Evaluating Energy-Efficient AUV Path Planning and Data Collection: Insights from a Novel Benchmark Study in UWSNs

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ABSTRACT

Underwater Wireless Sensor Networks (UWSNs) play a significant role in marine applications, including environmental monitoring, ocean floor mapping, and disaster response. However, the energy constraints of sensor nodes and Autonomous Underwater Vehicles (AUVs), as well as the high cost of underwater acoustic communication, present major design challenges. This paper introduces Energy-Conscious Optimization of AUVs (ECO-AUV), a new framework that uses energy-aware K-Means clustering and the A* heuristic search algorithm to improve underwater data collection. ECO-AUV is specially designed to minimize total energy expenditure by improving intra-cluster communication procedures and AUV navigation paths. The framework provides reliable data collection and transfer through dynamic route planning that accounts for environmental conditions such as ocean currents and seafloor anomalies. Extensive simulations were carried out to compare ECO-AUV with two recent hybrid methods: Particle Swarm Optimization (PSO) with Genetic Algorithms (GAs), and Artificial Bee Colony (ABC) with Ant Colony Optimization (ACO). Results demonstrate that ECO-AUV is significantly more energy-efficient, creates more optimized traversal patterns, offering a high Packet Delivery Ratio (PDR) of 98.5%. Additionally, the framework exhibits low computational complexity, enabling its application in real-time applications. These results establish ECO-AUV as a scalable, energy-efficient solution for strong underwater sensing and communication.

Keywords-autonomous underwater vehicle; energy-aware clustering; hybrid optimization; heuristic routing; marine monitoring system

I. INTRODUCTION

Underwater Wireless Sensor Networks (UWSNs) have emerged as vital infrastructures for various marine applications, including environmental observation, search-and-rescue missions, and undersea resource assessment [1-16]. These networks typically integrate static sensor nodes and mobile data collectors such as Autonomous Underwater Vehicles (AUVs), creating a complex ecosystem for underwater communication and mobility. However, the constrained energy resources of both sensor nodes and AUVs—aggravated by acoustic signal attenuation and vehicle traversal costs—pose significant design challenges [17-21]. Efficient path planning and energy-aware communication strategies are therefore crucial for extending network lifetime and ensuring reliable data delivery. Although evolutionary algorithms like Particle Swarm Optimization (PSO) and Genetic Algorithms (GAs) have been employed in prior research [22, 23], they often lack adaptability and coordination between clustering and navigation functions [24, 25]. Addressing this limitation, this work presents a cohesive hybrid model that combines energy-aware K-Means clustering with A* geometric path planning. This approach aims to optimize both intra-cluster communication and AUV navigation by integrating data collection and mobility planning into a unified decision-making framework. The proposed model is benchmarked against PSO with GA and Artificial Bee Colony (ABC) with Ant Colony Optimization (ACO) approaches under diverse environmental and operational conditions, revealing significant gains in energy efficiency, traversal optimization, and packet reliability.

Achieving high energy efficiency remains a cornerstone objective in the design of UWSNs due to limitations in battery capacity, unpredictable communication delays, and environmental challenges [3, 17]. Several clustering and path planning strategies have been developed to mitigate these issues, with hybrid techniques receiving increasing attention for their complementary strengths [23, 26].

Conventional clustering protocols like Low-Energy Adaptive Clustering Hierarchy (LEACH) attempt to conserve energy by assigning cluster head roles for data aggregation and relay [27]. However, their effectiveness is diminished in underwater environments where node energy levels and network topology are highly variable [22]. As an alternative, bio-inspired methods such as PSO and ABC algorithms have been utilized. PSO emulates collaborative behavior among agents to find optimal cluster configurations [23, 24], whereas ABC applies bee foraging dynamics for cluster head selection, especially in high-density node settings [25]. Graph-based algorithms like Dijkstra's and Bellman-Ford offer quick route computation but are less effective in dynamic underwater terrains [28]. Heuristic methods including GAs and ACO have shown greater adaptability. GAs evolve optimal paths through selection-based iterations [29, 30], whereas ACO mimics pheromone-based decision making to construct reliable navigation paths under uncertain aquatic conditions.

