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OPTIMIZING BUOYANT WIRELESS SENSOR NETWORKS: EVALUATING ALBATROSS ADAPTIVE ACOUSTIC ROUTING PROTOCOL FOR ENHANCED PERFORMANCE AND RELIABILITY

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ABSTRACT

The proposed Albatross Adaptive Acoustic Routing Optimization (AARO) protocol represents a breakthrough in IT-driven solutions for underwater wireless sensor networks. By leveraging adaptive routing mechanisms and bio-inspired optimization, AARO addresses critical challenges in underwater communication, including high energy consumption, network instability, and packet loss. This research contributes to IT by integrating intelligent routing decisions based on real-time environmental data, enhancing network longevity, and improving data transmission reliability. The findings demonstrate that AARO significantly outperforms existing protocols, offering a scalable and energy-efficient solution for buoyant WSNs. The research aligns with advancements in IT, enabling efficient data acquisition in marine exploration, disaster management, and environmental monitoring, reinforcing the role of IT in solving real-world challenges.

Keywords: *Buoyant WSN - Adaptive Acoustic Routing Protocol - Underwater Communication - Routing - Albatross Optimization.*

1. INTRODUCTION

Wireless Sensor Networks (WSNs) represent a transformative technology that has revolutionized data collection and monitoring across various domains[1]. These networks consist of small, autonomous sensor nodes with sensing, computing, and communication capabilities. WSNs are deployed in diverse environments, ranging from terrestrial to aquatic, to gather and transmit data in real-time[2]. One significant aspect of WSNs is their versatility, which manifests in various types tailored to specific application requirements[3]. Initially, the terrestrial WSNs were widely deployed in terrestrial environments such as forests, urban areas, and agricultural fields for applications like environmental monitoring, smart cities, and precision agriculture[4]. Then aerial WSNs utilize drones or unmanned aerial vehicles (UAVs) equipped with sensors for surveillance, disaster management, and wildlife monitoring. Finally, Buoyant WSNs operate underwater, leveraging acoustic communication for applications such as oceanographic research, marine habitat monitoring, and underwater exploration[5].

Buoyant Wireless Sensor Networks (B-WSNs) stand out in aquatic environmental sensing by strategically situating water surface sensors [6]. This unconventional approach introduces a highly flexible and dynamic platform for data collection, diverging from traditional underwater networks[7]. The significance of this paradigm shift extends to applications ranging from oceanographic research to rapid disaster response. Equipped with sensors designed for buoyancy and wireless communication, B-WSN represents a technological frontier where challenges of communication range variability, buoyant node mobility, and energy efficiency demand innovative solutions[8]. The transformative potential of B-WSN lies in its ability to redefine surface-level environmental monitoring, providing unprecedented insights into the complex dynamics of the world's water systems[9].

B-WSN emerge as an invaluable assets in the urgent mission to prevent oil spills. The floating sensors positioned on the water's surface enable proactive monitoring, early detection, and rapid response, offering a crucial defence against

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potential ecological catastrophes in aquatic environments[10]. The environmental ramifications of oil spills are profound, transcending marine ecosystems and wildlife habitats and impacting human health. The devastating effects of oil spills extend beyond the conspicuous surface contamination, delving deep into the intricate web of marine life[11]. Underwater organisms form the backbone of aquatic ecosystems and become unwitting victims of oil contamination, enduring pervasive and often irreversible consequences[12]. Simultaneously, coastal lands adjacent to the ocean, characterized by diverse ecosystems, bear the ecological burden of oil spills. The intricate interplay between terrestrial and marine environments amplifies the environmental repercussions, creating a ripple effect in both realms. As this research delves into the intricacies of oil spills, it becomes imperative to dissect the various dimensions of their impact, from water and soil contamination to species endangerment[13]. The pressing need for effective detection methods to swiftly identify and mitigate oil spill incidents is at the core of addressing these challenges[14].

Routing in B-WSN takes centre stage, shaped by the distinctive characteristics of floating sensors on the water's surface. Influenced by buoyant node mobility, the semi-static or dynamic network topology necessitates adaptive routing strategies. Multi-hop communication using acoustic or radio waves encounters challenges in transmission range variability dictated by water conditions[15]. Diverse data types, from control messages to complex environmental datasets, amplify the intricacies of B-WSN routing. Security concerns become prominent, demanding encryption, tamper-proofing, and secure routing protocol integration[16]. Scalability is pivotal, requiring adaptability to the evolving network size amid the dynamic underwater environment, emphasizing the unique challenges faced in B-WSN routing[17].

Information Technology plays a pivotal role in the evolution of Buoyant Wireless Sensor Networks (B-WSNs) by enabling intelligent, autonomous, and adaptive communication frameworks in underwater environments. Traditional IT-based routing solutions struggle with dynamic aquatic conditions, requiring novel approaches that integrate real-time decision-making, optimization algorithms, and energy-efficient mechanisms. The introduction of Albatross Adaptive Acoustic Routing Optimization (AARO) advances IT research by combining bio-inspired computing with adaptive networking strategies, ensuring high-performance communication in constrained underwater settings. The study contributes to IT by addressing fundamental challenges in data transmission, network resilience, and fault tolerance within complex environments. By leveraging IT advancements in algorithm design, network optimization, and real-time environmental adaptation, this research lays a foundation for next-generation underwater sensor networks, driving applications in marine monitoring, climate research, and ocean-based IoT deployments.

1.1. Problem Statement

Fault Tolerance in Unstable Environments poses a critical obstacle in B-WSN. The inherent unpredictability of these environments, characterized by water currents, turbulence, and other environmental factors, necessitates the development of robust routing protocols capable of effectively handling node failures and disruptions in communication paths. Traditional routing mechanisms are often inadequate in such dynamic settings, where buoyant sensor nodes face increased susceptibility to failures due to environmental stresses. The challenge extends beyond node failures, encompassing disruptions caused by factors like water turbulence, which can lead to intermittent communication paths. Addressing this challenge is paramount for ensuring the reliability and longevity of B-WSN deployments, especially in applications where continuous and uninterrupted data collection is critical, such as environmental monitoring and disaster response. Developing routing protocols with advanced fault tolerance mechanisms tailored for the unique challenges of B-WSN in unstable environments is crucial to unlocking the full potential of these networks in providing resilient and sustained wireless communication in dynamic aquatic settings.

1.2. Motivation

The motivation to address the challenge of Fault Tolerance in Unstable Environments within BWSN is grounded in the imperative need for sustained and reliable data communication in dynamic aquatic settings. The unpredictable nature of underwater environments, marked by water currents and turbulence, poses a formidable threat to the operational stability of buoyant sensor networks. Recognizing the significance of fault tolerance mechanisms is crucial in scenarios where these networks are deployed for critical applications like

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environmental monitoring and disaster response. The motivation stems from the understanding that interruptions caused by node failures or communication disruptions can hinder the timely and accurate collection of essential data, compromising the effectiveness of B-WSN in addressing environmental challenges. By developing routing protocols equipped with robust fault tolerance mechanisms tailored for unstable environments, this research endeavours to fortify the resilience of B-WSN, ensuring their sustained functionality despite environmental stresses. The motivation lies in advancing the capabilities of B-WSN to navigate the complexities of unstable aquatic environments, fostering their reliability in delivering uninterrupted communication paths and bolstering their potential for impactful applications in environmental preservation and disaster management.

1.3. Objective

The primary objective of this research is to design and implement a bio-inspired routing protocol for BWSN with a specific emphasis on enhancing fault tolerance in unstable aquatic environments. The goal is to draw inspiration from natural systems and develop innovative routing strategies that can adapt dynamically to node failures or communication disruptions caused by environmental factors such as water currents and turbulence. The objective is twofold: firstly, to enhance the reliability and robustness of B-WSN by incorporating advanced fault tolerance mechanisms, ensuring uninterrupted communication paths in the face of environmental challenges. Secondly, to explore the potential of bio-inspired principles, such as collective behaviours observed in marine organisms, to optimize routing paths in inherently unstable environments. By achieving these objectives, the research aims to contribute to developing resilient and adaptable B-WSN protocols that can thrive in unpredictable aquatic settings, ultimately improving the effectiveness of environmental monitoring, disaster response, and other critical applications reliant on continuous and reliable data communication.

2. LITERATURE REVIEW

"PiezoWave" [18] details an underwater piezoelectric energy harvester designed with magnetic coupling, adaptable to low-speed water flow conditions. This harvester converts kinetic energy from water movements into electrical energy, powering underwater sensors. Its adaptability to varying water speeds makes it versatile for sustaining underwater monitoring systems without external power. "TrustAUV" [19] presents a secure routing protocol incorporating trust management and Autonomous Underwater Vehicle (AUV)-aided path repairing for underwater acoustic sensor networks. The protocol establishes trust levels among sensor nodes to ensure secure data transmission. AUVs assist in repairing broken communication paths and maintaining network integrity and reliability. "DeepTrack" [20] proposes an end-to-end sensor scheduling method based on Double Deep Q-Network (D3QN) for underwater passive tracking in underwater sensor networks. The technique uses reinforcement learning to optimize the scheduling of sensor nodes, ensuring efficient tracking of underwater targets. This approach enhances the network's capability to monitor and track movements passively. "SafeCom" [21] introduces a robust mutual authentication and session key-sharing protocol tailored for underwater wireless sensor networks. This protocol ensures secure communication between sensor nodes by implementing robust authentication mechanisms and dynamic session key exchanges. Its robustness against potential threats makes it reliable for secure underwater data transmission.

