

## Research Article

# An Effective Data-Collection Scheme with AUV Path Planning in Underwater Wireless Sensor Networks

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Data collection in underwater wireless sensor networks (UWSNs) using autonomous underwater vehicles (AUVs) is a more robust solution than traditional approaches, instead of transmitting data from each node to a destination node. However, the design of delay-aware and energy-efficient path planning for AUVs is one of the most crucial problems in collecting data for UWSNs. To reduce network delay and increase network lifetime, we proposed a novel reliable AUV-based data-collection routing protocol for UWSNs. The proposed protocol employs a route planning mechanism to collect data using AUVs. The sink node directs AUVs for data collection from sensor nodes to reduce energy consumption. First, sensor nodes are organized into clusters for better scalability, and then, these clusters are arranged into groups to assign an AUV to each group. Second, the traveling path for each AUV is crafted based on the Markov decision process (MDP) for the reliable collection of data. The simulation results affirm the effectiveness and efficiency of the proposed technique in terms of throughput, energy efficiency, delay, and reliability.

## 1. Introduction

In the last decade, most systems have been investigated for dynamic environment. Probably, the most popular system in this area is the underwater wireless sensor network, which refers to the organized interconnection between various sensor nodes and other devices such as autonomous underwater vehicles (AUVs), which are situated in an observing domain to offer explicit applications, e.g., data collection without the intervention of humans [1–4]. Recent developments in various hardware and software technologies have provided underwater sensor nodes with identifying, sensing, processing, computing, and networking capabilities. Therefore, the UWSN vision includes many applications such as navigation, object localization, detection of mines, and environmental pollution monitoring [5–8]. AUVs are widely employed for these applications in gathering data from UWSNs. An AUV

that acts as a mobile sink may efficiently minimize sensor node transmission energy; the AUV could travel to the monitoring area for data gathering from the sensor node using a specified path plan. The AUV would travel, gather, and return to the surface sink to upload the collected data effectively. Figure 1 shows the UWSN [9].

In UWSNs, energy-efficient reliable data collection and aggregation is one of the most critical challenges to meet the requirements of quality of service (QoS), including transmission delay, a priority of data, reliability, and energy consumption [10]. Aggregation of data is an intelligent technique that aggregates data from many UWSN sensor nodes compressed by an aggregation feature to reduce the amount of inserted data traffic in the network [11, 12]. The prime objective of data aggregation is to execute an algorithm at sensor nodes to reduce redundant packet transmission to the sink through AUVs, reduce data transmission

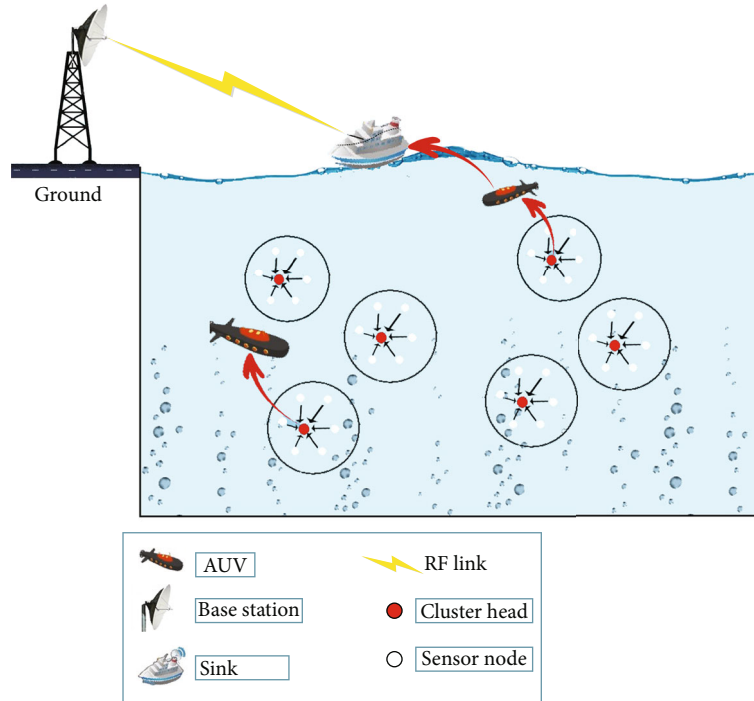


FIGURE 1: Diagrammatic representation of AUV-based UWSN.

delay, and improve energy use, ultimately enhancing network lifetime. This method gives UWSNs three advantages: (1) in the network, the injected data size is decreased; (2) the delay will be substantially decreased; (3) the transfer of fewer data will help nodes consume less energy, thus maximizing the lifetime of UWSNs.

Limited battery capacity affects sensor node lifespan and decreases system efficiency [13]. Therefore, it is essential to use an effective and energy-efficient data collection method for effective and sustainable UWSN efficiency. As wireless communications generate substantial amounts of energy during data aggregation in UWSNs [14, 15], achieving an efficient link between nodes and effective path planning of AUVs for data collection is a significant challenge.

Most of the existing data-collection approaches in UWSN can be categorized into hop-by-hop, cluster-based, and AUV-assisted [16–18]. In hop-by-hop, data packets are transmitted from the source sensor to the destination in a hop-by-hop manner. However, redundant packets are still a challenging issue in such approaches; therefore, we introduced a clustering technique in the proposed scheme to control the retransmission of packets. The cluster-based strategies organize UWSN into clusters in which each cluster head (CH) is designated to collect data from member sensor nodes and forward it to the sink/AUV. Improved network communication, well-organized topology management, and energy efficiency are the advantages of the clustering method. However, CH selection is a critical problem because CH uses more energy to collect and aggregate data before delivering it to its destination. The introduction of AUV is a promising method to save the wasted energy of sensor nodes during clustering. In AUV-based approaches, the sensor nodes/CHs connect with an AUV to conduct the collec-

tion process, and the AUV then transfers the collected data to the sink node. Due to regular AUV position changes, the transmission of control packets to maintain connections between all the sensor nodes, and the AUV results in a substantial amount of energy dissipation, which reduces the network lifetime. Furthermore, the sensor nodes located closer to the AUV use energy rapidly because of the repeated single-hop packet transmission. On the other hand, the sensor nodes far from the AUV sending data directly to the AUV will also consume substantial energy. Therefore, a cluster-based routing design can help minimize transmission energy use.

Although the above methods minimize the energy consumption and improve the life cycle of the UWSNs to some extent, they face additional challenges, including data priority and transmission delay [19–21]. Collection of data has different preferences, since underwater sensor nodes are being installed at diverse locations in the surveillance environment. Few sensor nodes can sense vital information that needs to be collected faster; therefore, the demise of sensor nodes with high priority data would have a larger effect on network stability as compared to other nodes. In UWSN, transmission delay can be specified as the time required to receive all sensor node-generated packets to the sink. In addition, in most of the current approaches in the literature, the sensor nodes near the sink node die earlier than the other sensor nodes, which are far from the sink node, making the whole network useless [22]. Therefore, deploying multiple AUVs is more efficient for resolving data priority problems in UWSNs, transmission delay, energy restriction, and heterogeneity [23, 24]. To use these AUVs effectively, the path planning of each AUV is an essential task, and it also affects network performance [25].

In AUV-based UWSN, the data-collection path taken by AUV could not be neglected. The parameters that rely on the AUV path are energy consumption, network dispersion, data-collection latency, and network lifetime. Fixing the AUV traversal path does not ensure the best and optimal path. To establish the optimal collecting path, we used the traveling salesman problem (TSP) to design the AUV traversal path from the sink to CHs. Many heuristic approaches, such as simulated annealing, greedy method, and genetic algorithm, have been employed to solve the TSP efficiently. In our situation, MDP was used to solve TSP by determining the optimum route to make it possible for the AUV to reach the CHs and then return to the surface sink. We also focused on the energy and data priority parameters of CHs when proposing a traveling path.

Recently, research has been carried out on the AUV-based data collection in UWSNs, such as the greedy and adaptive AUV pathfinding (GAAP) protocol presented by Gjanci et al. [26]. GAAP derives the AUV path to gather the sensed information from nodes and transmits this information to the sink node with the maximum value of information (VoI). GAAP imitates the best routes and obtains the volume of the data provided. Although it is ideal for AUV to tour all the sensor nodes, its prolonged tour time might cause delays in emergencies. Additionally, if AUV travels to all the sensor nodes, AUV must wait until all information is collected from each node before going into the next sensor node. It is possible to conserve transmission energy in UWSNs using AUVs to reach every sensor node and collect data from them. However, this method creates significant collection delays and limited throughput because of low AUV velocity. Thus, AUV-based UWSNs need to optimize network throughput and energy consumption. To encounter these problems, we are driven not only to design a path for an AUV to enhance network throughput and decrease its traveling time but also to establish a network in such a way that decreases energy consumption.

