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RESEARCH ARTICLE

Underwater Efficient Data Routing: Clustering-Travel Salesman Protocol (CTSP)

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ABSTRACT Preserving sensor nodes' energy in underwater sensor networks (UWSNs) stands as a crucial priority. UWSNs find key applications in ocean monitoring, offshore oil and gas exploration, and underwater robotic operations. Our study introduces a novel approach (CTSP) utilizing clustering alongside the Traveling Salesman (TS) Protocol to optimize data routing in UWSNs while minimizing energy usage. By adjusting the pathways of data transmission among sensor nodes, this method aims to curtail the network's overall power consumption. CTSP primarily relies on two fundamental components: TS and clustering. Leveraging the TS Protocol allows the determination of the most efficient route between any pair of sensor nodes within the network. The approach ensures that each sensor node transmits data solely to its nearest neighbor, thereby reducing the energy required for transmission. Utilizing the positions of sensor nodes as input, a clustering algorithm forms larger groups. Enhanced communication within clusters and reduced long-range communication between clusters contribute to energy conservation. Simulation results demonstrate that the proposed method significantly diminishes power consumption compared to traditional routing methods like the LEACH algorithm. Precisely, the CTSP method exhibits the potential to reduce energy usage by up to 50%, presenting a feasible option for energy-efficient data routing in underwater settings.

INDEX TERMS Clustering, data routing, energy efficiency, traveling salesman problem, underwater sensor networks.

I. INTRODUCTION

Subaquatic communication study has become more important recently [1] because it can be used in many areas, such as underwater robots, offshore energy development, and marine tracking. More and more Underwater Sensor Networks (UWSNs) are being used to help underwater devices communicate with each other effectively [2]. Still, it's hard to get energy-efficient data routing in UWSNs because sensor nodes only have limited energy resources. A lot of research has been done to figure out a way to solve this issue [3]. The main goal of the study in [4] is to create systems that make data transmission more efficient while using less energy. In the area of UWSNs, it is especially hard to make transportation systems that use less energy. Traditional methods often fail to take into account the fact that sensor nodes only have limited power. This causes networks to use too much energy and break down very quickly. Because of this, it is important to come up with new ways to make data routing work better while using less energy resources [5].

The complexity of the world under the sea makes it hard to make transportation systems that work well. Physical barriers

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TABLE 1. Related studies.

Protocol	Objective	Method	Quantity of sink nodes	Packet Delivery	Limitations
QDTR [20]	Reduce energy consumption and increase adaptability.	Reinforcement Learning	Single	Individual packet	Less applicable in densely populated networks
QLEDR [21]	Increase Network Lifetime	Reinforcement Learning	Single	Sensor Position	Link stability is not considered
MFPR [22]	Improve QoS	Bioinspired Optimization (Pollen)	Single	Individual Packet	No significant improvement in energy consumption
EERUCA [23]	Increase Network Lifetime	Cluster-Based Data routing	Single	Individual packet	High end-to-end delay
MLCEE [24]	Increase Network Lifetime	Cluster-Based Data Routing	Single	Individual Packet	No updating of Cluster Head
CTSP**	Increase Network Lifetime	Cluster-Based Data Routing (TSP integration)	Single	Individual packet	-
Proposed: **					

like rocks and marine life, as well as the fact that electromagnetic signals sent across the water are greatly attenuated and distorted [6], make it harder for sensor nodes to communicate with each other. Activities that happen underwater need good data routing [7]. Since regular route algorithms are unable to account for the limited power and unique conditions that sensor nodes face underwater, they fail to function well in these situations [8]. To get the most out of underwater communication for a wide range of uses and scientific study, it is important to make the best use of data routing and energy [9].

Combining grouping techniques with the TS Protocol [10] is the purpose of the suggested method is all about improving transit routes. Most approach tries to find energy-efficient ways for data to be sent between sensor nodes in order that it can be delivered between nodes that are close to each other [11]. A clustering method uses the locations of sensor nodes to form larger networks. This saves energy within clusters and makes it harder for them to communicate with each other over long distances. This method is an option for traditional routing algorithms that can be used in UWSNs. Its goal is to improve data routing efficiency while lowering power consumption [12]. Based on simulations, using this methodology might result in a fifty percent decrease in power usage over traditional techniques.

II. LITERATURE REVIEW

Due to the constraints of battery technology, the design of the communication protocol may aid in conserving energy. Lee et al. conducted a comparative investigation of several energy-efficient Medium Access Control (MAC) algorithms for Underwater Wireless Sensor Networks (UWSNs) depending on the network architecture [13]. Clustering assumes a crucial role in underwater sensor networks, contributing to improved energy efficiency, efficient data aggregation, streamlined resource management, and an extended network lifespan [14]. This process involves the segmentation of the network into smaller groups, known as clusters. Each cluster is overseen by a designated cluster head (CH) responsible for aggregating and relaying information from individual nodes within their assigned cluster. This organizational strategy effectively diminishes redundant transmissions and fosters optimized network operations [15].

In their study, Sun et al. devised a communication protocol that uses clustering as a means to collect and send data, resulting in a significant reduction in energy consumption for each sensor node [16]. The topology management strategy suggested by Jin et al. [17] enhances the coverage performance and extends the lifetime of underwater sonar detection networks (USDNs) by ensuring coverage and connectivity. Liu et al. developed a distributed node deployment technique using virtual forces to enhance the network coverage of a UWSN [18]. Wei et al. [19] developed a network topology control model for UWSNs that incorporates several features such as topology, energy consumption balance, and high resilience. The objective is to enhance data transmission and prolong the lifetime of UWSNs.

The use of the TSP in data routing strategy design is a unique and noteworthy addition to the field of energy-efficient communication protocols for UWSNs, given the body of current work in this area. Adding to the fundamentals, which were mostly concerned with node deployment, topology management, and clustering, the TSP adds a special dimension to enhance data routing and increase network longevity. A well-known network optimization issue is the TSP, which looks for the most effective route that visits a collection of nodes once each. The limitations of current methods are addressed by the proposed solution, which applies TSP principles to data routing in UWSNs.