Recent efforts focus on integrating clustering and routing to form robust hybrid models. PSO+GA frameworks combine swarm intelligence for clustering with evolutionary computation for route planning [23, 30], whereas ABC+ACO integrates biologically inspired cluster selection with adaptive path optimization [25, 29]. Despite their strengths, these solutions often entail high computational complexity and limited real-time flexibility [31, 32]. In contrast, the approach presented in this paper adopts a lightweight structure combining energy-weighted K-Means clustering and A* search to balance energy use and routing precision, especially under 3D and dynamic underwater constraints [33, 34].

This research makes several key contributions to the field of UWSNs. First, it presents a unified hybrid framework that effectively integrates energy-aware K-Means clustering with the A* heuristic-based routing algorithm, enabling both efficient data aggregation and adaptive AUV navigation. Unlike existing approaches, this model dynamically adjusts to varying underwater terrain and current conditions, thereby improving operational resilience. Second, it introduces an energy-weighted clustering mechanism that prioritizes node energy status during cluster formation, leading to more balanced energy usage across the network. Third, a comprehensive simulation strategy is employed to evaluate the model's performance under different node densities, environmental dynamics, and energy constraints. Through comparative analysis with PSO+GA and ABC+ACO methods, the proposed model demonstrates superior results in energy efficiency, communication reliability, and traversal time. Collectively, these contributions advance the development of scalable and energy-conscious solutions for real-world UWSN applications such as marine exploration, environmental monitoring, and underwater emergency response. The key contributions of this study are summarized as follows:

- It proposes a new kind of hybrid model named Energy-Conscious Optimization of AUVs (ECO-AUV) that integrates the energy-conscious K-Means clustering and the A* heuristic-based routing, to facilitate the energy-efficient and flexible AUV path planning in UWSNs.
- The framework proposes a modified K-Means clustering-based algorithm that considers the distance between nodes and their remaining energy, ensuring balanced cluster formation and prolonged node lifetime.
- The ECO-AUV framework is extensively compared with two popular hybrid algorithms, PSO+GA and ABC+ACO, in different conditions that include the variation of node density, energy, and underwater dynamics.

II. METHODOLOGY

A. Modeling Realistic UWSNs Environments

The UWSN considered in this study is designed as a realistic three-dimensional environment encompassing a horizontal span of 1000 × 1000 m and a vertical depth ranging from 10 m to 100 m [3]. This spatial configuration aims to replicate practical deployment conditions commonly encountered in marine applications such as environmental monitoring and seabed exploration. Sensor nodes are randomly positioned within this volume to reflect the non-uniform distribution typically observed in real-world underwater scenarios. Each node is initialized with a fixed energy level and equipped with a communication range of 100 m, following widely accepted UWSN configuration standards to ensure consistency and comparability of results [18, 25].

To capture the complex dynamics of underwater environments, the simulation incorporates two key environmental variables. First, seabed variability is modeled using sinusoidal elevation functions, which introduce undulating terrain features that affect the AUV's mobility and energy consumption during traversal [27]. Second, dynamic water currents are simulated as time-varying vector fields, exerting directional forces that influence the AUV's navigation paths. These hydrodynamic conditions necessitate intelligent and adaptive route planning strategies to minimize energy usage while ensuring reliable data collection [35]. Sensor nodes are configured to periodically generate data, which is aggregated at their respective cluster heads. The AUV then follows an optimized path, determined by the respective routing algorithm, to sequentially visit the cluster heads, retrieve the aggregated data, and forward it to a surface sink or relay station for transmission and analysis [26, 28]. This comprehensive modeling approach ensures a realistic and rigorous evaluation of the proposed methodology under diverse and dynamic underwater conditions. The overall system workflow is illustrated in Figure 1, showing the interaction between modules and the data flow within the ECO-AUV framework.

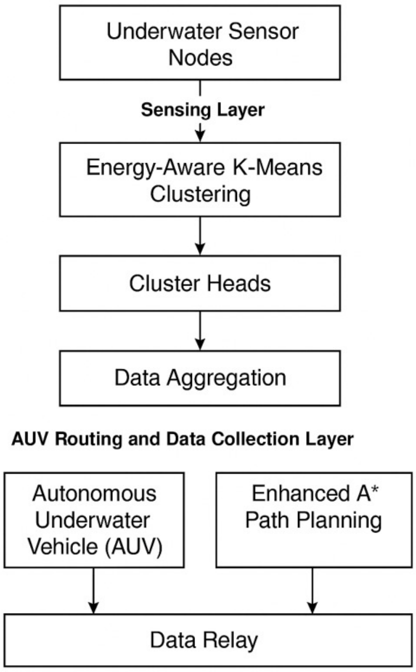

Fig. 1. System architecture of the proposed ECO-AUV framework.