This article suggests an efficient data-collection protocol for UWSN with AUV path planning based on the MDP (APP-MDP). The following are the main steps of our approach: to decrease AUV traveling time and increase energy efficiency, we employ a clustering approach. Each CH collects data from its member node and transfers it to the AUV. After clustering, CHs will be selected based on holding time, and then, the division of clusters into small groups is the means of an angle-based approach. After grouping, the sink node determines the MDP parameters for each AUV. It then calculates the optimal policy using a value-iteration process. This step helps with efficient path planning for each AUV visiting their particular group of CHs. The AUV transfers the collected data of CHs to the sink node. The simulation results verify the efficiency of our proposed scheme in optimizing energy consumption, reliability, and data transfer relative to recent UWSN data-collection approaches.

The main contributions of this article are summarized as follows: (1) the development of an energy-efficient method in UWSNs for the collection of data using AUVs; (2) the clustering of sensor nodes, applying angle-based grouping

strategy to arrange CHs in nonoverlapping and energy-efficient groups for providing an AUV; and (3) the development of a novel efficient method of path planning for AUVs using MDP to collect the data from CH groups.

The rest of the paper is arranged in the following manner: Section 2 describes the related work. Section 3 describes the network model and channel model. Section 4 describes the proposed mechanism, and Section 5 describes the simulation results and analysis.

## 2. Related Work

Data-gathering schemes are designed based on routing algorithms. Earlier studies have proposed many data-gathering schemes where the transmission of data is accumulated using clustering schemes or data gathering using hop-by-hop methods. In these methods, sensed information is sent hop-by-hop alongside the routing tracks. In this way, routing schemes assume an essential role in these methodologies. UWSN is unique concerning terrestrial wireless sensor networks (TWSN) because the sensor nodes drift with water streams automatically underwater. The intended protocol for TWSNs could not be functional for UWSNs straightforwardly. In this manner, the research focuses on structuring an AUV-based reliable and energy-proficient routing protocol. We divide the related work into the following subsections.

*2.1. Multihop Techniques.* In multihop techniques, the source node uses a relay node to direct the sensed data towards the sink nodes, positioned on the water's surface using routing mechanisms like the shortest-distance strategy and greedy approach. In HH-VBF [27], the direction of a virtual pipeline between the forwarding node and destination node was established. Every time at the next hop, the path of the virtual channel is adjusted to select the most favorable forwarding node. Additionally, the packets are transmitted through that vector, which was established in this plan, because adaptive adjustment of the virtual pipeline on hops will increase end-to-end delay, and much energy will also be consumed.

To overcome the problem of end-to-end delay, the authors in [28] anticipated a routing protocol layer-by-layer angle-based flooding (L2-ABF). This is deployed in layers and measures the sensor node depth. This method uses the multihop technique where all sensor nodes convey data to the destination node by calculating the flooding angle. The appropriate next forwarding node is nominated through the remaining energy. This paper attained a higher packet delivery ratio, and the energy consumption is also low. However, in any case, the decision of flooding angle is a troublesome assignment, particularly in sparse regions. If the flooding angle is not suitable, the possibility of transferring data may cause failure, so it was not appropriate in the sparse areas. Yu et al. presented the AHH-VBF [29] protocol for sparse regions. In this protocol, the radius of the virtual pipeline is adaptively accommodated for packet broadcasting. This protocol changes transmission power dynamically according to the next forwarder to compute holding times

from the source to destination nodes and reduce redundant transmissions to diminish energy consumption. However, each transmission of data through selected nodes will cause the node to die earlier, determined each time for data forwarding. Therefore, the network void hole problem occurs due to higher energy consumption.

To overcome the void hole problem, 2hop-AHH-VBF [30] considered various parameters such as the distance between receiver and sender, residual energy of next appropriate node, a threshold value for the number of nodes in the vector, and from a virtual vector, the distance of the chosen node. The purpose is to avoid consecutively choosing the same node. Well-organized battery dissipation is guaranteed using appropriate node recommendations. Energy calculation is performed at every hop to oblige any adjustments in the capacity for proper node determination as a next forwarder to obtain better results regarding network performance.

*2.2. Clustering Approaches.* For the reduction of end-to-end delay and better energy efficiency, clustering is the most capable method when planning the routing protocol for UWSNs. In UWSNs, because of the sparse deployment of sensors and harsh environments, clustering is not the same as terrestrial networks. The clustering technique is incorporated to manage the restricted energy constraints in UWSNs. A definitive goal of clustering is to separate the system into tiny areas and make a group of nodes. Each cluster elects one CH considering different parameters. CH totals the detected information and transfers it to the target node (sink node). Propagation distance between sensor nodes is reduced using clustering because only the CHs send the information, and these CHs have a small distance with each other.

Furthermore, this limits the consumption of energy by evading excess information packets. For communication among different clusters, a reasonable topology ought to be chosen. This determination relies upon the cluster size and separation among the sink node and CH [31]. The ideal number of clusters also influences UWSN execution. If the clusters are fewer, this implies that the size of the cluster will be bigger. In bigger estimated clusters, sensors beyond CH desire additional energy to direct the information towards CH. However, if the size of clusters is small, this will cause communication overhead. Therefore, the size of the cluster ought to be kept ideal, neither small nor huge. The perfect number of groups will eventually lessen energy use and improve system lifetime.

ACH2 is introduced in [32]. The primary factor of this scheme is that it is a localization-free process where the nodes are allied with CHs. This plan avoids back transmission and reduces propagation distance. This reduces energy use and results in an improved system lifetime. In this approach, first, based on a threshold value, CHs are chosen. The ideal number of cluster heads is determined based on the perfect distance; due to this method, the loads are adjusted among different clusters. The authors in this article have accomplished improved system lifetime and attained maximum packet delivery ratio (PDR) for UWSNs. How-

ever, a high communication delay occurred in this plan. In homogeneous networks, this strategy can be useful, but any dynamicity or unbalance in WSNs might cause intensive run-time issues, such as chronic energy consumption in specific CHs.

Clustering techniques are implemented in [33] for routing in UWSNs to improve network lifetime. Cluster-based routing protocols comprise the CH selection process and data communication process. First, the CH node is selected based on sensor nodes' residual energy and position information. All the cluster members forward data to their respective CH in its range in the data communication process. The CH node then compresses aggregated data and sends a composite compressed data packet to sink through multihop communication. Moreover, a collision occurs in data packet transmission, which is avoided using the time division multiple access (TDMA) technique. Due to the algorithm's centralised nature, it caused high communication overheads.

*2.3. AUV and Mobile Agent-Based Approaches.* The authors in [34] used the MDP paradigm to formulate the data-collection problem in mobile wireless sensor networks. The ideal movement routes for mobile agents collecting sensor node readings are defined. The mobile agent's location determined the states. The monitoring region is divided into a sector, and each mobile agent directs towards a predefined sector to collect data. The reward function indicates the node energy use and the number of readings gathered. The simulation results indicate that the approach presented surpasses traditional approaches, such as TSP-based approaches. However, the author did not consider the importance of data and residual energy parameters while formulating the MDP parameters. Due to less residual energy, some nodes need importance to collect data, which is why in our approach, we also include the importance of data parameters during MDP parameter formulation.

A mobile geocast routing protocol (3-D ZOR) [35] has been proposed for UWSNs, in which the network is distributed in 3-D ZOR areas. AUV is introduced to gather data from nodes in its vicinity, and the geographic zone where the AUV resides is called 3-D ZOR. At a predefined trajectory, the AUV moves and gathers sensed information from different 3-D ZORs. Sleep-awake mode is used by nodes for data forwarding. The operation of the routing protocol depends on two stages. First is collecting information from sensor nodes inside the 3-D ZOR areas and in the other phase wakes up those nodes to forward data to the AUV in the next 3-D ZOR. Only nodes in the 3-D ZOR forward data to the AUV to save the node power consumption. However, the authors did not consider that much nodes inside the coverage region should be employed to deliver the packet which is a key issue for this approach.

An AUV-based routing protocol in [36] has been proposed for UWSNs. The authors assumed random deployment of identical sensor nodes in the network. The sensor nodes then perform the clustering technique and mutually elect a CH node in each cluster. Each CH node further divides the clusters into subclusters and distinguishes a key

data-collection node called the PN node. To achieve energy conservation, AUV is introduced to gather data from PN. Thus, data collection from PN is done instead of CH as in conventional schemes. Therefore, using AUV for PN data collection achieves efficient sensor node transmission. This scheme enhances the data gain and diminishes the node's energy consumption. However, it experiences severe gathering delay when contrasted with multihop transfer strategies.

In addition, Javaid et al. [37] proposed an AUV-based routing protocol for UWSNs (AEDG) to maximize data reliability in the network. In AEDG, sensor nodes are associated with special nodes (called gateway nodes) using the shortest path selection algorithm (SPA) to improve the network lifetime. All other nodes are associated with special nodes to forward their sensed data. The special nodes accumulate data from member nodes and then forward it to the AUV, which consumes energy efficiently and ensures reliability. Thus, the least number of normal nodes (member nodes) is associated with special nodes to reduce overloading. The AUV traveling ways are not ideal, and the coordinated effort of AUVs between various GNs was an exceptionally troublesome assignment. The plan decreased the delay and member node's energy consumption; however, it might practice the problem of a hot zone.