Table 1 offers a comparative analysis of various communication protocols designed for UWSNs, each characterized by distinct objectives, methodologies, and limitations. The QDTR protocol in [20] focuses on reducing energy consumption and enhancing adaptability through Reinforcement Learning but exhibits limited suitability in densely populated networks. QLEDR in [21] aims to increase network lifetime using Reinforcement Learning, though it neglects the consideration of link stability. MFPR, employing Bioinspired Optimization (Pollen) in [22], aims to improve the Quality of Service but falls short of delivering a significant reduction in energy consumption. EERUCA [23] and MLCEE [24], both emphasizing increased network lifetime through Cluster-Based Data Routing, face challenges such as high end-to-end delay and a lack of Cluster Head updating, respectively.

III. UNDERWATER WIRELESS SENSOR NETWORK (UWSNs)

UWSNs are a type of sensor network that is designed to work in marine settings. They collect data from oceans, lakes, and waterways and are very important for environmental tracking, marine study, and underwater exploration [25]. The primary challenge with developing UWSNs is that sensor nodes require a great deal of power. To navigate around this obstacle, conserving energy must be the primary goal. Signal loss and distortion also make it hard to communicate underwater, so people have to use sound for communicating over larger distances, even though transmission rates are sluggish [5]. In order to figure out the way a UWSN works, it's necessary to evaluate factors like contact, range, and energy efficiency. Communication means that sensor nodes stay connected to the sink node. Coverage measures the extent of an area that is being watched by sensor nodes. Because the nodes' batteries cannot last long and it's hard to replace or charge batteries underwater, measuring their energy efficiency becomes very important [26].

UWSNs are made up of many sensor nodes that are spread out in different underwater areas. Each node has sensors, processing units, and wireless communication modules. Their main job is to gather information underwater and send it to sites on land or other points. To reach this goal, nodes must be able to work together without any problems [27]. But underwater communication is hard because of things in the world, like how water significantly distorts signals, which is made worse by objects including rocks, reefs, and marine life [28].

To get around these problems, researchers have come up with a number of different routing methods that aim to improve the handling of data packets, lower energy use, and make networks last longer. A popular approach is multi-hop routing, in which each node sends data bits to the friend that is closest to it until it reaches its final target [29]. Graph-based models are often used to demonstrate challenges with data transfer in UWSNs in a formal way. These models illustrate network points as vertices and communication lines as edges.

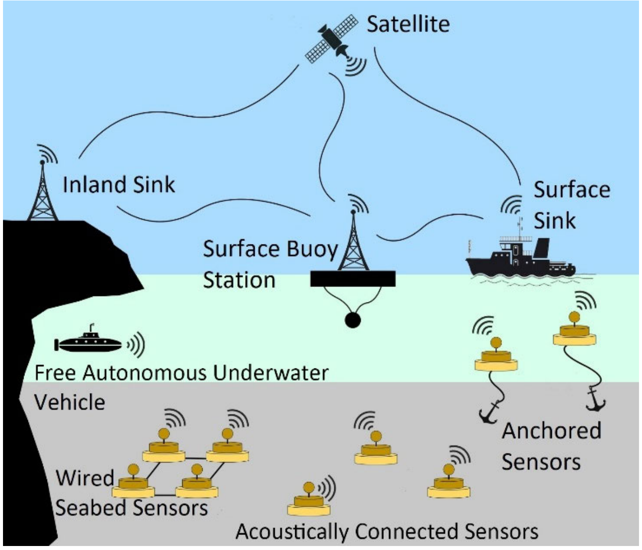

FIGURE 1. Diagram of underwater wireless sensor network.

TABLE 2. Simulation parameters.

Parameter	Value
Volume	200 x 200 x 200 m^3
Channel	Acoustic Channel
No. Nodes	300
No. Sinks	One on the Surface
Routing Protocol	K-Means Cluster-based protocol
Movement Model	Static Model
Propagation Model	Underwater Propagation
Traffic Type	CBR
CBR Flow	1, 2, 3, 4, 5, 6
Initial Energy of Nodes	5 Joules
Energy consumption /bit Transmitted	20 nJ/bit
Energy consumption /bit Received	5 nJ/bit
Transmission Range	18 m
Acoustic Signal Speed	1.5 – 1.6 km/s
Geometric Spreading	2 (spherical)
Avg Data Packet Size	< 150 bits
Data Transfer Rate	15 kbps
Simulation Time	500 sec
Number of Rounds	50

They try to find the best ways by considering things like the amount of energy they use, the duration a journey takes, and most often the network updates [30]. To solve route problems in UWSNs [31], [32], different optimization methods are used. These include mathematical programming methods like linear programming and integer programming, as well as evolutionary algorithms like genetic algorithms and particle swarm optimization.

IV. EXPERIMENTAL SETUP FOR UNDERWATER COMMUNICATION

The establishment of experiments for underwater communication necessitates meticulous deliberation of several elements in order to guarantee the acquisition of dependable and precise data. This section highlights the experimental configuration used in the proposed study. This paper presents the simulation configuration for cluster-based algorithms, with the use of the TS Problem solution to search for the optimal path. Additionally, performance measurements are used to assess the efficacy of the network.

A. SIMULATION SETUP FOR THE CLUSTER-BASED UNDERWATER ROUTING

The underwater sensor nodes are distributed at a random location, and a certain group of those nodes initiate constant bit rate (CBR) communication and send packets to the one sink node that is situated at the water's surface. In this simulation, the K-means cluster-based routing protocol is employed. The parameters and values for the underwater network simulation, are listed in Table 2:

The simulated area spans 200 × 200×200 m^3, accommodating 300 static nodes and one surface-based sink. The network operates in an acoustic channel with data traffic following a constant bit rate (CBR) model, using flows 1, 2, up to 6 kilobits per seconds (kbps). Each node starts with an initial energy of 5 Joule, and its transmission range is limited to 18 meters. The acoustic signal speed remains 1600 m/s, with a geometric spreading factor of 2 (spherical propagation). The data packets' average size is still below 150 bits, and the data transfer rate is maintained at 15 kbps. The simulation runs for 500 seconds, divided into 50 rounds. The values obtained from each round were compared to one another to get an average. By seeding the random number generator regarding the run number, we were able to regulate the degree to which the topology and network circumstances were unpredictable, as well as the time at which traffic started and stopped.

These revised settings form the basis for the underwater network simulation, facilitating the study of communication performance and energy utilization in an underwater environment.

