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Original Article

A Hybrid Algorithm for Optimising AUV Path Planning and Precise Node Localization in UWSNs Using Cluster-Based Geometric Search Method

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Abstract - *Underwater Wireless Sensor Networks (UWSNs) play a vital role in aquatic monitoring and marine exploration, yet they face persistent challenges due to limited communication bandwidth, energy constraints, and the complex mobility of Autonomous Underwater Vehicles (AUVs). This paper presents a novel hybrid optimization framework that combines an Energy-Aware K-Means clustering algorithm with a terrain-sensitive A* path planning method. The clustering mechanism groups sensor nodes based on both spatial coordinates and remaining energy levels, ensuring balanced data aggregation. Simultaneously, the enhanced A* algorithm navigates the AUV through energy-efficient paths, accounting for underwater terrain variations and current-induced drift. This integrated strategy enhances localization accuracy, reduces unnecessary AUV movement, and significantly extends network lifetime. Simulation results confirm that the proposed approach achieves substantial gains in energy efficiency, reducing energy consumption by over 80%, shortening traversal distance by 87.5%, and improving overall network sustainability by 91.4%. These outcomes demonstrate the effectiveness of the hybrid model in optimizing data collection and node coordination in dynamic, large-scale UWSNs.*

Keywords - *AUV path planning, Node localization, Geometric search model, A* algorithm, Energy-aware clustering.*

1. Introduction

Underwater Wireless Sensor Network (UWSN) applications are found in oceanographic measurements, marine biodiversity monitoring, and underwater surveillance. In contrast to terrestrial wireless systems, acoustic communications are used in UWSNs because radio and optical communications would be impractical in underwater environments. Nevertheless, the acoustic communication is limited by the large latency, small bandwidth, and large power requirements, which hinder successful data transmission and accurate localization of the node. These intrinsic constraints have been well understood in new surveys and reviews [1, 2].

The presence of Autonomous Underwater Vehicles (AUVs) improves the UWSN functionality since they serve as roaming data gatherers and repeaters in the network [3]. Although they can cover the network and shorten the transmission paths, AUVs have limited energy availability on board and difficulty working with underwater 3D terrain [4].

As it is demonstrated in Figure 1, the clustering of sensor nodes into groups with specific cluster heads helps to organize data aggregation better and enables energy-efficient routing of AUVs. Traditional methods of localization (Time-of-Arrival (ToA) and trilateration) are, however, characterized by low accuracy in the case of multipath propagation and degradation of the acoustical signal [5, 6]. Similarly, standard path planning algorithms do not usually consider terrain, the effect of current-induced drift and power limitation.

The clustering algorithm, such as K-Means and LEACH, would also not take into consideration the amount of residual energy, resulting in early node depletion many times. In order to overcome the above shortcoming, a hybrid optimization framework integrating Energy-Aware K-Means clustering with terrain-sensitive A* path planning algorithm is proposed in the proposed study.

The objective seeks to collaboratively optimize AUV navigation as well as node localization whilst prolonging network lifetime and guaranteeing communication effectiveness in heterogeneous environments pertaining to the dynamics of the underwater networking. The most important research gap is that no single, energy-conscious framework considers both node localization and energy-efficient AUV path planning in realistic underwater topologies.