Cheng and Li anticipated a data-gathering plan that underlined the significance of data [19]. The high load of data forwarding from deep underwater nodes to sink depletes their energy rapidly. The imbalanced energy expenditure of underwater nodes because of multihop transmission in deep water is efficiently mitigated by announcing AUVs to collect data from deep underwater nodes. It identifies the importance level of data and then gathers data in a distributed manner. A mechanism to swap layers is introduced to effectively solve long time delay and imbalance energy consumption problems by introducing AUVs for data collection, improving network performance, and achieving better network lifespan. Due to the extent of significant data, the impact of delay and energy consumption is unsatisfactory for the entire system.

For the most part, fewer researchers take hop-by-hop transmission or clustering for data gathering alone; a large portion of them have started to merge these two methods to deal with configuring better data accumulation schemes. In the future, when structuring novel methodologies, it is essential to know strategies for individual points of advantages and drawbacks. This article uses the benefits of different transmission modes of underwater wireless networks to show the interconnection between other sectors, which empowers efficient and distributed data-collection schemes from underwater nodes to the nodes at the water's surface. The ratio of data delivery underwater is meager, and the BER is very high due to UWSN harsh environment. Delivery ratio, energy consumption, and the bit error rate can be enhanced using decent-quality links. Therefore, better path planning with decent-quality links is a significant problem.

Clustering-based routing schemes extend the efficiency of the network to some extent, such as network lifetime and energy consumption. However, the challenges not considered during planning data aggregation schemes include

the delay of data transmission and the priority of data. Moreover, it is already discussed in the above literature that nodes near the sink consume energy faster than other sensor nodes that are far from sink nodes. Therefore, it is crucial to exploit the abilities of AUVs for the collection of data from underwater sensor nodes.

### 3. Network Model

In this article, the UWSN is shown as  $M = (N, L)$ , in which  $N$  is the number of sensor nodes and  $L$  is the links among sensor nodes. The networking area is considered to be  $A \times A \times A$ , and the sink node is placed at the surface in the center. The sensor nodes are homogeneous and have the same transmission capabilities. Sensor nodes are equally distributed around the networking area using a pressure gauge [38]. Each node determines its position using existing localization algorithms [39, 40], and the sink node knows the location of nodes. A sensor node  $S_i$  has the following properties:

- (i)  $D_{ij}$ :  $D_{ij}$  presents the Euclidean distance between the sensor node  $S_i$  and sensor node  $S_j$ , a fundamental factor in ensuring effective path planning for data collection through AUVs on UWSN
- (ii)  $Dis$ :  $Dis$  is the Euclidean distance between sensor node  $S_i$  and the destination node, a sink node that plays a vital part in recommending well-organized path planning for AUVs in UWSNs. In this proposed process, it is considered that the surface sink nodes remain fixed at the surface of the networking area, and the AUVs are repeatedly approaching or retreating from it
- (iii)  $RE_i$ :  $RE_i$  represents sensor node ( $S_i$ ) residual energy. During the initialization of the network, each sensor node has specific initial energy, which is dissipated by packets sending/receiving and processing tasks by the AUVs. The sink node energy is considered to be unlimited
- (iv)  $\beta_i$ : sensor node ( $S_i$ ) priority of data is demonstrated by  $\beta_i$ . As various sensor nodes are deployed at different monitoring areas, UWSN data collection has varying preferences. A sensor node provides critical data that needs to be collected early. Specifically, if a sensor node with high priority dies, the system's stability is diminished when a sensor node with low priority fails
- (v)  $Tr$ : this is the sensor node transmission radius

The suggested environment has  $k$  AUVs for the collection of data from CHs. Each AUV overall memory size is presumed to be  $P$ , while it has a space of memory represented by  $QP$  during data collection. The sensor nodes of the network are divided into clusters. Each sensor node in the network transmits its sensed information to its CH,

which provides enough memory to buffer the data obtained from cluster members. Additionally, the selected CHs are supposed to be clustered into  $R$  groups. After defining cluster head groups, for collection of data, sink node assigns AUV for every group. Thus, the CH groups and AUVs are equal in number, and this is represented by  $R$ . Table 1 lists all the notations.

**3.1. Channel Model.** The UWSN channel is a challenging communication medium due to poor communication quality and restricted bandwidth. The channel's time-varying and high-frequency selective aspects also make it challenging to develop an effective communications strategy. Different parameters influence the function of acoustic channels, such as water depth, temperature, and salinity. Figure 2 [41] demonstrates the relationship between water depth and acoustic speed using thermoclines. Equation (1) [42] shows the acoustic signal speed:

$$\begin{aligned} S = & 1555.85 + 3.481T - 4.204 \times 10^{-2} \\ & T^{-2} + 3.26310^{-2}T^{-3} + 1.230(Y - 25) + 1.53 \times \\ & 10^{-1}D + 1.565 \times 10^{-6}D^2 - 1.035 \times \\ & 10^{-2}T(S - 25) - 6.129 \times 10^{-14}TD^3, \end{aligned} \quad (1)$$

where  $S$  demonstrates the acoustic signal speed,  $T$  represents the temperature (0-28 degrees Celsius),  $Y$  reflects salinity (30-40 parts per thousand), and  $D$  represents the water depth (0-6000 meters). In UWSN, the acoustic channel attenuation is described [24].

$$A(d, fk) = d^\rho \alpha(fk)^d, \quad (2)$$

where  $\rho$  is the fixed spreading factor 1.5 and  $d$  in meters.  $\alpha(fk)$  represents the absorption coefficient, which could be shown by the empirical formula of Thorpe [24]:

$$10 \log \alpha(fk) = \frac{0.1f^2k}{1 + f^2k} + \frac{40f^2k}{4400 + f^2k} + \frac{2.75f^2k}{10^4} + 0.0003. \quad (3)$$

Equation (3) is ideal for high frequencies and equation (4) for lower frequencies.

$$10 \log \alpha(fk) = \frac{0.1f^2k}{1 + f^2k} + .01f^2k + .002. \quad (4)$$

The noise of underwater can be stated as [42]

$$N(f) = N_{th}(f) + N_w(f) + N_t(f) + N_s(f), \quad (5)$$

where  $N_{th}(f)$ ,  $N_w(f)$ ,  $N_t(f)$ , and  $N_s(f)$  specify thermal, waves, turbulence, and shipping noise. Mathematically, the level of noise frequency is low, and the attenuation frequency is high. The signal-to-noise ratio can be expressed as

$$\text{SNR}(f, d) = P(f) - N(f) - A(d, f), \quad (6)$$

where  $P(f)$  states transmission power,  $N(f)$  specifies noise, and  $A(d, f)$  represents attenuation.

In contrast to the aforementioned parameters, acoustic modems are an essential component of acoustic channels and influence communication. They are classified as acoustic modems for research and commercial acoustic modems. The properties of commercially available acoustic modems are summarized in Table 2 [43].

## 4. Mechanism of the Proposed Scheme

In Figure 3, the proposed scheme is shown. This method consists of two main steps.

- (1) First of all, sensor nodes are organized into clusters for better scalability. We employ the K-mean algorithm [44–46] as a clustering mechanism as it is pretty adaptive, resistant to outliers, and is shown to be efficient for clustering. After clustering, CHs are defined in each cluster, which is grouped using the angle-based [46] method into the same size sectors based on available AUVs. In the first stage, each group includes at least one CH near the sink to obtain the AUV and send back the AUV to the sink after collecting all CH group's data. Reliable, accurate, and nonoverlapping CH groups for AUV placement are the outcomes of this step
- (2) The second step was aimed at giving an effective path planning for each AUV employing the MDP to each CH group separately. The MDP is regarded for its effectiveness in maximizing uncertain decision-making [47–49]. Sensor nodes are prone to failures due to malfunctioning of various components such as hardware, software, and power, resulting in uncertainty and instability. MDP uses sophisticated decision-making techniques based on artificial intelligence to successfully trade off reliability, energy consumption, data priority, and delay. Using the value-iteration process [47], the optimal strategy (the best series of UWSNs nodes that each AUV can visit) is obtained until the parameters of the MDP are determined. In the cases where only the initial state is known [50], the approach is an appropriate forward induction. The value-iteration approach is the best option in our proposed model because only the AUV's first destination is defined

When each AUV path planning is established at the sink node, the sink node directs AUVs to collect data from groups of CH. The sink node determined the final condition to end or continue the mechanism. The overall mechanism is shown in Figure 4.

Figure 4 shows the flowchart of the proposed scheme. The scheme consists of two main phases. In the first phase, we have done clustering of sensor nodes and then grouping CHs to assign an AUV. In the second phase, the scheme exploits MDP parameters to model AUV path planning. After calculating MDP parameters, a method called value iteration is used to determine the best order of CHs, which the AUV should go to.

TABLE 1: Notations.

