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Adaptive energy-efficient and secure clustering-based routing architecture for underwater wireless sensor networks in marine environmental and ecosystem monitoring

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Introduction: Reliable long-term monitoring of coral reefs and other marine ecosystems is limited by the harsh underwater environment, restricted battery capacity of sensor nodes, and the high energy cost of acoustic communication. Underwater Wireless Sensor Networks (UWSNs) have emerged as a promising solution for marine environmental monitoring; however, challenges related to energy efficiency, secure communication, and reliable data collection remain significant.
Methods: This study proposes an integrated architecture for UWSNs that enhances energy efficiency, security, and data reliability. The framework combines a hybrid Adaptive Swarm Fitness Optimization–Golden Eagle Optimizer with K-Medoids clustering (ASFO–GEO–KM) for optimal cluster head selection, a Tiny Security (TinySec)-enabled Energy-aware Coral-Environmental Reliable Path (E-CERP) routing protocol, and Autonomous Underwater Vehicle (AUV)-assisted data collection. The ASFO–GEO–KM algorithm selects cluster heads based on residual energy, underwater link quality, and node density to improve load balancing and cluster stability. TinySec-enabled E-CERP provides authenticated, energy-aware multi-hop routing while accounting for underwater path loss and propagation delay. AUVs periodically collect aggregated data from cluster heads to reduce long-range acoustic transmissions and conserve node energy.
Results: Simulation results conducted in a realistic 3D marine environment demonstrate that the proposed framework outperforms existing approaches, including DEDG, AP, ALP, HECRA, GSA, and CTRGWO-CRP. The proposed system achieves a longer network lifetime, a higher packet delivery ratio, and significantly reduced routing overhead.
Discussion: By enabling secure, energy-efficient, and reliable underwater sensing, the proposed architecture supports long-term coral reef monitoring

and marine ecosystem observation. It facilitates early detection of environmental stressors, such as thermal anomalies and turbidity spikes, thereby improving marine ecosystem protection and supporting conservation-oriented decision-making.

KEYWORDS

AI, ASFO–GEO optimization, autonomous underwater vehicles, coral reef monitoring, energy-efficient routing, hybrid clustering, real-time environmental sensing, tinysec security

1 Introduction

Underwater Internet of Things (UIoT) technologies and underwater wireless sensor networks (UWSNs) have become essential tools to explore and monitor marine environments. These systems support a wide spectrum of applications, ranging from ecological conservation and environmental surveillance to maritime security, underwater resource exploration, and disaster prediction (Maheswari and Senthil Kumar, 2025; Saleem et al., 2025b; Shamshad et al., 2025). With recent advances in artificial intelligence, deep learning models are increasingly being considered to process the complex and voluminous data gathered by UWSNs, enabling enhanced pattern detection, anomaly identification, and predictive analytics in underwater environments (Kaur et al., 2024). UWSNs operate in demanding aquatic conditions to provide continuous data streams for tasks such as coral reef health assessment, deep-sea mining observation, and underwater pipeline inspection (Shwetha and Sannathammegowda, 2025).

Despite their potential, UWSNs face significant challenges due to the harsh nature of underwater communication. Acoustic signaling suffers from low bandwidth, high latency, multipath effects, and rapid signal attenuation. Additionally, underwater sensor nodes typically rely on non-rechargeable batteries, making energy conservation a critical design priority to ensure long-term network operation (Saleem et al., 2025a). These constraints significantly limit the performance, scalability, and lifetime of underwater sensing systems.

To alleviate energy consumption issues, clustering-based routing has become one of the most widely studied strategies in both terrestrial and underwater sensor networks (Saleem et al., 2024). In a clustered network, sensor nodes are organized into groups, each led by a cluster head (CH) that aggregates and forwards data. This hierarchical structure reduces the need for frequent long-distance transmissions, distributes workload more evenly across the network, and minimizes the formation of energy-draining communication hotspots (Panchal and Gajjar, 2025). Multi-hop routing within clusters further reduces power consumption and extends the network's overall operational lifespan.

Wireless sensor networks (WSNs) have, in general, revolutionized the way physical-world information is sensed, collected, and controlled. They consist of numerous low-power, self-configuring nodes interconnected through wireless links. These networks have become ubiquitous in both civilian and military applications, including smart homes, environmental monitoring, industrial automation, and climate observation (Bharany et al., 2023). Recognized as one of the most influential technologies of the 21st century, WSNs are categorized into terrestrial, surface, and underwater networks depending on their deployment domains (Kumar et al., 2025). While terrestrial WSNs have matured significantly, their design principles cannot be directly transferred to underwater environments due to the complex three-dimensional topology and unique hydrodynamic conditions of the ocean (Chang et al., 2019).

UWSNs comprise underwater sensing devices and underwater vehicles that communicate via acoustic signals. These sensors detect various environmental parameters within their sensing radius and forward the collected information to a surface sink node located above the water. UWSNs support numerous practical applications such as aquatic ecosystem monitoring, pollution tracking, underwater hazard detection, and fisheries management (Chen and Lin, 2012). However, because underwater sensor nodes have limited battery capacity, energy efficiency is a primary design consideration.

From a marine conservation and sustainability perspective, long-term and continuous monitoring is essential to understand coral reef degradation, biodiversity loss, and ecosystem resilience under accelerating climate change. Coral bleaching events, water quality deterioration, and habitat degradation are strongly influenced by environmental parameters such as temperature anomalies, turbidity, salinity, and dissolved oxygen concentration. Persistent and energy-efficient underwater wireless sensor network deployments enable a reliable observation of these parameters over extended periods, allowing the early detection of environmental stressors and abnormal ecosystem behavior. Such real-time sensing capabilities are particularly valuable in marine protected areas (MPAs), where continuous data streams support early-warning systems, evidence-based conservation planning, and adaptive marine ecosystem management while minimizing human intervention in fragile underwater habitats.

Clustering plays a significant role in conserving energy within UWSNs. After clusters are created, a CH is selected based on

Abbreviations: UIoT, Underwater Internet of Things; UWSN/UWSNs, Underwater Wireless Sensor Network/Networks; WSN/WSNs, Wireless Sensor Network/Networks; AI, Artificial Intelligence; DL, Deep Learning; CH, Cluster Head; AUV, Autonomous Underwater Vehicle; IoT, Internet of Things; QoS, Quality of Service; 3D, Three-Dimensional; MAC, Medium Access Control; SNR, Signal-to-Noise Ratio; UAV, Unmanned Autonomous Vehicle; RF, Radio Frequency; TX, Transmission; RX, Reception; PDR, Packet Delivery Ratio; E2E delay, End-to-End Delay; CH selection, Cluster Head Selection; sink node, Surface Sink Node/Base Station metrics such as remaining energy, node degree, physical distance, mobility, position, or signal strength. Bio-inspired swarm intelligence algorithms are often used to evaluate these metrics through fitness functions and to optimize the CH selection process (Duan et al., 2020). Introducing autonomous underwater vehicles (AUVs) into UWSNs further enhances energy efficiency. AUVs can collect data either directly from individual nodes or from CHs, minimizing the need for multi-hop transmissions. This approach reduces communication overhead, balances energy usage across nodes, and lowers end-to-end delay. As illustrated in Figure 1, the clustering structure groups underwater nodes and assigns a cluster head to coordinate data transmission.

However, employing AUVs introduces additional design considerations, such as optimal trajectory planning and location prediction. An AUV's movement path can be predefined or dynamically adjusted based on network conditions and data collection requirements. While a single AUV simplifies trajectory optimization, it may not efficiently cover large network areas. Therefore, deploying multiple AUVs is often recommended to expand coverage, reduce overall energy expenditure, and extend the network's operational lifetime (Alkanhel et al., 2022).

Unlike existing UWSN approaches such as DEDG, HECRA, and CTRGWO-CRP, which rely on single or loosely coupled optimization strategies, the proposed ASFO–GEO–HKM framework tightly integrates local and global optimization within the clustering process while jointly incorporating secure routing and AUV-assisted data collection. This system-level integration differentiates the proposed approach from prior works that focus on isolated clustering and routing improvements.

The key contributions of the work are summarized as follows:

1. We propose a hybrid ASFO–GEO-based K-Medoids clustering algorithm for UWSNs, combining adaptive swarm fitness optimization (ASFO) for local search and Golden Eagle Optimizer (GEO) for global refinement. This approach selects energy-efficient and reliable cluster heads, improving energy balance and reducing intra-cluster distance.
2. We introduce a TinySec-enabled E-CERP routing protocol for secure and energy-efficient multi-hop underwater communication. By integrating residual energy, link reliability, path-loss, hop count, and lightweight TinySec encryption, it ensures secure, low-latency data delivery for resource-constrained nodes.
3. We integrate AUV-assisted mobile data collection, where AUVs act as mobile data mules to reduce long-range transmissions, prevent cluster head buffer overflows, and extend network lifetime, enabling real-time monitoring without affecting network connectivity or security.
4. We develop a comprehensive underwater energy and path-loss model that captures realistic transmission, reception, and total energy based on spreading factors, absorption, and multipath effects, thereby enhancing routing and clustering reliability.
5. We design a complete UWSN architecture integrating hybrid clustering, secure routing, and AUV-assisted data collection. This holistic framework addresses energy efficiency, dynamic topology, acoustic propagation, and security, outperforming existing techniques in network lifetime, reliability, and secure data delivery.
6. We explicitly link network-level performance improvements to marine conservation outcomes, demonstrating how sustained, secure, and real-time underwater sensing enables coral reef health assessment, early environmental stress detection, and long-term ecosystem monitoring

To realize these contributions, we designed processes for hybrid clustering, secure routing, and AUV-assisted data collection. Energy efficiency was achieved through the optimal selection of cluster heads (CHs) and adaptive scheduling of node activity. The data gathering delay was minimized by coordinating AUV trajectories and efficient inter-cluster routing. The proposed architecture

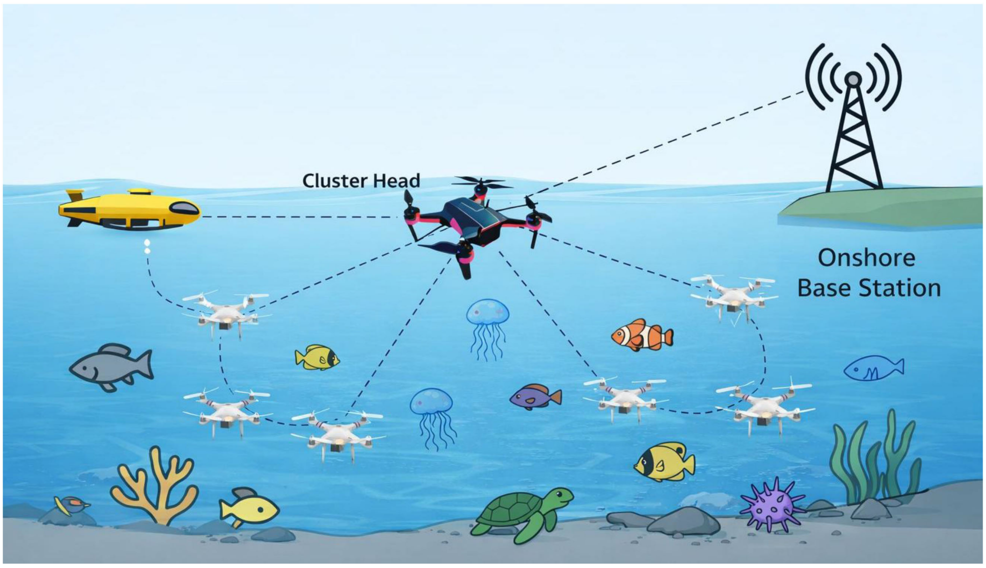

FIGURE 1
Clustering structure in underwater wireless sensor network.

utilizes two AUVs to collect data from sensor nodes deployed at different underwater depths, ensuring balanced load distribution and reliable, real-time monitoring.