B. TRAVELLING SALESMAN PROBLEM

The TS Problem is a basic optimization task to find the shortest feasible tour (set of cities) that a supposed salesman visits. The requirements are two: i) every city can be visited only once, and ii) the last city visited is the beginning location (returning). Since the TS problem is an NP-Hard problem, it requires computationally demanding procedures to find optimal solutions and the Heuristic algorithm provides an approximate solution. As the proposed model encompasses a comprehensive network of nodes, it necessitates a thorough solution process to effectively consider and determine the optimal path within the network of nodes. This issue is outlined by a matrix that has a list of cities together with the distances that separate each of those locations from one another. Mathematically speaking, it is modeled as an optimization function, with the goal of reducing the overall distance covered in a closed circuit as much as possible. The presence of constraints guarantees that each city will only be entered and exited a single time. As a result of this, a wide array of strategies, including both accurate and heuristic approaches, are used to locate effective answers. These include heuristic methods such as genetic algorithms and simulated annealing in addition to techniques such as branch and bound and bounding boxes. The applications of this problem go well beyond its initial setting in logistics, finding usage in domains as varied as robotics, circuit design, and DNA sequencing, among others [33].

Applying the TS Problem in a network, assuming the packet as the salesman role, can be seen as a routing problem where the solution is an efficient protocol, particularly in the context of underwater acoustic communication. An example of its mathematical formulation is the problem of minimizing a route among cities, given in eq. (1)-(3):

$$D_{ij} = min \sum\nolimits_{i \in C} \sum\nolimits_{j \in C, j \neq 1} \bar{D}_{ij}.x_{ij} \tag{1}$$

$$\sum\nolimits_{j \in C, j \neq i} x_{ij} = 1, \forall i \in C \tag{2}$$

$$J = min \sum\nolimits_{i=1}^{N} min_k \, \|x_i - \mu_k\|^2 \tag{3}$$

The eq. (1) is a key expression in optimization, particularly for TS Problem. It means the determination of the shortest distance (D_{ij}) between two cities, i and j, by minimizing the sum of distances over all possible combinations of cities while considering specific constraints. Here, $\bar{D}_{ij}$ represents the distance between city i and city j, and x_{ij} is a binary variable indicating whether a direct route is taken between the two cities, and here, C represents a set of elements or nodes. This formulation encapsulates the objective of finding the most efficient tour that visits each city exactly once, a central challenge in the TS Problem.

Eq. (2)-(3) represent each city visited and left respectively. Since the signal visited one node, it is not allowed to revise the same node within the path. Thus, repetition is strictly not allowed.

C. K-MEANS CLUSTERING

The use of K-means clustering, an unsupervised machine learning methodology, is implemented for the purpose of classifying a given dataset into a pre-established number of clusters, which are represented as K. The main goal of this technique is to minimize the within-cluster sum of squares (WCSS), also known as inertia, which measures the squared distances between data points and their respective cluster centroids [29]. The objective is to identify clustering that efficiently reduces the spread of data inside clusters, enabling a more concise depiction of the underlying patterns in the dataset. The objective of K-means is to minimize the total squared distance of data points to their respective cluster centroids as given in (3).

For each data point xi, find the nearest centroid μ_k based on Euclidean distance as depicted in (4). For each cluster, the centroid is recalculated using the meaning of the available data points assigned to it in (5).

$$k^* = argmin_k \, \|x_i - \mu_k\|^2 \tag{4}$$

$$\mu_k = 1/N_k \sum\nolimits_{x \epsilon C_k} (x) \tag{5}$$

D. BELLHOP MODEL AS AN UNDERWATER CHANNEL

The Bellhop model is a highly advanced modeling technique used in the field of underwater acoustics. It plays a crucial role in accurately predicting the propagation of sound in underwater environments. The proposed model integrates many elements, including water depth, temperature gradients, salinity variations, and seabed features, to effectively simulate the propagation properties of sound waves. The determination of Transmission Loss (TL) entails evaluating the reduction in acoustic signal strength as it propagates through water, considering the complex amplitudes of several propagation modes at a certain frequency. In addition, the model takes into account the absorption coefficient, which is contingent upon frequency and signifies the varying levels at which water absorbs various frequencies. The Bellhop model plays a vital role in various applications, including the development of efficient underwater communication systems, the improvement of sonar performance, and the facilitation of marine research. It achieves this by providing comprehensive insights into the complex interactions between sound waves and the underwater environment. The acoustic pressure $p(r, t)$ at a specific place r inside a fluid medium and at a certain time t is described by (6):

$$\nabla^2 p(r, t) + k^2 p(r, t) = 0, \tag{6}$$

also interpreted as the Helmholtz equation. The operator ∇^2 represents the Laplacian operator, which signifies the divergence of the gradient of a scalar field. The solution to the Helmholtz equation offers a crucial understanding of the complex dynamics that regulate the movement of sound waves in underwater settings. Within the framework of our proposed model for underwater communication networks, the information gained plays a crucial role as a fundamental basis. The solutions of the Helmholtz equation provide an in-depth understanding of the spatial and temporal attributes of acoustic pressure, enabling us to understand the intricate behaviors of waves in aquatic environments. This knowledge has an indirect impact on the signal-to-noise ratio (SNR) of underwater communication systems in the proposed model.

E. PERFORMANCE METRICS

To evaluate the performance of the proposed algorithm, we consider studying the energy consumption, and network lifetime.

The aggregate energy consumption of all sensor nodes (N) during the simulation is quantified in joules and demonstrated in (7).

$$T = \sum_{i=1}^{N} \left(P_{A,i} \times A_{t,i} + P_{S,i} \times S_{t,i}\right) \tag{7}$$

where for every i device, $P_{A,i}$ is its active power, $A_{t,i}$ is its activity time, $P_{S,i}$ is its power in sleep mode, $S_{t,i}$ is its sleep time, and T is the total energy consumed. The node lifetime can be defined by (8).

$$N_l = E_b / A \tag{8}$$

where A means the average power consumed, and E_b is the energy supplied by its battery.

The network lifetime metric is used to quantify the duration of operation for a sensor network, usually, the point in time when the first node in a network ceases to function. The term ''operational time'' refers to the duration in which a node can execute the assigned job as given in (9).

$$n\ell = (\mathcal{J}_\varepsilon - \omega_e) \Big/ \left(C_p + a_r \mathcal{R}_e\right) \tag{9}$$

Equation [9] estimates 'network lifespan' ($\boldsymbol{n\ell}$) in terms of network energy consumption. It probably estimates how long before the network fails or meets performance limits. The 'Initial Energy' ($\mathcal{J}_\varepsilon$) represents the initial energy level in the network, whereas 'Energy Loss' ($\boldsymbol{\omega_e}$) measures energy dissipation from network activities or external conditions. The 'Constant of Proportionality' ($\boldsymbol{C_p}$), 'Area' ($\boldsymbol{a_r}$), and 'Resistance' ($\mathcal{R}_{\boldsymbol{e}}$) may affect energy consumption, geographical coverage, and network energy efficiency. The equation uses beginning energy and energy loss rates to determine how long the network can operate, which is critical for enhancing network efficiency and extending its longevity.