Notations	Definition
$N$	Number of sensor nodes
$L$	Links of communication between sensor nodes
Dis	The Euclidean distance among sensor node $S_i$ and the destination node
RE $_i$	RE $_i$ represents sensor node ( $S_i$ ) residual energy
$\beta_i$	Sensor node ( $S_i$ ) priority of data
Tr	Sensor node transmission radius
D $_{ij}$	The Euclidean distance among the sensor node $S_i$ and sensor node $S_j$
$P$	AUV overall memory size
QP	Empty memory of an AUV
$R$	CH groups
$A$	Monitoring area
$\rho$	Fixed spreading factor
$\alpha(fk)$	Absorption coefficient
$D_{bs}$	Distance between the sensor nodes and sink
$T$	Time period
$\epsilon_{edtr}$	Dissipated energy for transmitting and receiving of single bit data
$G$	State space
N $_i$	Corresponds to CH $S_i$ transmission radius
R $_{ij}$	Corresponds to distance among CH $_i$ and CH $_j$
$M$	A set in which recent visited CHs data is stored
$Q^1 \text{ Re}(z_i, y_j)$	Revenue to select a CH which have a reduced amount of residual energy
Re $_j(i)$	CH $_j$ initial energy
Re $_j(t)$	Corresponds to CH $_j$ residual energy at a time $t$
$Q^2 \rho(z_i, y_j)$	Corresponds to priority of data of CHs
$\forall$	Risk region
$Q^1, Q^2, Q^3, \text{ and } Q^4$	Reward compensation coefficients

4.1. *Clustering and Grouping of CHs.* The cluster center will be measured first to decide the cluster's final number. Suppose the network's initial cluster center number is  $R$ , and the total node number is  $N$ . Given the average case, each group would have  $N/R$  nodes. Assume CHs forward data directly to the sink. Consider the network area is  $A * A * A$ . The ideal number of clusters according to [45] would be

$$R = \sqrt{\frac{NA}{\pi D_{bs}}}. \quad (7)$$

$D_{bs}$  is the distance between the sensor nodes and sink.

After the initial  $R$  cluster centers are obtained, we use the K-mean algorithm to cluster the network. Distance represents the proximity of nodes, and as a consequence, the usual measuring function is equivalent to the total of the square distances among the cluster center and nodes:

$$L = \sum_{i=1}^R \sum_{x \in C_i} D(C_i, x)^2. \quad (8)$$

The assortment of CHs will begin after clustering is done. The sink node will use the following equation to measure each node's holding time ( $Ht$ ) in each cluster. Each node has its own  $Ht$  which is different from other sensor nodes.

$$Ht = T + \rho \times \frac{Er}{E0}, \quad (9)$$

where  $T$  is the period time and  $\rho$  [1, 0.5] is any conflict avoiding value if nodes have equivalent residual energy. From equation (9), we can determine that if the residual energy of a node is high, thus the node will have a lower holding time than other nodes. It will have a better opportunity to choose as CH. When the holding time of a node expires, the node will be selected as CH, which has a lower holding time in the cluster. If multiple nodes have the same holding time ( $Ht$ ), the node with a high probability will be selected as CH. The probability can be determined using the following equation [22].

$$p = \frac{1}{e^n + 1}. \quad (10)$$

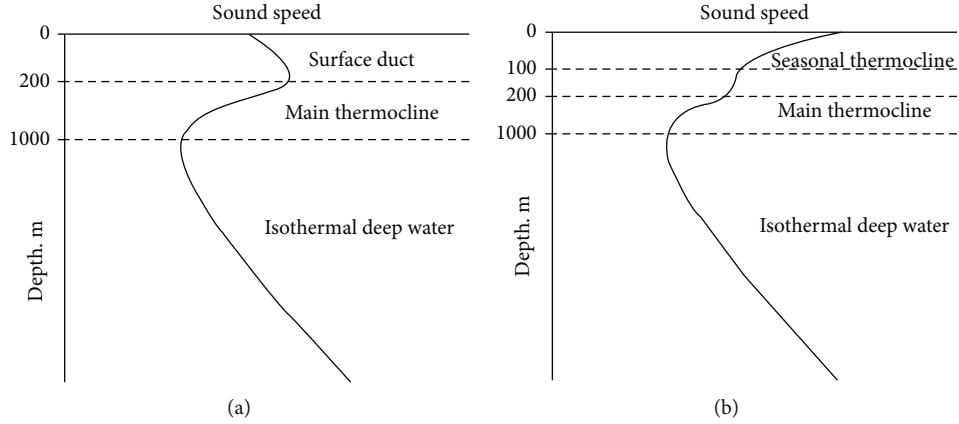


FIGURE 2: Relationship between water depth and acoustic speed using thermoclines for both winter (a) and summer (b) with depth of 200 m.

At this stage, to group CHs, the AAP-MDP system uses an angle-based method [46] to allocate one AUV to each influential and nonoverlapping group. The whole area is categorized into sectors having an equal size, depending on the expected quantity of AUVs. To find adequate AUVs (CH groups), we apply the following equation [46].

$$Y = \sqrt{\frac{A\varepsilon_{\text{edtr}} |N|}{\varepsilon_{\text{edtr}}(A/6) - E}}, \quad (11)$$

where  $A$  is the monitoring area sides and  $\varepsilon_{\text{edtr}}$  determines the dissipated energy for transmitting and receiving of single-bit-data.

In cluster head grouping, every group must first cover a CH near the surface sink and then a predetermined threshold value to obtain the AUV and send back to the surface sink after gathering all group data. The threshold value is calculated for UWSN based on its sensor node's transmission range. To group the CHs, if we implement traditional clustering approaches like the K-mean algorithm, certain clusters would be created at locations far away from the surface sink so no group member can share the AUV and collect data with the surface sink. While if the procedure of angle-based grouping is used, in the first step, each group covers at least one CH, which is placed closer to the surface sink to obtain the AUV for data collection. Therefore, using the angle-based method generates stable CH groups to assign an AUV. Generally, suppose the CHs grouping is not performed. In that case, several AUVs may be allocated to a single CH that raises the inserted traffic through the network and challenges the network delay-aware mechanism and energy efficiency.

**4.2. Formulation of MDP.** This section explains how the MDP model could be used for path planning of an AUV in a UWSN for CH groups. MDP is a statistical optimization framework for making a decision in unpredictable situations [34, 51, 52]. The model assumes that the UWSN is in a given state at any decision and selects one of the possible actions in that state. In addition, after that, due to the transition prob-

ability, UWSN is shifted to a new state, and a reward is obtained. The MDP shall be established by a tuple  $(S, A, P(y, z), R(y, z), \beta)$ , in which  $S$  corresponds to a finite set of states,  $A$  corresponds to a finite set of actions,  $P(y, z)$  corresponds to the distribution of the transfer probability over the group of states when action  $z$  is chosen in the state  $y$ , and  $R(y, z)$  is the reward function for performing action  $z$  at state  $y$ . The solution of a MDP is a policy that determines the action to be taken once a specific state occurs. The quality of a procedure is the expected sum of future rewards. A discount factor  $\beta$  discounts future rewards to ensure that the expected sum of rewards converges to a finite value. Among many potential policies, the optimal reward-optimizing policy ( $\pi^*$ ) is the main aim.

In the proposed method, MDP collaborates among sensor nodes, such as decision-making for AUV's next destination. The MDP parameters are explained for AUV path planning. The parameters of the MDP method are described below for modeling the path of an AUV:

**4.2.1. State Space  $[G]$ .** In our method, we analyze the CH group as a state in the UWSN network when an AUV travels to a particular sensor node/CH. The group state is indicated by a CH identifier on which AUV has been deployed. For path planning of an AUV, the state space is  $Z = [x_1, x_2, \dots, x_n]$ , where  $x_1$  corresponds to the AUV installed at a specific group.

**4.2.2. Action  $[A]$ .** In every group state, decision-making focused on action. In the proposed scheme, the action is a decision regarding the next CH towards which AUV travels. Consequently, some action would be taken if more CHs are available in the current CH transmission radius. In a CH group, for AUV path planning, the actions are measured as  $A = [y_1, y_2, \dots, y_n]$ , where  $y_1$  action demonstrates that the AUV moves towards CH  $S_i$ , and this is the AUV destination over the next phase. Therefore, under any conditions when the  $y_1$  action is chosen, the UWSN's next state would be  $x_i$ . Any action selected in either state would impact the chance of a change to another state over the next step.



TABLE 2: Acoustic modem properties.