2 Related work

This section examines earlier research publications and highlights their shortcomings. The sink at the opposite end receives the sensed environmental data. Routing is used to send data through intermediary sensors. This section also delves into the AUV's role in data collection.

A Q-learning-based data forwarding process was proposed in (Chang et al., 2019). Initially, the sensor identified its neighbors by broadcasting a beacon message via a sink. The angle of arrival and received signal strength indication (RSSI) were updated for the neighbor node. A forwarder was chosen using the Q-learning method based on the transmission probability if the sink node was not within the sensor's one-hop range. Both the forwarder and the source sensor lost energy as the number of forwarders increased. A geolocation routing methodology for AUV-assisted data collection was proposed by Chen et al (Chen and Lin, 2012). To gather data from the entire network, an AUV follows a predetermined route, visiting each sensor node in turn. The nodes remain inactive until the AUV approaches them, thereby minimizing energy use. The node in the local region awakens the node in the next area when the AUV arrives there. This approach obviously requires traversing the entire network of nodes, resulting in a lengthy AUV cruising path. Duan et al (Duan et al., 2020). proposed the objective of determining the best traversal path for the AUV to maximize the value of information (VoI) of the entire network. To do this, an equation for the total VoI is constructed using an analytical model that first describes the behaviors of the AUV, sensor nodes, and the difficult environment. The issue is then presented as a combinatorial optimization problem. Lastly, an optimal solution to this problem is presented using a branch-and-bound (BB) method.

The authors in (Alkanhel et al., 2022) proposed a unique DEDG 3D-UWSN framework that incorporates AUV-assisted data gathering to address the energy consumption and latency problems frequently observed in underwater sensor networks. The authors present Hassanat distance-based redundancy elimination to enhance data accuracy as well as MO-SHO-based clustering and sleep scheduling to increase the node lifespan. For intelligent AUV route prediction, an actor-critic model is employed, allowing for effective multi-head data collection. Furthermore, when AUV waiting durations exceed thresholds, a fuzzy-LeNet-validated three-step inter-cluster routing method ensures reliable communication. Compared with current UWSN techniques, the study shows increased network longevity, lower latency, and greater energy efficiency.

A UWSN was modeled as discontinuous concentric coronas in six partitions in (Bouabdallah, 2019). In this case, a source sensor node selected an intermediate sensor from each wedge, and the sensed data from those sensors was sent to the sink node along the route. However, it was laborious to reconcile the creation of a corona for a large-scale environment with energy usage. The energy-balanced, efficient, and reliable routing (EBER2) protocol is a depth-based routing technique introduced in (Wadud et al., 2019). Three restrictions were used to choose a forwarder: residual energy, potential forwarder node (PFN), and weighted depth difference. To convey the data, the sending nodes calculated the distance and selected the closest sink. The transmission of the sensed data from the network's nodes caused the sensor nodes closest to the sink to use more energy. Hop count and distance calculations were used to implement a self-organizing, scalable routing protocol (SOSRP) (Hindu et al., 2019). This protocol used message exchange to find neighbors, followed by hop count and distance estimation for path prediction. Data was transmitted via the path with the fewest number of hops. Because the chosen nodes in this work performed badly in terms of energy consumption, the path's stability was not robust. This work established an energy-efficient multipath routing (E2MR) that chose a forwarding node from the created priority table (Khalid et al., 2019). The entities of residual energy, distance, and priority value were built into the priority table through the exchange of control packets. The sensor's energy and depth were used to calculate the priority value. In this case, the forwarding node was chosen based on its higher priority rating. Effective routing was achieved by building a cluster, which ultimately reduced energy usage. The CH was selected by calculating the node's Bayesian probability and residual energy in a multi-layer, cluster-based, energy-efficient (MLCEE) protocol (Khan et al., 2019). Members were assigned time division multiple access (TDMA) time slots after the clusters were constructed (Ahmed et al., 2019). By calculating residual energy, hop count, and probability as fitness values, the CH selected a forwarding node.

Gjanci et al (Gjanci et al., 2017). employed multimodal communication to maximize the VoI of data sent to a surface sink while offloading node data to the AUV. The AUV is driven to gather data from nodes based on the VoI of their data using a greedy, adaptive AUV path-finding (GAAP) algorithm. The technique is appropriate to quickly gather data, but it does not ensure the accuracy of the information. An AUV-assisted routing methodology for UWSNs was proposed by Seokhoon et al (Yoon et al., 2012). The AUV employs short-distance, high-speed communication to send data to the sink node, medium-distance communication between the gateway node and common nodes, and long-distance, low-speed communication to select the gateway node. Via gateway node convergence, data packets from the common nodes are sent to the gateway node and then to the sink node. This successfully lowers the nodes' energy consumption, but it does not help the AUV travel a shorter distance. An enhanced AUV-assisted collecting strategy was presented by Javaid et al (Javaid et al., 2015). The AUV delivers a broadcast "hello" packet while traveling down the circular track that serves as the AUV collection path, which is positioned in the center of the network. The node that receives the "hello" packet uses the AUV to compute the RSSI and selects the node with the highest RSSI as the gateway node. Based on the RSSI, the other nodes create a data transmission tree with the gateway node. The gateway node receives data from the common node and forwards it to the AUV. The fixed circular trajectory tends to result in local hotspots, even if this method lowers the high energy consumption caused by multihop routing. A UWSN was partitioned into four cubes by Akbar et al (Akbar et al., 2016). One cube was randomly selected as the data collection region, and a communication node (CN) was installed in each of the remaining three cubes. Each area transmits information to its corresponding CN node, which then relays it to the AUV. This approach significantly lowers the AUV's mobile energy consumption, but it is not suitable for large-scale UWSN and ignores the nodes' communication radius.

In (Xia et al., 2023), the authors present an affinity propagation-based clustering method to enhance AUV-assisted data collection in sparsely deployed underwater sensor networks. To provide a more stable, energy-conscious grouping, the authors dynamically modify clusters based on node communication ranges and select cluster heads based on high residual energy. The cluster heads are visited using a traveling salesman problem (TSP)-optimized approach to reduce the AUV trip distance, enabling effective full-network data gathering. The suggested approach successfully reduces AUV trajectories and improves overall data retrieval efficiency in UWSNs, according to simulation results. The HECRA protocol, intended to improve the dependability and energy efficiency of AUV-assisted underwater sensor networks, is presented in (Shi et al., 2024). By including residual energy and node degree into the cluster-head selection procedure, the authors enhance the conventional LEACH and enable more robust and balanced clustering. Routing performance is further strengthened by further cluster creation and data transmission optimizations, such as depth-weighted forwarding and energy-based cluster joining. The technique significantly reduces transmission latency and improves data delivery by leveraging an AUV as a dynamic relay node. According to simulation data, HECRA performs better in terms of network longevity, energy retention, and effective packet delivery than current methods such as LEACH, EERBLC, and EECMR. EECMR, which divides the network into layers and selects cluster heads based on residual energy and node depth, was proposed by Nguyen et al (Nguyen et al., 2021). and can effectively extend network lifetime. However, the communication latency is high, and the communication between layers is overly dependent on relay nodes. Network topologies in recent 3D-UWSN experiments have mostly been created to improve data collection and routing efficiency, with a focus on prolonging network lifetime by conserving energy at sensor nodes. Nevertheless, several restrictions remain. Through clustering and sleep–wake scheduling, the AUV-assisted energy-efficient clustering (AEC) method (Khan MT et al., 2019) aims to lower energy usage. The AUV chooses the CH during its first traversal and then gathers data in the second. Because CH selection relies solely on the residual energy estimate, it is useless even if the wake-up period is determined by factors such as the sensing interval, guard delay, and data/ACK transmission delays. Additionally, relying solely on transmission and delay measures to estimate wake-up periods overlooks the energy behavior of sensor nodes, leading to suboptimal sleep-slot assignment and reduced network performance. To balance energy consumption in UWSNs, clustering-based data collection methods using AUVs have been proposed (Han et al., 2019). The AUV builds its itinerary according to the location-prediction-based ALP scheme, prioritizing nodes with shorter collection delays. Similarly, to maximize collection efficiency, bipartite K-means clustering uses an AUV to collect data based on node residual energy and distance. These methods still have significant delays, though, because the AUV gathers data from cluster heads one at a time rather than simultaneously, which lengthens the delivery time. Furthermore, using a single AUV significantly lengthens the tour, reducing the timeliness and effectiveness of data retrieval, and a longer AUV trajectory directly increases overall data collection latency.

In (R et al., 2025), a GSA-based clustering and routing method is introduced to improve energy-efficient data transmission. The algorithm operates through four phases—exploration, clustering, routing, and transmission—and performs effectively under both high and low node densities. The results show improvements of 33.06%, 11.77%, and 57.2% over EECMR, EERBLC, and LEACH, respectively.

In (Chen et al., 2025), the authors propose an enhanced gray wolf optimization-based clustering and routing protocol (CTRGWO-CRP) that integrates cloning strategy, t-distribution mutation, and opposition-based learning. These strategies improve exploration–exploitation balance, prevent local optima, and enhance convergence accuracy. A dynamic weighted fitness function that considers average residual energy and communication distance guides multi-objective optimization toward energy balance and transmission efficiency. The protocol also uses elite retention for cluster head selection and a multi-hop gradient-based relay mechanism for energy-efficient data transmission. The simulation results indicate that CTRGWO-CRP achieves a minimum improvement in network lifetime of 23.5%. The overview and analysis for the previous state of the art is summarized in Table 1.