"FusionDetect" [22] presents a cluster-based fusion detection method combining soft and hard decision-making processes for identifying non-cooperative targets underwater. The technique integrates data from clustered sensor nodes, enhancing detection accuracy. This dual decision-making approach ensures reliable identification of underwater targets that do not cooperate with detection efforts. "SpyDefense" [23] offers a distributed anti-theft topology control mechanism to protect against spy robots in insecure underwater acoustic sensor networks. The mechanism dynamically adjusts the network topology to safeguard sensitive data and communication paths. Its distributed nature ensures robust defense across the network, preventing unauthorized access and data breaches. "SpyDefense" [23] offers a novel solution to protect underwater acoustic sensor networks (UASN) from unauthorized access and espionage by underwater spy robots. This distributed anti-theft topology control mechanism dynamically adjusts the network topology to ensure secure communication pathways. By continually modifying the structure of the network, it reduces the risk of interception and data theft. Key contributions include the development of an

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adaptive topology control method that enhances security without compromising network performance, making it particularly suitable for sensitive underwater monitoring operations. This mechanism provides a robust defense strategy against potential security threats in underwater environments.

"MultiCluster" [24] proposes an energy-aware multilevel clustering scheme for underwater sensor networks. This scheme organizes sensor nodes into hierarchical clusters, optimizing energy use and extending network lifespan. Key contributions include the development of a multilevel clustering approach that balances energy consumption across the network, enhancing sustainability and performance in underwater environments. "DeepOp" [25] introduces an opportunistic routing protocol based on reinforcement learning that utilizes depth information for energy efficiency in underwater sensor networks. This protocol dynamically adjusts routing decisions based on learned depth profiles, optimizing energy use and improving data transmission reliability. Key contributions include using reinforcement learning to enhance routing efficiency and incorporating depth information to adapt to underwater topography. "ExpertRelay" [26] presents a partial expert-based adversarial relay learning strategy for underwater acoustic sensor networks. This strategy employs expert systems to guide relay decisions, enhancing routing efficiency and security. Key contributions include integrating expert-based learning with the adversarial strategy to improve data transmission and protect against potential threats in underwater communication.

"GridDeploy" [27] proposes a grid-based deployment scheme to enhance network performance in underwater acoustic sensor networks. This scheme organizes sensor nodes in a grid pattern, optimizing coverage and connectivity. Key contributions include the development of a structured deployment approach that improves network efficiency and reliability, making it suitable for large-scale underwater monitoring applications. "SubseaOps" [28] explores the potential for automatic subsea operations using real-time underwater optical wireless sensor networks. This system enables high-speed optical communication and real-time data processing, facilitating automated underwater tasks. Key contributions include integrating optical wireless technology with real-time operational capabilities, advancing underwater exploration, and monitoring automation. "HybridRoute" [29] presents a routing protocol for underwater acoustic-optical hybrid networks incorporating packet hierarchy and void processing techniques. This protocol efficiently manages data packets and addresses communication voids, ensuring reliable data transmission. Key contributions include the use of hierarchical packet management and void processing to optimize routing in hybrid communication environments, enhancing overall network performance.

"ClusterLoc" [30] explores localization methods for wireless and multimedia sensor networks using clustering techniques. This approach groups sensor nodes into clusters to improve localization accuracy and reduce computational complexity. Key contributions include the development of clustering-based localization strategies that enhance the precision and efficiency of sensor node positioning. "FireflyDeploy" [31] presents a node deployment strategy based on the multi-population firefly algorithm. This algorithm simulates the behavior of fireflies to find optimal node positions, ensuring efficient coverage and connectivity. Key contributions include using multi-population optimization to improve deployment outcomes and providing a robust solution for underwater sensor networks. Selection of appropriate bio-inspired optimization algorithm will result in better results in all research domain [32]-[63].

"MO-CBACORP" [64] proposes a multi-objective, cluster-based adaptive cognitive routing protocol for underwater monitoring wireless sensor networks. The protocol focuses on energy efficiency and security, utilizing cognitive techniques to route data while conserving energy adaptively. It enhances network resilience against potential threats and ensures efficient data transmission in underwater environments. "HOCOR" [65] introduces a hybrid optimization-based cooperative opportunistic routing protocol designed for underwater sensor networks. This protocol combines optimization techniques to enhance routing decisions, ensuring efficient data transmission. It leverages cooperative strategies among sensor nodes to adjust routing paths based on real-time network conditions. Key contributions include integrating hybrid optimization methods with cooperative routing, which significantly improves the network's adaptability and performance in underwater environments.

3. ALBATROSS ADAPTIVE ACOUSTIC ROUTING OPTIMIZATION (AARO)

3.1. Adaptive Acoustic Routing

Adaptive Acoustic Routing (AAR) represents a pioneering approach in B-WSNs, particularly tailored for buoyant applications operating in dynamic and unstable environments. AAR harnesses acoustic signals to establish reliable communication pathways amidst challenging conditions, offering robust fault tolerance and adaptability. This innovative routing protocol optimizes data transmission efficiency by dynamically adjusting routing paths based on real-time environmental cues, ensuring uninterrupted data flow in fluctuating scenarios. AAR ensures reliable and efficient data communication in dynamic and unpredictable underwater environments by leveraging adaptive algorithms, environmental sensing, and fault tolerance mechanisms.

3.1.1. Environmental Sensing:

Environmental Sensing encompasses the comprehensive monitoring and analysis of various environmental parameters crucial for determining optimal routing paths and adapting to dynamic underwater conditions. In this stage, the network nodes employ a range of sensors to gather real-time data on factors such as water currents, temperature gradients, and spatial obstacles. This Environmental Sensing in AAR involves the integration of sensor measurements into environmental models to estimate relevant parameters. One fundamental aspect is the utilization of hydrodynamic models to characterize water currents. One such model is the Navier-Stokes equation expressed as Eq.(1).

$$\frac{\partial u}{\partial t} + (u.\nabla) = -\frac{1}{\rho}\nabla p + v\nabla^2 u + f \tag{1}$$

where u represents the velocity field, p denotes pressure, ρ signifies fluid density, v represents kinematic viscosity, and f denotes external forces.

Another critical parameter in underwater environments is temperature distribution, which impacts acoustic wave propagation. The heat equation governs the temperature distribution T over time t and space x is represented mathematically in Eq.(2).

$$\frac{\partial T}{\partial t} = \alpha\nabla^2 T \tag{2}$$

where α denotes thermal diffusivity. Environmental Sensing involves characterizing spatial obstacles using obstacle detection algorithms. One commonly employed method is probabilistic obstacle mapping, which utilizes Bayesian inference to estimate the likelihood of obstacles given sensor measurements. The occupancy grid mapping algorithm expresses the probability $P(O_i|Z_{1:t})$of an obstacle $O_i$at a grid cell based on sensor measurements $Z_{1:t}$up to time t.

$$P(O_i|Z_{1:t}) = \frac{P(Z_t|O_i, Z_{1:t-1})P(O_i|Z_{1:t-1})}{P(Z_t|Z_{1:t-1})} \tag{3}$$

where in Eq.(3), $P(Z_i|O_i, Z_{1:t-1})$represents the probability of obtaining sensor measurements Z_t given the presence of an obstacleO_i,$P(O_i|Z_{1:t-1})$signifies the prior probability of an obstacle at the grid cell, and $P(Z_t|Z_{1:t-1})$denotes the probability of obtaining sensor measurements Z_t.

In addition to obstacle detection, Environmental Sensing entails estimating signal propagation characteristics in underwater environments. One crucial parameter is acoustic attenuation, which quantifies the decrease in signal intensity over distance. The Thorp attenuation model expresses acoustic attenuation α in dB/km as a function of frequency f and depth d is represented mathematically in Eq.(4).

$$\alpha(f, d) = 0.00f^2 + 0.002d + 0.003 \tag{4}$$

where f represents frequency in kHz and d denotes depth in meters.

3.1.2. Node Localization:

Node Localization enables the network to establish a spatial awareness framework, essential for devising optimal routing paths and mitigating signal propagation challenges inherent in buoyant underwater environments. It employs acoustic ranging techniques to estimate the distances between neighbouring sensor nodes. One widely utilized method is Time of Arrival (TOA) ranging, which leverages the time taken for acoustic signals to propagate between nodes. The TOA estimation equation is mathematically expressed in Eq.(5).

$$d = \frac{c.\Delta t}{2} \tag{5}$$

where d represents the distance between nodes, c denotes the speed of sound in water, and Δt signifies the time difference of arrival between transmitted and received signals. Node Localization encompasses applying Angle of Arrival (AOA) techniques to determine the directional angles between nodes. The AOA estimation equation is expressed in Eq.(6).

$$\theta = arctan\left(\frac{y}{x}\right) \tag{6}$$

where θ represents the angle of arrival, and x and y denote the spatial coordinates of the target node relative to the reference node. Node Localization involves the integration of ranging measurements from multiple reference nodes to triangulate the precise position of the target node. Triangulation algorithms, such as Multilateration, utilize the geometric relationships between reference nodes and the target node to calculate its position. The Multilateration is expressed in Eq.(7).

$$(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2 = d_i^2 \quad (7)$$

where (x_i, y_i, z_i) represents the coordinates of the i^{th}reference node, and $d_i$denotes the distance between the target node and the i^{th}reference node. Node Localization in AAR incorporates robust error estimation and mitigation techniques to account for measurement inaccuracies and environmental disturbances. Weighted Least Squares (WLS) estimation is a standard method to minimize localization errors by assigning weights to range measurements based on their reliability. The WLS objective function is shown in Eq.(8).

$$min_{\hat{x}} \|Ax - b\|_W^2 \quad (8)$$

where $\hat{x}$ denotes the estimated position vector, A represents the design matrix containing ranging measurements, b signifies the observed ranging values, and W denotes the weight matrix.