Modem	Modulation scheme	Range (m)	Depth (m) (typical-max)	Data rate (bps)	C.F (kHz)	Bit error rate	BW (kHz)	Power consumption (W) (TX)	Power consumption (W) (RX)	Temperature (°C) (min-max)
S2CM HS	S2C	300	200-200	62500	160	10-Oct	80	3.5	0.8	0-60
S2CM 48/78	S2C	1000	200-2000	31200	63	10-Oct	30	18	0.8	0-60
S2CM 42/65	S2C	1000	200-2000	31200	53.5	10-Oct	23	18	0.8	0-60
S2CM 18/34	S2C	3500	200-2000	13900	26	10-Oct	16	35	0.8	0-60
S2CR 48/78	S2C	1000	200-2000	31200	63	10-Oct	30	18	1.1	0-60
UWM2000	BASS	1500	2000-4000	17800	35.7	10-Sep	17.9	2	0.8	(-5) to 45

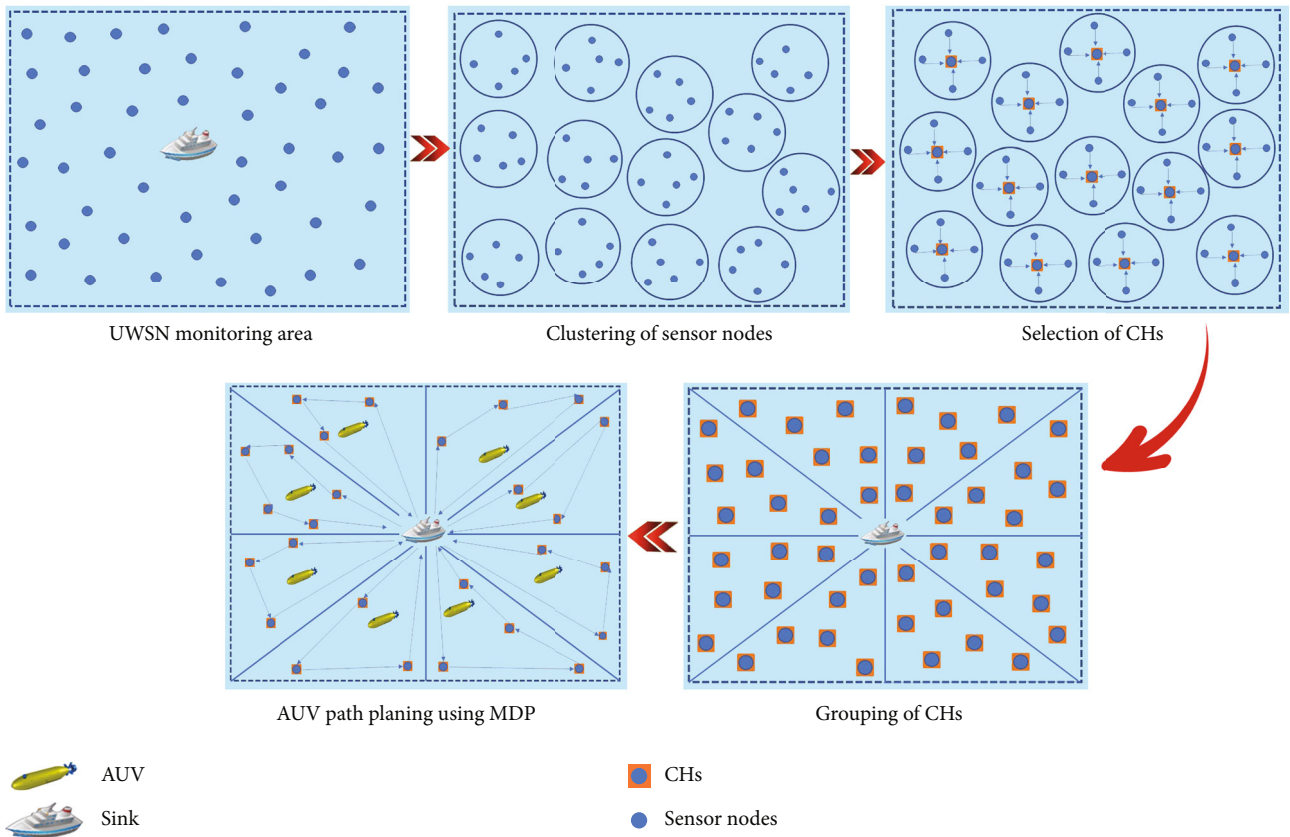


FIGURE 3: Proposed scheme.

4.2.3. *Transition Probabilities.* While taking action, in the following two modes, the transition probabilities would be considered to be null.

- (i) If the CH  $S_j$  location is outside the CH  $S_i$  (AUV present location) transmission radius, CH  $S_i$  will not transfer AUV towards CH  $S_j$ . Thus, the transition probability will be zero in this mode by choosing action  $Y_j$

- (ii) If an AUV has obtained CH  $S_j$  data in the current phase,  $S_i$  could not be picked further before the phase is finished. Therefore, choosing the action  $Y_j$  the transition probability will be zero

In other cases, the transition probability of choosing the  $Y_j$  action is marked among the CH Euclidean distance. So, at either state of the UWSN system, the transition probability would be determined as follows:

$$P(y_i, y_z) = \begin{cases} 0, & R_{ij} > N_i, \\ 0, & j \in M, \\ PR(y_i, y_z), & \text{otherwise.} \end{cases} \quad (12)$$

In the above equation,  $N_i$  corresponds to CH  $S_i$  transmission radius,  $R_{ij}$  corresponds to distance among CH  $i$  and CH  $j$ .  $M$  is a set in which recent visited CH data is stored in the current phase. At first, when the UWSN starts,  $M$  is zero. Thus, the AUV collects information from each CH attached to the  $M$  list. The key goal of state  $j \in M$  is for the AUV only to visit a CH once. At each round, the CHs visited by the AUV would have no chance to acquire the AUV again. The function  $j$  also means the list of any CH and can be expressed as  $[1, 2, 3, \dots, n]$ . At last,  $PR(y_i, y_z)$  could be found using the following formula:

$$PR(y_i, y_z) = \text{CDF}(R_{ij}), \quad (13)$$

where  $R_{ij}$  corresponds to cumulative distribution function.

**4.2.4. Reward Function ( $R(y, z)$ ).** This function uses penalties and revenue to measure the model's outcome when the  $y_j$  action is chosen at the  $z_i$  state. The reward function is determined as follows:

$$R(z_i, y_j) = q_1 \text{Re}(z_i, y_j) + q_2 \rho(z_i, y_j) + q_3 G(z_i, y_j) - q_4 \text{Pe}(z_i, y_j), \quad (14)$$

where  $q_1 \text{Re}(z_i, y_j)$  specifies revenue to select a CH with a reduced amount of residual energy, using this revenue is to collect information from CHs that die quicker than the others to improve UWSNs efficiency.

To fulfill these limitations:

- (i) If the CH  $j$  residual energy is below the threshold value, the AUV cannot be received, and the data is sent to the other CH or sink. In this scenario, the selection of CH  $j$  as the next destination for AUV will be considered null
- (ii) Alternatively, AUV will select the CH as the next destination with less residual energy

It is important to note that the threshold value for CH  $j$  is the total energy desirable to accept the AUV and transfer it to the subsequent CH or sink node.

$$\tau = E_j(A) + E_j(T). \quad (15)$$

$\text{Re}(z_i, y_j)$  could be calculated such as

$$\text{Re}(z_i, y_j) = \text{Re}_j(i) - \text{Re}_j(t), \quad (16)$$

where  $\text{Re}_j(i)$  is the CH  $j$  initial energy while  $\text{Re}_j(t)$  corresponds to CH  $j$  residual energy at a time  $t$ .

$q_2 \rho(z_i, y_j)$  corresponds to the priority of data of CHs. The AUV prefers to collect the data of those CHs that prioritize more than other CHs. The goal is to manage high-value

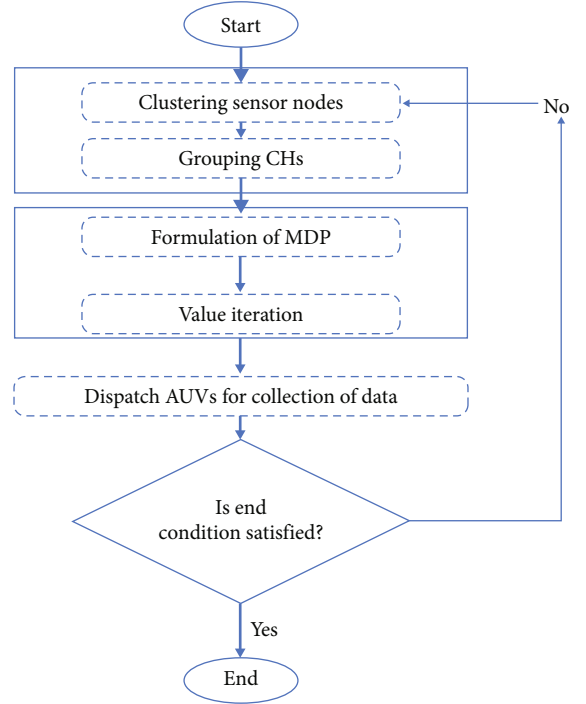


FIGURE 4: Flow chart of the proposed mechanism.

data in advance to avoid data loss if the AUV data memory is full.  $q_2 \rho(z_i, y_j)$  could be determined as

$$q_2 \rho(z_i, y_j) = \begin{cases} \beta_1, & \text{Low,} \\ \beta_2, & \text{Medium,} \\ \beta_3, & \text{High.} \end{cases} \quad (17)$$

In which  $\beta_1, \beta_2$ , and  $\beta_3$  are revenue that takes data priorities into account. It must be considered that data priority parameters can require various values based on the specifications of the different UWSN applications.

$G(z_i, y_j)$  is to select CHs as the AUV next destination near the sink than the ones not yet reached to sink. Since the amount of valuable data in AUV memory expands when accessing each CH, AUV tends to reach the sink progressively to reduce injected network traffic; therefore, the energy usage of the CHs and the lifespan of the sensor nodes as a whole will be improved.

$$G(z_i, y_j) = \begin{cases} \partial, & d_{js} < d_{ms}, \\ 0, & \text{Else.} \end{cases} \quad (18)$$

$\partial$  is revenue and assumed to be the next destination of the AUV to choose the closest CH to the sink, where  $d_{js}$  corresponds to Euclidean distance among the sink node and AUV selected CH as the next destination and  $d_{ms}$  is the smallest Euclidean distance among sink and unmet CHs. In different applications, this parameter may have changed values.

