International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 16 (2024) pp. 395–415

Article

Optimize the Network Topology in Underwater Sensor Networks (UWSNs) to Improve the Localization

Kamal Kumar Gola [1,*], Gulista Khan [2] and Sagar Gulati [3]

[1] Department of Computer Science and Engineering, College of Smart Computing, COER University, Roorkee 247667, Uttarakhand, India
[2] Department of Computer Science and Engineering, Faculty of Engineering, Teerthanker Mahaveer University, Moradabad 244001, Uttar Pradesh, India; gulista.khan@gmail.com
[3] School of Computer Science and Information Technology, JAIN (Deemed-to-be University), Bengaluru 560069, Karnataka, India; sagarg40@gmail.com
* Correspondence author: kkgolaa1503@gmail.com

Received date: 1 March 2024; Accepted date: 21 March 2024; Published online: 10 July 2024

Abstract: Underwater Wireless Sensor Networks (UWSNs) offer significant advantages due to their wide-ranging applications, largely dependent on the placement of sensor nodes. Effective algorithms for locating or identifying underwater target objects via UWSNs hinge on the sensor nodes' ability to accurately determine their surroundings, making this a key area of research. Enhancing localization for large-scale mobility in UWSNs is challenging due to adverse aquatic conditions, considerable node mobility, and the extensive scale of the network. Many experts have refined localization algorithms or developed new methods to improve target node accuracy, advancing the field. This work improves the node localization in UWSNs. It uses Time Difference of Arrival (TDOA) to measure distances and the Red Vulture Optimization Algorithm (RVOA) for precise localization. The method also employs Euclidean distances and window prediction to reduce errors and delays. The node mobility model predicts velocity and position over time. The proposed work is compared with existing methods like MPL, GA-SLMP, SLMP, and LSLS, demonstrating superior performance in energy efficiency, delay, prediction error, and localization coverage.

Keywords: underwater wireless sensor network; optimization; localization algorithm; mobility; underwater node location

1. Introduction

In comparison to conventional wireless sensor networks (WSNs), underwater wireless sensor networks (UWSNs) provide a novel tool for genetic research [1]. As 70% of the Earth's surface is covered by water, there is a huge need for extensive research into monitoring and exploring different aspects of the ocean environment; hence, this system consists of multiple sensors and vehicles deployed to perform concert monitoring. In comparison to its width and length, the height of the WSN terrestrial deployment region is minimal. In most instances, the localization issue is analogous to the localization issue of a 2D plane.

Consequently, depending on the application, underwater localization can be accomplished in two dimensions (2D) on a particular depth plane or in three dimensions (3D) in a specific volume of water. In addition, the location of the node of ground-based WSNs remains consistent during deployment. There is no dynamic evolution of the network structure, and external factors have no bearing on node movements. However, due to the impact of ocean currents and other environmental variables, underwater nodes might wander. The performance characteristics of electromagnetic waves employed by sensor nodes on land—compared to submerged network nodes. UWSN has numerous typical applications, including marine surveillance, monitoring, industrial sensing, tsunami and flood warning systems, military, etc. As the underwater sensor nodes may communicate via acoustic waves, it is unnecessary to deploy costly and complex individual ocean monitoring equipment when utilizing UWSNs.

1.1. Localization Techniques

Different technologies, such as medium access control (MAC) and secure routing protocols, localization methods, and time synchronization systems [2], have been investigated for UWSNs. When discussing sensor nodes in UWSNs, we can categorize them as either reference nodes, unknown nodes, or anchor nodes. Unknown nodes collect surrounding data. To discover undiscovered nodes in the Network, anchor nodes are accountable. A reference node is a node whose location is unknown and an initial anchor node [3,4]. The localization process refers to the method by which an unidentified node learns its location by exchanging sparse messages with a small set of recognized anchor nodes or unknown nodes utilizing specialized localization technologies. Since node localization is the backbone of the UASN application, it is clear why it is crucial in sensor networks. Because the location of a node is essential for helpful data collection in UASNs, research into node-locating technologies is necessary. To be valid, sensor data typically requires localization [5]. This correlation between hop count and link length is problematic due to its effect on energy use and throughput. It is possible for a localization protocol's measurement to become outdated and produce position estimations that are wildly wrong if the process takes too long to converge. The estimation based on the localization method [6] monitors the estimated locations over time to fix the error and latency. The two main ways UWSNs determine individual nodes' positions today are range and range-free-based localization. Standard measuring techniques used in range-based localization include the time difference of arrival (TDOA), received signal strength (RSS) [7], and angle of arrival (AOA) [8], time of arrival (TOA). To determine the one-way distance, the TOA formula compares the signal's transmission and reception timestamps. The sensor and the remote node must be online precisely for this strategy to work. When using TDOA-based localization [9], sensor nodes must be perfectly synchronized so that the time difference between when a signal is sent and when it reaches each node may be calculated.

