47] attempt "soft" power increases before "hard" physical movement, reducing energy consumption.

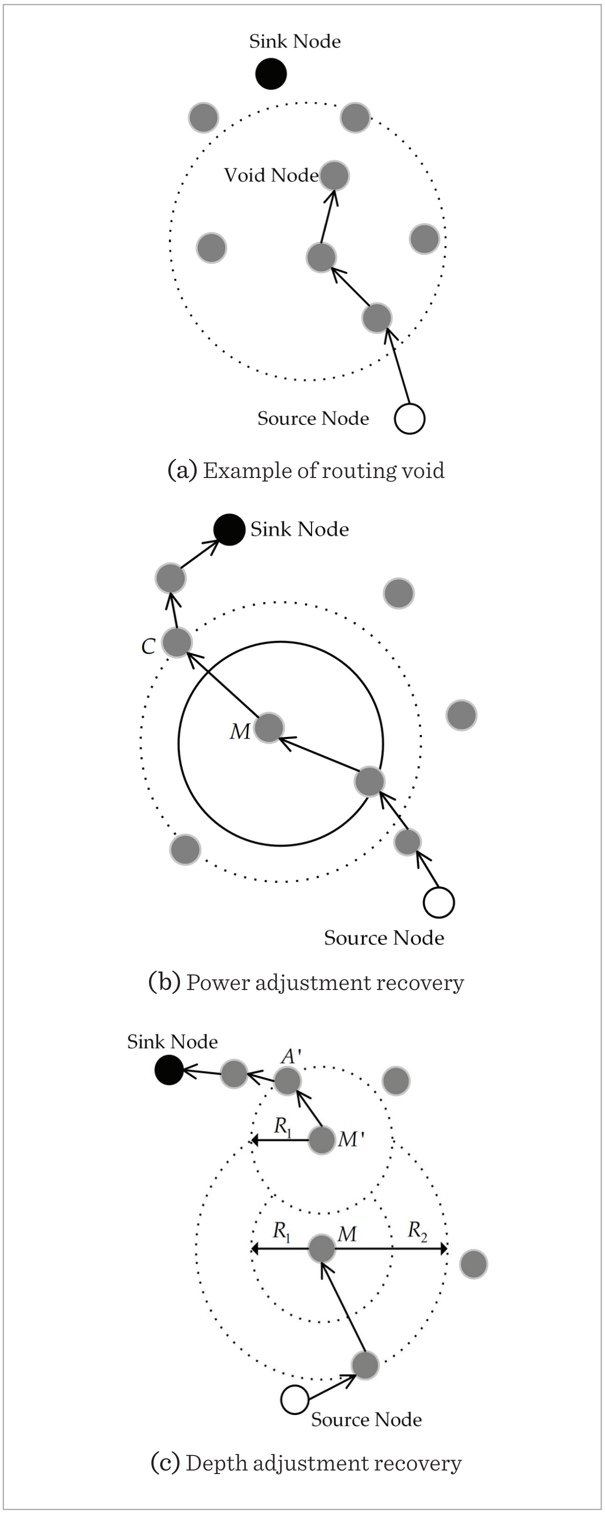
Figure 8 illustrates GEDPAR's phased recovery. Identifying a void when all neighbors are farther from the sink (Figure 8(a)), it initiates power adjustment recovery (Figure 8(b)), expanding transmission range. If maximum power fails, depth adjustment recovery (Figure 8(c)) vertically moves the node to establish a path. This logical chain—problem definition, low-cost, then high-cost solutions—forms GEDPAR's energy-efficient core. Tuning communication parameters offers lightweight topology control compared to physical movement. For instance, the PCAMAR algorithm [60] adjusts communication range via power control, while the Normalized Advancement Based Totally Opportunistic Routing Algorithm (NA-TORA) with VA protocol [77] adjusts transmission angle and range. These energy-efficient, low-latency methods depend heavily on network density.

Applied to acousto-optic hybrid networks, the Packet Hierarchy and Void Processing (PHVP) protocol by Zhu et al. [122] initially adjusts optical parameters when encountering a void in high-speed links. If unsuccessful, it switches to reliable acoustic communication to circumvent the void. This leverages hybrid network advantages, balancing efficiency and robustness. However, protocol complexity and dedicated hardware make it viable primarily for future heterogeneous underwater networks.

3 Comparison and Analysis of Methods

Routing protocol performance heavily depends on the simulation environment. Table 1 summarizes these environments and key results from representative studies. Direct horizontal comparisons are not recommended due to varying parameters. Instead, the table illustrates relative protocol strengths within specific test environments.

Figure 8
Void identification and staged recovery mechanism of GEDPAR protocol.