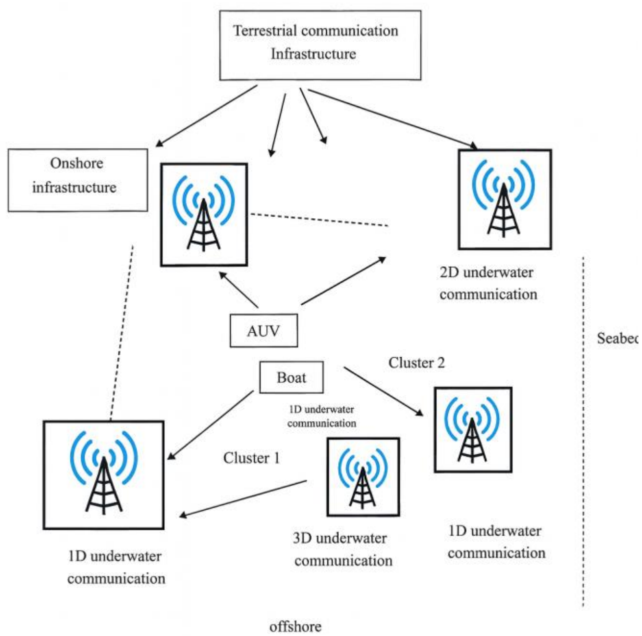

Fig. 1 Cluster-based UWSN architecture

The majority of available works consider each of these elements on its own, thus losing the chance to optimize everything holistically, and having a much greater impact on data gathering trustworthiness, energy costs, and network life cycle. The proposed study is aimed at creating the groundwork of a holistic solution to the two issues of AUV path planning and node localization in UWSNs. The new method will replace the old one with an energy-aware mechanism of cluster formation using the K-means algorithm, which will consider both spatial distribution and remaining energy levels of sensor nodes to improve cluster formation efficiency. A terrain-adaptive path planning model is constructed on a modified A* algorithm, allowing the AUV to navigate the complex three-dimensional underwater environment in an energy-saving and accurate way [7]. This combination of the two components into one continuous hybrid framework allows the system to optimize both localization accuracy and energy consumption at the same time. Simulation studies are also used to verify the effectiveness of the new solution, comparing results with other existing methods by the most important measures like total energy consumption, path length and localization accuracy. Enhancement of network lifetime and the overall effectiveness of data collecting in a dynamic, large-scale underwater network is therefore the eventual aim of the model.

2. Related Works

Proper localization of sensor nodes is core to developing reliable data distribution and retrieval in UWSNs [8]. Traditional range-based localization methods, like trilateration and Time-of-Arrival (ToA), can provide poor solutions because of difficulties in underwater localization, like attenuation of an acoustic signal, multipath signal propagation, and environmental randomness [9]. To contain such drawbacks, researchers have developed alternative approaches such as anchor-free localization techniques and learning-based models, which can accommodate the dynamics of the underwater environment.

The abundant literature review of UWSNs localization techniques emphasizes the existing improvements in acoustic modeling, optimal distributed sensor node deployment and drift correction schemes that are applicable to augment the positioning capability in hostile aquatic environments [10]. The AUVs have also proved useful in facilitating the node localization and data gathering functions. Nevertheless, although they have their uses, AUVs have some problems, like navigational mistakes, slow updating of localization, and high energy requirements, especially in three-dimensional aquatic regions with varying currents.

The study of path planning of AUVs has gained the most attention from researchers since it directly affects energy efficiency and data collection performance. Different metaheuristic optimization approaches, such as Particle Swarm Optimization (PSO) [11], Ant Colony Optimization (ACO) [12], and Artificial Bee Colony (ABC) [13], have been used to create energy-effective routes in uncertain underwater circumstances. The method of reinforcement learning is also becoming popular because of its ability to learn and adjust to changes in the surroundings in real time. Some of the deterministic methods that have been used and are well acknowledged are geometric search algorithms like A*, hailed by their simple decision-making structure and tractability [14]. Nevertheless, the classical versions of A* do not usually take into account the underwater peculiarities of energy and terrain conditions. In order to mitigate these problems, there has been an upgrade of the evolutionary algorithms, such as energy-aware genetic algorithms that have been used in routing situations where multi-hops are involved and have demonstrated better results in energy optimization and efficiency in routing [15].