V. CORE CHALLENGES OF UNDERWATER SENSOR NETWORK

This specific section focuses on an in-depth exploration of the underlying problems inherent in underwater-based communication systems, which is crucial for the successful implementation of effective underwater communication networks. The considered limitations here include the signal attenuation, restricted bandwidth, and the intricate factors imposed by underwater terrain.

A. LIMITED BANDWITH

The best way to have a long-range in underwater communications is by using acoustical frequencies. The problem is that bandwidth is limited for high attenuation of water over 100 kHz (40 dB/km at 100 kHz, but 300 dB/km at 1MHz). For this reason, high-frequency transmissions which may carry more data, are more susceptible to attenuation and distortion. So underwater communication frequency range must be carefully chosen to improve the data transmission rate and minimize signal decay [1]. Besides that, other physical effects have a negative influence on the propagation as distortion [34], the channel's noise, and interferences. Underwater communication paths limit bandwidth, which affects data transmission modulation and coding schemes. The coding methods provide redundancy to data transmission to improve reliability, but this approach needs greater bandwidth, which may impede data transmission in underwater routes with limited capacity [35]. Underwater communication's limited bandwidth must be addressed to enhance

UWSN data delivery. Innovative signal processing technologies like error-correcting codes and multi-carrier modulation, as well as underwater communication systems with wider bandwidths, may achieve this [36]. The bandwidth restriction in underwater communication is commonly measured using Thorp's attenuation, given by

$$\propto (f, T, D) = \propto_0 \left(\frac{f}{f_0}\right)^2 \left(\frac{T_0}{T}\right)^{1.5} exp\left[-\beta \frac{D}{1+\alpha D}\right] \quad (10)$$

This equation describes saltwater sound attenuation by the absorption coefficient $\propto$ dependent on frequency (f,Hz), temperature (T, °C), and depth (D, meters). The coefficient α_0 is measured at 1 kHz reference frequency (f_0) and 20°C reference temperature (T_0). Additionally, the coefficients α and β are empirical, reflecting unique undersea features.

B. HIGH LATENCY

In underwater communication, "high latency" is the time between transmitter and receiver data transmission. This is another major industrial issue. Due to underwater conditions, underwater communication has a substantially greater delay than terrestrial communication. Water sound travels at 1500 meters per second. So, compared with air, underwater sound is more efficient, but electromagnetic waves in air are the dominant propagation mechanism for wireless communications at a much higher velocity. Consequently, underwater communications suffer from a very long signal transmission delay which may cause considerable echo and reverberation effects and can interfere with the original signal. This interference makes broadcast and reflected signals hard to distinguish. Prolonged latency may also cause packet loss, transmission delays, or even the end of the communication connection. Dynamic settings, when the undersea channel changes often, are especially convenient [37].

Multiple solutions to excessive latency have been offered by researchers. These options include using low-latency communication protocols like TCP and UDP and developing efficient error and congestion management methods. Advanced signal processing methods like adaptive equalization, channel estimation, and interference cancellation may help underwater communication systems perform better and reduce latency [38]. Underwater communication latency (L) may be estimated by

$$L = \frac{2D}{c} + \frac{d}{R}, \quad (11)$$

where $2D/c$ denotes the vertical round-trip transit time from the signal source to the sea surface and back, and d/R shows the time required to transmit data horizontally at distance d at a data rate R.

C. SIGNAL ATTENUATION

Underwater communication is plagued by signal attenuation. Electromagnetic waves decrease in water. Attenuation varies on transmitter-receiver distance, signal frequency, water temperature, and salinity. Transmission failures and data loss result from signal degradation. Signal exponential decay in water limits underwater sensor node transmission range. High-frequency transmissions may lower attenuation. These signals are weaker yet more informative. While low-frequency transmissions have less attenuation, they cannot transmit as much information [39]. Several methods, including adaptive modulation, signal coding, and signal amplification, have been suggested as potential solutions to the problem of signal attenuation. Amplification of a signal raises its strength in order to compensate for the impact of attenuation; nevertheless, it requires more energy and has the potential to interfere with the transmission of other signals. Signal coding adds redundancy to the signal in order to identify and fix mistakes, while adaptive modulation modifies the modulation scheme depending on the quality of the signal in order to increase the signal-to-noise ratio. Adaptive modulation is used to get a better signal-to-noise ratio. In situations when there is a reduction in the strength of a received signal, these strategies may make underwater communication more reliable and effective [40].

D. NOISE

Noise may disrupt any communication system, but underwater communication is more difficult. Marine life, water currents, ships, and other underwater vehicles may all make noise. Noise degrades communication signals, making it hard to extract useful information from them. Because noise generates signal unpredictable fluctuations, it may impede data delivery [41]. Noise reduction may be achieved by signal processing techniques like error correction coding or noise filtering. Signal redundancy is added using error corrective coding. This allows the receiver to reassemble data even if noise destroys some of it. The method of "noise filtering" eliminates or dampens incoming signal noise. This is commonly done using noise-suppressing filters [42]. These solutions may improve transmission signal quality, but they need more bandwidth and computing power. It's important to find a balance between noise reduction and underwater communication system resources [32], [43], [44]. A model often used to consider underwater communication noise is the Ambient Noise Level (ANL), given by

$$ANL(f, D) = ANL_0 + 20log_{10}\left(\frac{f}{f_0}\right) + 10log_{10}\left(\frac{D}{D_0}\right), \quad (12)$$

where ANL_0 denotes the reference noise level (usually dB re 1 μPa), f the signal frequency (Hz), f_0 the reference frequency (Hz), D the water depth (meters), and D_0 the reference depth (meters) used to quantify deviations. The ANL includes both natural and human-caused underwater noise, and it is important to note that noise formulation may vary depending on the underwater environment's location, marine animals, and human activities.