3.1.3. Dynamic Path Selection:

Dynamic Path Selection leverages the information gathered from Environmental Sensing and Node Localization to adaptively adjust routing decisions, ensuring efficient data transmission in B-WSNs. This Dynamic Path Selection involves formulating an objective function incorporating node positions, environmental conditions, and network constraints to determine optimal routing paths. One commonly used objective function is the Weighted Sum of Costs (WSC), which quantifies the cost associated with each potential routing path. The aim of the WSC function can be expressed as Eq.(9).

$$F = \sum_{i=1}^{N} w_i . c_i \quad (9)$$

where F represents the overall cost of the routing path, $w_i$denotes the weight assigned to the factor, and i^{th}signifies the cost associated with the i^{th} factor.

Dynamic Path Selection entails the utilization of routing algorithms that dynamically adjust routing paths based on current network conditions. One such algorithm is the Ant Colony Optimization (ACO), inspired by the foraging behaviour of ants. In ACO, artificial ants traverse the network graph, depositing pheromone trails on visited paths proportional to their quality. The probability $P_{ij}$of selecting the j^{th} node as the next hop from the i^{th} The node is calculated mathematically expressed in Eq.(10).

$$P_{ij} = \frac{\tau_{ij}^{\alpha} . \eta_{ij}^{\beta}}{\sum_{k \in Neighbors(i)} \tau_{ik}^{\alpha} . \eta_{ik}^{\beta}} \quad (10)$$

where τ_{ij}represents the pheromone level on the edge between nodes i and j, η_{ij} denotes the heuristic information, α and β are parameters controlling the influence of pheromone trails and heuristic information, and $Neighbors(i)$denotes the neighbouring nodes of node i.

Dynamic Path Selection integrates adaptive routing strategies that dynamically adjust routing paths based on real-time environmental cues. Reinforcement learning techniques, such as Q-learning, enable nodes to learn optimal routing policies through interaction with the environment. The Q-learning update rule is expressed mathematically in Eq.(11).

$$Q(s,a) = (1 - \alpha) . Q(s,a) + \alpha . [r + \gamma . max_{a'} Q(s', a')] \quad (11)$$

where $Q(s,a)$ represents the quality of taking action a in state s, αdenotes the learning rate, r signifies the immediate reward, γ denotes the discount factor, s' denotes the next state and a' denotes the following action.

3.1.4. Acoustic Transmission

Acoustic Transmission leverages acoustic signals as the primary communication medium, harnessing their ability to propagate through water with minimal attenuation and interference.

Acoustic Transmission involves characterizing the propagation of acoustic waves in underwater environments using wave equations. One fundamental equation governing acoustic wave propagation is the Wave Equation, which describes the propagation of pressure waves p through a medium and is expressed in Eq.(12).

$$\nabla^2 p - \frac{1}{c^2} \frac{\partial^2 p}{\partial t^2} = 0 \quad (12)$$

where c represents the speed of sound in the medium. It also incorporates models that account for attenuation effects on acoustic signal propagation. The Exponential Attenuation Model expresses the decrease in acoustic signal intensity I over distance $r$as.

$$I(r) = I_0 . e^{-\alpha r} \tag{13}$$

where in Eq.(13), I_0represents the initial signal intensity, and α denotes the attenuation coefficient.

Acoustic Transmission involves applying modulation techniques to encode data into acoustic signals. Frequency Shift Keying (FSK) is a commonly used modulation scheme that modulates the acoustic signal's carrier frequency based on the transmitted digital data. The FSK modulation is shown in Eq.(14).

$$s(t) = A. sin(2\pi f_c t + 2\pi \Delta f . data(t)) \tag{14}$$

where $s(t)$ represents the modulated signal, A denotes the amplitude, f_c signifies the carrier frequency, Δf denotes the frequency shift, and $data(t)$represents the digital data to be transmitted. It integrates error control coding techniques to enhance the reliability of data transmission in the presence of noise and channel impairments. Forward Error Correction (FEC) codes, such as Reed-Solomon codes, add redundant information to transmitted data to enable error detection and correction at the receiver. The Reed-Solomon encoding is represented mathematically in Eq.(15).

$$c = m. G \tag{15}$$

where c represents the codeword, $m$denotes the message vector, and G signifies the generator matrix.

3.1.5. Routing Optimization

It constitutes a critical phase to maximize the efficiency and robustness of data transmission within B-WSNs operating in dynamic underwater environments. Routing Optimization leverages adaptive algorithms to dynamically adjust routing parameters and strategies, ensuring optimal data delivery while mitigating the impact of environmental uncertainties and network dynamics. This Routing Optimization involves formulating objective functions that balance performance metrics, such as energy consumption, latency, and throughput, to determine optimal routing paths. One commonly used objective function is the Multi-Objective Optimization (MOO) function, which seeks to optimize multiple conflicting objectives simultaneously. The MOO function can be expressed mathematically in Eq.(16).

$$Minimize\ f(x) = \left(f_1(x), f_2(x), \dots, f_k(x)\right) \tag{16}$$

where $f_i(x)$ denotes the i^{th} the objective function and x represents the routing parameters.

In addition to the objective function, Routing Optimization integrates adaptive routing algorithms that dynamically adjust routing paths based on real-time environmental cues and network conditions. Genetic Algorithms (GA) are famous for optimizing routing paths in AAR. In GA, candidate routing paths are represented as chromosomes, and genetic operators such as crossover and mutation are applied to evolve optimal solutions. The fitness function $F(x)$evaluates the performance of each routing path, guiding the search towards better solutions.

Routing Optimization incorporates mechanisms to balance energy consumption across sensor nodes to prolong network lifetime. Energy-aware routing protocols aim to minimize energy consumption by selecting paths with lower energy requirements. The energy consumption model is expressed mathematically in Eq.(17).

$$E = \sum_{i=1}^{N} P_i . t_i \tag{17}$$

where E represents the total energy consumption, $P_i$denotes the power consumption of node i, and t_i signifies the transmission time of node i.

3.1.6. Fault Tolerance Mechanisms

It assumes paramount significance in bolstering the resilience and reliability of data transmission within B-WSNs navigating dynamic underwater environments. Fault Tolerance Mechanisms in AAR are devised to mitigate the adverse effects of node failures, signal interference, and environmental disturbances, ensuring uninterrupted data delivery and network performance. This Fault Tolerance Mechanisms entail integrating redundancy strategies to enhance the robustness of data transmission in the presence of node failures. One commonly employed redundancy technique is Route Redundancy, which involves establishing multiple backup routing paths to circumvent failed nodes or disrupted communication links. The probability of successful data delivery P_s with route redundancy can be calculated, as shown in Eq.(18).

$$P_s = 1 - \prod_{i=1}^{n} \left(1 - P_{s_i}\right) \tag{18}$$

where P_{s_i}represents the probability of successful data delivery on the i^{th} routing path. The Fault

Tolerance Mechanisms in AAR integrate error detection and correction techniques to identify and rectify data errors caused by noise and channel impairments. Cyclic Redundancy Check (CRC) codes are commonly used for error detection, where a checksum is appended to transmitted data, and receivers can verify data integrity by recalculating the checksum and comparing it with the received checksum. The CRC checksum is represented mathematically in Eq.(19).

$$Checksum = remainder\left(\frac{Data \times 2^k}{Generator}\right) \quad (19)$$

where Data represents the transmitted data, k denotes the number of bits in the generator polynomial, and Generator signifies the polynomial used for CRC calculation.

It incorporates mechanisms for packet retransmission to recover from lost or corrupted data packets. Automatic Repeat reQuest (ARQ) protocols, such as Selective Repeat (SR) and Go-Back-N (GBN), enable receivers to request retransmission of missing or erroneous packets from senders. The probability of successful packet retransmission P_r can be calculated as shown in Eq.(20).

$$P_r = 1 - (1 - P_s)^n \quad (20)$$

where n denotes the number of retransmission attempts. It also integrates adaptive strategies for adjusting error correction and retransmission parameters based on network conditions. Adaptive ARQ protocols dynamically adjust retransmission timeouts and packet window sizes to optimize data delivery performance while minimizing overhead. The Adaptive ARQ update rule adjusts the retransmission timeout T_{TO} based on measured round-trip times RTT and estimation of packet loss probability P_{loss}:

$$T_{TO} = RTT + k.\sqrt{P_{loss}} \quad (21)$$

where in Eq.(21), k is a constant factor.

3.1.7. Adaptive Parameter Tuning

This phase is critical in optimizing the performance and adaptability of the routing protocol within B-WSNs operating in dynamic underwater environments. Adaptive Parameter Tuning involves dynamically adjusting routing parameters based on real-time environmental cues, network dynamics, and performance metrics. This ensures optimal data delivery while mitigating the impact of uncertainties and variations. Adaptive Parameter Tuning encompasses formulating adaptive algorithms that dynamically adjust routing parameters to optimize performance metrics such as energy consumption, latency, and throughput. One commonly used adaptive algorithm is the Gradient Descent algorithm, which iteratively updates routing parameters to minimize a cost function. The parameter update equation in Gradient Descent is mathematically expressed in Eq.(22).

$$\theta_{t+1} = \theta_t - \alpha \nabla J(\theta_t) \quad (22)$$

where θ_t represents the parameter vector at iteration t, α denotes the learning rate, and $J(\theta_t)$ signifies the cost function. It integrates reinforcement learning techniques that enable nodes to learn optimal routing policies through interactions with the environment. One such technique is Q-learning, where nodes update Q-values based on observed rewards and penalties. The Q-learning update rule adjusts the Q-values based on the observed rewards and penalties, guiding nodes toward better routing decisions.