(a) Example of routing void

(b) Power adjustment recovery

(c) Depth adjustment recovery

Table 1

Comparison of quantitative performance indicators for routing protocols based on network topology and geometric location. (Performance data in this table are extracted from the original cited studies. Due to significant differences in simulation environments (e.g., node density, network scale, and simulation tools), these data are intended for individual protocol assessment and should not be compared directly.) Note: PN: Protocol Name; Scen.: Scenarios; Sim.: Simulation tools; Sinks: Number of sink nodes; Pkt. (b): Packet size in bytes; Comp.: Comparison protocols; PDR: Packet Delivery Ratio; Net. Life: Network lifetime; Energy: Energy consumption. The same applies to Tables 2-3.

PN	Scen.	Sim.	Sinks	Pkt.(b)	Comp.	PDR	Delay(s)	Net. Life(round)	Energy (J)
EAVARP	3D	NS-2	1	50	DBR, E-PULRPDBR	94%	56	1400	750
E2RV	3D	Customiza-tion	1	200	EDOVE, WDFAD, DBR	86%	320	140 (number of dead nodes)	2700
DVOR	3D	NS-2	1	50	DBR, DUOR	98%	0.6	-	-
GEDPAR	3D, mobile	MATLAB	1	50	GEDAR, LMPC	95%	40	Better than GEDAR	Below than GEDAR
NA-TORA with VA	3D	MATLAB	4	50	NA-TORA	93%	1	2000	500
LF-VARP	3D	MATLAB	1	256	DBR, E-DBR, DEP	95%	60	1800	~25% lower than DBR
NVBF	3D	NS-3	1	64	VBF, Co-VBF, AHH-VBF	92%	14	1400	~22% lower than VBF
EEGPSR	2D, moving	NS-2	1	64	GPSR	96%	0.21	-	410

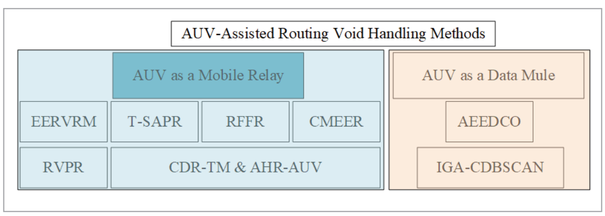
3.2. AUV-aided Routing Method

1 Core Ideas and Technical Principles

Figure 9 summarizes the latest AUV-based routing methods. AUV-aided routing presents a novel paradigm for addressing the routing void problem. This approach is fundamentally based on the introduction of highly mobile AUVs that actively intervene to restore network connectivity. These methods are broadly classified into categories such as passive repair, proactive repair, and collaborative data collection [54, 83].

Figure 9

AUV-assisted routing void handling method.



2 Key Technologies and Representative Protocol Analysis

Initial AUV void handling used passive dispatch. EERVRM [31] answers physical failures; T-SAPR [120] isolates malicious nodes before deploying AUV relays. This cycle causes delay. The RVPR protocol [86] monitors energy and link quality to predict failures, preemptively dispatching an AUV via PSO, though sampling consumes resources. Figure 10 illustrates RVPR's workflow. Nodes monitor neighbors' interruption times; falling below thresholds triggers repair. The AUV uses PSO for relay locations, maximizing connectivity, minimizing travel. Preemptive relocation repairs links before void formation, ensuring transmission.

Addressing single-AUV limits, REVOHPR [12] and CEER [2] explore multi-AUV collaborative remediation. Clustering Method for Energy Efficient Routing (CMEER) optimizes paths, reducing energy but lacking robustness. Reliable and Fault-tolerant Forwarding Routing (RFFR) improves unpredictable routing, enhancing stability but needing large-scale validation. AEEDCO [124] employs AUV data ferries via K-means and PSO to reduce energy despite latency. Finally, IGA-CDBSCAN [103] utilizes genetic algorithms for path planning.

3 **Comparison and Analysis of Methods**

The performance evaluation of routing protocols is inextricably linked to the simulation environment, which fundamentally dictates the applicability of the research findings. Table 2 provides a comprehensive summary of the simulation environments and key results of representative AI-based protocols. The table details their application scenarios, simulation tools, network size, benchmarking protocols, and core performance metrics.

3.3. Routing Methods based on Artificial Intelligence

1 **Core Ideas and Technical Principles**

AI-based routing, particularly machine learning, offers a novel paradigm addressing dynamic underwater routing voids [85]. Endowed with autonomous learning, node agents learn forwarding strategies maximizing long-term rewards (e.g., PDR, network lifetime) [10, 53] by sensing network states, enabling proactive void avoidance [94].