E. POWER CONSTRAINTS

The consideration of power limitations in underwater communication is of utmost importance when building systems that are both dependable and energy efficient. A fundamental equation used to express power limitations is given by the Friis transmission equation,

$$P_r = \frac{P_t G_t G_r \lambda^2}{(4\pi d)^2} \tag{13}$$

With P_r the received power, P_t the transmitted power, G_t and G_r are the gains of the transmitter/receiver antennas respectively, λ is the signal wavelength, and d the distance between the transmitter and receiver.

VI. CLUSTERING-TRAVEL SALESMAN PROTOCOL (CTSP)

The flowchart of the proposed routing process CTSP is shown in Fig. 2, and detailed mathematical steps are presented in Algorithm 1. It begins by initializing the system, whereby 300 nodes are placed strategically in a three-dimensional area as given in. Each node is assigned coordinates (x, y, z) that range from 1 to 200 (meters). In the subsequent stages, the nodes are methodically categorized into clusters. The accomplishment of this task involves the computation of Euclidean distances between individual nodes and probable centroid spots within the given space. After the assignment of nodes to clusters, the next phase is to enhance the depiction of cluster centroids by taking into account the spatial arrangement of nodes inside the network. The 4th step in Algorithm 1, is to select the Cluster Head (CH) by assigning that role to the node that displays the minimum Euclidean distance to the centroid.

The proposed model incorporates the energy consumption associated with the transmission, reception, and amplification of signals, together with the spatial separation between nodes. Through the incorporation of these factors, the algorithm calculates the aggregate energy expenditure associated with the transmission of messages between nodes. Furthermore, the use of TS Problem is employed to ascertain the optimal routes for data transmission inside clusters.

After the establishment of optimal pathways, the algorithm creates routing tables for each node, as determined by the TS Problem solutions. In addition, the method enables communication across clusters by using a mechanism of transitioning between CHs. This approach enhances network-wide coherence by optimizing inter-cluster communication via the determination of the next hop for each node. In future iterations, the algorithm takes into consideration the need to update CHs among those nodes having energy reserves below a preset threshold (set of Candidates for CH). The node of this set with the greatest energy reserves and shortest distance to the centroid becomes the new CH. This dynamic selection serves to maintain an uninterrupted and energy-efficient network functionality.

The primary goal of this research focuses on extending the network lifetime achieved through the careful selection of optimal routes, driven by our proposed algorithm. The underwater communication landscape is intricately influenced by diverse environmental factors such as salinity, temperature variations, limited bandwidth, and other critical parameters. In the framework of this study, the proposed algorithm gives precedence to mitigating energy loss, recognizing the formidable challenge posed by replenishing energy for submerged nodes. It is essential to note that the results presented in this study were obtained under ideal conditions. While acknowledging the importance of assessing the algorithm's performance across various underwater terrains and considering environmental variations, the emphasis of this study remains on the core objective of implementing the proposed algorithm for energy-efficient routing.

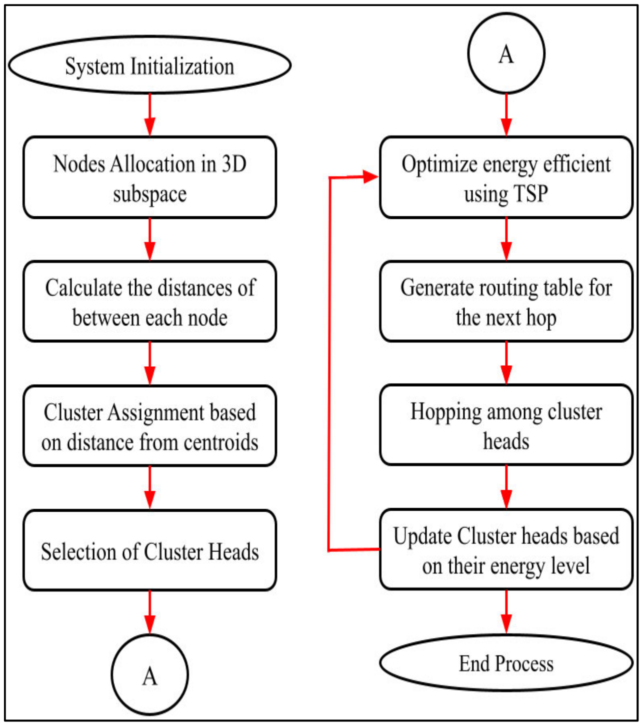

FIGURE 2. Control flow of CTSP.

Algorithm 1

Input:(simulation parameters in Table 1)
Output: - -
%Random node positioning
for $i = 1{:}\ N$ ***do # N: number of Nodes***
  $p_i \leftarrow$ **random** $(x, y, z) \in (200 \times 200 \times 200)$
endfor
%Distances between nodes calculation
$D_{ij} = []$
for $i,k = 1{:}\ N$ ***do***
  $d_{ik} = \sqrt{(x_i - x_k)^2 + (y_i - y_k)^2 + (z_i - z_k)^2}$
  $D_{ik}.append(d_{ik})$
end for
%Applying kMean Clustering
function *kMean(Data, k):*
  $C_k = [\ ]$
  for *k = 1: n do*
    C_k*.append(random(pi))*
  end for
  % Repeat until convergence:

```
    for q in enumerate(pi) do
      C_k = argmin ||q − C_k ||2
      for t in enumerate(C) do
        d_t = sqrt( Σ_{i=1}^{n} (q − C_k)^2 )
      C_k = argmin_k (d_t)
    end for
  end for
end function
Choosing Cluster Head
CH_k = argmin_{i∈C_k} d_t
function optimized_energy_efficient_path(C_k, D_ij) :
  Calculate total energy from node i to node j
  E_ij = E_Tx + E_Rx + E_amp * D_ij
  %Calculate x_ij based on proper Cluster Heads
  fori in C_k do
    for j in C_k do
      if j!= 1:
        x_ij[i][j] = 1
      else:
        x_ij [i][j] = 0
      end for
  end for
  % Ensure each node is connected to only one node in the cluster
  for i in C_k do
    connected_nodes_count = 0
    for i in C_k  do
      if j != i:
      connected_nodes_count + = x_ij[i][j]
      #Node i is connected to only one other node in the cluster
    end for
  end for
end function
%Routing Table for the Next Hop (NH):
if x_ij= 1 :
  NH_i = j
Hop Among Cluster Heads
for i in range(1,N) do
  NH_i = argmin_k (NH_i^k)
end for
%Identify nodes with low energy below threshold. After 1st round,
%identify the node with low energy denoted by L_EN below the
%threshold E_th, E_i is the energy of an individual node.
for i in C_k do
  L_EN = {i∈C_k|E_i < E_th}
end for
%Candidate Cluster Head (CH_k) will have the most amount of
%energy reserve as compared to the other nodes in the same cluster
%k. New Cluster Head is denoted by (NCH).
CH_i = {j∈C_k|E_j > E_i, j ≠ i}
for j in CH_k do
  d_j = sqrt( (x_j − x_c)^2 + (y_j − y_c)^2 )
end for
NCH_i = argmin_{j∈(CH_i)} d_j
%Selection of the new Cluster Head for the next round
CH_k = NCH_i
```