Adaptive Parameter Tuning incorporates mechanisms for adaptive modulation and coding schemes that dynamically adjust modulation and coding parameters based on channel conditions and data transmission requirements. Adaptive Modulation and Coding (AMC) techniques aim to maximize data throughput while maintaining reliable communication. The selection of modulation and coding parameters is based on channel quality indicators such as signal-to-noise ratio (SNR) and bit error rate (BER). The adaptive modulation and coding are expressed mathematically in Eq.(23).

$$R_{AMC} = \sum_{i=1}^{M} SNR_i.P_i \quad (23)$$

where R_{AMC} represents the achievable data rate, M denotes the number of modulation and coding schemes, SNR_i signifies the SNR for the i^{th}scheme, and P_i deotes the probability of selecting the i^{th}scheme. It also integrates mechanisms for dynamic adjustment of routing thresholds and parameters based on network conditions. Threshold-based routing protocols adaptively adjust threshold values to control route establishment and maintenance. The adaptive threshold update is depicted in Eq.(24).

$$\begin{aligned} &Threshold_{adaptive} \\ &= \beta.Threshold_{static} \\ &+ (1 - \beta).Threshold_{dynamic} \end{aligned} \quad (24)$$

where $Threshold_{adaptive}$ represents the adaptive threshold value, $Threshold_{static}$ denotes the static threshold value, $Threshold_{dynamic}$ signifies the dynamic threshold value, and β denotes the weighting factor.

3.2. Albatross Optimization (AO)

Albatross Optimization (AO) draws inspiration from the unique characteristics and behaviours of albatrosses, particularly their exceptional flying abilities and efficient foraging strategies. AO aims to emulate these characteristics to develop an optimization algorithm capable of efficiently exploring search spaces and finding optimal solutions to complex problems. Albatrosses are renowned for their remarkable soaring flights, utilizing dynamic soaring techniques to harness wind energy and cover vast distances with minimal effort. AO incorporates mechanisms for adaptive exploration and exploitation of search spaces, dynamically adjusting search strategies to navigate complex solution landscapes efficiently. Albatrosses exhibit efficient foraging behaviours, efficiently locating and exploiting food resources over large oceanic areas. AO leverages this characteristic by incorporating adaptive resource allocation and exploitation mechanisms, enabling the algorithm to efficiently identify and exploit promising solution regions while avoiding premature convergence to suboptimal solutions. Simply AO harnesses the characteristics of albatrosses to develop a robust optimization algorithm capable of efficiently solving complex optimization problems by dynamically adjusting search strategies and resource allocation based on real-time environmental cues and solution landscape characteristics.

3.2.1. Initialization

Initialization involves creating an initial population of candidate solutions, each representing a potential solution to the optimization problem. It begins by defining the search space for the optimization problem. Let Xdenote the search space, which consists of all possible candidate solutions. Each candidate solution x_i is represented as a vector of decision variables.

$$x_i = (x_{i1}, x_{i2}, \dots, x_{in}) \tag{25}$$

where in Eq.(25), n represents the dimensionality of the search space, and x_{ij}denotes the j^{th}decision variable of the i^{th}candidate solution. Then, it involves generating an initial population of candidate solutions within the defined search space. This is typically done using random or heuristic-based methods to ensure diversity and coverage of the solution space. Let P_0denote the initial population, consisting of Ncandidate solutions is shown in Eq.(26).

$$P_0 = (x_1, x_2, \dots, x_n) \tag{26}$$

where N represents the population size, random or heuristic-based methods assign values to the decision variables within their bounds to generate each candidate solution. Let LB_j and UB_j denote the lower and upper bounds of the j^{th}decision variable, respectively. The initialization process ensures that each decision variable x_{ij} falls within its specified bounds, as shown in Eq.(27).

$$x_{ij} \in [LB_j, UB_j],\ \ \forall_i \in \{1,2, \dots, N\}, \forall_j \in \{1,2, \dots, N\} \text{ where } LB_j \le x_{ij} \le UB_j. \tag{27}$$

Initialization may incorporate additional constraints or considerations specific to the optimization problem, such as feasibility or domain-specific requirements. Let $G(x_i)$ denote the constraint function, which evaluates the feasibility of the candidate solution x_i. The initialization process ensures that each candidate solution satisfies all constraints and is mathematically represented in Eq.(28).

$$G(x_i) \le 0, \qquad \forall i \in \{1,2, \dots, N\} \tag{28}$$

where $G(x_i)$represents the constraint value for the candidate solution x_i.

3.2.2. Dynamic Soaring

The adaptive flying techniques of albatrosses to navigate through complex solution spaces efficiently. Dynamic Soaring involves dynamically adjusting search strategies based on local search space characteristics and environmental cues, akin to how albatrosses adjust their flight paths to harness wind energy for efficient long-distance travel. It incorporates mechanisms for adaptive exploration and exploitation of the solution space. Let X denote the search space and $f(x)$ represent the objective function to be optimized. The goal is to iteratively update candidate solutions to improve their fitness, represented by the objective function value. One approach in Dynamic Soaring is to employ adaptive step size control mechanisms to dynamically adjust the step size of search movements based on the local landscape of the search space. Let δ_i denote the step size for the candidate solution x_i at iteration t. The adaptive step size control is mathematically expressed in Eq.(29).

$$\delta_{i,t+1} = \delta_{i,t} + \alpha . \Delta f_{i,t} \tag{29}$$

where $\alpha$is a control parameter, and $\Delta f_{i,t}$ represents the change in the objective function value for the candidate solution x_i from iteration t to $t+1$. Another approach in Dynamic Soaring involves incorporating adaptive inertia mechanisms to balance exploration and exploitation. Let v_i denote the velocity vector for the candidate solution x_i at iteration t. The adaptive inertia is mathematically expressed in Eq.(30).

$$v_{i,t+1} = \omega . v_{i,t} + \beta . \Delta x_{i,t} \quad (30)$$

where $\omega$and β are inertia parameters, and $\Delta x_{i,t}$represents the change in the position of a candidate solution x_i from iteration t to $t+1$.

Dynamic Soaring may incorporate local search intensification and diversification mechanisms to explore and exploit promising search space regions effectively. Let x_{best} denote the best candidate solution found so far, and x_{rand} represent a randomly selected candidate solution from the population. The intensification and diversification are expressed mathematically in Eq.(31) and Eq.(32).

$$x_{intensfied} = x_{best} + \gamma . (x_{best} - x_{rand}) \quad (31)$$

$$x_{diversified} = x_{best} + \delta . (x_{rand} - x_{best}) \quad (32)$$

where γ and δ are parameters controlling the intensity and diversity of the search, respectively, Dynamic Soaring in AO may incorporate mechanisms for adaptive local search neighbourhood exploration to explore promising solution regions efficiently. Let $N(x_i)$ denote the local search neighbourhood of the candidate solution x_i, and x_{new}represent a new candidate solution generated within the local search neighbourhood. The adaptive neighbourhood exploration is mathematically expressed in Eq.(33).

$$x_{new} = x_i + \epsilon . (x_{best} - x_i) \quad (33)$$

where ϵcontrols the size of the local search neighbourhood.

3.2.3. Adaptive Exploration and Exploitation

Adaptive Exploration and Exploitation are crucial in balancing the trade-off between exploration and exploitation to navigate the solution space efficiently. This step involves dynamically adjusting search strategies to explore promising solution regions while exploiting valuable information to converge towards optimal solutions. Adaptive Exploration and Exploitation integrate mechanisms for adaptive control of exploration and exploitation rates based on the evolving characteristics of the search space and the performance of candidate solutions. One approach in adaptive exploration and exploration is incorporating adaptive mutation rates, which control the exploration rate by determining the probability of making random perturbations to candidate solutions. Let p_{mut} denote the mutation probability at iteration t. The adaptive mutation rate can be calculated in Eq.(34).

$$p_{mut,t+1} = p_{mut,t} + \gamma . \Delta f_{best,t} \quad (34)$$

where γ is a control parameter, and $\Delta f_{best,t}$ represents the change in the objective function value of the best candidate solution from iteration t to $t+1$.

Another approach is incorporating adaptive crossover rates, which control the exploitation rate by determining the probability of exchanging information between candidate solutions. Let p_{cross} denote the crossover probability at iteration t. The adaptive crossover rate is calculated as shown in Eq.(35).

$$p_{cross,t+1} = p_{cross,t} + \delta . \Delta f_{mean,t} \quad (35)$$

where $\delta$is a control parameter, and $\Delta f_{mean,t}$ represents the change in the mean objective function value of the population from iteration t to $t+1$. It also may incorporate mechanisms for adaptive selection pressure control to balance the diversity and convergence of the population. Let p_{select} denote the selection pressure at iteration t. The adaptive selection pressure equation can be expressed mathematically in Eq.(36).

$$p_{select,t+1} = p_{select,t} + \eta . \Delta f_{max,t} \quad (36)$$

where η is a control parameter, and $\Delta f_{max,t}$ represents the change in the maximum objective function value of the population from iteration t to $t+1$. This Adaptive Exploration and Exploitation in AO may incorporate adaptive population size control mechanisms to balance exploration and exploitation. Let N denote the population size at iteration t. The adaptive population size equation can be mathematically expressed in Eq.(37).

$$N_{t+1} = N_t + \epsilon . \Delta f_{std,t} \quad (37)$$

where ϵ is a control parameter, and $\Delta f_{std,t}$ represents the change in the standard deviation of the objective function values of the population from iteration $t$to $t+1$.