Nevertheless, few efforts on such integration have been found in current literature, and many approaches consider each problem separately. The current study can cover this gap by suggesting a coherent paradigm where clustering-based localization is matched with the terrain-aware AUV path planning. They also emphasize the usefulness of a scalable deployment model and effective adaptation capabilities to adapt to the erratic and unfavorable environment that is more typical of an underwater sensor network [16]. Although major progress has been achieved regarding node localization and AUV path planning in UWSNs, these important issues are considered in isolation rather than in their entirety. The vast majority of localization systems, both range-based and anchor-free ones, find it difficult to work in an underwater environment, hindered by issues like signal attenuation, multipath propagation and node drifting [17, 18]. Despite being proposed to enhance smart estimation to increase the accuracy of outcomes, some learning-based models have ignored the mobility and dynamism of energy involved in AUVs, which are extremely critical when it comes to gathering data and coordinating a network. At the same time, several studies have been conducted, either on metaheuristic or geometric methods of AUV navigation optimization. Algorithms such as PSO, ACO and A * have proven useful in energy-aware routing, but tend not to integrate with real-time localization information or tend not to factor in terrain and non-stationary variability within cost functions [19]. Moreover, most known models fail to use the residual energy of sensor nodes in clustering, thereby resulting in premature node failures and energy imbalance.

An obvious research gap in the existing literature is the lack of a unified approach that can handle energy-efficient localization and intelligent AUV path planning in a realistic underwater scenario, where both sources of energy and dimensional restrictions must be considered. The urgent requirement of hybrid models that not only optimize AUV path but also provide balanced clustering considering the spatial distribution of the sensor nodes and energy availability of sensor nodes is still a reality to be fulfilled. Filling this gap would greatly enhance the data collection efficiencies, lengthen the life of a network, and increase the flexibility of the UWSNs in multifaceted and large-scale applications.

3. Methodology

A simulation environment was built to mimic real-world underwater operational scenarios to assess the efficiency of the proposed hybrid algorithm. The simulated area is 1000x1000 meters with a depth of 10-100 meters, which contains a three-dimensional space suitable for detecting the layers of the environment underwater. This volume is randomly deployed with 100 sensor nodes, which enables the observation of spraying to be done at varying levels of depth. The nodes communicate on the basis of acoustic signalling, and these signals perform better in an underwater environment than the use of radio frequency. All the nodes are set to have a transmission limit of 100 meters. The node's data is aggregated at eight known cluster heads and later transmitted by the cluster heads to four surface sinks. These surface sinks act as a link and relay the information to permanently fixed base stations, which are above the surface of the water. AUV has the responsibility of, through the centroid, navigating through clusters to gather information, thus enhancing reliability on communication and lessening the energy load of the individual nodes. The simulation assumes a data transmission rate of 1000 bits per second for each sensor node. Energy consumption is modeled with a rate of 50×10^{9} joules per bit for both transmission and reception. Additionally, AUV movement is associated with an energy cost of 10 joules per meter. Environmental factors such as seabed roughness and underwater currents are also considered, introducing respective energy penalties of 1.5× and 2× to reflect realistic underwater traversal challenges. This simulation framework enables testing the proposed clustering and path planning mechanisms under dynamic and energy-constrained conditions. A visual representation of the complete workflow, illustrating the integration of energy-aware clustering and terrain-informed AUV path optimization, is provided in Figure 2.