2 **Key Technologies and Representative Protocol Analysis**

Research primarily focuses on Reinforcement Learning (RL), especially Q-Learning variants, alongside integrating RL with other optimization algorithms [117]. Figure 11 summarizes these RL-based void handling methods.

EDORQ [67] combines Q-Learning with depth routing, balancing energy and prolonging lifetime. Its reward integrates forward distance, residual energy, and delivery rate. Voids trigger backward-broadcast recovery, but Q-table maintenance and broadcasting increase memory and latency. Insufficient sparse-region exploration slows convergence, increasing packet loss.

Figure 12 illustrates EDORQ's detect-and-recover mechanism. Lacking shallower neighbors, nodes enter recovery, setting a void flag to 1 and broadcasting. Neighbors suspend depth rules, competing via Q-values. The successful node resets the flag to 0, resuming greedy routing. This rule suspension forms the core mechanism.

QL-EEBDG refines cluster-head weights, extending network lifetime but remaining confined to passive repair with large convergence delays [52]. Proactively avoiding voids, QIH in-

Figure 10

Flowchart of the RVPR algorithm.

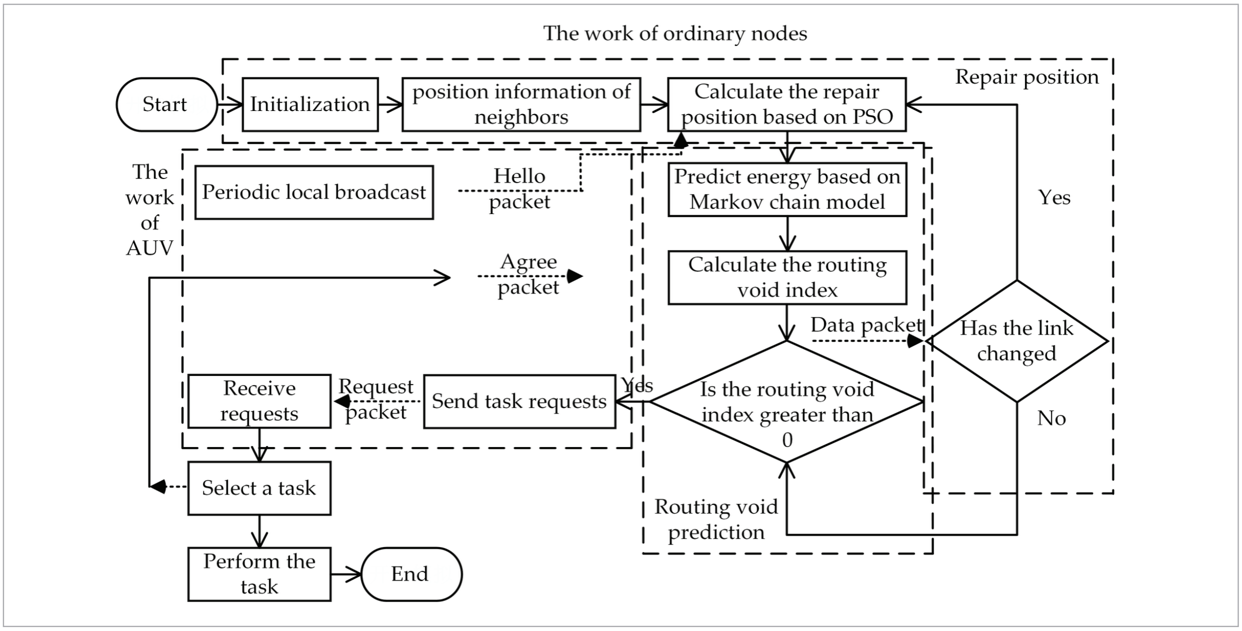


Table 2

Comparison of simulation settings and performance for AUV-assisted routing protocols. (Data from cited studies. Due to varying simulation environments, results are for individual protocol assessment only, not direct comparison.)

PN	Scen.	Sim.	Sinks	Pkt.(b)	Comp.	PDR	Delay(s)	Net.Life	Energy (J)
RVPR	3D, sparse network	-	1	100	DBR, VAPR	98	~4.5	>2500s	~12000
T-SAPR	3D, presence of malicious nodes	MATLAB	1	50	AODV, D-AODV	>95%	~2.8	~ 70% residual energy (1500 rounds)	~20% lower than AODV
EERVRM	3D	MATLAB	1	1024	DBR, RECRP	93%	~56	3000 rounds	~35% lower than DBR
CDR-TM & AHR-AUV	3D, clustering	MATLAB	1	-	DASA, E-PULRP	>95%	~16	~ 3000 rounds	~28% lower than DASA
CMEER	3D, multi-AUV	Aqua-sim	1	50	E-PUL-RP, DBR	>95%	Below than E-PULRP	Better than E-PULRP	~22% lower than E-PULRP
AEEDCO	3D	MATLAB	1	50	DBR, E-PULRP	Close to 100%	Higher (depending on AUV speed	Better than DBR	~60% lower than DBR
RFFR	3D, uncertain environment	MATLAB	1	50	DBR, VAPR, RVPR	>95%	Lower than RVPR	Better than RVPR	~15% lower than RVPR
IGA-CDBSCAN	3D	MATLAB	1	50	LEACH, DEEC	98%	About 135 s (higher)	~ 1600 rounds	~30% lower than LEACH