3.2.4. Resource Allocation

Resource Allocation plays a critical role in efficiently allocating computational resources to candidate solutions based on their potential for Improvement. Resource Allocation ensures that computational efforts are directed towards promising regions of the search space, thereby enhancing the convergence rate and effectiveness of the optimization process. Resource Allocation involves mechanisms for dynamically allocating computational resources, such as computational budget or evaluation opportunities, to candidate solutions based on their performance and potential for Improvement. One approach in Resource Allocation is to incorporate mechanisms for adaptive evaluation frequency control, which determines how frequently candidate solutions are evaluated or updated. Let λ denote the evaluation frequency parameter. The adaptive evaluation frequency is mathematically expressed in Eq.(38).

$$\lambda_{t+1} = \lambda_t + \alpha.\Delta f_{best,t} \tag{38}$$

where $\alpha$is a control parameter, and. $\Delta f_{best,t}$ represents the change in the objective function value of the best candidate solution from iteration t to $t+1$. Another approach is to integrate mechanisms for adaptive sampling density control, which determines the density of candidate solutions in different regions of the search space. Let ρ denote the sampling density parameter. The adaptive sampling density equation can be formulated as:

$$\rho_{t+1} = \rho_t + \beta.\Delta f_{mean,t} \tag{39}$$

where β is a control parameter, and $\Delta f_{mean,t}$ represents the change in the mean objective function value of the population from iteration t to $t+1$. It may incorporate mechanisms for adaptive termination criteria control, which determine the conditions under which the optimization process terminates. Let τdenote the termination criteria parameter. The adaptive termination criteria is mathematically expressed in Eq.(40).

$$\tau_{t+1} = \tau_t + \gamma.\Delta f_{max,t} \tag{40}$$

where γ is a control parameter, and $\Delta f_{max,t}$ represents the change in the maximum objective function value of the population from iteration t to $t+1$.

Resource Allocation in AO may incorporate mechanisms for adaptive elitism control, which determine the proportion of top-performing candidate solutions preserved in each iteration. Let ϵdenote the elitism parameter. The adaptive elitism equation is expressed in Eq.(41).

$$\epsilon_{t+1} = \epsilon_t + \delta.\Delta f_{std,t} \tag{41}$$

where δ is a control parameter, and $\Delta f_{std,t}$ represents the change in the standard deviation of the objective function values of the population from iteration t to $t+1$.

3.2.5. Iterative Improvement

This phase focuses on iteratively refining candidate solutions through optimization iterations. It aims to progressively enhance the quality of candidate solutions by incorporating feedback mechanisms and adaptive strategies for guiding search direction. Iterative Improvement involves mechanisms for updating candidate solutions based on their performance and the evolving characteristics of the search space. Let P_t denote the population of candidate solutions at iteration t,and $f(x_i)$ represent the objective function value of the candidate solution x_i.

Iterative Improvement incorporates mechanisms for adaptive mutation control, which determine the extent of perturbations applied to candidate solutions. Let μ denote the mutation control parameter. The adaptive mutation control is expressed as a mathematical equation in Eq.(42).

$$\mu_{t+1} = \mu_t + \alpha.\Delta f_{mean,t} \tag{42}$$

where α is a control parameter, and $\Delta f_{mean,t}$ represents the change in the mean objective function value of the population from iteration t to $t+1$. The integrated mechanism is also for adaptive crossover control, which determines the extent of information exchange between candidate solutions. Let ξ denote the crossover control parameter.

$$\xi_{t+1} = \xi_t + \beta.\Delta f_{max,t} \tag{43}$$

where in Eq.(43), β is a control parameter, and $\Delta f_{max,t}$ represents the change in the maximum objective function value of the population from iteration t to $t+1$. This may incorporate adaptive selection pressure control mechanisms, which determine the pressure exerted on candidate solutions during selection processes. Let σdenote the selection pressure control parameter. The adaptive selection pressure control is mathematically expressed in Eq.(44).

$$\sigma_{t+1} = \sigma_t + \gamma.\Delta f_{std,t} \tag{44}$$

where γ is a control parameter, and $\Delta f_{std,t}$ represents the change in the standard deviation of the objective function values of the population from iteration t to $t+1$.

The Iterative Improvement in AO may incorporate mechanisms for adaptive population size control, determining the number of candidate solutions retained in each iteration. Let Ndenote the population size at iteration t. The adaptive population size control is mathematically expressed in Eq.(45).

$$N_{t+1} = N_t + \delta.\Delta f_{best,t} \tag{45}$$

where δ is a control parameter, and $\Delta f_{best,t}$ represents the change in the objective function value of the best candidate solution from iteration t to $t+1$.

3.2.6. Convergence Criteria:

Convergence Criteria are essential in determining when to terminate the optimization process based on predefined criteria. It ensures that the optimization process stops when conditions are met, indicating satisfactory solution quality or resource utilization. This Convergence Criteria involves defining conditions or thresholds based on which the optimization process is terminated. Let ϵ denote the convergence threshold parameter, which represents the desired level of solution quality or resource utilization. One common convergence criterion is improving the objective function value over successive iterations. Let Δf_{min} denote the minimum Improvement in the objective function value between successive iterations. The convergence criterion based on Improvement is mathematically expressed in Eq.(46).

$$\Delta f_{min} \leq \epsilon \tag{46}$$

where ϵ represents the desired minimum improvement threshold.

Another convergence criterion is based on the stagnation of the population, where there is little to no change in the objective function values of candidate solutions over multiple iterations. Let Δf_{avg} denote the average change in the objective function values of the population over $k$iterations. The convergence criterion based on stagnation is expressed mathematically in Eq.(47).

$$\Delta f_{avg} \leq \epsilon \tag{47}$$

where ϵ represents the desired maximum change threshold. It may incorporate mechanisms for tracking the diversity of the population and terminating the optimization process when the diversity falls below a certain threshold. Let σ_{min} denote the minimum acceptable diversity threshold. The convergence criterion based on diversity is mathematically expressed in Eq.(48).

$$\sigma_{min} \leq \sigma_t \tag{48}$$

where σ_t represents the diversity of the population at iteration t.

Convergence Criteria in AO may incorporate mechanisms for monitoring the computational budget or evaluation opportunities and terminating the optimization process when the allocated resources are fully utilized. Let η denote the maximum computational budget or evaluation opportunities. The convergence criterion based on resource utilization is mathematically expressed in Eq.(49).

$$evaluations \geq \eta \tag{49}$$

where evaluations represent the total number of evaluations performed during the optimization process, convergence Criteria in Albatross Optimization involve defining conditions or thresholds based on which the optimization process is terminated.

3.3. Combining Albatross Optimization (AO) with Adaptive Acoustic Routing (AAR)

Introducing "Albatross Adaptive Acoustic Routing Optimization (AARO)", a fusion of AO and AAR for B-WSNs. This innovative approach combines the efficient exploration and exploitation capabilities of AO with the adaptive routing strategies of AAR to optimize communication pathways in buoyant WSNs. AARO aims to dynamically adjust routing paths based on environmental cues and solution landscape characteristics, enhancing the reliability and efficiency of data transmission in buoyant WSNs. This fusion leverages albatrosses' soaring capabilities and AAR's adaptive routing strategies to create a robust and efficient optimization framework for B-WSNs.

3.3.1. AARO Environmental Sensing:

AARO Environmental Sensing focuses on deploying sensor nodes to gather crucial environmental data relevant to buoyant WSNs. This step is pivotal in providing real-time information about the surrounding environment, enabling informed decision-making in subsequent optimization processes. It involves defining the environmental variables of interest and deploying sensor nodes to measure them. Let E represent the environmental variables to be sensed, including parameters such as temperature, pressure, humidity, and water quality.

$$e_i = (e_{i1}, e_{i2}, \dots, e_{im}) \quad (50)$$

where in Eq.(50), m represents the dimensionality of the environmental variable e_i, and e_{ij} denotes the j^{th}component of e_i. Then, sensor nodes will be deployed strategically to measure the environmental variables across the buoyant WSN. Let S represent the set of sensor nodes deployed in the WSN, with each sensor node s_k having a specific location l_k. The deployment of sensor nodes can be mathematically represented in Eq.(51).

$$S = \{s_1, s_2, \dots, s_n\} \quad (51)$$

where n represents the total number of sensor nodes deployed in the WSN.

To ensure comprehensive coverage of the buoyant environment, the placement of sensor nodes must be optimized to maximize the coverage area while minimizing redundancy. Let Cdenote the coverage area of the WSN, which is a function of the sensor node locations $L$and the sensing range R the coverage area C can be mathematically expressed in Eq.(52).

$$C = \bigcup_{k=1}^{n} \{l_k \in L: \|l_k - l_i\| \leq R, \forall l_i \in L\} \quad (52)$$

where $\|l_k - l_i\|$ represents the Euclidean distance between the sensor node $s_k$and sensor node s_i, and R represents the sensing range of the sensor nodes. Environmental sensing may involve adaptive sensor node deployment mechanisms to adjust sensor node locations dynamically based on environmental dynamics. Let D represent the deployment strategy, which determines the optimal locations for sensor nodes based on environmental data and optimization objectives.

$$D = arg\ min_L f(E, L) \quad (53)$$

where in Eq.(53), $f(E, L)$ represents the objective function of evaluating the effectiveness of sensor node deployment in capturing environmental data.