1.2. Problem Statement

The diversity and uniqueness of the ocean's environment, UWS nodes have significantly greater, energy consumption, noise, cost, and interference and then their terrestrial equivalents. The range-based algorithm necessitates more complex ranging technology, which in turn necessitates more resources (both financial and otherwise) to operate. Range-free localization techniques heavily rely on the stability of the underlying internet services to ascertain the node's position. To address these concerns, we deploy an efficient localization approach capable of pinpointing mobile nodes in UWSN. Based on the distance from the anchor node, the precision of the distance estimate, and the latency in transmitting the information, this algorithm determines a fitness function. In addition, future node positions are predicted using prediction-based localization methods. Due to node mobility and slow acoustic wave speed, location predictions are inaccurate.

Therefore, the movement needs to be considered during localization methods to produce more accurate and reliable location estimates.

1.3. Contribution

With the growing interest in maritime resource exploitation, underwater wireless sensor networks are a new area of investigation. Underwater WSNs localize. Due to the complexity of the aquatic environment, underwater wireless sensor networks, especially large-scale mobile networks, have trouble achieving synchronous localization. We reduced range error by improving the Time Difference of Arrival (TDOA) model.

Long propagation delays, node mobility, and error probability plague UWSNs. Hybrid optimization yields a stable and scalable energy relationship between unlocalized and mobile sensor nodes, optimizing network lifespan and energy use.

Due to prediction inaccuracy, prediction-based node localization cannot predict node mobility. Estimation-based methods avoid prediction mistakes and delays.

The remaining portions of this document are structured as follows: In Section II, the relevant work related to the location of undersea nodes is described. In Section III, the model that is relevant to UASNs is presented as well as the localization of mobility node algorithm that was suggested. The findings of the simulation as well as an appraisal of its performance are detailed in Section IV. The conclusion can be found in Section V at the very end. Enhancements are planned for Section VI in the Future.

2. Comparison of Few Existing Work

Optimizing the network topology in Underwater Sensor Networks (UWSNs) is essential for improving localization accuracy. Effective topology management addresses challenges such as signal attenuation, multipath propagation, and high latency typical of underwater environments. By strategically placing nodes and employing advanced algorithms like localization-based clustering or adaptive node mobility, the network can achieve more reliable communication paths and precise position estimation. As shown in Table 1, a comparative analysis of different optimization techniques reveals that localization-based clustering significantly reduces energy consumption and enhances accuracy compared to traditional flat network topologies. Conversely, adaptive node mobility methods provide greater flexibility and resilience in dynamic underwater conditions, despite potentially higher computational complexity. Additionally, combining acoustic communication with optical or electromagnetic methods can further improve localization, leading to robust and energy-efficient underwater sensor networks.

Table 1. Comparison of Existing work.

Author	Method Name	Objectives	Simulation Tool	Advantage	Disadvantage
Yan, Jing, et al. [10]	Mobility Prediction Using Asynchronous Localization Algorithm	To eliminate the effect of asynchronous clocks and compensate for the mobility of sensor nodes, an asynchronous localization algorithm with mobility prediction	MATLAB 2016B	Solve the issue of synchronization of the clock and error node mobility prediction	Computation Complexity
Ullah, Inam, et al. [11]	Distance-angle based algorithm	Reduced the error-based estimation using distance-based and angle-based localization algorithms	Not Mentioned	Promote the finding of errors and accuracy of sensor location	Needed to reduce the localization estimation error
Saeed, Tareq Y et al. [12]	A robust 3-D localization method	Achieving the accurate estimation the missing inter-node distances in transmission distance of underwater optical sensors	Not Mentioned	To solve the issue of node-link connectivity	Needed to enhance the localization accuracy
Saeed, Nasir, et al. [13]	Received signal strength (RSS) based localization framework	By estimating the shortest paths, the energy consumption and error are pruned.	MATLAB	Reducing the estimation error in accurate	Energy Consumption is not concentrated