Figure 11

Method for detecting and repairing routing voids based on RL.

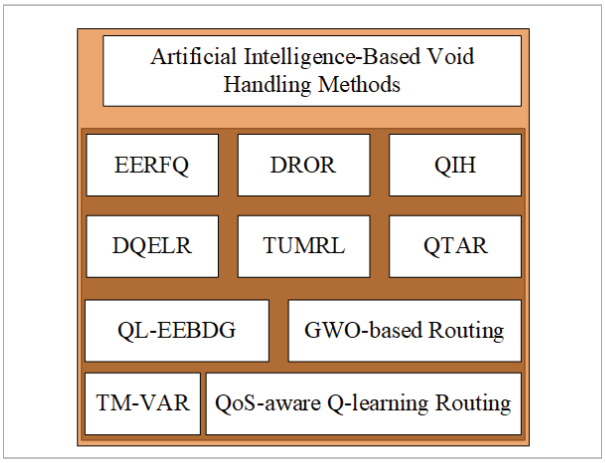
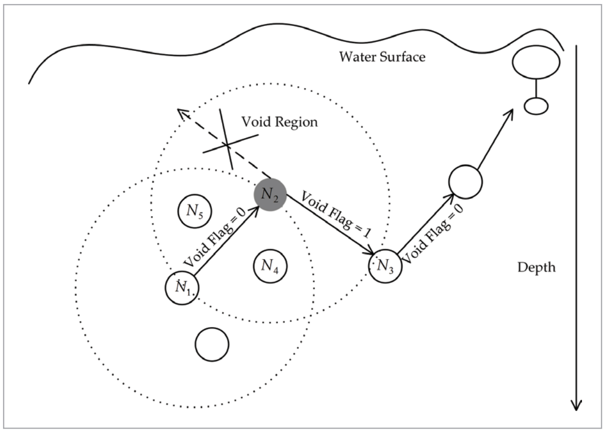


Figure 12

Schematic diagram of the void recovery mechanism of the EDORQ protocol.



troduces negative rewards proportional to distance; however, ranging error sensitivity causes oscillations, and Q-table reliance creates storage bottlenecks [75].

Handling high-dimensional states, DQELR replaces Q-tables with deep neural networks, improving accuracy but incurring heavy computation and weight-download costs [84]. Similarly, FLRAF uses fuzzy logic and neural networks, enhancing predictive accuracy. Despite computationally challenging constrained nodes, it signifies intelligent forwarding trends [11]. QTAR mitigates global disconnection by excluding critical bridge nodes, though 2-hop probing imposes high energy overhead [72].

Integrating security and diverse services is crucial. TM-VAR introduces an energy and link-quality trust model bypassing "logical holes," enhancing reliability but increasing maintenance from frequent assessments and metric storage [109]. TUMRL embeds trust updating into RL, dynamically isolating malicious nodes, though broadcasts increase control traffic and vulnerability [32]. For differentiated QoS, DROR and SAQR incorporate delay rewards, overcoming single-objective limits but requiring manual weight tuning exceeding underwater hardware capabilities [91, 114].

Finally, GWO-based Routing balances energy and link quality via swarm intelligence [27]. Ensuring active void avoidance, complex computations might introduce slight delays.

3 Comparison and Analysis of Methods

Table 3 summarizes tools, scale, and benchmarks for representative studies, providing essential background to assess the validity of each study's conclusions.

Table 3

Comparison of network design and performance for AI-based routing protocols. (Data from cited studies. Due to varying simulation environments, results are for individual assessment only and not for direct comparison.)