B. Energy-Aware K-Means Clustering

This work introduces an integrated solution combining energy-efficient clustering and adaptive path planning to optimize data retrieval and reduce power consumption in UWSNs. Sensor nodes are clustered based on both spatial proximity and energy efficiency. Initial cluster centroids are selected using node location data. Node assignments to clusters are based on a weighted cost function incorporating communication energy requirements and environmental factors such as terrain difficulty and water current strength. The centroids are iteratively adjusted until balanced clusters are achieved.

Following clustering, the AUV determines an energy-optimal route that connects all cluster heads using the A* search algorithm. The heuristic used in A* considers both Euclidean distance and energy deviations caused by underwater current vectors. This ensures real-time route adjustments in response to dynamic environmental conditions. By coupling clustering and navigation within a unified system, the proposed model optimally balances communication overhead and mobility energy consumption. The framework is designed for scalability, environmental adaptability, and low computational overhead, making it well-suited for real-world 3D underwater sensor deployments.

C. Benchmarking Against Existing Hybrid Models

To assess the performance of the proposed model, it is evaluated against two advanced hybrid frameworks: PSO+GA and ABC+ACO. The PSO+GA model integrates PSO for efficient cluster formation with GAs for route optimization. Although this combination enhances energy efficiency, it tends to suffer from significant computational overhead, particularly in dynamic network environments. On the other hand, the ABC+ACO framework employs ABC algorithms for clustering and utilizes ACO to adaptively generate routes. While this approach demonstrates strong adaptability to changing environmental conditions, it also demands considerable processing resources, which can hinder its scalability and real-time application.

In contrast to the aforementioned models, the proposed approach combines energy-efficient clustering with real-time path planning using the A* algorithm. This method incorporates a heuristic routing strategy that considers both spatial distance and energy fluctuations caused by current dynamics, enabling a more adaptive and resource-aware solution for underwater navigation and communication. A comparative overview of the discussed algorithmic frameworks is presented in Table I, outlining their primary features, strengths, and limitations within the scope of underwater sensor network applications.

TABLE I. COMPARATIVE OVERVIEW OF BENCHMARK HYBRID ALGORITHMS

Feature	K-Means + A*	PSO + GA	ABC + ACO
Clustering approach	Energy-aware K-Means	PSO	ABC
Path planning approach	A* geometric search	GA	ACO
Energy efficiency	High	Moderate	Moderate
Adaptability	High	Moderate	High
Computational complexity	Low to moderate	Moderate	High
Scalability	High	Moderate	Moderate

D. Simulation Setup

The simulation is carried out in a three-dimensional UWSN environment, covering a horizontal area of 1000 × 1000 m with depth variations ranging from 10 m to 100 m. A total of 100 sensor nodes are randomly distributed to mimic real-life underwater deployment patterns. Each node is initialized with 2 J of energy and a communication range of 100 m, reflecting commonly adopted settings in UWSN studies. To emulate authentic underwater conditions, the simulation incorporates two major environmental factors.

First, the underwater terrain is represented using sinusoidal elevation models to reflect natural seabed irregularities, which influence the movement cost of the AUV. Second, dynamic ocean currents are simulated as time-varying vector fields that impact the AUV's path and energy consumption. The AUV is tasked with gathering data from designated cluster heads by following an optimal path determined by the tested algorithm. Its energy usage is modeled at a rate of 10 J/m of travel, adhering to typical AUV performance characteristics.