Shams, Rehan, et al. [14]	Joint Algorithm of Multi-Hop Localization and Time Synchronization	By using a multi-hop environment, the author extend the range and enhance the network connectivity to provide more accurate localization and Synchronization technique.	Not Mentioned	Error reducing in node localization finding	Data collision and clock skew
Han, Guangjie, et al. [15]	Delay optimization and data collection based on the Prediction algorithm	Reducing the prediction-based data transmission delay in AUV-UASNs)	MATLAB	Latency is minimized for data distribution and node location finding	Error is not calculated accurately
Zhang, Wenbo, et al. [16]	movement prediction location	Node movement prediction is developed to achieve accurate transmission	MATLAB	Power Consumption is low, and High accuracy in node prediction	High energy consumption
Rao, Madhuri, et al. [17]	Cat Swarm Optimization (CSO)	Node mobility is achieved according to the Articulation point in UASN	Not Mentioned	Good convergence High reliability	High energy consumption
Datta, A. et al. [18]	Doppler shift-based localization genetic algorithm-based optimization technique	Promote the unknown node finding accuracy	MATLAB	Minimize the error, improve accuracy	High Computation time
Sun, Yujiao, et al. [19]	Virtual force and particle swarm optimization (VF-PSO).	For maximum coverage achieved the purpose, tracking is performed on the mobile node according to the ideal position.	Not Mentioned	Good Coverage Performance, Convergence speed, Energy consumption	Does not consider the problem of information transmission between nodes.
Shah S. et al. [20]	LFEER Co-LFEER	The efficient localization-free routing protocol for energy management	MATLAB	Energy is increased, PDR of the Network is improved	High delay
Shanthi, M. B., and Dinesh K. et al. [21]	FRAME Work based on probabilistic model	Minimizing the attacks in node information transmission	Not Mentioned	Improve Node localization, Effectiveness Security	Effective solutions to address this are lacking

3. Proposed Methodology

3.1. Network Model

A three-dimensional acoustic sensor network is currently being developed to monitor the oceanographic environment. This Network consists of a gateway buoy located at the surface, a network of sensor nodes consisting of a floating node and an Anchored Node implemented at the seafloor, and a satellite-connected onshore station. A wired connection between each sensor and the gateway node is the first potential approach that can be considered (buoy). Adjusting the cable length allows for fine-grained control over the sensor's working depth. In addition, the anchored sensor node has a connection to a pump-inflatable buoy. To maintain a consistent depth for the sensor node, the buoy's primary function is to drag the sensor closer to the surface of the water. Real-time data is generated by all components of the UASN, including buoys and underwater sensor nodes on the ocean floor. This data is then transmitted by satellite to a base station or an onshore station. The base station and the deep water-based station (Offshore) of the Network are utilized to collect, process, integrate, and send data information while also determining the locations of nodes. Figure 1 illustrates the Network's recommended model for the system.