PN	Scen.	Sinks.	Pkt. (b)	Comp.	PDR	Delay(s)	Net.Life (round)	Energy (J)
DQELR	3D, MATLAB	4	512	QELAR, DBR	92%	3.2s	The first node dies after about 1800 rounds	~20% lower than QELAR
EDORQ	3D, NS-2	3	128	DBR, DUOR	98% (at 500 nodes)	0.6 s (at 500 nodes)	-	-
TUMRL	3D, MATLAB	1	250	R-UWSN, GTMS, TBF	Packet loss rate less than 5%	2.5s	The remaining energy is about 15% higher than the comparison protocol	-
QL-EEBDG	3D, NS-3	1	64	DBR, EDBR, QL-EECHA	92%	About 75s (higher)	The first node died afterabout 900 rounds	~25% lower than DBR
GWO-based Routing	3D, MATLAB	1	512	EEDBR, WDFAD-DBR, EDOVE	97%	-	About 20% better than EEDBR	~22% lower than EEDBR
QIH	2D, Python	1	128	GPSR, CARP	99%	10-20% lower than GPSR	-	-
QTAR	3D, NS-3	1	64	QELAR, EEDBR	94%	1.7s	The residual energy is about 8% higher than QELAR	~18% lower than QELAR
DROR	3D, MATLAB	4	-	DBR, R-CARP, Q-learning based	95%	0.8s	-	~30% lower than DBR
SAQR	3D, NS-2	4	50	DBR, EDBR, QELAR	97.5%	s	The residual energy is about 5% higher than QELAR	~15% lower than QELAR
TM-VAR	3D, NS-3	-	512	EEDBR, REP	96%	2.5s	~20% higher than EEDBR	~15% lower than EEDBR

4. Future Research Directions

4.1. Research Directions and Challenges Based on Network Topology and Geometric Location

Recent UWSN void avoidance favors Topology-Geometry mechanisms, constructing 3D k-NN graphs to detect neighbor-free regions [19, 64, 105]. Superimposing energy or density creates potential-energy-guided graphs bypassing voids [39, 76]. Mobile relays actively repair local topology [17]. Packaging geometric metrics for Deep Deterministic Policy Gradient (DDPG) optimizes one-hop power [79, 89], achieving PDR $\geq$ 95% and suppressing void rates to 3%-7% [19, 74, 76, 79].

1 **Future Challenges**

Topology-geometry void detection faces challenges in dynamic, large-scale UWSNs: (1) Lack of Temporal Memory and Accurate Prediction: Instantaneous K-NN graphs lacking past link drift memory increase next-hop prediction Mean Squared Error (MSE), compromising reliability. (2) Conflict Between Static Weights and Network Lifespan: Potential-energy-guided graphs lack global survival feedback. Routing through healthy nodes accelerates depletion, triggering voids and shortening lifespan. (3) Decoupling of Replanning Cycles and Environmental Change: High acoustic latency forces 30s-60s global replanning, lagging behind ~20s environmental changes, causing structural failures, making periodic replanning unsustainable.

2 **Proposed Enhanced Framework**

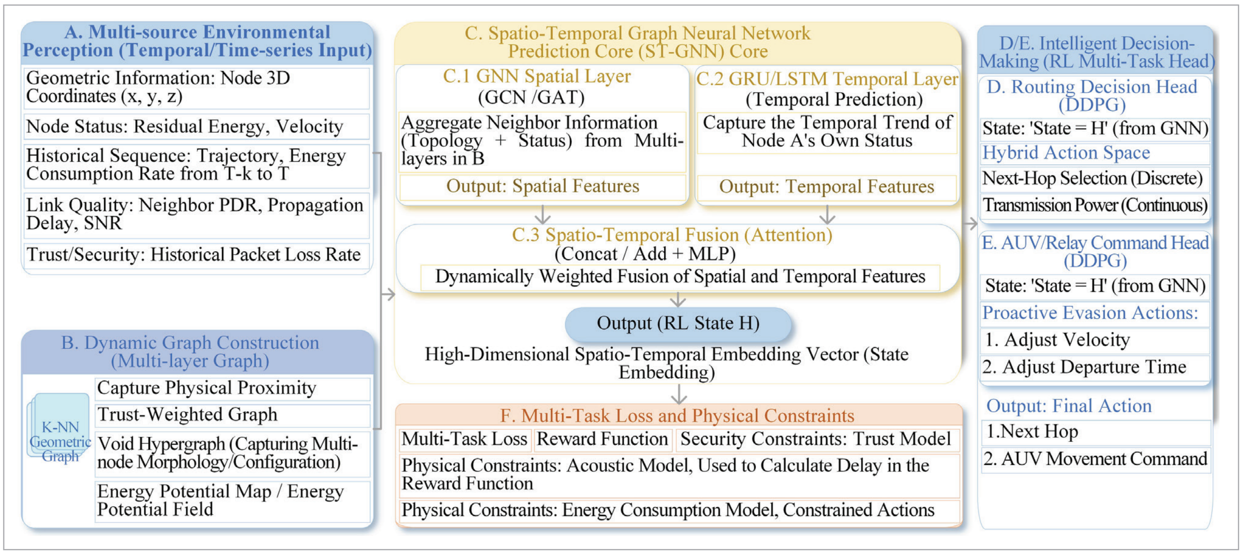
We propose the framework in Figure 13 (Dynamic Geometric Graph-Spatio-Temporal Fusion-Multi-Task DDPG), embedding three modules: (1) Temporal Geometric Edge Weighting: Concatenates energy weights with trends extracted via 1D-CNN from PDR, SNR, and coordinate changes $\Delta(x,y,z)$. A Graph Convolutional Network (GCN) processes these to predict link failures 0.8-1.2s early. (2) Life-Cycle Self-Correction: Embeds surviving nodes' slope as a learnable coefficient. Paths with decreasing survival counts increase energy costs, compelling RL agents to select detours. (3) Local Micro-Reconstruction: If a 2-hop diameter void persists for 5s, mobile relays execute a 10m gradient-based displacement, patching topology within 20s [9].