E. Evaluation Strategy and Test Scenarios

To evaluate the effectiveness of both the proposed model and the benchmark algorithms, six primary performance metrics were employed. These include energy consumption, which captures the total energy expended by both the sensor nodes and the AUV during data collection; path length, representing the total distance traveled by the AUV; and elapsed time, denoting the duration taken to complete the data-gathering mission. Additionally, Packet Delivery Ratio (PDR) reflects the reliability of communication by measuring the proportion of successfully transmitted packets. Average remaining energy assesses the leftover energy in sensor nodes after the operation, whereas clustering efficiency gauges how well the algorithm reduces intra-cluster communication energy. To ensure a thorough evaluation under varied and realistic conditions, three experimental scenarios were simulated. These include node density variation with 50, 100, and 150 nodes to test scalability; environmental dynamics involving different seabed topographies and ocean current strengths to examine adaptability; and energy constraints by initializing nodes with 1.5 J, 2 J, and 2.5 J to evaluate performance under limited power availability. Together, these scenarios offer a well-rounded analysis of the algorithm's resilience, flexibility, and overall effectiveness in complex underwater sensor network environments.

III. RESULTS AND DISCUSSION

A. Energy Consumption, Path Length, and Reliability

The proposed hybrid model, which integrates energy-aware K-Means with the A* geometric search algorithm, was evaluated against two established benchmark approaches—PSO+GA and ABC+ACO, using the previously defined performance metrics. The comparative outcomes, detailed in Table II, demonstrate the enhanced effectiveness of the proposed method, particularly in terms of reduced energy consumption, improved PDR, and greater traversal efficiency. These results underscore the model's capability to outperform existing techniques in dynamic underwater sensor network environments.

TABLE II. COMPARATIVE PERFORMANCE ANALYSIS

Metric	K-Means + A*	PSO + GA	ABC + ACO
Energy consumption (J)	0.000295	0.000319	0.000335
Path length (m)	3005	3192	3355
Elapsed time (s)	95	110	120
PDR (%)	98.5	96.2	95.8
Average remaining energy (J)	0.85	0.80	0.78
Clustering efficiency (%)	93	88	90

The analysis of the comparative results reveals that the proposed K-Means + A* model outperforms the benchmark algorithms across most evaluation metrics. It achieves the lowest energy consumption (0.000295 J), shortest elapsed time (95 s), and highest PDR (98.5%), indicating superior energy efficiency, faster data collection, and more reliable communication. Additionally, it maintains the highest average remaining energy (0.85 J) and clustering efficiency (93%), demonstrating effective energy conservation and optimal cluster formation. In contrast, PSO+GA and ABC+ACO exhibit higher energy usage and longer operation times, highlighting the overall advantage of the proposed approach in dynamic underwater environments.

The proposed hybrid model demonstrates a clear and consistent performance advantage over the benchmark algorithms across all key evaluation metrics. Specifically, it achieves a notable reduction in energy consumption, approximately 7.5% lower than PSO+GA and about 12% lower than ABC+ACO. These savings are primarily attributed to the model's efficient clustering mechanism and optimized routing strategy using the A* algorithm, which together contribute to a shorter data collection path and reduced traversal time. As a result, the AUV completes its mission more quickly and with less energy expenditure.

Figure 2 highlights the proposed model's clear advantages in energy efficiency, path optimization, and data transmission reliability. It achieves a high PDR of 98.5%, reflecting minimal data loss in dynamic underwater conditions. With an average residual energy of 0.85 J, the model reduces intra-cluster communication, thereby extending network lifespan. Compared to PSO+GA and ABC+ACO, the proposed algorithm shows the lowest energy use, shortest completion time, highest remaining energy, and superior clustering efficiency. ABC+ACO consumes the most energy and time, whereas PSO+GA performs moderately but fails to lead in any metric.

B. Insights and Practical Implications

The combined clustering and path-planning strategy employed in the proposed framework significantly enhanced energy efficiency while maintaining a manageable computational load. The integration of the A* algorithm, known for its heuristic-based search capabilities, enabled the system to rapidly respond to changing underwater environmental conditions, such as varying current strengths and terrain irregularities. Simultaneously, the use of energy-aware K-Means clustering contributed to more balanced and efficient intra-cluster communication, preventing premature node depletion and extending overall network lifespan.

Figure 3 compares energy consumption, elapsed time, and average remaining energy of K-Means + A*, PSO + GA and ABC + ACO. The ECO-AUV model (K-Means + A*) shows the least energy consumption and time, and the greatest residual energy, which means that it is the most efficient and can prolong the life of the network. Conversely, the ABC + ACO algorithm is the least performing, whereas the PSO + GA algorithm returns moderate results. These results highlight the potential of ECO-AUV in energy minimization in dynamic underwater environments.