3 Materials and methods

The proposed methodology is expected to improve UWSNs for real-time coral reef monitoring by combining an adaptive clustering-based routing model with AUV-controlled mobile data collection. The architecture builds on a two-step hybrid clustering algorithm, i.e., ASFO-GEO-based hybrid K-Medoids clustering, to form clusters with lower energy consumption and more reliable clustering and on a TinySec-enabled E-CERP (Energy-aware Coral-Environmental Reliable Path) routing protocol to guarantee secure and trustworthy multi-hop communication between sensor nodes and AUV data mules. It is aimed at addressing the nature of UWSNs, including node energy constraints, challenges of underwater propagation, and mobile network topology.

By enabling secure, energy-efficient, and long-term underwater sensing, the proposed methodology directly supports continuous coral reef monitoring, early detection of environmental stressors, and reliable data acquisition for marine ecosystem assessment and conservation-oriented decision-making.

First, sensor nodes are randomly distributed throughout the coral reef's three-dimensional underwater space. The ASFO–GEO-based hybrid K-Medoids clustering (Algorithm 1 in Supplementary Material) is applied to cluster the data using adaptive swarm fitness

TABLE 1 Summary of existing underwater wireless sensor network (UWSN) routing and data collection techniques, highlighting key features and major limitations.

Ref.	Method/protocol	Key features	Limitations/shortcomings
(Chang et al., 2019)	Q-learning-based data forwarding	Neighbor discovery via beacon; forwarder selection based on Q-learning; energy consumption monitored	Energy loss increases with number of forwarders; limited to one-hop neighbor range
(Chen and Lin, 2012)	Geolocation routing for AUV-assisted data collection	AUV follows predetermined route visiting each sensor; nodes stay inactive until AUV arrives	Long AUV cruising path; inefficient for large networks
(Duan et al., 2020)	Optimal AUV traversal using VoI	Combinatorial optimization; branch-and-bound solution; analytical modeling of AUV, sensors, environment	Computationally complex; scalability issues for large networks
(Alkanhel et al., 2022)	DEDG 3D-UWSN	MO-SHO clustering, sleep scheduling; Hassanat distance-based redundancy elimination; actor-critic AUV route prediction; fuzzy-LeNet inter-cluster routing	Complexity in implementation; multiple techniques integrated may increase overhead
(Bouabdallah, 2019)	Discontinuous concentric coronas	Partitioned network; source selects intermediate sensors; multi-hop to sink	Laborious for large-scale networks; complex corona creation; energy intensive
(Wadud et al., 2019)	EBER2 protocol	Depth-based forwarder selection (residual energy, PFN, weighted depth); closest sink selection	Nodes near sink deplete energy faster; hotspot issues
(Hindu et al., 2019)	SOSRP	Self-organizing; hop count and distance for path prediction; message exchange for neighbors	Poor energy efficiency; unstable path selection
(Khalid et al., 2019)	E2MR	Multi-layer cluster-based routing; priority table using residual energy, distance, priority value	Forwarding nodes chosen based on priority may not optimize overall energy
(Khan et al., 2019)	MLCEE	Cluster-head (CH) selection using Bayesian probability and residual energy; TDMA scheduling	May not adapt efficiently to dynamic network changes; overhead in CH computation
(Gjanci et al., 2017)	GAAP (multimodal communication with AUV)	Greedy adaptive AUV path-finding; VoI-based data gathering	Quick collection but may reduce accuracy; not robust to dynamic changes
(Yoon et al., 2012)	AUV-assisted routing	Short-, medium-, long-distance comm.; gateway node convergence	Reduces node energy consumption but does not shorten AUV trajectory
(Javaid et al., 2015)	Enhanced AUV-assisted collection	Circular track AUV path; RSSI-based gateway node selection; data tree for nodes	Fixed trajectory causes local hotspots; multihop energy consumption still high
(Akbar et al., 2016)	Cube-based UWSN partitioning	Random data collection cube; CN nodes in other cubes; data relayed to AUV	Not suitable for large-scale UWSNs; ignores node communication radius
(Xia et al., 2023)	Affinity propagation clustering	Dynamic cluster formation; high residual energy CH selection; TSP-based AUV path optimization	Focused on sparse networks; may require complex computation
(Shi et al., 2024)	HECRA	Residual energy and node degree for CH selection; depth-weighted forwarding; energy-based cluster joining	Complexity in cluster formation; may require multiple traversals
(Nguyen et al., 2021)	EECMR	Layered network; CH selection using residual energy and depth	High communication latency; over-reliance on relay nodes
(Khan MT et al., 2019)	AEC	CH selection in first AUV traversal; sleep-wake scheduling	Uses only residual energy for CH selection; ignores sensing and transmission delays
(Han et al., 2019)	ALP-based/bipartite K-means clustering	AUV itinerary based on node residual energy & predicted location	Single AUV increases tour length; sequential cluster collection causes delays
(R et al., 2025)	GSA-based clustering and routing	Four-phase: exploration, clustering, routing, transmission; works in high/low densities	Comparative improvements shown, but may still face scalability issues
(Chen et al., 2025)	CTRGWO-CRP	Gray wolf optimization with cloning, t-distribution mutation, opposition-based learning; multi-objective optimization; elite retention for CH	Complexity in implementation; high computational overhead

optimization (ASFO) to explore the data locally and the Golden Eagle Optimizer (GEO) to exploit the data globally. This hybrid optimization ensures that the CHs are selected based on multiple criteria, including residual energy, link quality, node density, and so on, while balancing power consumption and intra-cluster node distance. The K-Medoids algorithm's centrality ensures that the cluster medoids are representative nodes, thereby minimizing the risk of premature energy exhaustion in heavily loaded nodes.

Once the clusters have been created, then the TinySec-enabled E-CERP routing (Algorithm 2 in Supplementary Material) is invoked to determine safe and energy-efficient multi-hop paths between the cluster members and the cluster heads, and then to the AUV mobile data collectors. The routing algorithm in E-CERP uses residual node energy, and TinySec furnishes data integrity and secrecy by lightweight encryption and authentication. Each node is surrounded by a neighbor table, which is constructed using acoustic distances, energy-trust measures are computed, and the next hop that is the most reliable for sending packets is selected. This adaptive routing scheme is particularly useful in underwater environments, where link or node failures are frequent. The energy usage of submersible sensor nodes is reduced by implementing the AUV-based mobile data mules. Another benefit of AUVs is that they can follow a predetermined path and collect information periodically with each cluster head, contracting long-range transmissions and extending the network's lifespan. This plan for collecting mobile data is accompanied by a cluster-based routing system to deliver real-time measurements of coral reef parameters without interfering with network connectivity or data security. The suggested model is an UWSN for real-time monitoring of the sea and coral reefs. The UWSN consists of immobile underwater sensor nodes (SNs), mobile AUVs, relay nodes, and a surface base station (BS). Sporadically, the AUVs may be used as data mules in the water to block long-range acoustic transmission, reduce packet losses, and extend network life.

3.1 Network model

As expressed in Equation 1, the network comprises a collection of N underwater sensor nodes, denoted as $N = \{n_1, n_2, \ldots, n_N\}$, uniformly distributed within the spatial domain $V(x, y, z)$.

$$N = \{n_1, n_2, \ldots, n_N\} \tag{1}$$

This network comprises N sensors installed in a 3-D volume that continuously monitor environmental parameters in undersea scenario. K-Medoids are used together with ASFO to cluster nodes in an energy-efficient manner. In this algorithm, each CH amasses data, uses TinySec security, and channelizes packets to relays or AUVs. The BS lies on the surface of the water, creating a data sink in the middle. The environmental parameters that each node measures periodically include temperature, turbidity, salinity, and dissolved oxygen.

These parameters are widely used indicators of coral reef health, eutrophication, and hypoxic stress, making them essential for assessing ecosystem degradation, enabling the early detection of ecological disturbances, and supporting timely conservation and marine management interventions.

The K-Medoids + Adaptive Sailfish Optimisation (ASFO) is used to cluster nodes into k clusters. A CH is present in each cluster and is responsible for aggregating the sensed data, performing secure TinySec-based encryption, and forwarding the packets to the nearest relay node or AUV. As expressed in Equation 2, the BS is located at the coordinates $BS = (x_{bs}, y_{bs}, z_{bs} = 0)$, where the z -coordinate is set to zero to represent its placement at the surface level.

$$BS = (x_{bs}, y_{bs}, z_{bs} = 0) \tag{2}$$

The general architecture of the UWSN is shown in Figure 2.

3.2 Underwater acoustic energy consumption model

Underwater communication relies on acoustic waves, which depend on distance, absorption, and spreading. The energy consumed by sensor nodes is influenced by these factors, making accurate modeling essential for designing energy-efficient protocols and extending network lifetime in UWSNs. The model determines

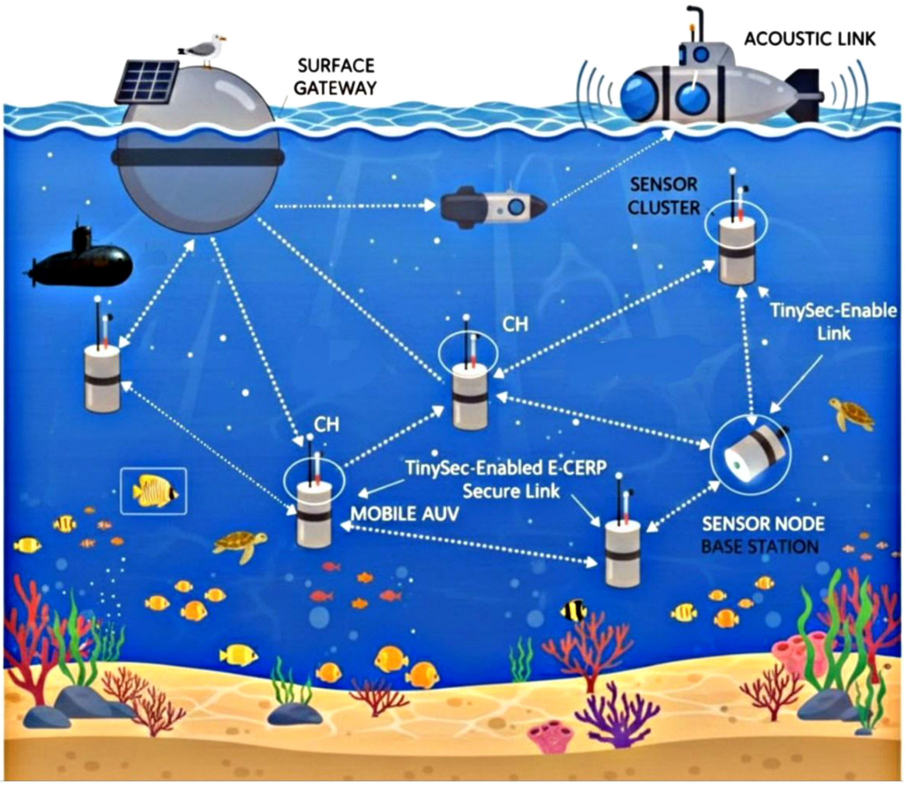

FIGURE 2
Architecture of underwater wireless sensor network.

the transmission, reception, and total energy in terms of acoustic amplifier parameters. The distance–frequency path-loss model, based on distance and frequency, captures realistic underwater attenuation, enabling the precise estimation of energy consumption under different environmental conditions. As expressed in Equation 3, the transmission energy for an M-bit data packet over distance d is computed using:

$$E_{tx}(M,d) = E_{elec}M + E_{amp}(d)M \tag{3}$$

where E_{elec} accounts for electronic circuitry and $E_{amp}(d)$ represents distance-dependent amplifier energy.