4.2. Research Directions and Challenges Based on AUV

AUV path planning evolves toward intelligent integration. Researchers improved Rapidly-exploring Random Tree (RRT) algorithms via heuristics [16]

Figure 13

Future research directions based on network topology and geometric location.



or optimized sampling [108], and enhanced Artificial Potential Field (APF) deadlock-breaking [110]. Hybrid 3D algorithms—like cuckoo search with particle swarm [56] or non-linear prediction with QPSO [13]—are mainstream. Deep Q-Network (DQN) assists trajectory planning [46]; control strategies address underactuated UUV execution [113]. Multi-source fusion [62], fuzzy inference [61], and collaborative clustering [7] optimize efficiency.

1 Future Challenges

AUV void repair conflicts with AUV mechanisms, UWSN characteristics, and planning-control chains: (1) Disconnection between AUV Kinematic Constraints and Geometric Paths: APF and RRT generate infeasible paths, ignoring minimum turning radii, forcing excessive energy consumption to smooth trajectories, exacerbating decoupling and oscillation. (2) Sensing Uncertainty and Non-Robustness of Decision-Making: Relying on noisy sonar, methods assuming complete information lack fuzzy logic or fusion to quantify uncertainty, compromising repair reliability. (3) Conflict between Real-time and Optimality: Hybrid intelligent algorithms yield superior solutions, but high computational overhead prevents millisecond-level replanning.