3.3.2. AARO Node Localization:

Node Localization is crucial in determining the precise locations of sensor nodes within the buoyant WSN. Accurate node localization enhances the effectiveness of data collection and routing strategies, contributing to the overall efficiency and reliability of the optimization process. It involves estimating the locations of sensor nodes based on environmental data collected in the previous step. Let L denote the set of estimated locations of sensor nodes and $\hat{L}$ represent the set of actual locations of sensor nodes. The localization process aims to minimize the discrepancy between the estimated locations L and the exact locations $\hat{L}$. One approach in Node Localization is to employ distance-based localization techniques, such as trilateration or multilateration, using measurements from multiple reference points. Let d_{ij} denote the measured distance between the sensor node $i$and reference point j, and r_{ij} represent the estimated distance between the sensor node $i$and reference point j. The localization error ϵ_i for sensor node i can be mathematically represented in Eq.(54).

$$\epsilon_i = \sum_{j=1}^{m} |d_{ij} - r_{ij}| \quad (54)$$

where m represents the number of reference points used in the localization process. Another approach is to employ signal strength-based localization techniques, where the received signal strength indicator (RSSI) or TOA of signals transmitted between sensor nodes and reference points is used to estimate distances. Let s_{ij} denote the measured signal strength between the sensor node $i$and reference point j, and $\hat{s}_{ij}$ represent the estimated signal strength between the sensor node $i$and reference point j. The localization error ϵ_i for the sensor, node i can be represented mathematically in Eq.(55).

$$\epsilon_i = \sum_{j=1}^{m} |s_{ij} - \hat{s}_{ij}| \quad (55)$$

where $m$represents the number of reference points used in the localization process. This Node Localization may incorporate iterative optimization algorithms, such as gradient descent or simulated annealing, to iteratively refine the estimated locations of sensor nodes based on environmental data and localization measurements. Let L_t denote the estimated locations of sensor nodes at iteration t, and ΔL_t represent the change in the estimated locations from iteration t to $t + 1$. The iterative optimization process can be expressed mathematically in Eq.(56).

$$L_{t+1} = L_t + \alpha.\Delta L_t \tag{56}$$

where α is a control parameter governing the step size of the optimization process.

3.3.3. AARO Dynamic Path Selection:

Dynamic Path Selection focuses on dynamically determining communication pathways based on environmental conditions and the locations of sensor nodes. This step plays a crucial role in optimizing data transmission routes in B-WSNs, ensuring efficient and reliable communication in varying environmental conditions. This Dynamic Path Selection involves selecting communication pathways that minimize signal attenuation, interference, and energy consumption while maximizing data transmission efficiency. Let Pdenote the set of communication pathways available in the B-WSN and $w$represent the weight vector associated with each pathway in terms of its suitability for data transmission. One approach in Dynamic Path Selection employs a weighted graph representation, where nodes represent sensor nodes, and edges represent potential communication pathways between sensor nodes. Let $G = (V, E)$ denote the weighted graph representing the B-WSN, where Vrepresents the set of sensor nodes and Erepresents the set of edges representing potential communication pathways. The weight of each edge e_{ij} between sensor nodes $i$and $j$can be determined based on environmental factors, and the distance between sensor nodes is mathematically represented in Eq.(57).

$$w_{ij} = f\left(environmental\ factors, \left\|I_i - I_j\right\|\right) \tag{57}$$

where I_i and I_j represent the locations of sensor nodes i and j, respectively. Another approach incorporates dynamic routing algorithms, such as dynamic programming or reinforcement learning, to adaptively select communication pathways based on real-time environmental data and network conditions. Let R denote the set of routing policies and $Q(s, a)$ represent the Q-value associated with the state-action pair (s, a), where s represents the current state of the network, and a represents the action taken to select a communication pathway. The Q-value can be updated iteratively using the Q-learning update rule shown in Eq.(58).

$$Q(s, a) = Q(s, a) + \alpha.\left(r + \gamma.max_{a'}Q(s', a') - Q(s, a)\right) \tag{58}$$

where α represents the learning rate, γ represents the discount factor, r represents the reward obtained by selecting action a in state s, and s' represents the next state of the network.

Dynamic Path Selection may incorporate load balancing and congestion avoidance mechanisms to optimize data transmission efficiency and prevent network bottlenecks. Let λ denote the load on each communication pathway, and λ_{max} represent the maximum allowable load. The dynamic adjustment of communication pathways can be expressed mathematically in Eq.(59).

$$\lambda_{ij} = \frac{\lambda_{ij}}{\lambda_{max}} \tag{59}$$

where λ_{ij} represents the adjusted load on the communication pathway e_{ij}.

3.3.4. AARO Acoustic Transmission:

Acoustic Transmission focuses on transmitting data using acoustic signals in buoyant environments. Acoustic Transmission is crucial for communication in B-WSNs due to the limitations of traditional electromagnetic signals in underwater or aquatic environments. It involves modelling the propagation of acoustic signals through water and optimizing transmission parameters to maximize data transmission efficiency. Let d_{ij} denote the distance between sensor node $i$and sensor node j, and T_{ij} represent the time taken for acoustic signals to travel between sensor nodes i and j. The propagation delay δ_{ij} of acoustic signals can be expressed mathematically in Eq.(60).

$$\delta_{ij} = \frac{d_{ij}}{c} \tag{60}$$

where c represents the speed of sound in water. Acoustic transmission may involve mechanisms for adaptive modulation and coding schemes (MCS) to adjust the transmission parameters based on environmental conditions and network requirements to optimize data transmission efficiency. Let MCS_{ij} represent the modulation and coding scheme used for data transmission between sensor nodes i and j, and SNR_{ij} represent the signal-to-noise ratio of the communication link between sensor nodes i and j. The optimal MCS can be selected based on the channel conditions and required data rate. Maximizing the data transmission efficiency is mathematically represented in Eq.(61).

$$MCS_{ij} = argmax_{MCS}SNR_{ij} \tag{61}$$

Another aspect of Acoustic Transmission is to optimize the transmission power levels to ensure reliable communication while minimizing energy consumption. Let P_{tx} represent the transmission power level of sensor nodes and P_{min} and P_{max} represent the minimum and maximum allowable transmission power levels, respectively. The transmission power P_{tx} can be adjusted dynamically based on the distance between sensor nodes and the channel conditions, ensuring reliable communication with minimal energy expenditure is represented mathematically in Eq.(62).

$$P_{tx} = \begin{cases} P_{min}, \ if \ d_{ij} \geq d_{max} \\ P_{max}, \ if \ d_{ij} \leq d_{min} \\ \dfrac{P_{min} + P_{max}}{2}, \ \ otherwise \end{cases} \tag{62}$$

It may involve error detection and correction mechanisms to mitigate the effects of channel impairments, such as multipath propagation and Doppler effects, on data transmission reliability. Let BER_{ij} represent the bit error rate of the communication link between sensor nodes i and j, and BER_{max} represent the maximum allowable bit error rate. Error correction codes can be employed to correct errors in transmitted data, ensuring reliable communication in noisy underwater environments is expressed mathematically in Eq.(63).

$$BER_{ij} \leq BER_{max} \tag{63}$$

Acoustic Transmission in AARO involves modelling and optimizing the propagation of acoustic signals through water to maximize data transmission efficiency and reliability in buoyant WSNs.

3.3.5. AARO Routing Optimization:

Routing Optimization focuses on optimizing the routing paths to maximize data transmission efficiency and reliability in buoyant WSNs. This Routing optimization plays a crucial role in determining the most efficient pathways for data transmission, considering factors such as distance, signal strength, and energy consumption. It involves selecting routing paths that minimize the transmission delay while ensuring reliable communication between sensor nodes. Let D_{ij} denote the transmission delay between sensor nodes i and j, and E_{ij} represent the energy consumption associated with data transmission between sensor nodes i and j. The total transmission delay T_{total} and total energy consumption E_{total} can be represented mathematically in Eq.(64) and Eq.(65).

$$T_{total} = \sum_{(i,j)\in P} D_{ij} \tag{64}$$

$$E_{total} = \sum_{(i,j)\in P} E_{ij} \tag{65}$$

where P represents the set of selected routing paths. Routing optimization may employ optimization algorithms such as integer linear programming (ILP) or GA to find the optimal set of routing paths that minimize the total transmission delay and energy consumption while satisfying constraints such as bandwidth availability and reliability requirements. Let X_{ij} denote the binary decision variable indicating whether the routing path between sensor nodes i and j is selected or not. The optimization problem can be represented mathematically in Eq.(66).

$$\begin{gathered} minimize \ \ T_{total} \\ Subject \ to \ E_{total} \leq E_{max} \\ X_{ij} \in \{0,1\}, \quad \forall (i,j) \in P \end{gathered} \tag{66}$$

where E_{max} represents the maximum allowable energy consumption. Routing Optimization may incorporate mechanisms for load balancing and fault tolerance to ensure robustness and reliability in data transmission. Let L_{ij} denote the load on the routing path between sensor nodes i and j, and L_{max} represent the maximum allowable load on any routing path. The load balancing constraint can be expressed mathematically in Eq.(67).

$$L_{ij} \leq L_{max}, \qquad \forall (i,j) \in P \tag{67}$$

Routing Optimization may consider dynamic routing strategies that adaptively adjust routing paths based on real-time environmental data and network conditions. Let SNR_{ij} represent the signal-to-noise ratio of the communication link between sensor nodes i and j, and SNR_{min} represent the minimum required signal-to-noise ratio for reliable communication. The routing decision can be made based on the available SNR, as shown in Eq.(68).

$$X_{ij} = \begin{cases} 1, & if \ SNR_{ij} \geq SNR_{min} \\ 0, & otherwise \end{cases} \tag{68}$$

Simply Routing Optimization in AARO involves selecting routing paths that minimize transmission delay and energy consumption while ensuring reliable communication and robustness in buoyant WSNs.