As expressed in Equation 4, the acoustic amplifier energy E_{amp} (d) is defined by a piecewise formulation. For distances $d \le d_0$, the energy is proportional to $\in_{sp}d^2$, whereas for distances $d > d_0$, it increases according to $\in_{mp}d^k$, reflecting the higher attenuation in long-range underwater communication.

$$E_{amp}(d) = \begin{cases} \in_{sp}d^2 \ , d \le d_0 \\ \in_{mp} \ d^k, d > d_0 \end{cases} \tag{4}$$

where

- $k \in [2,4]$ underwater spreading factor.
- d_0 = threshold distance.
- $\in_{sp}, \in_{mp}$ = spreading and multi-path energy constants.

Near-field transmission primarily depends on spreading energy, while far-field communication is dominated by multipath effects, requiring higher energy. This distinction is critical for designing efficient transmission strategies.

As expressed in Equation 5, the receiving energy $E_{rx}(M)$ is calculated solely based on the electronic circuitry consumption, modeled as $E_{elec}M$ for an M-bit message.

$$E_{rx}(M) = E_{elec}M \tag{5}$$

Equation 6 defines the total node energy consumption E_{sum} by combining the transmission energy E_{tx} and the receiver energy E_{rx}.

$$E_{sum} = E_{tx} + E_{rx} \tag{6}$$

Monitoring the total energy of each node is essential to predict network lifetime and optimize routing and clustering strategies in UWSNs.

Equation 7 gives the path-loss model as a function of distance and frequency.

$$PL(d,f) = d^k.\, a(f)^d \tag{7}$$

where $a(f)$ is the absorption coefficient based on acoustic frequency. Modeling path-loss in this manner ensures the realistic simulation of signal attenuation and improves the accuracy of energy consumption estimates in underwater environments.

This energy consumption model forms the basis to evaluate the performance of UWSN protocols under realistic underwater conditions. Incorporating distance-dependent transmission, reception, and path-loss, it enables an accurate prediction of node energy usage and network lifetime. This section provides the foundation to design energy-efficient routing and clustering strategies that optimize overall network performance.

3.3 CH selection using K-Medoids + ASFO + GEO hybrid optimization

K-Medoids is used to form clusters, reducing intra-cluster distance and generating stable starting medoids. This initial clustering minimizes long-range transmissions and lays the foundation for energy-efficient communication in UWSNs. ASFO then discerns CHs that squander less energy based on remaining energy, distance to the BS, link quality, and other parameters. GEO also digs into and refines CH positions to escape local maxima and enhance network stability. The hybrid fitness furnishes the best distribution of CHs and high acoustic reliability. Overall, this hybrid CH selection approach improves energy balance, reduces packet loss, and extends network lifetime.

Clustering stabilizes UWSN operation by minimizing long-range transmissions. The proposed CH selection integrates:

• Phase 1 — K-Medoids initialization.

As shown in Equation 8, the initial medoids are selected from the set of underwater sensor nodes to serve as the preliminary representatives for cluster formation:

$$c = \sqrt{N} \tag{8}$$

Equation 9 defines the initial cluster center for each medoid, establishing the starting point for iterative refinement during the K-Medoids process:

$$L = \frac{1}{N} \sum_{i=1}^{N} x_i \tag{9}$$

As expressed in Equation 10, the average deviation is computed to evaluate the compactness of nodes within each cluster relative to their assigned medoid:

$$D = \frac{1}{N} \sum_{i=1}^{N} |x_i - L| \tag{10}$$

Equation 11 represents the optimization objective of the K-Medoids algorithm, which seeks to minimize the total intra-cluster distance by iteratively updating medoids:

$$J = \sum_{I=1}^{N} \frac{\min}{\text{m} \in \text{medoids}} \quad ||x_i - m|| \tag{11}$$

This ensures well-formed clusters with minimized intra-cluster distances, reducing the overall energy consumption.

• Phase 2 —ASFO optimization for global CH selection.

As shown in Equation 12, the ASFO algorithm computes the fitness of each candidate CH using a weighted combination of residual energy, distance to the base station, and link quality:

$$F_{ASFO} = w_1 \ E_{res} + w_2 \frac{1}{d_{\{BS\}}} + w_3 LQ \tag{12}$$

where

- E_{res} = residual energy.
- $d_{\{BS\}}$ = distance to BS.
- LQ = link-quality score.

By considering multiple parameters, ASFO identifies CHs that optimize energy usage, connectivity, and link reliability.

• Phase 3—Golden Eagle Optimizer (GEO) refinement.

To avoid premature convergence, the GEO optimizer refines CH positions using attack and cruise phases.

Velocity update: As shown in Equation 13, the GEO optimizer updates the velocity of each candidate solution using both individual best (p_{best}) and global best (g_{best}) positions, enabling adaptive movement during the attack and cruise phases.

$$v_i^{t+1} = v_i^t + \alpha \, (p_{best} - x_i^t) + \beta (g_{best} - x_i^t) \tag{13}$$

Position update: Equation 14 defines the position update rule, where each candidate's new position is obtained by adding the updated velocity to the previous position, allowing an exploration of the search space.

$$x_i^{(t+1)} = x_i^t + v_i^{t+1} \tag{14}$$

This step ensures global exploration, preventing the algorithm from getting trapped in local optima and improving cluster head placement.

Hybrid fitness function: As expressed in Equation 15, the hybrid fitness function combines the ASFO fitness F_{ASFO} and GEO fitness F_{GEO}, weighted by $\lambda_1$and λ_2, respectively.

$$F_{Hybrid} = \lambda_1 \; F_{ASFO} + \lambda_2 \; F_{GEO} \tag{15}$$

This ensures optimal CH placement, better energy balance, and reduced acoustic packet loss.

Overall, the hybrid CH selection approach combines clustering, global optimization, and refinement to achieve energy-efficient and reliable CH placement in UWSNs. K-Medoids forms stable clusters; ASFO selects CHs based on energy, distance, and link quality; and GEO refines positions to avoid local optima. These phases together reduce energy consumption, minimize packet loss, and extend network lifetime, ensuring stable underwater network operation under dynamic conditions.

3.4 TinySec—Integrated secure data transmission

TinySec provides lightweight authentication and encryption tailored for resource-limited underwater sensor nodes. By integrating security directly into the network protocol, TinySec ensures data confidentiality and integrity without significantly increasing computational or energy overhead. Both TinySec-Auth and TinySec-AE maintain message integrity and confidentiality while keeping the computational demands minimal. CHs include the energy cost of security operations in their aggregation calculations, ensuring an accurate modeling of node power consumption. The integration ensures secure, low-latency packet delivery in underwater environments. TinySec is adapted for underwater nodes by tuning cryptographic complexity to match the limited processing capabilities and energy constraints of UWSNs.

TinySec-Auth (authentication only): As shown in Equation 16, TinySec-Auth constructs the packet P by appending the message authentication code (MAC) to the plaintext message M, ensuring message integrity and sender authenticity without applying encryption.

$$P = M \,||\, MAC(K, M) \tag{16}$$

This ensures that the message has not been tampered with during transmission and verifies the sender's authenticity. No encryption is applied here, so it uses less energy compared to full encryption.

TinySec-AE (authenticated encryption): Equation 17 defines the ciphertext C obtained by encrypting the message $M$with key K. Equation 18 constructs the final packet P by concatenating the ciphertext and its corresponding MAC, ensuring both confidentiality and integrity.

$$C = ENC_K(M) \tag{17}$$

$$P = C \,||\, MAC(K, C) \tag{18}$$

This provides both *confidentiality* and *integrity*. Even if an attacker intercepts the packet, the message cannot be read (encrypted), and any modification is detectable (MAC).

Node-level computational cost: As expressed in Equation 19, the security-related computational energy E_{sec} is modeled as the sum of hashing, XOR operations, and key-related processing.

$$E_{sec} = E_{hash} + E_{xor} + E_{key} \tag{19}$$

This allows accurate *energy modeling* of security operations in underwater nodes, which is critical due to their limited power.

Secure CH aggregation energy: Equation 20 defines the secure aggregation energy at the cluster head as the sum of normal aggregation energy E_{agg} and the additional security cost E_{sec}.

$$E_{agg-sec} = E_{agg} + E_{sec} \tag{20}$$

This helps model the *realistic energy cost* of secure data aggregation, so routing or clustering protocols can account for the energy impact of security.

Overall, integrating TinySec provides a balanced trade-off between security and energy efficiency, ensuring that underwater data remains confidential and tamper-proof while supporting low-latency network operation.

3.5 E-CERP cross-layer routing for UWSN

The Energy-Efficient Cross-Layer Expedient Routing Protocol (E-CERP) enables energy-aware data forwarding in UWSNs by integrating multiple network layers. By combining neighbor discovery, link-quality estimation, hop-count metrics, and adaptive transmission control, E-CERP ensures reliable communication while minimizing energy consumption. Parent nodes are selected based on link cost, residual energy, and underwater path-loss. Transmission power is adaptively adjusted using transmission power control (TPC) to reduce acoustic energy wastage. This cross-layer design improves the reliability of CH-to-relay/AUV communication and reduces packet loss in energy-constrained underwater networks.

i. Neighbor discovery:

Each node broadcasts HELLO packets containing ID, hop-count H, and residual energy.

Link reliability:

As shown in Equation 21, the link reliability $L(n,m)$ between nodes n and m is computed as the ratio of the average received signal strength to a predefined threshold, providing an indication of link quality.

$$L(n,m) = \frac{RSSI_{avg}(n,m)}{RSSI_{thr}} \tag{21}$$

This equation computes the reliability of the link between nodes nnn and mmm by comparing the average RSSI to a threshold. Higher L(n,m) values indicate more reliable links.

Link cost calculation:

Equation 22 defines the link cost between nodes n and m as a weighted combination of the inverse link reliability, residual energy, and underwater path-loss $PL(d,f)$.

$$Cost(n,m) = \gamma_1 \ L(n,m)^{-1} + \gamma_2 \frac{1}{E_{\mathrm{res}}} + \gamma_3 \ PL(d,f) \tag{22}$$

Provides a quantitative metric for selecting the most energy-efficient and reliable links.

ii. Parent node selection.