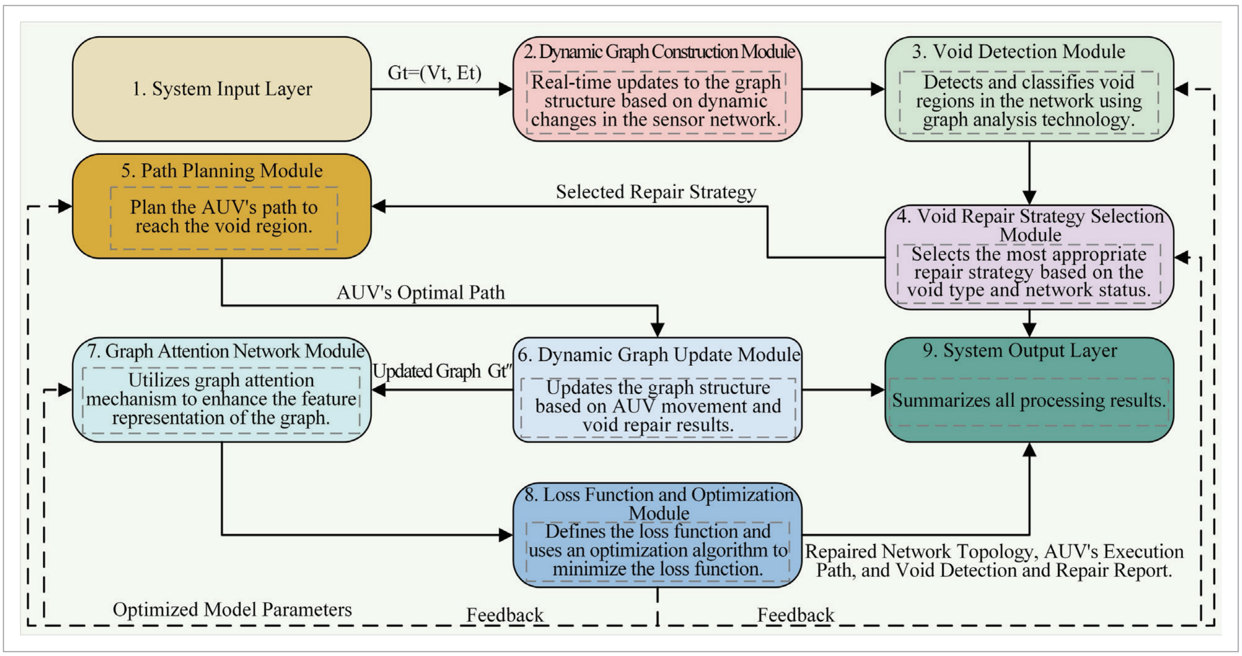
2 Proposed Enhanced Framework

We propose a layered collaborative dynamic repair framework (Figure 14) balancing optimality, real-time performance, executability, and mission orientation: (1) Perception Layer – Fusion and Fuzzy Modeling: Multi-sensor fusion and fuzzy logic model sonar uncertainty, generating 3D fuzzy threat potential fields replacing binary maps. (2) Planning Layer – Hybrid Planning and Temporal Optimization: Combines offline planning (QPSO or cuckoo search) with real-time repair. Improved RRT algorithms and Receding Horizon strategies decompose long-term planning into short sub-problems.

(3) Execution Layer – Smoothing and Tracking under Kinematic Constraints: Path points undergo B-spline smoothing for continuity. A finite-time tracking controller executes trajectories for underactuated UUVs. (4) Decision Layer – Mission-Oriented Intelligent Decision-Making: Cost functions include distance, safety, energy, and deviation. DQN trains decision-makers to adjust cost weights via status and threats.

Figure 14

Future research directions based on AUVs.



4.3. Research Directions and Challenges Based on AI

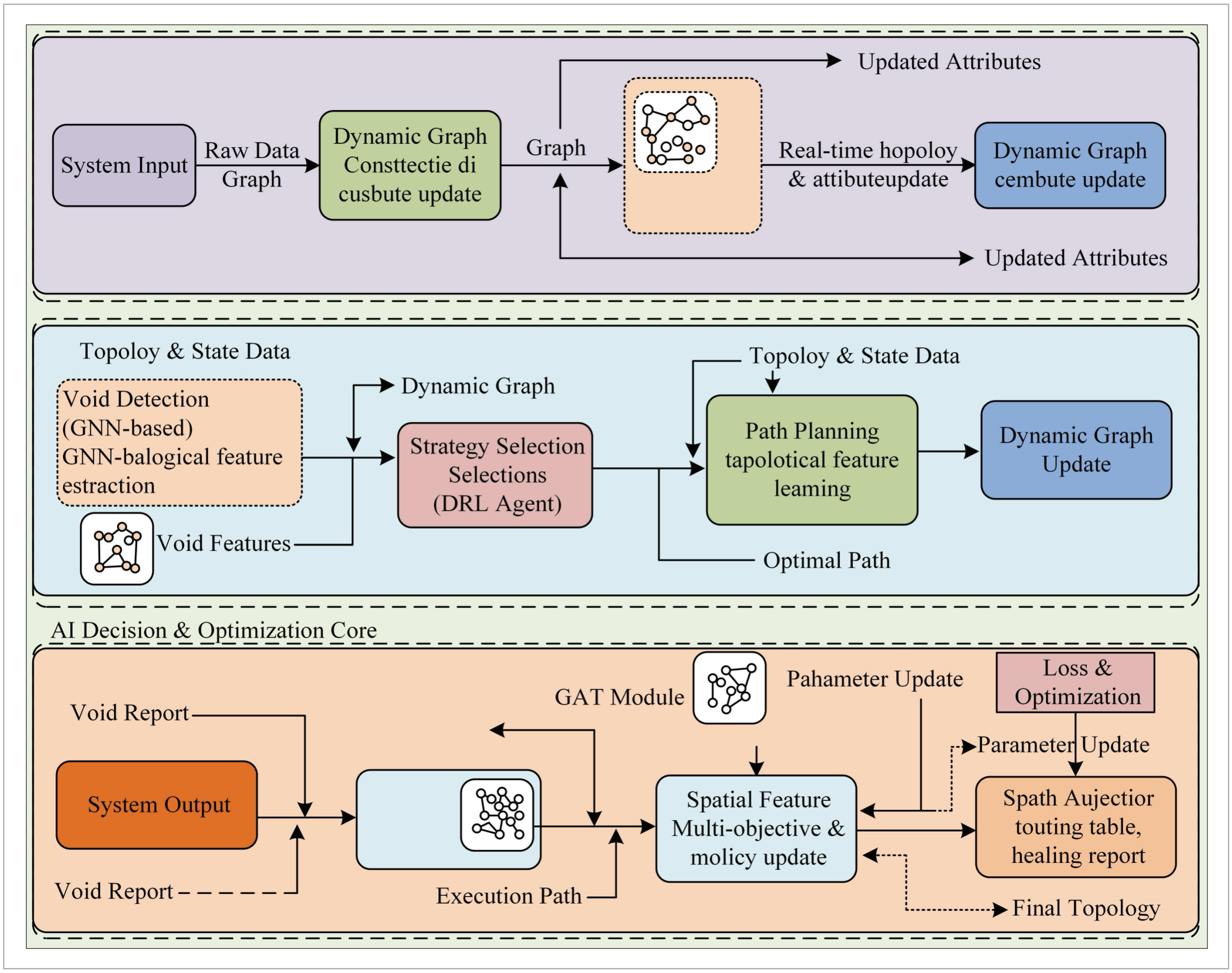
AI-driven AUV research in UWSNs shifts toward intelligent integration. [36] optimizes multi-AUV task allocation via Soft Actor-Critic (SAC); [40,102] review node energy and void limitations. In security and sensing, [95] proposes bio-inspired anti-eavesdropping routing, and [21] designs an Adaptive Multi-modal Sensing Framework (AMSA). Regarding trust, [22] utilizes LSTM for adaptive malicious node identification; [59] applies Q-learning for dynamic layered routing. Reinforcement learning (RL) enhances system-level efficiency and load balancing [94,121]. [123] demonstrates BP-NN's potential processing non-linear underwater data.