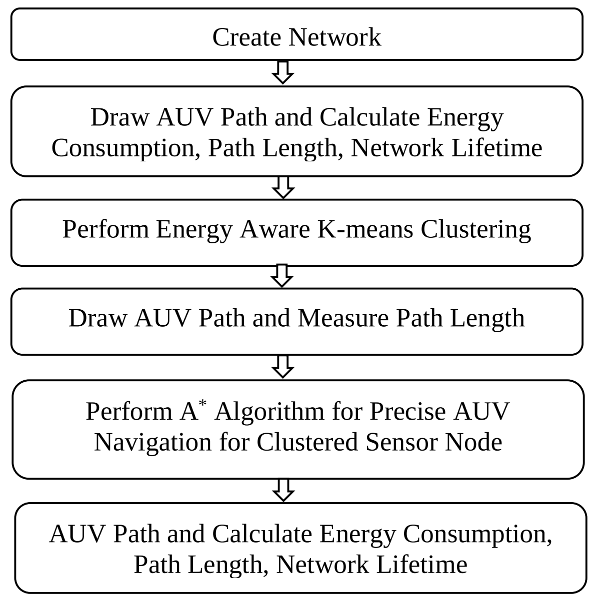

Fig. 2 Workflow of the proposed hybrid algorithm

Table 1. Simulation parameters

Parameter	Value
Deployment Area Dimensions (x,y)	[1000, 1000] meters
Depth Levels of Sensor Nodes	[10, 20, 30, 40, 50, 60, 70, 80, 90, 100] meters
Communication Range of Sensor Nodes	100 meters
Number of Surface Sinks	4
Number of Base Stations	4
Number of Cluster Heads	8
Number of Sensor Nodes	100
Data Rate per Sensor Node	1000 bits/s
Energy Consumption for Transmitting 1 bit	50e-9 J/bit
Energy Consumption for Receiving 1 bit	50e-9 J/bit
Base Energy Consumption for Moving 1 meter	10 J/m
Additional Energy Factor for Moving Over Terrain	1.5
Additional Energy Factor for Moving Against Currents	2

The simulation parameters outlined in Table 1 define the operational framework used to evaluate the performance of the proposed UWSN model. The deployment area spans a two-dimensional space of 1000×1000 meters with sensor nodes distributed across ten discrete depth levels ranging from 10 to 100 meters, enabling a multilayered sensing environment. Each sensor node communicates acoustically within a 100-meter range, and the network infrastructure includes four surface sinks, four base stations, and eight cluster heads to manage data aggregation from 100 sensor nodes. The nodes transmit data at a rate of 1000 bits per second, consuming 50×10^{9} joules for both transmission and reception of each bit. The energy cost associated with AUV movement is set at 10 joules per meter, with additional energy penalties applied to account for traversal over uneven terrain (1.5×) and resistance from underwater currents (2×). These parameters collectively provide a realistic underwater simulation environment for analyzing the efficiency of the proposed hybrid clustering and path planning algorithm.

The standard K-Means clustering algorithm [20] has been modified to suit the energy constraints that underwater sensor networks have. The modified implementation differs from its traditional counterparts in that the modified implementation considers residual energy levels of sensor nodes as an important parameter in cluster formation, as opposed to its traditional counterparts, which only require spatial proximity in cluster formation. Starting the clustering process involves initializing the nodes randomly regarding their coordinates as the centroids. During each iteration, the total energy used to send data to all centroids will be determined by the nodes. However, not only the energy used in the communication will be considered, but also the environmental conditions, like terrain roughness and resistance caused by a current. The nodes are then paired off to the cluster that offers the least total cost of energy. After this reassignment, new centroids are calculated according to the new cluster memberships. The operation is repeated till the convergence point is reached by the cluster structures. The algorithm estimates a more balanced energy consumption on nodes by taking energy awareness into the clustering logic, which reduces intra-cluster transmission expenses and enables the sensor lifetime to extend further without leading to premature depletion of the individual sensors.

To successfully overcome the peculiarities of the undersea scenarios, the classic A* algorithm is modified to a three-dimensional, terrain-sensitive algorithm. Under the water, this space is discretized in this adaptation into a three-dimensional grid so that the AUV can consider the alternative choices in the directions of movement in the depth dimension, their horizontal location, and environmental conditions. The algorithm uses a reformed cost that combines the base movement energy with some extra costs incurred due to obstacles present in the environment, like irregular sea floor and crossflow in the water. The search heuristic uses a Euclidean distance, which is subsequently narrowed down by resistance factors representing terrain elevation and flow intensity variables to ensure that energy-efficient paths are selected. The algorithm keeps lists of open and closed nodes during search, and transitions are chosen based on their minimization of total energy consumption and not their distance per se. After arrival at the destination node, the optimal path is recovered by backtracking on parent nodes. Environment-sensitive enhancement in this mode can dynamically adjust the trajectory of the AUV according to environmental changes, which greatly saves energy costs and achieves good navigational performance in general.