As expressed in Equation 23, each node n selects its parent $Pa r(n)$ from among its neighbors by minimizing the sum of the neighbor's individual cost and the cost of the link connecting them.

$$Par(n) = \arg \min_{\mathrm{m} \in \mathrm{N(n)}} [Cost(m) + Cost(n,m)] \tag{23}$$

Each node n selects a parent $Par(n)$ from its neighbors $N(n)$ that minimizes the sum of the neighbor's own cost and the link cost to that neighbor. Ensures energy-aware, reliable routing by selecting the optimal parent node for data forwarding.

iii. Transmission power control (TPC).

Ideal underwater acoustic transmission power:

Equation 24 models the ideal acoustic transmission power $P_{tx}(n)$ for node n based on channel gain values and hop count, ensuring efficient energy usage during communication.

$$P_{\mathrm{tx}}(n) = \frac{1}{H_n}[ln \ \ (I) + \ln \ \ (H_n \sum j = 1 H_n \frac{1}{h_j}) \tag{24}$$

Upper bound: As shown in Equation 25, an upper bound on the transmission power $X_{tx}(n)$ is established to prevent over-amplification and limit unnecessary energy expenditure.

$$X_{\mathrm{tx}}(n) = \frac{1}{H_n}[ln \ \ (I) + ln \ \ (H(n))] \tag{25}$$

Adaptive TPC reduces energy wastage and prolongs node and network lifetime while maintaining reliable acoustic communication.

3.6 Integration with AUV-assisted data collection

Equation 26 describes the AUV's time-dependent trajectory $\tau(t)$, defined by its three-dimensional coordinates:

$$\tau(t) = (x(t), y(t), z(t)) \tag{26}$$

As expressed in Equation 27, the total data collection time T_{AUV} is computed based on the AUV's travel distance and speed:

$$T_{AUV} \quad = \quad \sum\nolimits_{c=1}^{k} \frac{D_{AUV}}{v_{AUV}} \tag{27}$$

Equation 28 defines the CH waiting time W_c as the difference between the AUV arrival time and the CH's transmission time, ensuring proper scheduling:

$$W_c \quad = \quad T_{AUV} - \ T_{tx} \tag{28}$$

This minimizes multi-hop acoustic routing and prevents buffer overflow in CHs.

AUVs periodically visit CHs along predefined trajectories to collect aggregated underwater data. This reduces multi-hop acoustic forwarding and prevents energy drain on intermediate nodes. CH waiting time and AUV data collection duration are modeled to ensure timely retrieval. AUV assistance significantly improves network lifetime and avoids buffer overflow at CHs.

This capability is particularly beneficial for long-term coral reef and coastal ecosystem monitoring, where uninterrupted data collection is critical for detecting gradual ecological changes and triggering early conservation responses.

As illustrated in Figure 3, the proposed framework operates in three integrated phases.

The proposed methodology synergistically integrates hybrid clustering, secure cross-layer routing, and AUV-assisted data collection to enhance the performance of underwater wireless sensor networks. Initially, the ASFO-GEO-based hybrid K-Medoids algorithm forms energy-efficient clusters by selecting cluster heads based on residual energy, link quality, and node density while minimizing intra-cluster distances. TinySec-enabled E-CERP routing then establishes secure and reliable multi-hop paths, incorporating neighbor discovery, link-cost metrics, and adaptive transmission power to reduce acoustic energy consumption. The integration of TinySec ensures message confidentiality, authentication, and integrity without imposing significant computational overhead. Furthermore, AUVs periodically visit cluster heads along predefined trajectories to collect aggregated data, reducing multi-hop transmission, preventing buffer overflow, and extending network lifetime. These components together provide a robust framework that balances energy efficiency, network reliability, data security, and real-time monitoring capabilities, addressing the inherent challenges of underwater communication, dynamic topology, and constrained node resources.

4 Results

The proposed ASFO-GEO-based hybrid K-Medoids clustering and TinySec-enabled E-CERP routing framework is implemented and evaluated in MATLAB. A three-dimensional underwater environment is modeled to reflect realistic sensor deployment, acoustic channel characteristics, and node mobility constraints. The simulations analyze energy consumption, network lifetime, packet delivery ratio, and end-to-end delay under different network sizes and node densities. MATLAB provides flexibility to incorporate complex optimization algorithms such as ASFO and

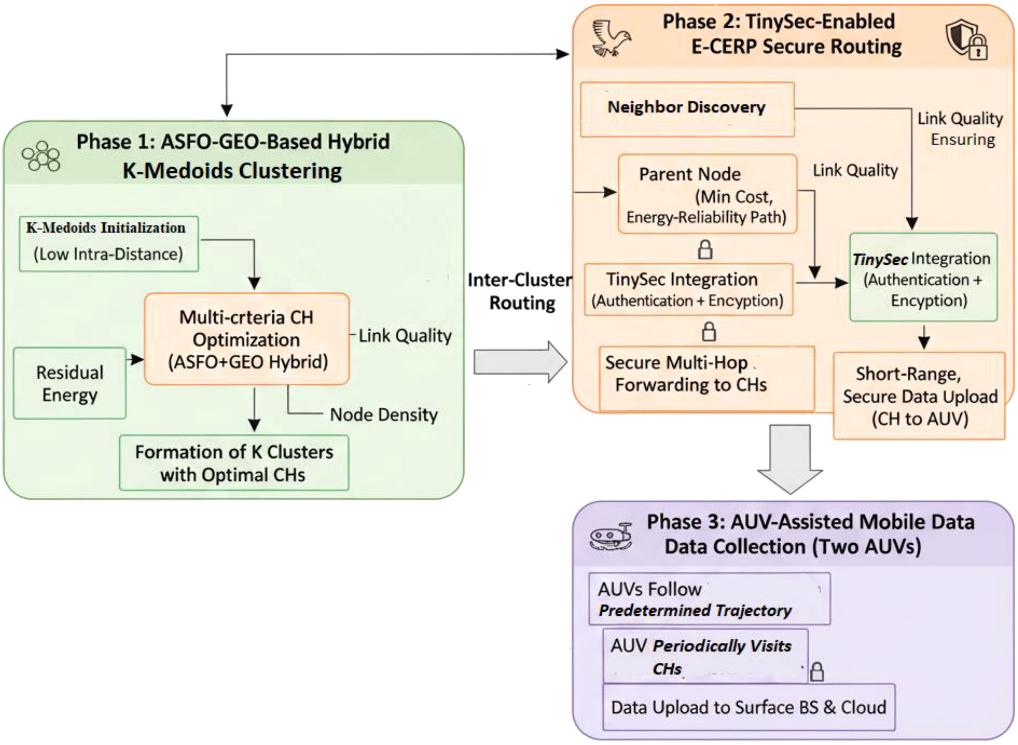

FIGURE 3
Proposed three-phase secure and energy-aware framework for UWSNs.

GEO and secure communication with TinySec and AUV-assisted data collection trajectories. By simulating multiple scenarios, the framework's performance is compared with that of existing routing and clustering protocols, demonstrating its energy efficiency, reliability, and security in underwater wireless sensor networks. Table 2 provides the complete set of simulation parameters used to model the 3D UWSN environment and deployment conditions.

The simulation parameters in Table 2 are selected to represent shallow-water marine environments such as coral reefs and coastal ecosystems. The maximum deployment depth of 50 m reflects typical reef monitoring scenarios reported in underwater sensor network studies. Acoustic communication is modeled at 30 kHz, a frequency widely used in short-range, shallow-water UWSNs due to its favorable trade-off between attenuation and bandwidth. Ambient underwater noise and acoustic channel impairments, including absorption and spreading loss, are implicitly captured through distance-based energy consumption and packet delivery performance metrics. Sensor nodes are assumed to be quasi-static, as commonly considered for bottom-mounted reef sensors, while the influence of underwater currents is indirectly accounted for through randomized node deployment. These assumptions are consistent with widely adopted UWSN simulation models in existing literature.

To validate the effectiveness of the proposed ASFO–GEO–HKM protocol, a comprehensive simulation study is conducted in MATLAB, comparing it with existing protocols such as DEDG (Alkanhel et al., 2022), Improved AP (Xia et al., 2023), ALP (Khan MT et al., 2019), HECRA (Shi et al., 2024), GSA (R et al., 2025), and CTRGWO-CRP (Chen et al., 2025). The evaluation focuses on key performance indicators, including the number of alive nodes, network lifetime, end-to-end delay, residual energy, packet delivery ratio, successful packet transmissions, and routing overhead. These metrics collectively provide a detailed understanding of energy efficiency, reliability, latency, and overall network performance in three-dimensional UWSNs. The following subsections present a detailed analysis of each parameter to demonstrate the superiority of the proposed approach.

4.1 Alive nodes vs. number of rounds

Figure 4 illustrates the variation in the number of alive sensor nodes over 2,000 operational rounds for seven algorithms: DEDG (Alkanhel et al., 2022), improved AP (Xia et al., 2023), ALP (Khan MT et al., 2019), HECRA (Shi et al., 2024), GSA (R et al., 2025), CTRGWO-CRP (Chen et al., 2025), and the proposed ASFO–GEO–HKM method. This metric reflects the energy efficiency, load balancing capability, and network durability of the underlying clustering and optimization strategies. At the beginning (round 0), all schemes start with approximately 150 active nodes, indicating identical initial deployment conditions. As the number of rounds increases, a gradual decline in surviving nodes is observed across all methods due to cumulative energy consumption during sensing, communication, and clustering. The DEDG and improved AP algorithms show the fastest decay in node survivability, with steep drops after the 500–800-round interval. ALP and HECRA demonstrate slightly better endurance due to improved data collection scheduling and adaptive clustering. GSA and CTRGWO-CRP outperform the previous four methods by

TABLE 2 Simulation parameters.

Parameter	Value
Initial node energy	5 J
Data packet size	200 bits
Transmit power	2 W
Receive power	0.1 W
Number of sink nodes	1
Acoustic frequency	30 kHz
Number of rounds	2,000–2,600
Communication radius RRR (m)	50
AUV movement speed vvv (m/s)	5
AUV movement power pmovep_{move}pmove (W)	50
Time of data collection TcollectT_{collect}Tcollect (s)	2
Time of data upload TuploadT_{upload}Tupload (s)	5
Minimum power psp_sps (W)	0.01
AUV broadcast data volume q1q_1q1	100
Nodes' sent and received data volume q2q_2q2	500
Time per unit of data TqT_qTq (s)	0.005
Energy consumption per bit ese_ses (J/bit)	50
Amplification factor (J/bit·m²)	100
Area length xxx	500 m
Area width yyy	500 m
Depth zzz	50 m
Node deployment	Random uniform distribution

maintaining a higher number of active nodes throughout the simulation. In particular, CTRGWO-CRP extends the mid-lifetime phase by leveraging enhanced gray wolf optimization with cloning and perturbation strategies. However, the proposed ASFO–GEO–HKM consistently maintains the highest number of alive nodes from the early rounds up to the termination point at 2,000 rounds. The proposed model retains around 70–75 nodes at round 2,000, whereas the closest competitor (CTRGWO-CRP) drops to approximately 45–50 nodes.