1 **Future Challenges**

AI-based void repair faces algorithm bottlenecks and UWSN dynamic mismatches: (1) Complexity vs. Real-time Performance: High demands of RL, Q-learning, and LSTM overwhelm constrained nodes, hindering millisecond-level repair and causing packet loss. (2) Model Dependency and Environmental Uncertainty: Existing schemes favor passive rerouting. BP-NNs' accuracy relies on input quality, severely degrading in non-linear environments when voids form, threatening reliability. (3) Decoupling of AUV Assistance and Static Routing: Independent AUV path planning underutilizes AUVs for precise void filling. (4) Lack of Energy Balance: Dynamic layered proto-

Figure 15

Future research directions based on AI.



cols cause premature death of nodes near large voids, failing sustainable topologies.

2 **Proposed Enhanced Framework**

We propose an Intelligent Routing Void Processing Framework fusing BP-NN prediction, dynamic layering, and AUV collaborative repair: (1) BP-NN Prediction Mechanism: Neural networks predict voids using residual energy, depth, and historical communication quality, enabling proactive prevention. (2) Dynamic Layering Strategy: Utilizing predictions, this adjusts node layers and forwarding probabilities, diverting traffic to prevent congestion. (3) AUV Collaborative Repair Mechanism: Predicting severe, un-bypassable voids, BP-NN dispatches an AUV for relay or energy replenishment.

Figure 15 illustrates the workflow: post-initialization and data collection, BP-NN executes real-time training and prediction. Based on risk levels, the system selects conventional greedy forwarding or routing repair (including AUV collaboration), forming a closed-loop intelligent routing management system.

5. Conclusion

This study provides a comprehensive review of routing void detection and repair technologies in UWSNs. Moving beyond a mere literature summary, findings reveal profound patterns in the field's technological paradigm evolution, demonstrating a clear transition from static geometric constraints toward dynamic intelligence. Initially, research focused on rigid, geometry-based detour rules passively responding to voids. This evolved into proactive management, where AUV-aided mobility and AI-driven prediction work in tandem to preemptively mitigate network partitions. The core logic shifts from detection and repair toward prediction and avoidance, reflecting deeper integration of temporal and spatial network features. Furthermore, a visible move from single-entity optimization toward collaborative swarm intelligence occurs, where synergy between fixed nodes and mobile AUVs defines next-generation resilient architectures.

To achieve significant breakthroughs, future research must transcend traditional networking boundaries and embrace interdisciplinary integration. One high-potential direction involves bio-inspired swarm intelligence; integrating marine school behavior patterns into reinforcement learning models enhances AUV swarm adaptability in unpredictable currents. Additionally, digital twins and edge computing offer a transformative approach. Constructing high-fidelity underwater digital twins allows real-time void simulation, enabling edge-deployed AI models to optimize topology before physical failures. Another frontier is acousto-optical hybrid communications. Leveraging high-bandwidth optical links alongside long-range acoustic reliability requires cross-layer routing protocols that intelligently switch modes based on real-time turbidity and noise. In conclusion, UWSN reliability's future lies in fusing advanced AI, underwater physics, and collaborative robotics, providing a roadmap for next-generation, void-resilient systems.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, author-ship, and/or publication of this article.

Data Sharing Agreement

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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