4. Results and Discussion

4.1. UWSN Simulation Environment

A realistic UWSN network was simulated by building a simulation environment. This will consist of 100 sensor nodes randomly placed over an area of 1000 x 1000 meters, enabled by the four surface sinks and four base stations that will ease data relay. One of the AUVs was to follow a randomly generated path to retrieve data from the network, constituting an unoptimized baseline condition. Figure 3 demonstrates the initial topology of the network before implementing the optimization of the strategies. The base level of performance was identified to determine a reference for future assessment. They entail a total amount of energy expenditure of 160,806.98 joules, a total amount of traversal time in 24 118.02 seconds, and the cumulative path length of 48,236.05 meters. Also, the approximate initial network lifetime was 94,996.10 seconds. These numbers provide an accentuation on the inefficiencies of non-optimized AUV motion as well as unorganized communication between nodes. The original network architecture employed during the baseline assessment is shown in Figure 4.

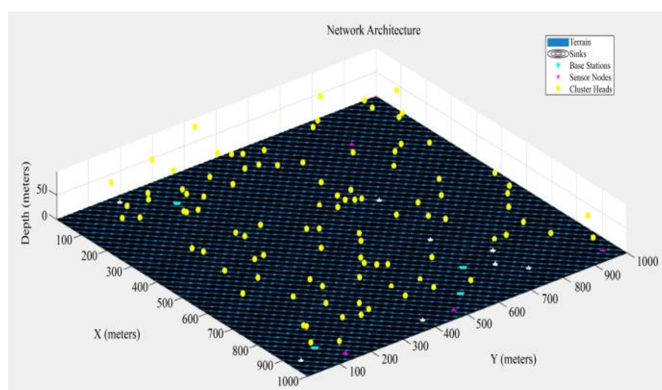

Fig. 3 Initial UWSN topology with randomly deployed sensor nodes and surface sinks

4.2. Performance of Clustered Network Architecture

To demonstrate the merits of a clustering algorithm to arrange the distribution of sensor nodes into energy-efficient subsets, taking both the spatial and left-over energies of the nodes, a proposed algorithm of Energy-Aware K-Means was used. In each cluster, a node whose energy-based properties were optimized was deemed the cluster head, whose responsibility would be to gather data from member nodes and transmit the same to the AUV. In the algorithm, it was able to create clear clusters, each headed by a selected node as presented in Figure 4. This ordered clustering greatly alleviated the communication load levels of individual sensors by encouraging close distance, intra-cluster communication, and cutting down on the redundant forwarding of data. After the clustering, the network energy consumption was reduced to 30,962.38 joules, which was 80.75 percent of the energy consumption in the baseline scenario. Such a remarkable reduction proves the effectiveness of the clustering strategy in saving energy costs and improving the sustainability and durability of the UWSN as a whole.

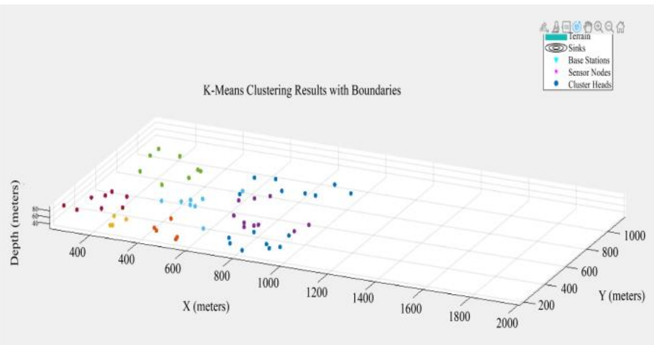

Fig. 4 Reorganized UWSN layout after applying energy-aware K-means clustering

4.3. Effectiveness of AUV Path Optimization

After the clustering stage, the AUV route was optimized by using a terrain-aware A* algorithm to start calculations from the current AUV location using the cluster centroids. This optimization step-up path planning mechanism was considering environmental conditions, including seabed topography and effects of underwater currents, where a more energy-efficient 3D trajectory could be produced.

The resultant optimized path shown in Figures 5 and 6 reveals a tremendous decrease in the complexity of traversing. Due to the optimization in the program, the cumulative time spent on data collection was reduced significantly from 24,118.02 seconds to 3,015 seconds, improving it by about 87.5%.