4.2 Network lifetime performance

The network lifetime performance illustrated in Figure 5 provides a comprehensive comparison of the proposed ASFO–GEO–HKM protocol against several widely used routing schemes, including DEDG (Alkanhel et al., 2022), Improved AP (Xia et al., 2023), ALP (Khan MT et al., 2019), HECRA (Shi et al., 2024), GSA (R et al., 2025), and CTRGWO-CRP (Chen et al., 2025). The figure presents the first node dies (FND), half nodes dead (HND), and last node dies (LND) metrics, allowing a clear visual assessment of each protocol's stability and endurance. Among the compared methods, DEDG (Alkanhel et al., 2022) exhibits the earliest FND and HND values, indicating faster energy depletion and limited stability. The mid-range protocols—Improved AP (Xia et al., 2023), ALP (Khan MT et al., 2019), and HECRA (Shi et al., 2024)—show noticeable improvements, reflected by progressively taller bars for FND and HND, owing to more efficient clustering and data-gathering mechanisms. The optimization-based GSA (R et al., 2025) and CTRGWO-CRP (Chen et al., 2025) further enhance performance by delaying node deaths, with HND values approaching 1,700–1,750 rounds, demonstrating improved energy balancing. However, the figure clearly highlights that the proposed ASFO–GEO–HKM protocol outperforms all comparative schemes, achieving the highest bar heights across all three metrics—FND (1,600 rounds), HND (2,000 rounds), and LND (2,600 rounds). This substantial enhancement confirms the effectiveness of integrating ASFO optimization, GEO-based trajectory support, and HKM clustering to maximize network stability and extend the operational lifetime of underwater sensor networks.

4.3 End-to-end delay

The end-to-end delay graph illustrates the temporal performance of various routing protocols in a 3D UWSN environment. End-to-end delay is the total time a data packet

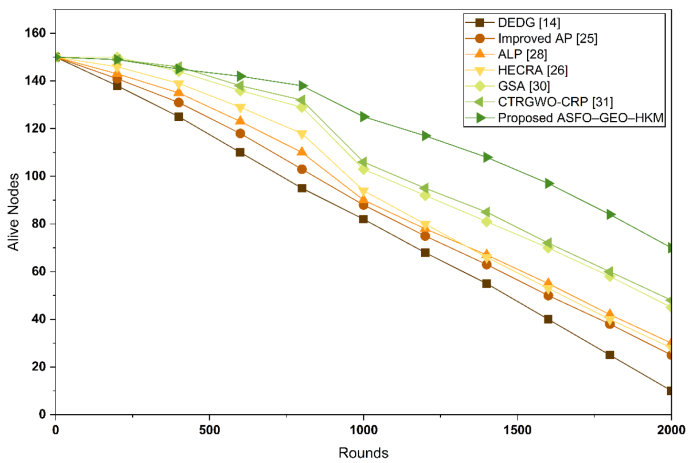

FIGURE 4
Alive nodes vs. number of rounds.

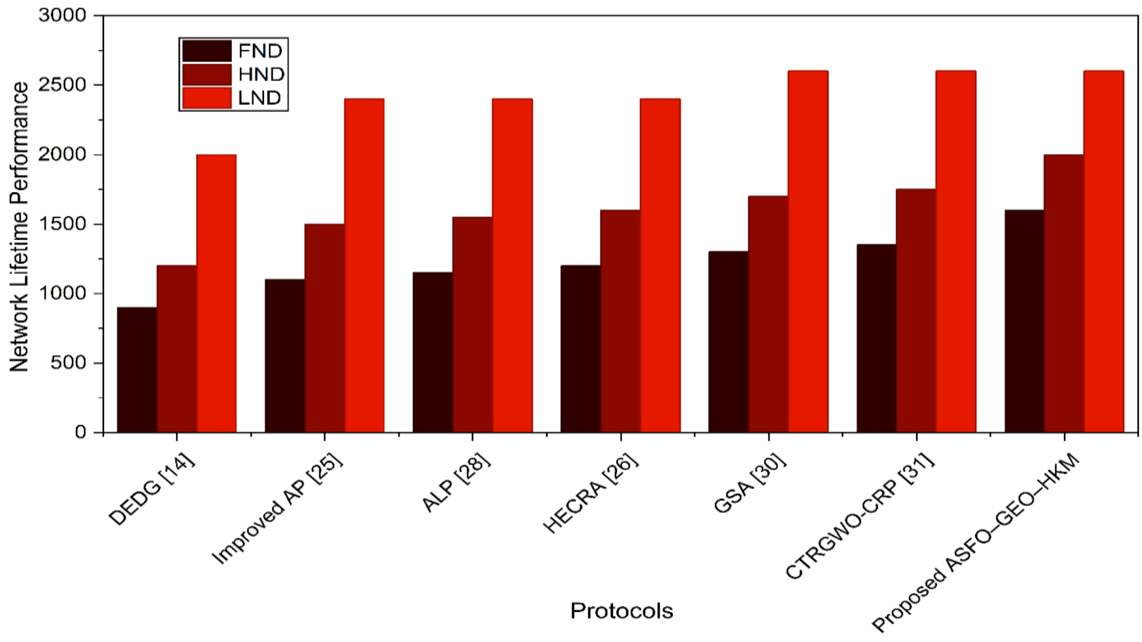

FIGURE 5
Network lifetime comparison (FND, HND, LND).

takes to travel from a source node to the sink, including propagation, transmission, queuing, and processing delays. As shown in the graph, all protocols exhibit an increasing delay trend with the number of rounds due to network aging, energy depletion, and increasing traffic congestion. Among the compared protocols, DEDG (Alkanhel et al., 2022) consistently shows the highest delay, ranging from 0.48 s at 0 rounds to 1.10 s at 2,000 rounds, indicating lower efficiency in handling packet forwarding during prolonged operation. Improved AP (Xia et al., 2023) and ALP (Khan MT et al., 2019) show moderate improvements, with delays of 0.98 and 0.95 s, respectively, at the final round, demonstrating their optimization in cluster formation and routing decisions. HECRA (Shi et al., 2024) and GSA (R et al., 2025) further reduce delay by leveraging energy-aware and swarm intelligence strategies, achieving delays of 0.90 and 0.85 s, respectively, at 2,000 rounds. The CTRGWO-CRP (Chen et al., 2025) algorithm performs better (0.88 s at 2,000 rounds) thanks to its enhanced gray wolf optimization-based clustering and path selection. Notably, the proposed ASFO–GEO–HKM protocol outperforms all other methods, maintaining the lowest delay across all rounds, ranging from 0.40 to 0.75 s at 2,000 rounds. This superior performance can be attributed to the hybrid K-Medoids clustering, geographic-based routing, and adaptive selection mechanisms that minimize transmission hops and balance energy consumption, thereby significantly reducing network latency. Overall, the proposed ASFO–GEO–HKM offers a clear advantage for latency-sensitive applications in UWSNs.

Figure 6 illustrates the end-to-end delay performance of various routing protocols over increasing rounds.

While AUV-assisted data collection introduces a store–carry–forward communication paradigm that can potentially increase data delivery latency, its impact is implicitly reflected in the end-to-end delay results presented in Figure 6. In the proposed ASFO–GEO–HKM framework, delay is mitigated through energy-aware clustering, reduced multi-hop transmissions, and scheduled AUV data retrieval from cluster heads, which together limit excessive buffering and queuing delays. The observed delay values (0.40–0.75 s) indicate that, despite AUV mobility, the proposed approach maintains lower latency compared to purely acoustic multi-hop routing schemes. For time-sensitive monitoring applications requiring near-real-time response, such as anomaly detection or short-term environmental alerts, the framework remains suitable within moderate latency constraints. However, applications demanding strict real-time guarantees may require tighter AUV scheduling or hybrid transmission strategies, which are identified as future research directions.

4.4 Residual energy comparison (joules)

The residual energy graph represents the remaining energy of sensor nodes over successive rounds in a 3D UWSN, providing insights into the energy efficiency and network lifetime of different routing protocols. Residual energy is critical in UWSNs, as nodes operate on limited battery power, and energy depletion directly impacts network connectivity and data delivery. Initially, all protocols start with 1.0 J of energy, but as the rounds progress, energy consumption due to data transmission, reception, and clustering operations causes a gradual decrease. Among the protocols, DEDG (Alkanhel et al., 2022) exhibits the fastest energy depletion, dropping to only 0.03 J at 2,000 rounds, highlighting its inefficiency in energy management. Improved AP (Xia et al., 2023) and ALP (Khan MT et al., 2019) show moderate improvements, maintaining 0.09 and 0.10 J at 2,000 rounds, respectively, due to better cluster head selection and routing strategies. HECRA (Shi et al., 2024) and CTRGWO-CRP (Chen et al., 2025) further enhance energy conservation by employing

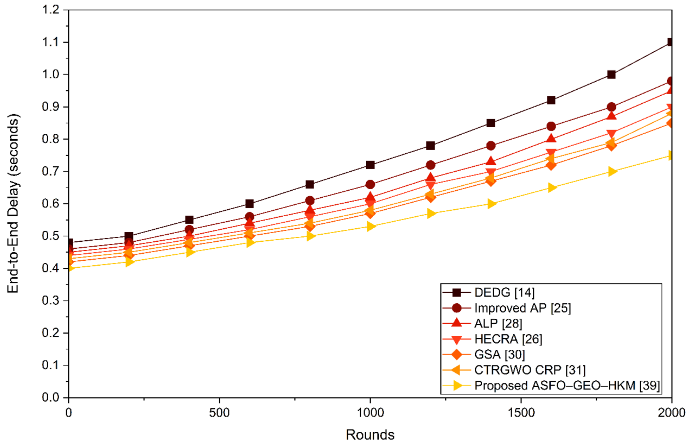

FIGURE 6
End-to-end delay vs. number of rounds.

energy-aware and optimization-based routing, achieving residual energies of 0.09 and 0.12 J, respectively, at the end of simulation. GSA (R et al., 2025) demonstrates superior performance (0.18 J) by utilizing swarm intelligence for balanced energy distribution among nodes. Notably, the proposed ASFO–GEO–HKM consistently maintains the highest residual energy throughout all rounds, with 0.24 J at 2,000 rounds, indicating its efficient hybrid K-Medoids clustering and geographic-based routing mechanism, which effectively reduces redundant transmissions and balances energy load. Overall, the ASFO–GEO–HKM protocol shows a clear advantage in prolonging network lifetime while preserving energy, outperforming all existing comparative methods. Figure 7 illustrates the residual energy performance of various routing protocols over increasing rounds.