VII. RESULTS

The illustration in Fig.3a portrays a simulation submerged ecological setting including a total of 300 nodes that are placed in a random manner. The aforementioned nodes symbolize devices or sensors that are strategically placed in a submerged environment, such as a body of water such as a lake, ocean, or a controlled undersea facility. Each node is equipped with a diverse range of sensors or equipment specifically designed to gather data regarding the submerged environment. The arrangement of nodes is characterized by randomness, indicating the absence of any discernible pattern or grid structure. It is most likely the intention to improve the comprehensiveness of the data gathered from the undersea region that randomization was purposefully used in the sampling procedure. It is crucial to recognize that the perceived randomness may result from natural environmental factors like hydrodynamic forces or dominant currents. Data transmission and reception are made easier by the nodes' communication features. Real-time monitoring may need the nodes to transmit information to the sink node via a multi-hop technique, which could be of utmost importance.

The outcome of implementing K-means clustering on the underwater environment, which was previously discussed in Fig.3a and consisted of 300 nodes, is depicted in Fig.3b. The K-means clustering algorithm is a robust method for doing data analysis, wherein a given dataset is partitioned into K separate and non-overlapping subsets or clusters. In this particular scenario, the variable K has been assigned a value of 5, signifying that the algorithm has been directed to partition the 300 nodes into five separate clusters according to their spatial proximity. The clusters have been assigned distinct colors in order to visually depict the grouping of nodes, facilitating the identification of nodes belonging to each respective cluster. Each separate cluster is represented by a unique color, so facilitating a visually discernible differentiation between them. The clustering process plays a vital role in the organization of nodes into meaningful groupings, serving many applications in the field of underwater monitoring and research. The primary objective of the clustering algorithm is to decrease the variation within each cluster while simultaneously maximizing the degree of separation between clusters. This implies that the nodes contained within a cluster exhibit a higher degree of similarity amongst themselves compared to nodes that belong to different clusters. Through the process of clustering, researchers and scientists are able to enhance the efficiency of their data analysis endeavors. The researchers can now direct their attention towards the analysis and interpretation of the data obtained from each individual cluster. This analytical approach has the potential to unveil distinct patterns, trends, or irregularities within each respective group. This approach ultimately improves the efficacy and efficiency of underwater monitoring and research operations.

K-means clustering on 300 underwater nodes yielded centroids in Fig.3c. Centroids are important center points that represent their clusters, revealing the spatial arrangement and properties of associated nodes. Centroids help identify a cluster's head. Fig.3d depicts the grouped nodes focusing on the CHs. CHs manage communication inside their clusters, making them vital to the network. CHs are identified by strategically using cluster centroids and node-starting energy levels. Every node in a cluster starts with a certain amount of energy, which represents its communication capabilities.