Likewise, the travel range of the AUV diminished by 92.88 percent, reducing to only 6,030 meters, as compared to the previous 48,236.05 meters. In contrast, the average network lifetime improved remarkably to 8,132 seconds, which is 91.44 percent more than that calculated in the previous case. These improvements highlight the efficiency of the terrain-informed paths planning strategy, which ensured reduced redundant movement and energy consumption and enabled the AUV to complete its data collection tasks with greater operational efficiency.

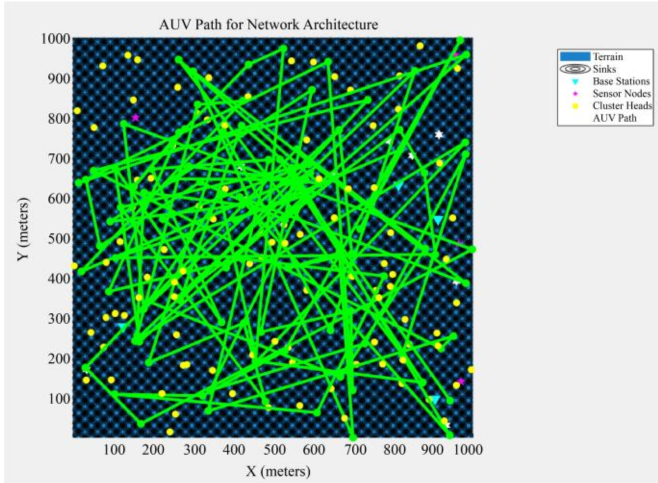

Fig. 5 Comparative visualization of AUV traversal paths: random path before optimization

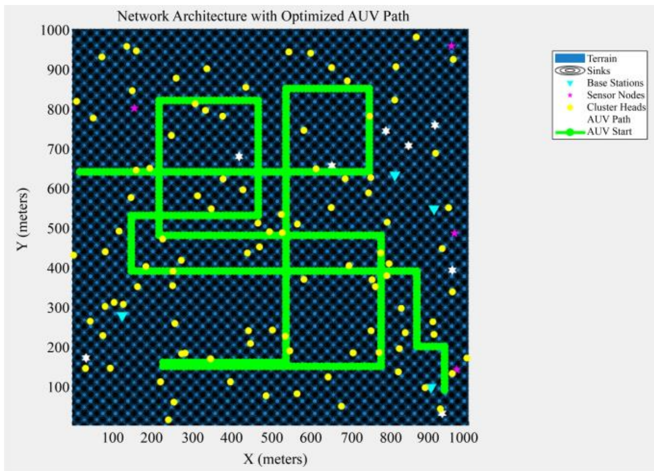

Fig. 6 Comparative visualization of AUV Traversal paths: optimized AUV route using terrain-informed A* algorithm

4.4. Comparative Performance Analysis

The visual presentation of the performance metrics in Table 2 shows a very high degree of influence of the proposed hybrid optimization framework in terms of the efficiency and sustainability of the UWSNs. The largest change showing substantial progress is energy consumption, which went down by 80.75% (160,806.98 joules to 30,962.38 joules). This is a significant saving due to the fact that the energy-aware clustering mechanism lowers the distance transmissions of the data as aggregation of the information is carried out at a local level by the cluster heads. It has also been seen that the optimal path planning has saved 24,118.02 seconds of the total time required by the AUV to traverse a set of goals and has brought the time down to 3,015 seconds, or 87.5 percent improvement. This means that the AUV managed to undertake its data collection much faster and efficiently. The distance travelled was also reduced significantly to an equivalent of 6,030 meters against the previous distance of 48,236.05 meters, showing that the IAA algorithm was useful in reducing unwanted movements of the stairs. Finally, there was a significant increase in network lifetime, which was 8,132 seconds, an improvement of 91.44% in contrast to 94,996.10 seconds. Despite the fact that the absolute measure of the network lifetime seems to be smaller after the optimization process has occurred, that are the result of dynamic cluster behavior and an active use of AUVs, the realized optimized framework results in substantially higher productivity per energy unit consumed. Together, these enhancements justify the viability of the clustering and path planning approach combined in improving the performance of UWSN operations within the bounds of real-life limitations.