At last,  $P(z_i, y_j)$  is the penalty for choosing the CHs arriving in the area of risk. The AUV is less interested in

```

1: Input: initial energy of all sensor nodes, set of Pi (data priority), sink and sensor node location
2: Output: optimal policies  $\pi^*$ 
3: Begin
4: While Compute  $D_{ij}$ 
5:   Compute Dis
6:   Calculate R
7:   Cluster sensor nodes via k-medoids method
8:   Group the CHs
9:   For every AUV
10:    Compute P (y, z) and Compute M (y, z)
11:    Obtain optimal policy via value-iteration process
12:   End for
13:   Transfer AUV with path plan  $\pi^*$  to all CH groups
14:   Sink receive AUV data and revive its memory
15: End while
16: End

```

ALGORITHM 1: AUV path planning using MDP.

choosing the CHs on the boundaries of the monitoring area as their next location.

$$P(z_i, y_j) = \begin{cases} d_j, & rm - \forall < d_{js} < rm, \\ 0, & \text{Else,} \end{cases} \quad (19)$$

where  $\forall$  is the risk region and  $rm$  is the monitoring area radius. At last, it should be remembered that  $q_1, q_2, q_3$ , and  $q_4$  are the reward compensation coefficients.

**4.3. Path Planning for AUV and Collection of Data from CHs Using AUV.** This segment proposes a path planning framework for AUVs in CH groups, which exploits the value-iteration method [34, 52, 53]. This process utilizes the transition probabilities for future states, and then, the cumulative compensation or value  $V(y, z)$  is determined for the action  $y$  taken in the state  $z$ . For any state, the optimum action is the action that gives a full reward. Indeed, the  $Q$  values are determined depending on an optimal strategy for a given step.

(i) Initialize  $V(y, z) = 0$

(ii) Repeat  $V(y, z) = R(y, z) + \max_{y^*} \sum_z P(y, z, y^*) V(y^*, z^*)$

This procedure will be continued and repeated before the last cycle occurs. Methods of forwarding induction, like the value-iteration method, must be ideal for situations where only the initial condition is specified (the sensor node's initial data is specified in our prescribed system). Algorithm 1 demonstrates the ultimate mechanism operation.

As shown in Algorithm 1, the initial energy of sensor nodes, residual energy, the priority of data, and the location of sensor nodes are considered inputs of the suggested model. When the framework starts to work, all the sensor nodes broadcast their properties across the entire network. Therefore, it can be stated that the sink knows the sensor node's features in the beginning. It determines all sensor

TABLE 3: Simulation parameters.

Parameters	Value
Monitoring area	1km * 1km* 1km
Sensor nodes	1000
Initial energy of AUV	15KJ
Initial energy of sensor nodes	5kJ
Sensor nodes transmission range	200 m
Speed of AUV	6 m/s
Channel bandwidth	10 kHz
Transmission power	0.303 watt
Receiving power	.022 watt
Speed of acoustic signal	1.5 km/sec

nodes' total energy. If each cluster member has the energy to transmit information to the CH, and, respectively, if CH has the required energy to obtain and send back the AUV to the subsequent location, the sink node will measure the sensor node Euclidean distance and also measures the Euclidean distance between the sensor node and sink. First of all, the K-mean algorithm is used to cluster the network. After clustering, CH is determined in each cluster using equation (7). The sink node divided CHs into groups using the angle-based method for assigning AUV to each group.

Next, the sink node determines MDP parameters for each AUV. It then calculates the optimal policy through the value-iteration process (the optimal path of the sensor nodes that any AUV can visit); this stage helps in efficient path planning for each AUV visiting their particular group of CHs. The sink collects AUV data, and after receiving its data, the sink node replenishes the data memory of AUV. After that, the overall energy of sensor nodes is rechecked; if the nodes have much power to send data to CHs and CHs have much energy to receive AUV and dispatch that to other locations, then the process will be repeated; otherwise, it will end.

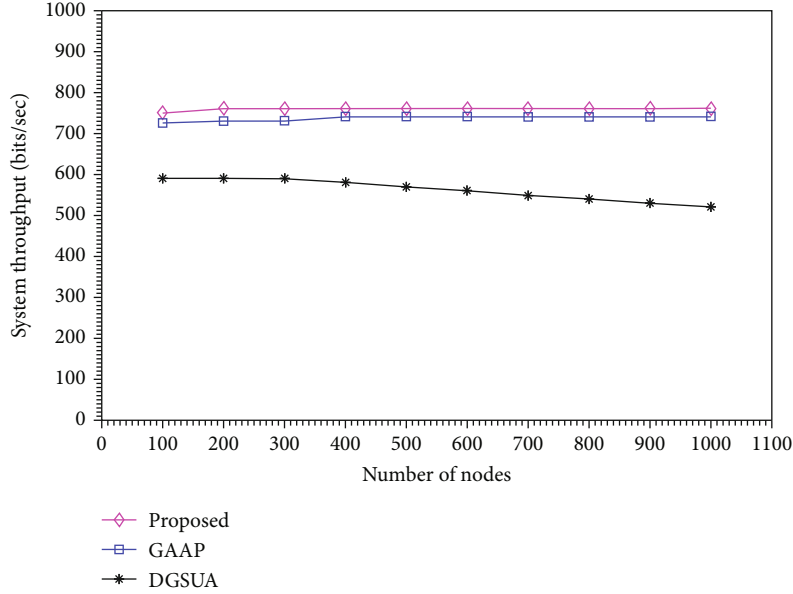


FIGURE 5: System throughput.

## 5. Simulation Results and Analysis

**5.1. Simulation Setup.** Extensive simulations were carried out for the assessment of the proposed method. Since the physical layer of UWSNs varies between acoustic modems, we determined these characteristics using Evologics acoustic modems; they are commercially available products with varying features. We used the S2CR18/34 modem, and the parameters are described in Table 3. In addition, the network parameters are set as follows, a 1 km \* 1 km \* 1 km deep-sea UWSN was developed where the data-collection sink drifts at the surface. Sensor nodes are installed uniformly at different locations, and multiple AUVs are used for data collection in this simulation. The AUV manages emergencies at the fastest speed. In this analysis, the AUV unit consumption rate is 7 J/m [9]. On land, the SenCar consumption rate is 5 J/m [54], and the AUV's energy consumption increases due to water resistance. It is assumed that the AUV can collect 2048 bits of the system data. We exploit the IEEE 802.15.4 [55] performance dataset, in which 1000 sensor nodes from the dataset are highlighted that are suitable for UWSN applications. Further simulation parameters are described in Table???. For evaluating the MDP-based optimal policy, we use a MATLAB MDP toolbox [56] to apply our policy iteration algorithm. We choose the parameters of the node based on intense Motes (XSM) [57]. The XSM motes contain acoustic, magnetic, temperature, and infrared sensors.

We compare the performance of our proposed scheme with a data-gathering scheme using AUVs (DGSUA) [58] and the greedy and adaptive AUV pathfinding (GAAP) [26] approach. GAAP derives the AUV route from gathering the sensed information from nodes and transmitting this information to the sink node with maximum value of information (VoI). DGSUA designs several AUV movement and coordination processes in data processing. These schemes

aim to fix the issues of route planning and task assignments of AUV to enhance the reliability of the UWSN. To analyze possible solutions equally and accurately, we follow the same cluster number and network topology. These algorithms' output is measured in throughput, energy efficiency, collection delay, and reliability. A better approach is intended to minimize collection delay, reduce energy consumption, increase throughput, and boost reliability.

**5.2. System Throughput.** The throughput of a system refers to the rate at which data packets are received at the sink. Figure 5 shows the system's throughput; since the strategy of multi-AUV in DGSUA performs the collection of data quickly, but the time required for the collection of data is too scattered, not focused on higher-data packet clusters and nodes. The GAAP algorithm takes a long time to perform data collection, preferably selecting sensor nodes with more data packets to maintain maximum throughput. The proposed approach combines the above two frameworks and decreases the cumulative time to gather data, thus preserving a high throughput.

**5.3. Energy Efficiency.** The ratio of total packets received to total energy consumed by the network to deliver these packets is called energy efficiency. Figure 6 indicates the energy efficiency levels obtained for the three methods. The multi-AUV navigation direction is mechanical and fixed in DGSUA; therefore, DGSUA energy efficiency is comparatively poor, especially when the number of nodes is limited in the network. This paper's suggested algorithm logically organizes the AUV path depending on actual circumstances. Navigation of path planning using MDP decreases high energy consumption compared to other schemes. The figure shows that our suggested method has higher energy efficiency than the other two methods.