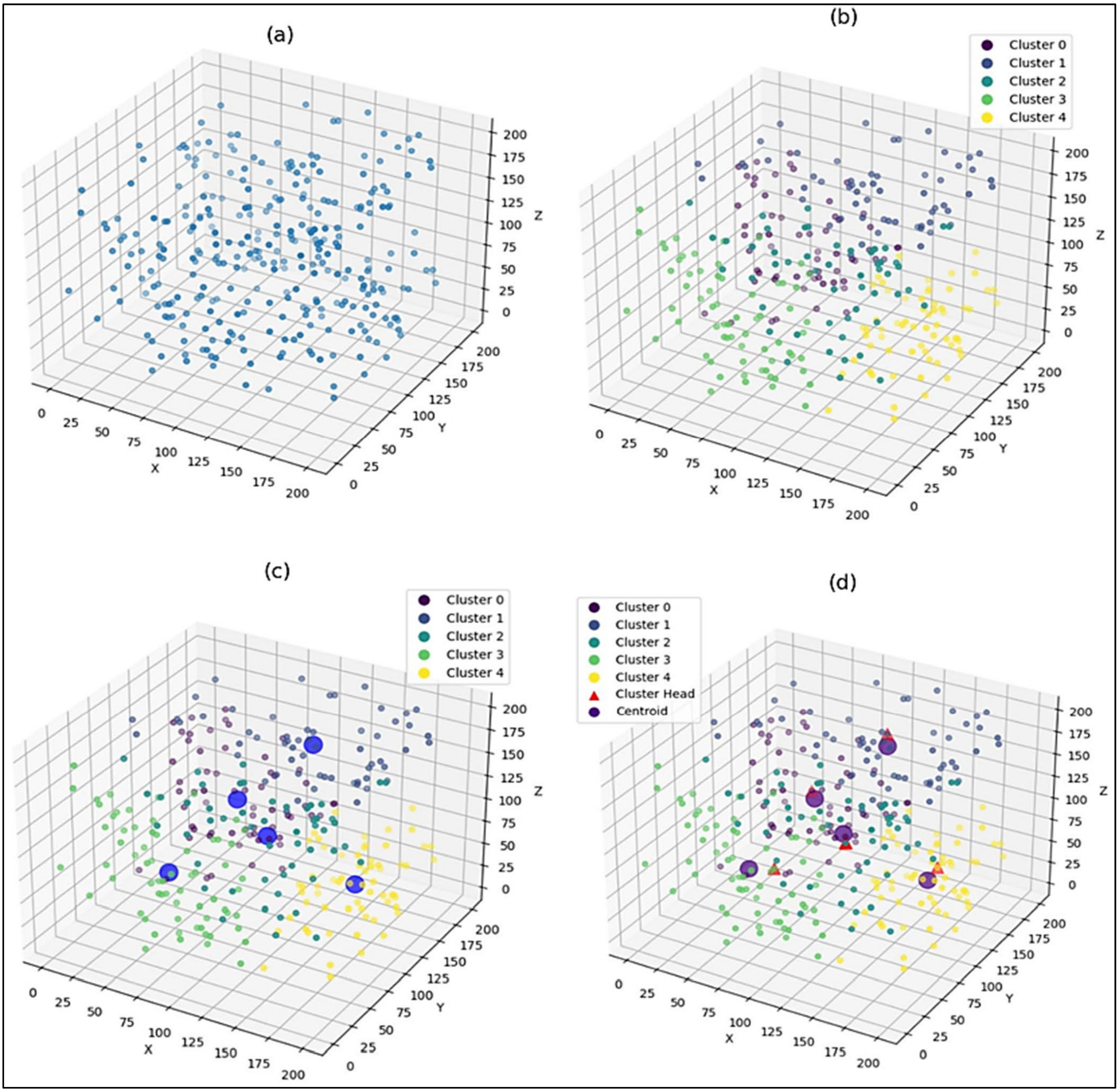

FIGURE 3. **(a) Random Node allocation in underwater environment. (b) Assigning clusters with K-means clustering. (c) Finding Centroids of each cluster. (d) Identify the CH in using Centroids and Energy level for each cluster.**

Energy distribution is essential to network longevity and efficiency. The selection of CHs is essential because they facilitate cluster communication (Fig.3d). By cluster center proximity and beginning energy levels, these nodes are chosen. This ensures that the CH is in the center and has enough energy to manage communication activities. The cluster's nodes transmit and receive information, which uses energy and reduces each node's resources. Reassessment is required when a CH's energy level drops below a threshold. A CH update indicates a duty transfer to another node.

Table 3 presents a comprehensive record of the distances, expressed in meters, that exist between every CH and the sink node in the network. The utilization of this table is essential in the resolution of the TS Problem and the determination of optimal routes. As an example, the measured distance between CH 0 and CH 1 is roughly 31.89 meters. In contrast, it is worth noting that the distance separating CH 2 and the Sink Node is significantly greater, measuring around 158.11 meters. The TSP table plays a crucial role as a fundamental tool in the planning

TABLE 3. Distances (meters) between CH and Sink Node using TSP.

	CH 0	CH 1	CH 2	CH 3	CH 4	Sink
CH 0	0	31.89	96.62	30.69	57.99	103.11
CH 1		0	74.99	38.48	38.95	90.72
CH 2			0	80.77	120.04	158.11
CH 3				0	68.42	107.24
CH 4					0	120.42
Sink						0

TABLE 4. Optimal routes from node 4 to the sink node (round 1).

Route	Energy Consumption (nJ)
Node 4 → CH 4 → CH 3 → Sink Node	**109.36**
Node 4 → CH 4 → CH 1 → Sink Node	115.95
Node 4 → CH 4 → CH 0 → Sink Node	139.69
Node 4 → CH 4 → CH 2 → Sink Node	155.07
Node 4 → CH 4 → Sink Node	120.42

and management of networks within the complex undersea environment.

Table 4 provides a comprehensive analysis of the possible pathways from Node 4 to the Sink node, together with the energy consumption associated with the transmission of information. In the round presented (1), the node 4 belongs to cluster 4. The energy expenditure associated with this activity is roughly 109.36 nanojoules (*nJ*), which is significantly lower compared to the energy consumption of other pathways.

The identification of an ideal route holds great significance due to its potential to substantially extend the operational lifespan of nodes. The conservation of power resources in nodes through the minimization of energy consumption during data transmission enables an extended capacity for active participation in network operations. Energy replenishment alternatives are significantly constrained in underwater situations, making this aspect extremely critical. Additionally, the implementation of this ideal route guarantees the maintenance of dependable and efficient communication, hence enhancing the overall efficacy of the network.

CTSP incorporates error mitigation strategies to cater for the observed redundancy in the transmitted information and error correction. These procedures are incorporated to mitigate the impact of high error rates and endure reliable communication between the nodes. Communication between nodes is also hampered by the limited bandwidth. To tackle this problem, it is important to introduce a compression scheme to minimize the utilization of the available bandwidth. By using channel coding, effective communication is made possible even in situations when bandwidth is limited. The proposed strategy makes use of dynamic power management techniques to improve the sensor network's energy efficiency. The protocol minimizes energy usage by dynamically adjusting power levels in response to the network's operating needs. This helps to extend the network's lifespan overall, which is an important goal with limited energy resources. Effective energy use in difficult underwater settings is crucial, and CTSP helps to make operations more sustainable and energy-efficient by minimizing unnecessary data transmission and lowering the energy demand on individual sensor nodes. Even if the nodes are densely populated, it will only increase the network lifetime as more nodes means there are enough cluster heads to switch.

TABLE 5. Optimal routes from node 1 to the sink node (round 2).

Route	Energy Consumption (*nJ*)
Node 1 → CH 1 → CH 4 → Sink Node	88.51
Node 1 → CH 1 → CH 3 → Sink Node	**87.08**
Node 1 → CH 1 → CH 0 → Sink Node	110.82
Node 1 → CH 1 → CH 2 → Sink Node	126.49
Node 1 → CH 1 → Sink Node	90.72

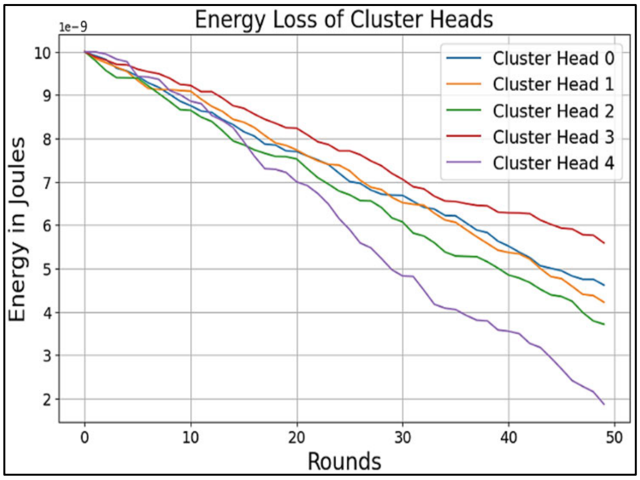

FIGURE 4. Energy dissipation of each CH for 50 rounds.