4.5 Number of successful packet transmissions (per round)

The graph depicting the number of successful packet transmissions per round reflects the reliability and efficiency of data delivery in the 3D UWSN. Successful packet transmissions indicate the network's ability to forward data from source nodes to the sink without loss, which is influenced by routing efficiency, energy availability, and network congestion. Initially, all protocols start at zero transmissions, but as rounds progress, the number of successful transmissions increases for all methods. DEDG (Alkanhel et al., 2022) shows the lowest performance, reaching only 35,900 packets by 2,000 rounds, reflecting limited routing efficiency and higher packet losses. Improved AP (Xia et al., 2023) and ALP (Khan MT et al., 2019) achieve moderate improvements, with 40,600 and 42,900 successful transmissions, respectively, due to better cluster formation and path optimization. HECRA (Shi et al., 2024) and CTRGWO-CRP (Chen et al., 2025) further enhance delivery reliability, achieving 44,900 and 48,200 packets, respectively, by utilizing energy-aware and optimization-based routing strategies. GSA (R et al., 2025) demonstrates superior performance, delivering 49,200 packets at the final round by employing swarm intelligence for adaptive path selection. Notably, the proposed ASFO–GEO–HKM protocol outperforms all comparative protocols, achieving 53,300 successful

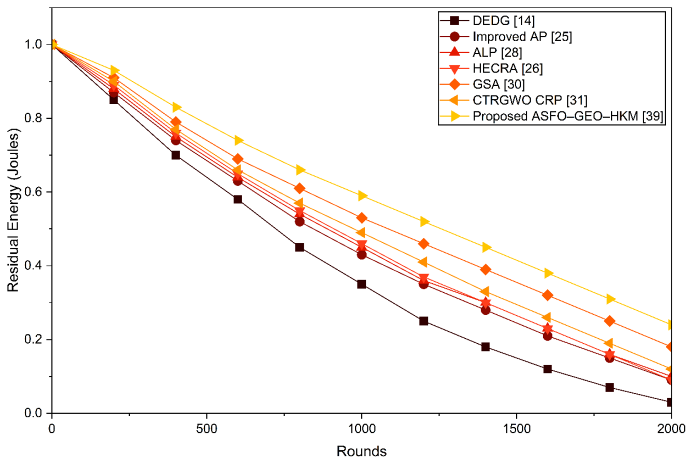

FIGURE 7
Residual energy comparison (joules).

transmissions at 2,000 rounds. This improvement is attributed to its hybrid K-Medoids clustering combined with geographic-based routing, which minimizes packet drops, balances network load, and maintains high energy levels across nodes. Overall, ASFO–GEO–HKM exhibits the highest reliability and throughput, making it highly suitable for data-intensive and latency-sensitive UWSN applications. Figure 8 illustrates the number of successful packet transmissions over increasing rounds.

4.6 Packet delivery ratio

The packet delivery ratio (PDR) graph represents the efficiency and reliability of data transmission in a 3D UWSN, defined as the ratio of successfully received packets at the sink to the total packets sent. A higher PDR indicates better network reliability, effective routing, and minimal packet loss, which are crucial in UWSNs due to high propagation delays, limited bandwidth, and energy constraints. As the number of rounds increases, PDR generally declines for all protocols, reflecting node energy depletion, increased link failures, and congestion. DEDG (Alkanhel et al., 2022) exhibits the lowest PDR, dropping from 39% at 200 rounds to 1% at 2,000 rounds, indicating a significant packet loss under prolonged operation. Improved AP (Xia et al., 2023) and ALP (Khan MT et al., 2019) maintain moderate PDRs, with final values of 2% each, due to improved cluster head selection and routing mechanisms. HECRA (Shi et al., 2024) and CTRGWO-CRP (Chen et al., 2025) achieve slightly higher PDRs, reaching 3% and 5% respectively, benefiting from energy-aware routing and optimization-based path selection. GSA (R et al., 2025) performs better, sustaining a 5% PDR at 2,000 rounds by leveraging swarm intelligence for balanced load and efficient path discovery. Remarkably, the proposed ASFO–GEO–HKM protocol maintains the highest PDR across all rounds, achieving 7% at 2,000 rounds. This superior performance arises from its hybrid K-Medoids clustering and geographic-based routing, which minimize packet drops, optimize transmission paths, and balance energy consumption, thereby ensuring higher reliability in data delivery. Overall, ASFO–GEO–HKM demonstrates clear advantages in sustaining packet delivery efficiency under challenging UWSN conditions. Figure 9 illustrates the number of packet delivery ratios over increasing rounds.

4.7 Routing overhead (%)

The routing overhead graph illustrates the ratio of control packets to data packets transmitted in the network, expressed as a percentage, which reflects the additional communication burden and energy expenditure incurred during routing. High routing overhead indicates inefficiency, as more energy is consumed in control message exchanges rather than in actual data transmission, which is particularly critical in energy-constrained 3D UWSNs. As observed, all protocols show an increasing overhead trend over successive rounds due to network expansion, node energy depletion, and more frequent cluster reformation. DEDG (Alkanhel et al., 2022) exhibits the highest overhead, reaching 55% at 2,000 rounds, highlighting significant energy wastage. Improved AP (Xia et al., 2023), ALP (Khan MT et al., 2019), and HECRA (Shi et al., 2024) achieve moderate improvements, maintaining overheads of 45%, 42%, and 39%, respectively, benefiting from more efficient clustering and routing mechanisms. GSA (R et al., 2025) and CTRGWO-CRP (Chen et al., 2025) further reduce overhead to 33% and 36% at the final round through adaptive swarm intelligence and optimization-based cluster management. The proposed ASFO–GEO–HKM protocol consistently achieves the lowest overhead, only 31% at 2,000 rounds, due to its hybrid K-Medoids clustering and geographic-based routing, which minimize unnecessary control messages while balancing energy load among nodes. This demonstrates that ASFO–GEO–HKM not only enhances

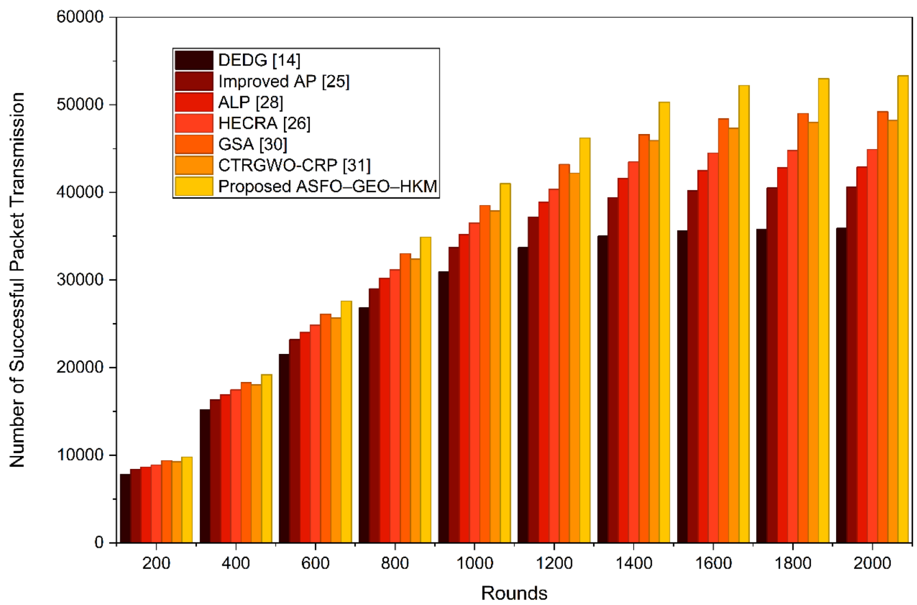

FIGURE 8
Successful packet transmissions per round.

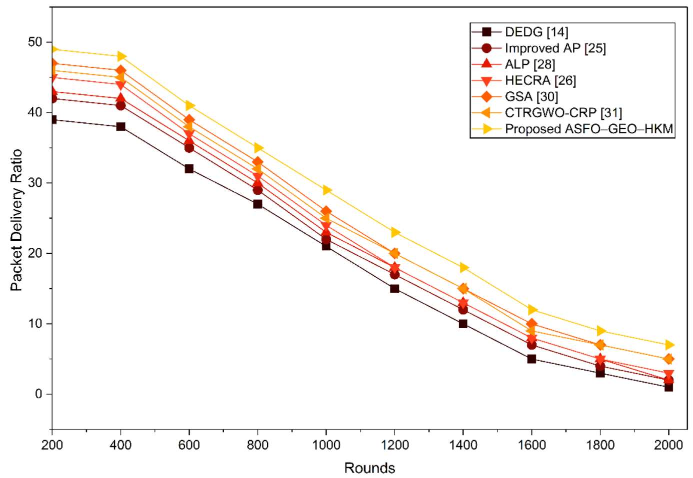

FIGURE 9
Packet delivery ratio (PDR) vs. rounds.

data delivery and network lifetime but also optimizes network resource utilization, making it more energy-efficient than existing protocols. Figure 10 illustrates the routing overhead of various routing protocols over increasing rounds.

4.8 Average performance comparison

To provide a consolidated view of network performance, the average metrics for each protocol across all simulation rounds are presented in Table 2. The table summarizes key indicators including average alive nodes, network lifetime, end-to-end delay, residual energy, number of packets per round, packet delivery ratio (PDR), and routing overhead. The results indicate that the proposed ASFO–GEO–HKM protocol outperforms all comparative methods across all metrics. Specifically, it maintains the highest average number of alive nodes (120.45) and the longest network lifetime (2,066.67 rounds), highlighting its superior energy efficiency and load balancing. The average end-to-end delay is significantly lower (0.459 s) compared to other protocols, demonstrating its effectiveness in reducing latency. In terms of energy utilization, ASFO–GEO–HKM achieves the highest average residual energy (0.605 J), confirming that its hybrid K-Medoids clustering combined with geographic-based routing minimizes unnecessary energy consumption.