3.3.6. Fault Tolerance Mechanisms:

Fault Tolerance Mechanisms focus on implementing strategies to ensure the robustness and reliability of data transmission in buoyant WSNs. Fault tolerance mechanisms play a crucial role in mitigating the effects of communication failures, node malfunctions, and environmental disturbances, thereby maintaining the uninterrupted operation of the network. Fault Tolerance Mechanisms involve designing redundancy schemes and error recovery mechanisms to detect and recover from faults in the network. Let R_{ij} represent the redundancy level of the communication link between sensor nodes i and j, and R_{max} denote the maximum allowable redundancy level. The redundancy level R_{ij} can be adjusted based on the communication link's criticality and the network's reliability requirements, which are represented mathematically in Eq.(69).

$$R_{ij} \leq R_{max}, \forall(i,j) \in P \quad (69)$$

One approach in Fault Tolerance Mechanisms is to employ automatic retransmission mechanisms to resend lost or corrupted data packets. Let BER_{ij} represent the bit error rate of the communication link between sensor nodes i and j, and BER_{max} represent the maximum allowable bit error rate. Retransmission can be initiated if the bit error rate exceeds the threshold, which is expressed mathematically in Eq.(70).

$$BER_{ij} > BER_{max} \quad (70)$$

Another strategy is implementing error detection and correction codes to detect errors in transmitted data packets. Let C represent the error correction code used for data transmission, and $n$denote the number of redundant bits added to the original data. The error correction capability ECC_{ij} can be represented mathematically in Eq.(71).

$$ECC_{ij} = \frac{n}{n+k} \quad (71)$$

where k represents the number of bits in the original data packet. It may incorporate node redundancy and self-healing mechanisms to ensure continuous network operation in the event of node failures. Let N represent the set of sensor nodes in the network, and RR_{ij} denote the node redundancy ratio between sensor nodes i and j. The node redundancy ratio can be adjusted based on the sensor nodes' criticality and the network's reliability requirements, which is expressed in Eq.(72).

$$RR_{ij} \leq RR_{max}, \ \forall(i,j) \in N \quad (72)$$

Fault Tolerance Mechanisms may include dynamic routing and load balancing mechanisms to adaptively reroute data packets in real-time to bypass faulty nodes or links. Let L_{ij} denote the load on the routing path between sensor nodes i and j, and L_{max} represent the maximum allowable load. The load balancing constraint can be adjusted dynamically to reroute traffic away from congested or faulty paths, as shown in Eq.(73).

$$L_{ij} \leq L_{max}, \ \forall(i,j) \in P \quad (73)$$

Simply Fault Tolerance Mechanisms in AARO involve implementing redundancy schemes, error recovery mechanisms, node redundancy, and dynamic routing strategies to ensure the robustness and reliability of data transmission in buoyant WSNs. By mitigating the effects of communication failures and environmental disturbances, Fault Tolerance Mechanisms contribute to maintaining uninterrupted operation and enhancing the overall performance of AARO.

3.4. Advantages of AARO:

AARO offers advantages for B-WSNs, enhancing their efficiency, reliability, and adaptability. By integrating adaptive routing strategies with acoustic communication technologies, AARO addresses the unique challenges underwater environments pose, providing a robust data transmission and networking framework. Below are several critical advantages of AARO:

- **Enhanced Environmental Adaptability:** AARO leverages environmental sensing capabilities to dynamically adjust routing paths based on real-time environmental data. By monitoring factors such as water temperature, pressure, and salinity, AARO can adapt routing paths to changing environmental conditions. This adaptability ensures optimal network performance, even in harsh and unpredictable underwater environments.
- **Improved Energy Efficiency:** AARO optimizes energy consumption by intelligently routing data through the network, minimizing the energy expended by individual sensor nodes. Through dynamic path selection and routing optimization, AARO reduces the overall energy burden on the network, prolonging the sensor nodes' operational lifespan and enhancing the WSN's sustainability.
- **Increased Data Transmission Reliability:** By employing acoustic communication technologies, AARO overcomes the limitations of traditional electromagnetic signals in underwater environments, such as high attenuation and limited range. Acoustic signals exhibit

superior propagation characteristics in water, enabling more reliable data transmission over longer distances. This increased reliability ensures that critical data is delivered accurately and promptly, even in challenging underwater conditions.

- **Adaptive Fault Tolerance Mechanisms:** AARO incorporates robust fault tolerance mechanisms to mitigate the impact of communication failures, node malfunctions, and environmental disturbances. By implementing redundancy schemes, error recovery mechanisms, and dynamic routing strategies, AARO ensures the uninterrupted operation of the network and maintains data integrity in the face of adverse conditions.
- **Optimal Resource Allocation:** AARO optimizes resource allocation within the WSN, efficiently utilizing network bandwidth, storage capacity, and processing capabilities. By dynamically allocating resources based on the current network load and data transmission requirements, AARO maximizes the utilization of available resources, minimizing congestion and improving overall network performance.
- **Scalability and Flexibility:** AARO offers scalability and flexibility, allowing the WSN to adapt to changing network dynamics and scale seamlessly to accommodate varying deployment scenarios. Whether deployed in a small-scale research project or a large-scale environmental monitoring operation, AARO can efficiently manage network resources and adapt routing strategies to meet the application's specific requirements.
- **Real-time Data Processing and Analysis:** AARO facilitates real-time data processing and analysis, enabling timely decision-making and response to environmental events. By integrating data analytics capabilities directly into the routing framework, AARO can process and analyze sensor data on the fly, providing valuable insights into underwater ecosystems and facilitating scientific research and environmental monitoring efforts.

4. SIMULATION SETTINGS AND PARAMETERS

Simulation refers to designing a real-world system model and conducting experiments on this model to understand its behavior under various conditions. This method is essential for analyzing systems that are too complex or impractical for direct observation. ns-3 is an open-source network simulator that supports multiple network simulations, including wireless, wired, and hybrid networks. It allows for detailed modeling of network protocols, devices, and traffic patterns. Researchers and developers use ns-3 to test and validate new network technologies and protocols in a controlled, virtual environment.

Table 1. Simulation Settings And Parameters

PARAMETER	SETTINGS
Simulator	ns-3
Simulation Time	1000 seconds
Network Topology	3D Grid
Number of Nodes	100
Node Placement	Random (buoyant movement)
Mobility Model	Random Waypoint
Routing Protocol	Adaptive Acoustic Routing (AAR)
Channel Model	Underwater Acoustic Channel
Transmission Range	250 meters
Packet Size	64 bytes
Traffic Type	CBR (Constant Bit Rate)
Application Layer	UDP
Propagation Delay	UniformRandomVariable(0.01)
MAC Layer	IEEE 802.11
Energy Model	Basic Energy Model
Simulation Output	Trace files and pcap files

The settings outlined in this table provide a comprehensive framework for simulating buoyant WSNs using the AAR protocol in ns-3.

5. RESULTS AND DISCUSSIONS

In B-WSNs, the packet delivery ratio (PDR) is a critical performance metric that measures the ratio of successfully delivered data packets to the total sent. This metric is vital for assessing the reliability and efficiency of various routing protocols. Figure 1 illustrates the PDR for

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three routing protocols: MO-CBACORP, HOCOR, and AARO across different node densities. AARO consistently outperforms both MO-CBACORP and HOCOR in terms of PDR. At a node density of 50, AARO achieves the highest PDR of 76.13%, whereas MO-CBACORP and HOCOR reach 56.55% and 62.91%, respectively. This trend continues as node density increases; at a density of 500 nodes, AARO maintains a PDR of 63.82%, significantly higher than MO-CBACORP (33.04%) and HOCOR (45.84%). On average, AARO achieves the highest PDR of 69.924%, compared to HOCOR's 54.456% and MO-CBACORP's 45.498%. These findings highlight AARO's superior capability in ensuring reliable packet delivery in buoyant WSN environments. The results suggest that AARO is the most effective protocol for maximizing packet delivery enhancing overall network performance and reliability.

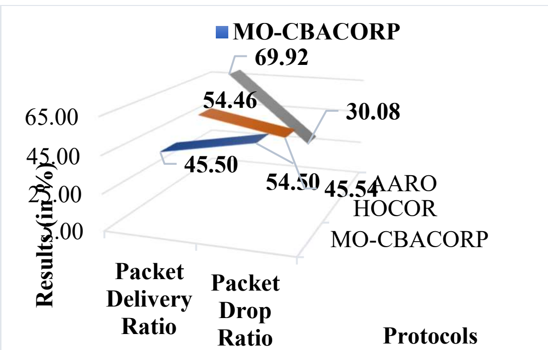

Figure 1. Packet Delivery Ratio / Packet Drop Ratio

The packet drop ratio (PDPR) is an essential performance metric in B-WSNs, indicating the percentage of data packets that fail to reach their destination. A lower PDPR signifies better network performance and reliability. The results, illustrated in Figure 1, show the PDPR for three routing protocols, MO-CBACORP, HOCOR, and AARO, across various node densities. AARO consistently exhibits the lowest PDPR, outperforming both MO-CBACORP and HOCOR. At a node density of 50, AARO achieves the lowest PDPR of 23.87%, while MO-CBACORP and HOCOR report 43.45% and 37.09%, respectively. This trend persists as node density increases; at a density of 500 nodes, AARO maintains a PDPR of 36.18%, significantly better than MO-CBACORP (66.96%) and HOCOR (54.16%). On average, AARO achieves the lowest PDPR of 30.076%, compared to HOCOR's 45.544% and MO-CBACORP's 54.502%. These findings underscore AARO's superior capability in minimizing packet loss in buoyant WSN environments. The results suggest that AARO is the most effective protocol for ensuring reliable data transmission and reducing packet loss, enhancing overall network performance and reliability.