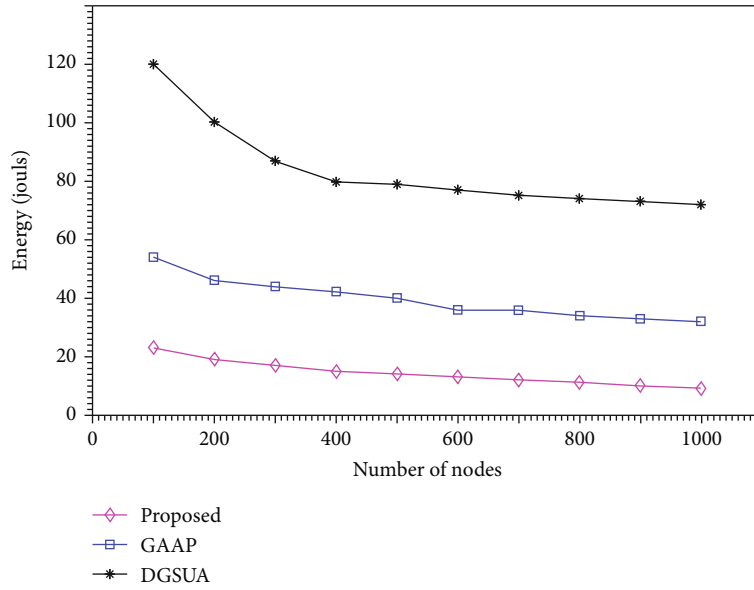


FIGURE 6: Energy efficiency.

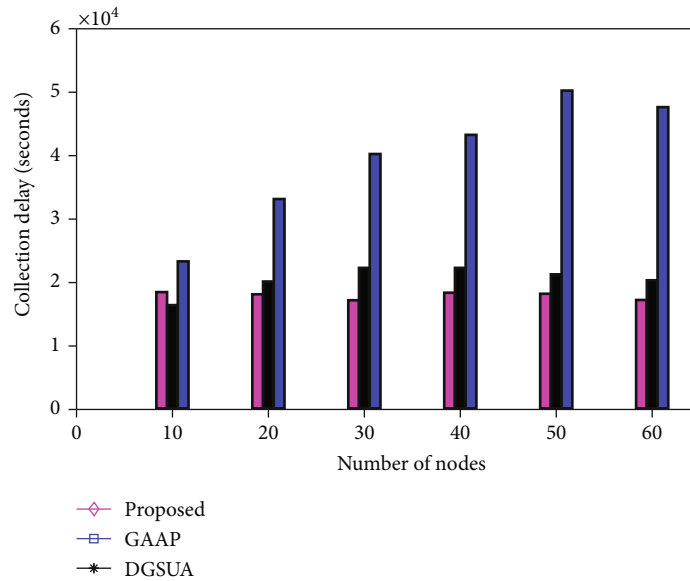


FIGURE 7: Collection delay.

5.4. *Collection Delay.* Figure 7 shows that as the number of nodes increases, DGSUA and APP-MDP collection delay remains relatively constant, while GAAP collection delay increases. APP-MDP has the shortest collection delay as compared to others. DGSUA has a minor collection delay as compared to the GAAP algorithm. The reason is that, in the GAAP algorithm, the AUV must visit each node for the collection of data which in turn increases the collection delay. In contrast, in other algorithms, the AUV only visits the selected CHs to collect data. That is why its collection delay is more minor. Furthermore, as DGSUA does not produce the optimum results of CH groups relative to APP-MDP, the distance can be longer among CHs. Therefore,

the DGSUA collection delay might be higher as compared to APP-MDP. Comparatively, the proposed scheme has a minor collection delay due to the algorithm’s appropriate path planning for AUV.

5.5. *Execution Time of AUVs and Their Itinerary Length.* Figure 8 indicates AUVs’ execution time visiting all CHs and how long they will return to sink. It contrasts our methodology with other current protocols (DGSUA, GAAP). As shown, the time of execution of routing protocols increases with the increasing number of sensor nodes. Among other routing protocols, GAAP has the maximum execution time, due to its poor plan to move sensor nodes closer to the sink.

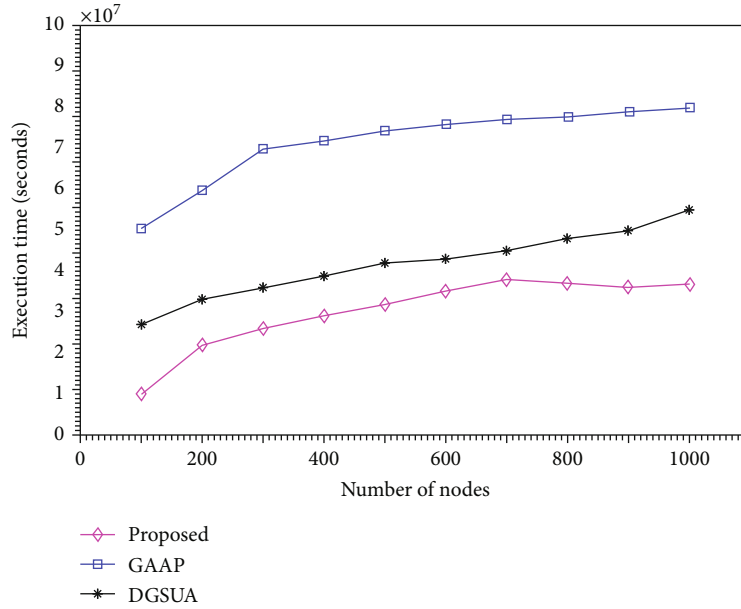


FIGURE 8: AUVs' execution time.

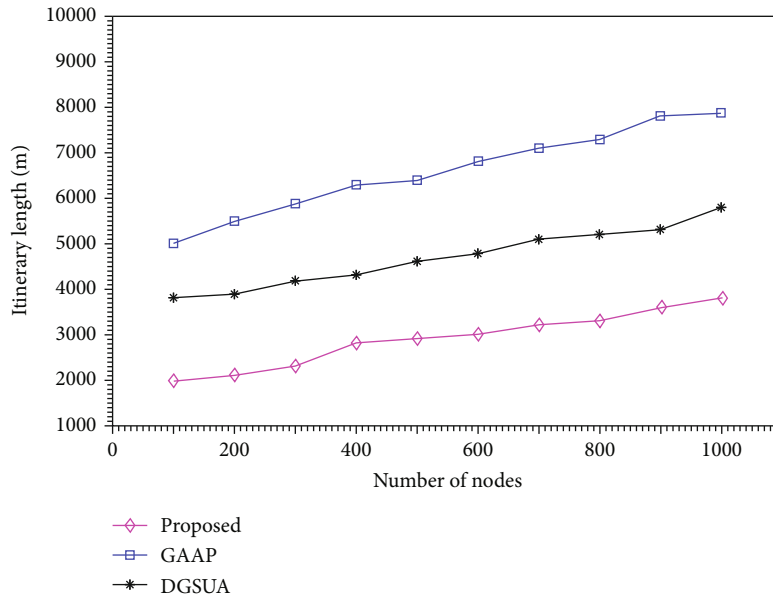


FIGURE 9: Itinerary lengths of AUVs.

DGSUA has less execution time as compared to the GAAP algorithm. Our proposed approach has the lowest execution time compared to all other routing protocols due to using multiple AUVs and collecting data spending less time on each CH using optimal route planning.

Figure 9 indicates the itinerary length of AUVs for different routing protocols. The size of our suggested protocol is short as compared to other protocols. This is because planning an optimal route for AUVs using MDP and the strategy to plan AUV routes between CHs only, not among all sensor nodes. GAAP has the longest route due to its poor plan to select the closest sensor node as its destination and schedul-

ing AUV routes for all sensor nodes, not only for CHs. DGSUA has a short itinerary length compared to GAAP because of multi-AUVs.

5.6. *Energy Consumption Fairness.* The network lifespan is linked to the fairness of energy consumption. This metric shows the energy consumption levels of all sensor nodes during the network operating time. Thus, when the fairness of energy consumption is less, it will increase the network's lifespan and produce more live sensor nodes over a period. Figure 10 shows the standard deviation (SD) chart of energy consumed by active sensor nodes. SD is a metric to evaluate

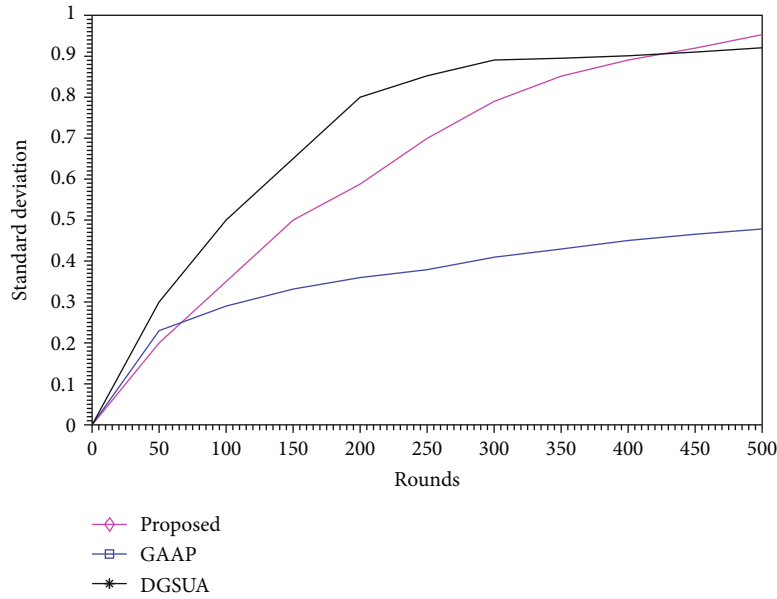


FIGURE 10: SD of consumed energy.