Furthermore, the proposed protocol delivers the highest average number of packets per round (30,682) and the highest average PDR (27.1%), indicating improved reliability and throughput. Notably, it also maintains the lowest average routing overhead (19.7%), reflecting efficient control message management and reduced energy wastage. Comparative protocols, including DEDG

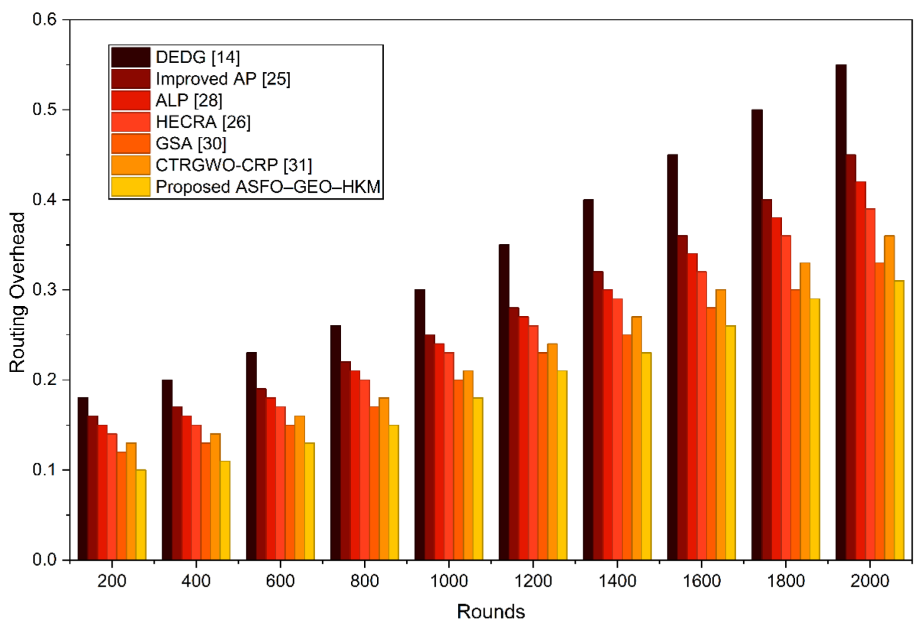

FIGURE 10
Routing overhead (%) vs. rounds.

(Alkanhel et al., 2022), Improved AP (Xia et al., 2023), ALP (Khan MT et al., 2019), HECRA (Shi et al., 2024), GSA (R et al., 2025), and CTRGWO-CRP (Chen et al., 2025), exhibit lower performance across these metrics, confirming the advantages of ASFO–GEO–HKM in prolonging network lifetime, enhancing reliability, and optimizing overall network efficiency. Overall, this comprehensive analysis validates the effectiveness of the proposed protocol in addressing critical challenges of 3D underwater wireless sensor networks, such as energy efficiency, latency, and reliable data delivery. Table 3 presents the average performance comparison of the evaluated routing protocols across key network metrics.

5 Discussions

The simulation results clearly demonstrate that the proposed ASFO–GEO–HKM protocol significantly outperforms existing UWSN protocols, including DEDG (Alkanhel et al., 2022), Improved AP (Xia et al., 2023), ALP (Khan MT et al., 2019), HECRA (Shi et al., 2024), GSA (R et al., 2025), and CTRGWO-CRP (Chen et al., 2025). An analysis of alive nodes over the network lifetime indicates that ASFO–GEO–HKM maintains the highest number of active nodes across all rounds, with the first node dead at 1,600 rounds, half of the nodes dead at 2,000 rounds, and the last node dead at 2,600 rounds, achieving the maximum observed network lifetime. This improvement is primarily attributed to the tightly integrated hybrid ASFO–GEO-based K-Medoids clustering mechanism, which jointly exploits local adaptive optimization and global refinement to select energy-efficient and reliable cluster heads, balance intra-cluster load, and minimize unnecessary energy consumption during communication.

Furthermore, the end-to-end delay of ASFO–GEO–HKM remains consistently lower than that of competing protocols, reaching only 0.75 s at 2,000 rounds, indicating effective minimization of packet propagation time and network congestion. Residual energy analysis shows that nodes retain higher energy levels throughout network operation, while overall energy efficiency is enhanced through optimized cluster formation and geographic-based routing. The proposed protocol also achieves the highest number of successful packet transmissions and packet delivery ratio, demonstrating reliable and secure data delivery. Notably, routing overhead is the lowest among all compared approaches, highlighting reduced control message exchanges and minimal energy wastage. Collectively, these results confirm that ASFO–GEO–HKM provides a balanced and efficient solution for energy management, reliable communication, and low-latency operation in underwater wireless sensor networks.

From a marine conservation and ecosystem protection perspective, these performance improvements have direct practical implications. The extended network lifetime and sustained residual energy enable uninterrupted, long-term monitoring of sensitive marine environments, which is essential to detect gradual ecological changes such as coral bleaching, water quality deterioration, hypoxic stress, and habitat degradation. The improved packet delivery ratio and reduced end-to-end delay support near-real-time acquisition of environmental data, facilitating the early detection of environmental stressors and timely response through early-warning systems. Moreover, the integration of lightweight security via TinySec ensures the integrity and trustworthiness of collected data, which is critical for conservation-oriented decision-making, particularly in marine protected areas (MPAs) where reliable evidence is required for ecosystem management and policy formulation. By minimizing the need for frequent redeployment and reducing human intervention, the proposed framework supports sustainable, low-impact monitoring strategies aligned with long-term marine ecosystem conservation objectives.

Despite the promising performance observed in the simulation, several practical considerations must be addressed for real-world deployment. Underwater sensor nodes are typically constrained by limited battery capacity, low processing capability, restricted memory, and simple acoustic modems, which may limit the complexity of optimization and security mechanisms. The proposed ASFO–GEO–HKM framework mitigates these limitations by employing distributed, energy-aware clustering and routing decisions and by executing hybrid optimization periodically rather than continuously. In addition, the use of lightweight TinySec-

TABLE 3 Average performance comparison of routing protocols.

Metric	DEDG (Alkanhel et al., 2022)	Improved AP (Xia et al., 2023)	ALP (Khan MT et al., 2019)	HECRA (Shi et al., 2024)	GSA (R et al., 2025)	CTRGWO-CRP (Chen et al., 2025)	Proposed ASFO–GEO–HKM
Average alive nodes	81.64	89.27	93.00	94.82	105.27	107.36	120.45
Average lifetime (rounds)	1,366.67	1,666.67	1,700	1,733.33	1,866.67	1,900	2,066.67
Average delay (s)	0.742	0.683	0.617	0.628	0.597	0.610	0.459
Average residual energy (J)	0.416	0.479	0.491	0.496	0.557	0.518	0.605
Average packets per round	22,382	25,682	26,332	27,081	28,064	28,350	30,682
Average PDR (%)	19.1	21.1	22.0	22.8	24.8	24.2	27.1
Average routing overhead (%)	34.2	28.0	26.5	25.1	21.6	23.2	19.7

based security introduces minimal computational and energy overhead, ensuring secure communication without compromising node longevity. AUV-assisted data collection, although effective in reducing energy consumption, is subject to operational constraints such as limited endurance, navigation accuracy, environmental disturbances, and maintenance requirements.

The scalability of the proposed ASFO–GEO–HKM framework is maintained through its hierarchical and distributed architecture, which limits control overhead as the network size or monitoring area increases. Hybrid K-Medoids clustering localizes communication within clusters, ensuring that routing and data aggregation operations scale with cluster size rather than the total network size. Energy-aware and adaptive cluster head selection prevents premature node depletion, enabling stable operation even in dense deployments. AUV-assisted data collection further enhances scalability by decoupling long-range data transmission from sensor nodes, making the framework well suited for long-term, large-scale deployments in coral reef ecosystems requiring minimal human intervention.

6 Conclusion

In this work, a novel hybrid ASFO–GEO-based K-Medoids clustering framework is presented in conjunction with a TinySec-enabled E-CERP secure routing protocol and AUV-assisted mobile data collection for three-dimensional underwater wireless sensor networks. By integrating adaptive swarm fitness optimization with the global exploration capability of the Golden Eagle Optimizer, the proposed clustering strategy effectively selects energy-aware and reliable cluster heads, thereby improving load balancing, reducing unnecessary energy consumption, and significantly extending network lifetime. The TinySec-enabled E-CERP protocol ensures secure, energy-efficient, and low-latency multi-hop communication by jointly considering residual energy, link reliability, hop count, and lightweight authentication, while AUV-assisted data retrieval reduces costly long-range acoustic transmissions and mitigates cluster head exhaustion.

Beyond algorithmic and performance improvements, the proposed architecture demonstrates strong practical relevance for marine environmental monitoring and conservation applications. Its ability to sustain long-term, secure, and reliable operation makes it particularly suitable for continuous coral reef health assessment, where persistent monitoring of parameters such as temperature, salinity, turbidity, and dissolved oxygen is critical. The framework also supports biodiversity observation and ecosystem assessment by enabling stable data collection across spatially distributed sensor deployments in sensitive marine habitats. Moreover, the improved reliability and reduced latency achieved by the proposed approach provide a foundation for early-warning systems capable of detecting coral bleaching events, water quality degradation, and other ecological disturbances in near real time.

Comprehensive simulations conducted in a realistic three-dimensional underwater environment confirm that the proposed ASFO–GEO–HKM framework consistently outperforms six benchmark protocols—DEDG, AP, ALP, HECRA, GSA, and CTRGWO-CRP—across all key performance metrics, including network lifetime, average delay, residual energy, packet delivery ratio, successful packet transmissions, and routing overhead. These results validate that the proposed framework offers a scalable, energy-efficient, and secure solution for sustained underwater monitoring, effectively bridging the gap between advanced UWSN optimization techniques and deployable systems for long-term marine ecosystem protection.

7 Future scope

The proposed ASFO–GEO–HKM framework establishes a strong foundation for future research and real-world deployment in underwater wireless sensor networks supporting marine ecosystem monitoring. One promising direction is the integration of *adaptive AUV trajectory planning* driven by real-time network conditions and environmental feedback, which could further reduce data collection latency and improve coverage efficiency in dynamic underwater environments. The deployment of multiple cooperative AUVs or hybrid mobile–static sink architectures may enhance fault tolerance, reduce collection delays, and improve resilience in large-scale coral reef monitoring scenarios.

The incorporation of machine learning and artificial intelligence techniques, such as reinforcement learning and deep neural networks, offers further potential for predictive modeling of node energy depletion, link reliability, and environmental dynamics. Such capabilities could enable more intelligent clustering, routing, and anomaly detection, improving responsiveness to sudden ecological changes. Enhancing three-dimensional underwater localization accuracy would also strengthen spatial data interpretation, cluster formation, and precise identification of ecosystem stress zones.

From a conservation and sustainability perspective, extending the framework toward the Internet of Underwater Things (IoUT) and hybrid IoT–UWSN architectures could facilitate broader applications, including marine habitat conservation, offshore infrastructure monitoring, fisheries management, and disaster prediction. On the security front, integrating advanced lightweight mechanisms such as intrusion detection systems, trust management models, or blockchain-based authentication could further improve data integrity and resilience against malicious attacks. Overall, ASFO–GEO–HKM represents a robust and extensible solution that can evolve to support intelligent, autonomous, and long-term monitoring of fragile marine ecosystems under real operational constraints.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

JS: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. SB: Conceptualization, Project administration, Resources, Software, Supervision, Writing – review & editing. AA: Formal analysis, Resources, Writing – review & editing, Software, Visualization. HG: Formal analysis, Resources, Writing – review & editing, Funding acquisition, Project administration, Supervision, Validation. AR: Funding acquisition, Resources, Software, Supervision, Validation, Writing – review & editing. AS: Data curation, Investigation, Software, Writing – review & editing.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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