Figure 4 shows PDR and clustering efficiency in three hybrid models. ECO-AUV provides the best PDR (98.5%) and clustering efficiency (93%), demonstrating high communication reliability and low intra-cluster overhead. PSO + GA and ABC + ACO achieve worse results in both measures. These findings prove that ECO-AUV is quite appropriate to operate in dynamic and resource-limited UWSNs reliably and with minimum energy consumption.

The scalability and adaptability of the proposed algorithm qualify it for use in real deployments of UWSNs. Its performance is fit for purpose in regard to critical marine operations such as post-disaster data gathering, oceanographic investigations, and ecosystem observation. Having minimal computational and energy requirements, it can be of practical use in underwater resource-limited scenarios.

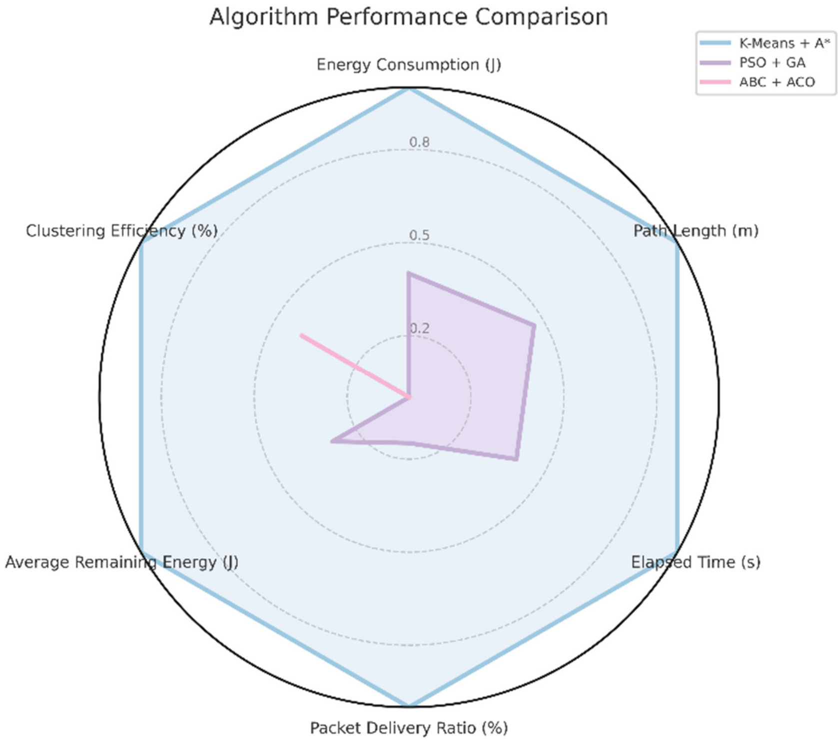

Fig. 2. Radar chart comparing the performance of the proposed algorithm.