Table 2. Comparative analysis of performance metrics

Metric	Pre-Optimization	Post-Optimization	Improvement (%)
Total Energy Consumption (J)	160,806.98	30,962.38	80.75%
Total Elapsed Time (s)	24,118.02	3,015	87.50%
Total Path Length (metres)	48,236.05	6,030	87.50%
Network Lifetime (s)	94,996.10	8,132	91.44%

Table 3. Comparative analysis of performance metrics

Approach	Localization Method	Path Planning	Energy Efficiency Improvement	Path Length Reduction
[11]	Static	PSO	~45–55%	~50%
[12]	Static grid-based	Ant Colony Optimization	~50–60%	~55%
[13]	Location-aware clustering	Basic heuristic	~55–65%	Not explicitly mentioned
[14]	Trilateration-based	Modified A* (2D)	~60%	~65%
[15]	Energy-aware routing	Genetic Algorithm	~65–70%	~70%
Proposed Hybrid Framework	Energy-aware K-Means Clustering	Terrain-informed 3D A*	80.75%	87.5%

In order to illustrate the efficacy of the formulated hybrid framework, a critical evaluation (Table 3) of some of the eminent approaches in the realm of UWSN localization and AUV path planning was carried out. The chosen benchmarks contain metaheuristic approaches, like PSO, ACO, and ABC; deterministic approaches, like the enhanced A* algorithm; and evolutionary approaches, including energy-based GA. The results are attributed to the fact that the framework can develop balanced clusters that are based on both residual energy and spatial proximity and, subsequently, used within the AUV to be adaptively able to traverse over complicated topographies with energy-efficient routes.

To complement the simulation results, an analytical model was developed to quantitatively assess key performance indicators such as energy efficiency, localization precision, and path optimization. This model calculates the total energy expenditure by considering the cumulative data transmission, reception, and AUV mobility costs. Specifically, the transmission energy E_{tx} (Transmission energy) is computed as the product of the transmission energy per bit, the size of the data packet, and the distance between the transmitting and receiving nodes. The AUV's movement energy (E_{move}) includes the base energy required for traversal and additional penalties incurred due to terrain roughness and water current resistance over the traveled distance. The overall energy consumption (E_{total}) is the sum of transmission and mobility energy. The total path length is derived by summing the Euclidean distances between consecutive waypoints in the AUV's route. Network lifetime is estimated by aggregating the ratios of residual energy to the energy consumed for data transmission at each node. These formulations provide a standardized approach to evaluating the energy-performance trade-offs of the proposed framework and serve as a theoretical foundation for validating its scalability and applicability in real-world underwater scenarios.

5. Conclusion

This study presents a novel hybrid optimization framework that integrates Energy-Aware K-Means clustering with a terrain-informed A* path planning algorithm to enhance the operational efficiency of UWSNs. By jointly addressing the challenges of energy-efficient node localization and AUV navigation, the proposed model significantly reduces overall energy consumption and improves network longevity. The energy-aware clustering mechanism ensures balanced data aggregation by considering both spatial distribution and residual energy of sensor nodes. At the same time, the terrain-adaptive A* algorithm enables the AUV to traverse optimized, low-energy routes that account for environmental constraints such as seabed roughness and underwater currents. Simulation results demonstrate the effectiveness of the approach, achieving over

80% reduction in energy usage, an 87.5% decrease in path length and elapsed traversal time, and a 91.4% improvement in network lifetime compared to non-optimized baselines. These outcomes underscore the potential of the integrated model in addressing scalability, energy limitations, and routing complexity in dynamic underwater environments. Future research will extend this framework to support multi-AUV coordination, real-time reconfiguration in response to environmental changes, and experimental validation using physical testbeds. Such advancements will further strengthen the applicability of this model in mission-critical underwater applications such as environmental monitoring, oceanographic surveying, and subsea infrastructure inspection.

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