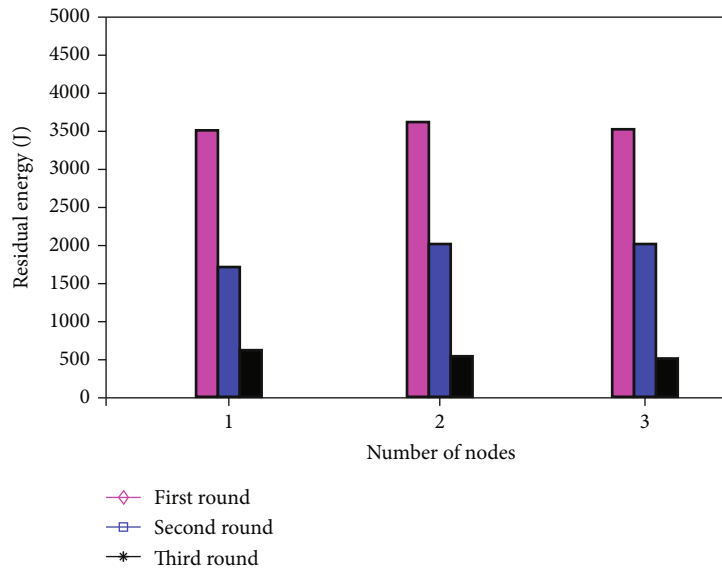


FIGURE 11: Different AUVs' residual energy.

the amount of energy consumption dispersion by sensor nodes per cycle. Small SD reveals that energy consumption values tend towards the mean, although a huge SD specifies that the values of energy consumption are distributed across a broad range.

As seen in Figure 10, in the first 50 rounds, our method SD is 25.95% smaller than the DGSUA SD. The low value of SD indicates that the energy consumption of all sensor nodes is near the average in our proposed system, which indicates a fair allocation of the network workload across the sensor nodes. In this case, the sensor nodes allocated to some network portions do not expire earlier. The framework would also perform well to meet the requirements of critical

applications, like tsunami warnings and pollution monitoring.

Moreover, in the first 450 rounds, our method SD is 50.95% smaller than the GAAP SD. As the rounds progress, our proposed mechanism has a higher SD than the other two techniques. This is because the active sensor nodes are reduced in GAAP and DGSUA techniques after a specified time, and a rapid reduction in their SD is also reasonable because of the reduced alive sensor nodes.

**5.7. Reliability.** UWSN's reliability is evaluated in this section, which is the critical factor in determining the system's ability to execute its defined tasks under specified conditions.

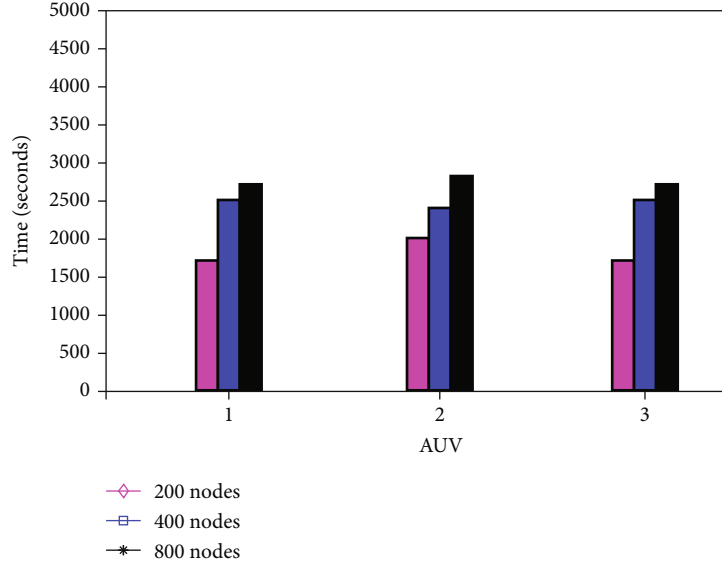


FIGURE 12: Different AUVs' accomplish time.

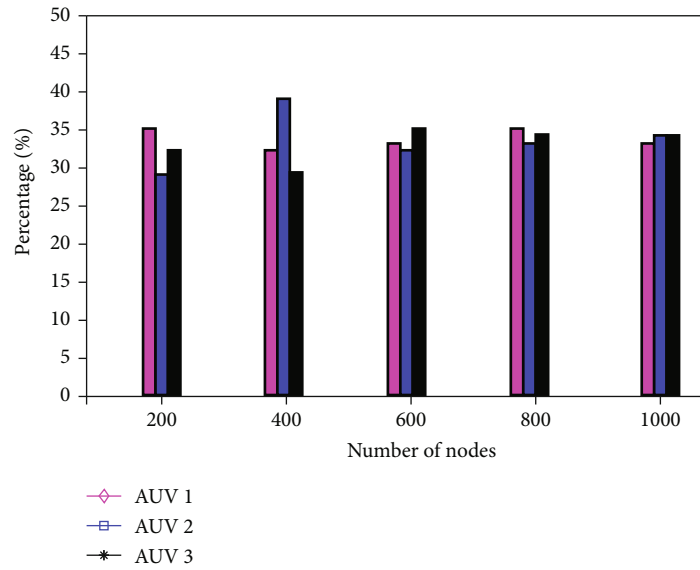


FIGURE 13: AUVs' load balancing.

TABLE 4: Reliability.

APP – MDP	DGSUA	GAAP
0.02564	0.01832	0.01875

To avoid the loss of sensitive data, the AUVs tend to collect high priority data if an AUV data memory is being filled. So, system reliability is described as the data priority, which could be calculated as

$$R = \frac{LP + 2MP + 3HP}{LG + 2MG + 3HG}. \quad (20)$$

*LP*, *MP*, and *HP* are low, medium, and high priority data numbers and have been reached to the sink. *LG*, *MG*, and *HG* provide low priority, medium priority, and high priority data that some sensor nodes generate. As described in Table 4, the APP-MDP mechanism improves system reliability by 1.39 to 1.36 times in contrast with other methods.

**5.8. Single AUV Performance.** Multi-AUV is often used for data processing in the underwater sensor network. Route planning and task assignment for AUV are essential; both are related to network lifetime and AUV load balancing. Therefore, the system's efficiency of a single AUV is given substantial consideration during the simulation. The amount of AUVs is typically calculated upon network size



and data priority requirements. For the simulation, we considered only three AUVs and separately numbered them.

Figure 11 indicates each AUV's residual energy when the execution rounds increase. The AUVs' initial energy is considered by one-third of the total energy, and for others, it is regarded as the same. After each data gathering round, the energy needed by the AUV stays the same to prevent a single AUV executes more activities and absorbing faster energy.

Figure 12 shows the time each AUV spends executing its task; this is significantly varying due to different route sizes in the region assigned to it. This influences the whole task's completion period. Figure 13 demonstrates the AUV's load balancing, particularly as the number of nodes increases. The supremacy of the geographic division of CHs in groups and route planning using MDP is thoroughly expressed.

In short, the efficiency of several AUVs is essentially the same without considering the impact of specific conditions such as AUV failures and data importance. This flexibility is beneficial to the system's stability in achieving the task.

## 6. Conclusions

A data-collection protocol for UWSNs based on AUV path planning has been developed in this work. The collection of data is one of UWSN's primary concerns. Using multiple AUVs with efficient and reliable path planning for data collection from sensor nodes significantly decreases the total network energy consumption. It fulfilled QoS criteria, such as data priority, reliability, and delay. The APP-MDP method is proposed in this article. It provides efficient and reliable path planning for AUVs to collect the data from sensor nodes. We divided this method into two steps. The first step is the clustering of sensor nodes using the k-medoids algorithm. After clustering, CHs are specified in each cluster, which is grouped employing angle-based technique into same size sectors for providing of AUVs. In the second step, APP-MDP takes advantage of the MDP using many factors, such as sensor node residual energy and its priority of data, and Euclidean distance between the sink and sensor nodes to deliver efficient and reliable path planning for AUVs in CH groups. Finally, the value-iteration method determines the best route after UWSN modeling. The simulation results affirm that the proposed technique has increased throughput and reduced energy consumption compared to other techniques. Our proposed technique enhances network reliability. The findings show that our proposed approach is better than all the other existing approaches; it takes less execution time and has the shortest itinerary length than others.

In the future, using the APP-MDP as a basis, we intend to research real-world environments. In UWSNs, data gathering based on AUV is a fascinating approach from a practical research perspective. There is still a lot of work to be done on how to maneuver around in real situations under the effects of obstacles, drifting of water, and wind, so we will keep working on that.

## Data Availability

Data will be provided upon request.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

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