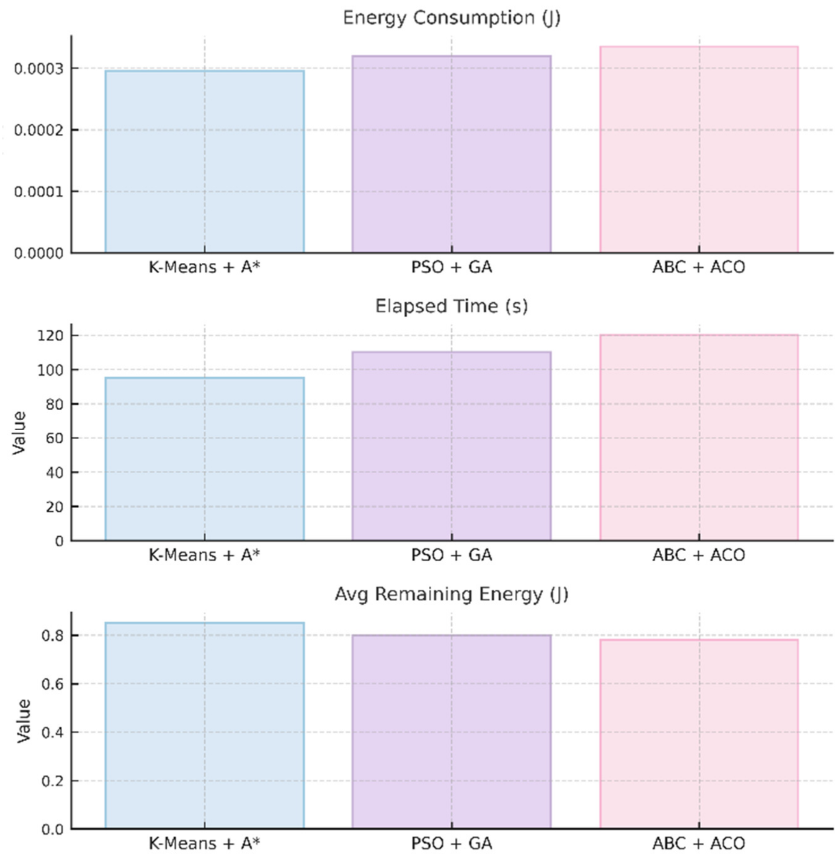

Fig. 3. Comparison of energy consumption, elapsed time, and remaining energy.

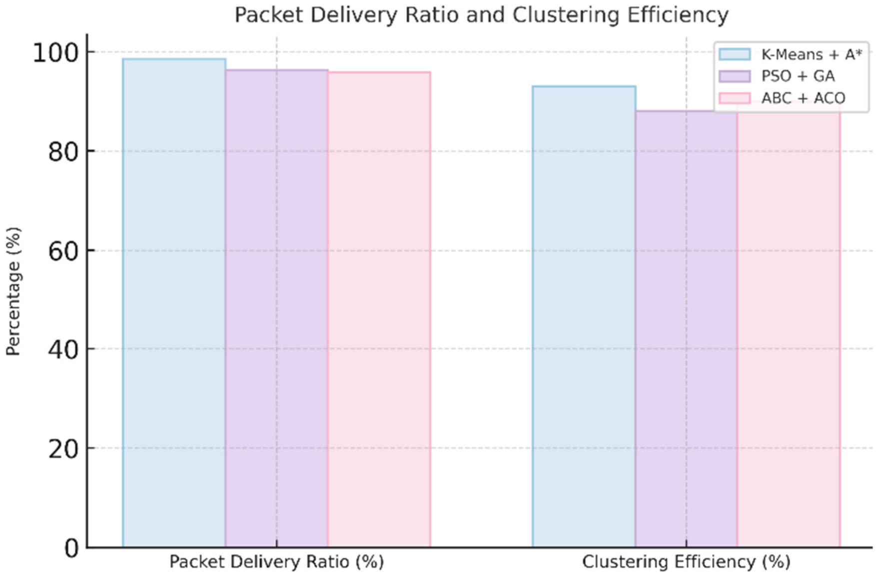

Fig. 4. Comparison of PDR and clustering efficiency.

IV. CONCLUSION

This article introduces a new hybrid system that integrates energy-aware K-Means clustering and the A* heuristic-based path calculation to augment communication proficiency and self-guided mobility in Underwater Wireless Sensor Networks (UWSNs). The model is also optimal in intra-cluster message exchange and efficient in the use of energy by Autonomous Underwater Vehicles (AUVs) when collecting data. In simulations conducted under various conditions and compared with benchmark models such as Particle Swarm Optimization (PSO) combined with Genetic Algorithms (GAs) and Artificial Bee Colony (ABC) combined with Ant Colony Optimization (ACO), the proposed system demonstrated adaptability and computational efficiency, outperforming the benchmarks in energy savings of up to 12%, Packet Delivery Ratio (PDR) up to 98.5%, path optimization, and residual energy. The article builds a solid ground for the development of energy-efficient, adaptive data gathering in UWSNs in the future. Future possibilities include generalizing the framework to multi-AUV control, allowing real-time sensory input, and evaluating it on real robots. It can be further made more practical by incorporating blockchain to provide a secure method of data transfer and reinforcement learning to make autonomous decisions. In total, the framework provides an intelligent and robust solution to the dynamic underwater environment.

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