Table 5 provides an overview of the possible pathways for the subsequent phase of communication from Node 1 to the Sink node. Every row in the table represents a unique path that has been meticulously planned to optimize energy efficiency during data transmission. Among the many paths considered, it is noteworthy that through CH 3, it exhibits superior energy efficiency, as it incurs an expenditure of roughly 87.08 nanojoules. By choosing this method, nodes have the ability to enhance their energy efficiency, therefore prolonging their operational longevity in circumstances where resources are limited. In this second round, node 1 belongs to cluster 1 as its relaying it informs CH 1.

With the objective of studying the energy dynamics inside the network, the Fig.4 presents the energy consumption trends of the CHs, particularly highlighting the energy usage of Cluster 4. The evidence suggests that Cluster 4 is undergoing a significant depletion of its energy supplies at a quick pace. The observed phenomena can be ascribed to the significant

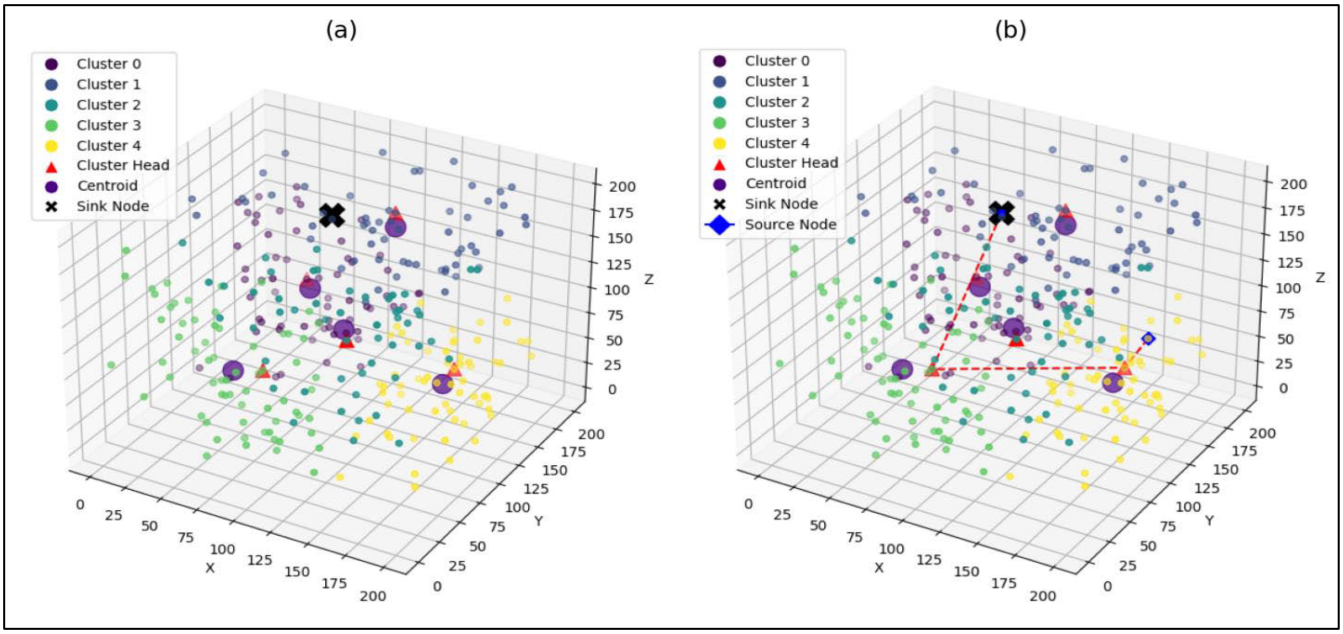

FIGURE 5. **(a) Sink node included. (b) Optimal path for the first round of transmission.**

spatial separation between the Sink node and the source, leading to extended pathways for data transmission. Furthermore, the CH of Cluster 4 is positioned at a considerable distance from the remaining CHs, hence intensifying its energy depletion. The state of isolation experienced by this cluster necessitates a heightened dependence on its internal energy reserves for the purpose of data transmission, thereby leading to a greater rate of energy consumption in comparison to the remaining clusters. In contrast, the remaining clusters demonstrate a more even distribution of energy expenditure. The closer proximity of the nodes to both neighboring clusters and the Sink Node enables the establishment of more direct and efficient channels for data transfer. The close closeness between nodes results in reduced transmission distances, leading to energy conservation and increased longevity of the CHs. Cluster 0 exhibits notable energy conservation practices, which can be attributed to its advantageous positioning in relation to the Sink Node and its CH.

Fig. 5 highlights the fundamental significance of network topology in the domain of energy management. Clusters that are located closer to important network nodes, such as the Sink Node, have the potential to experience a decrease in energy consumption. On the other hand, clusters situated in the outskirts of the network experience increased energy requirements as a result of longer transmission routes. This observation underscores the necessity of employing smart cluster placement and routing algorithms that give precedence to energy efficiency. By implementing this approach, nodes are able to more effectively distribute their energy resources, hence reducing the occurrence of early energy depletion and optimizing the overall lifespan of the network. Fig. 5(a) introduces a sink node, whereas Fig. 5(b) displays the most optimum path indicated in table 2. Table 3 depicts the sample for the 2^{nd} round of communication, in this case the source node belongs to Cluster 1.

VIII. CONCLUSION

This research introduces a method for enhancing the efficiency of data routing in UWSNs via the integration of the Traveling Salesman Protocol (TSP) and clustering methodologies. Our suggested solution efficiently addresses the primary challenge of saving energy in sensor nodes working in underwater conditions. Our proposed methodology focuses on optimizing the paths used by sensor nodes for transmitting data, to substantially reduce the network's total power consumption. The approach used in our study utilizes two essential elements, namely the Traveling Salesman Problem (TSP) and clustering. The use of the Traveling Salesman Problem (TSP) enables the calculation of the optimal route connecting any two sensor nodes inside the network. This mechanism guarantees that every node solely sends data to its nearest neighbor, hence decreasing the energy consumption needed for transmission. Furthermore, our clustering technique leverages the spatial coordinates of sensor nodes to establish coherent groupings. Because of this phenomenon, there is an improvement in communication inside clusters and a decrease in the need for communication between distant clusters, leading to significant energy conservation. The findings of our study have wide-ranging ramifications for many applications inside underwater habitats. Our approach shows potential for transforming data routing tactics, ranging from marine surveillance and offshore oil and gas development to the use of underwater robots. The incorporation of the Traveling Salesman Problem (TSP) with clustering techniques not only guarantees the achievement of optimum data transmission but also significantly enhances the longevity of sensor networks. This is especially important in circumstances where the task of recharging or changing batteries is very difficult.

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