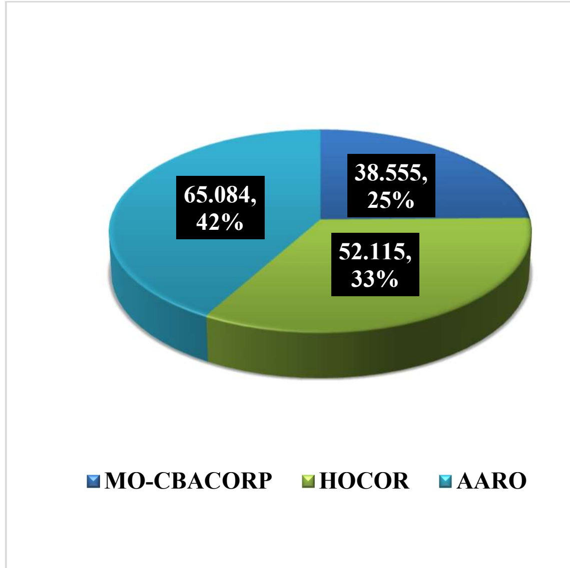

Figure 2. Throughput

Throughput in B-WSNs measures the rate at which data packets are successfully delivered over a communication channel. It is typically expressed in kilo bits per second (kbps). High throughput indicates efficient data transmission and effective network performance. Referring to Figure 2, the data compares throughput values for four routing protocols, MO-CBACORP, HOCOR, HOMP, and AARO, under varying node densities. AARO stands out with the highest throughput across all densities. At 50 nodes, AARO records a throughput of 58.46 kbps, surpassing MO-CBACORP (33.85 kbps), HOCOR (47.69 kbps), and HOMP (54.84 kbps). This advantage remains consistent as node density rises. With 500 nodes, AARO's throughput peaks at 72.96 kbps, higher than HOMP's 70.81 kbps, HOCOR's 56.34 kbps, and MO-CBACORP's 43.79 kbps.

Averaging the throughput values across all densities, AARO achieves 65.084 kbps, leading over HOMP's 62.845 kbps, HOCOR's 52.115 kbps, and MO-CBACORP's 38.555 kbps. These results indicate that AARO is highly effective in ensuring superior data transmission rates in buoyant WSNs, making it the best choice for optimizing network performance and reliability.

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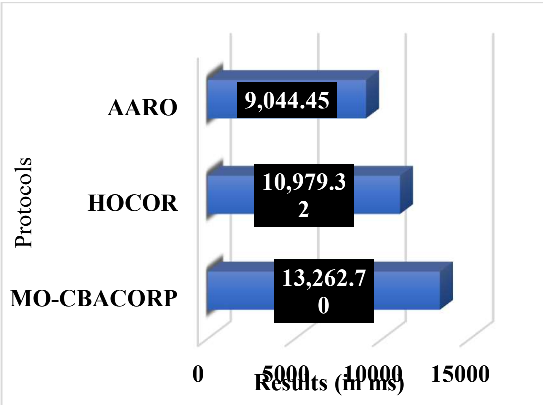

Figure 3. Delay

Delay in B-WSNs represents the time a data packet takes to travel from its source to its destination and its measured in milliseconds (ms). Lower delay indicates a more efficient network with faster data transmission. Based on the data in Figure 3, the delay for four routing protocols, MO-CBACORP, HOCOR, HOMP, and AARO, has been evaluated across different node densities. AARO consistently achieves the lowest delay values compared to the other protocols. At a node density of 50, AARO shows a delay of 8727 ms, significantly lower than MO-CBACORP's 12835 ms, HOCOR's 10189 ms, and HOMP's 9133 ms. As the node density increases, AARO continues to maintain its performance advantage. With 500 nodes, AARO records a delay of 9381 units, still outperforming MO-CBACORP (13916 ms), HOCOR (12646 ms), and HOMP (9814 ms). The average delay across all node densities further highlights AARO's efficiency, with an average delay of 9044 units. This is notably lower than HOMP's 9373.21 ms, HOCOR's 10979.32 ms, and MO-CBACORP's 13262.7 ms. These results demonstrate that AARO is highly effective in minimizing transmission delay in buoyant WSNs, making it the preferred choice for applications requiring rapid and reliable data delivery.

Energy consumption is a critical parameter in Buoyant Wireless Sensor Networks (WSNs) as it directly impacts the network's operational lifespan and efficiency. Lower energy consumption signifies better energy efficiency, enabling longer-lasting network operation.

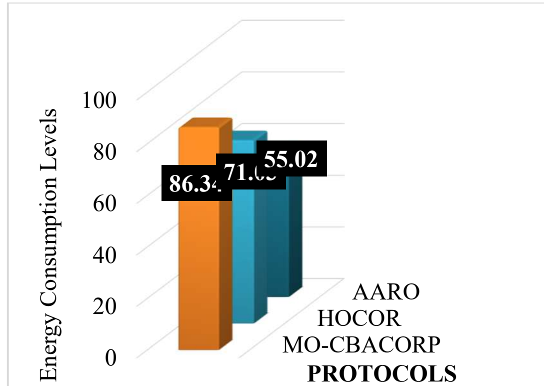

Figure 4. Energy Consumption

Figure 4 compares energy consumption for four routing protocols, MO-CBACORP, HOCOR, HOMP, and AARO, across node densities. AARO demonstrates the lowest energy consumption across all node densities. For instance, at a node density of 50, AARO consumes 48.347% of energy, which is significantly lower than MO-CBACORP's 77.773%, HOCOR's 61.276%, and HOMP's 51.797%. This trend persists across higher node densities, with AARO recording 62.183% at 500 nodes, while MO-CBACORP, HOCOR, and HOMP consume 94.080%, 81.888%, and 65.786%, respectively. The average energy consumption further highlights AARO's efficiency, with an average of 55.01694%. HOMP averages 58.56702%, HOCOR averages 71.03069%, and MO-CBACORP averages 86.34424%. These results indicate that AARO is the most energy-efficient protocol among the evaluated ones. Its superior performance in minimizing energy consumption makes it an ideal choice for applications in buoyant WSNs, where conserving energy is crucial for maintaining prolonged and reliable network operations.

5.1. Critical Evaluation

(a). Critique of Results:

- The results in Section 5 already highlight the performance of the Albatross Adaptive Acoustic Routing Optimization (AARO) protocol in terms of packet delivery ratio, throughput, delay, and energy consumption.
- AARO demonstrates superior performance across all evaluated metrics compared to existing protocols like MO-CBACORP and HOCOR. However, a discussion on the limitations of AARO, such as potential energy overhead due to adaptive routing adjustments, can be added to critique the results.

- The impact of increasing node density on computational overhead and latency in real-world deployments can be discussed.

(b). Difference from Prior Work:

- The literature review section already outlines existing routing approaches such as MO-CBACORP, HOCOR, and other underwater routing protocols.
- A dedicated subsection before the conclusion can explicitly compare AARO's novelty over prior work, emphasizing its dynamic soaring-inspired optimization, adaptive parameter tuning, and fault tolerance mechanisms.
- This section can highlight how AARO achieves a balance between energy efficiency and reliable data transmission compared to conventional underwater routing protocols that either focus on energy conservation or reliability but not both.

(c). Areas Still Needing Attention:

- The paper can discuss unresolved challenges such as the effect of acoustic interference in highly dense buoyant sensor networks, potential trade-offs in multi-hop communication under varying underwater conditions, and adaptability to different marine environments.
- Future research directions can include integrating reinforcement learning-based autonomous routing decision-making and hybrid communication models (acoustic + optical) to further enhance efficiency.

5.2. Threats to Validity Justification

The study acknowledges potential threats to validity that could influence the generalizability and reliability of the results. Internal validity concerns arise due to the simulation-based evaluation, as real-world underwater conditions such as unpredictable water currents, varying acoustic interference, and environmental noise might not be fully replicated. While the ns-3 simulator provides an accurate representation of underwater communication models, real-time deployment complexities may introduce variations. External validity is addressed by ensuring that the evaluated scenarios cover diverse node densities and mobility patterns, yet further validation through field experiments would strengthen the applicability of the findings. Construct validity is maintained by selecting performance metrics such as packet delivery ratio, throughput, delay, and energy consumption, which comprehensively reflect the efficiency of underwater routing protocols. Conclusion validity is reinforced by using comparative analysis against well-established protocols (MO-CBACORP, HOCOR, and HOMP), ensuring that improvements in performance metrics are statistically significant.

5.3. Selection of Critique Criteria Justification

The critique criteria were selected to evaluate the effectiveness of AARO in comparison to state-of-the-art routing protocols based on fundamental network performance indicators. Packet delivery ratio (PDR) and packet drop ratio (PDPR) were chosen to assess data reliability and transmission success. Throughput was evaluated to measure the efficiency of data transmission across varying node densities. Delay was analyzed to determine the protocol's responsiveness, critical for time-sensitive underwater applications. Energy consumption was selected as a key metric to assess the sustainability of the protocol in prolonged operations. The combination of these metrics ensures a holistic evaluation, addressing core challenges in Buoyant Wireless Sensor Networks (B-WSNs) and justifying the superiority of AARO over existing methods.

6. CONCLUSION:

The evaluation of the Albatross Adaptive Acoustic Routing Optimization (AARO) protocol underscores its potential to enhance the efficiency, reliability, and adaptability of Buoyant Wireless Sensor Networks (B-WSNs). The results validate that AARO significantly improves packet delivery ratio, throughput, and energy efficiency while reducing delay and packet drop ratio compared to existing protocols. The integration of bio-inspired optimization and adaptive routing strategies ensures robustness in dynamic underwater environments, making AARO a promising solution for marine monitoring, disaster management, and environmental sensing. The strengths of this study lie in its novel bio-inspired optimization approach, adaptability to fluctuating underwater conditions, and efficient energy management mechanisms. The simulation-based evaluation in ns-3 provides a rigorous comparison against benchmark protocols, demonstrating the effectiveness of AARO across various network densities. Despite these advantages, certain weaknesses remain. The study relies on simulations rather than real-world deployments, which may not fully capture environmental uncertainties such as acoustic interference and hardware limitations. Additionally, the computational complexity of AARO's adaptive mechanisms requires further optimization to ensure feasibility in large-scale implementations. This research marks a significant step toward enhancing underwater communication systems through intelligent routing. However, real-world validation and further refinements, including hybrid communication models and reinforcement learning-based optimizations, will be necessary to maximize AARO's scalability and adaptability. Future work will focus on practical deployments and fine-tuning computational efficiency, ensuring that AARO meets the evolving demands of underwater sensor networks.

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