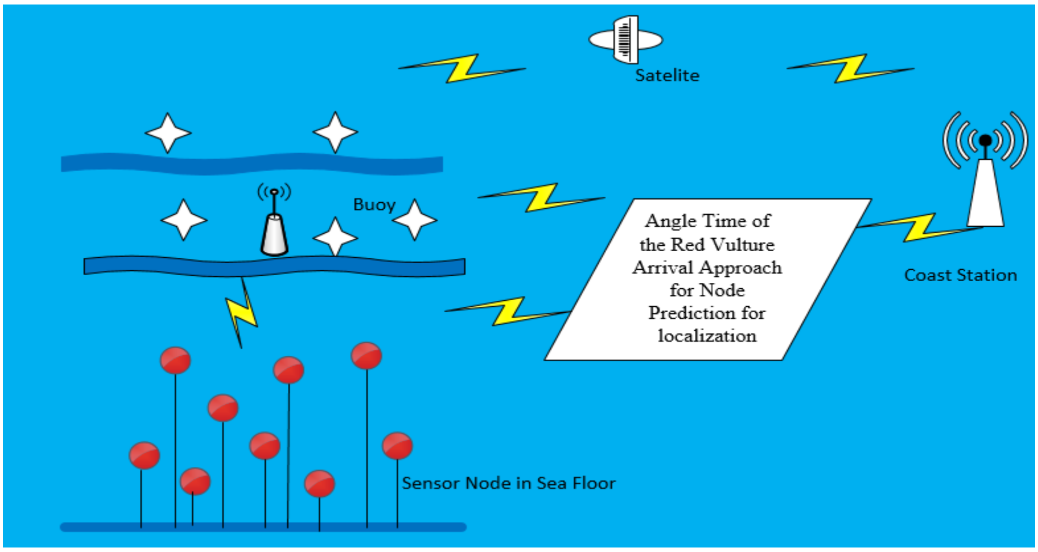


Figure 1. Underwater Acoustic Sensor Network Architecture Model.

3.2. Communication Model

The most power-hungry parts of sensor nodes in underwater acoustic communications are those responsible for exchanging information between them. Attenuation and energy loss in the signal are triggered by environmental conditions such as background noise, pH, and temperature in the underwater channels. Since the transmission mode accounts for 80% of the maximum energy consumption, adjusting the transmitter's power output can significantly impact power usage. To keep the model as simple as possible, only the energy cost of sending and receiving packets by nodes was considered in this study. The power requirements of acoustic sensors for transferring data packets between sensor nodes in Equation (1) as below,

$$Energy_{Transpower}(fd) = Power_{Transpower}Time_{Transpower} = Power_{Min}Attent_{fd}Time_{transpower} \tag{1}$$

The time duration of transmitting the packet is expressed for a node as,

$$Time_{transpower} = \frac{l}{\lambda}.B(l) \tag{2}$$

where l denotes packet size in bits, $B(l)$ represents bit rate, and λ indicates coding efficiency.

The parameter for calculating the power attenuation of an acoustic signal with a constant frequency in an environment that is submerged in water is as follows,

$$Attent_{fd} = fd^{pf}PowerAtten^{fd} \tag{3}$$

where pf is the power factor indicating the model's acoustic communication type, with pf = 1 representing cylindrical propagation and pf = 2 representing spherical propagation. Signal frequency affects power attenuation parameter fd. When compared to the amount of energy that is used for transmitting data, the amount of energy that is used for receiving data in UASNs is comparatively low, $Power_{Min}$ Is (in J), the power attenuation function is: and may be stated as,

$$Attent(packetsize, fr) = l^{pf}\alpha(fr^{l}) \tag{4}$$

where fr indicates frequency, $\alpha\ (f)$ denotes absorption coefficient $^{dB}/_{m}$.

The following equation provides the absorption coefficient,

$$\alpha\ (f) = 0.11 \times \frac{fr^2}{1+fr^2} + 44\ \times \frac{fr^2}{4100+fr^2} + 2.75 \times 10^{-4}\ \times fr^2 + 0.003 \tag{5}$$

The energy consumption is presented when sending the 1-bit data in the sensor node as,

$$Energy_{receivepower}\ =\ Power_{Min}Energy_{process} \tag{6}$$

where $Energy_{process}$ es energy an acoustic sensor node consumes whenever one bit of data is being processed. When compared to the amount of energy that is used for transmitting data, the amount of energy that is used for receiving data in UASNs is comparatively low.

3.3. Proposed Algorithm

Range measurements allow us to determine how far away the unknown is from our fixed points. Several options exist for range-based methods, each optimized for a different physical characteristic used in range estimation. Regular nodes can make references to unknown nodes and reference points. Beacon nodes are those whose locations are known, while unknown nodes are those for whom no data is available. The signal from the mysterious node will be broadcast to the neighborhood one by one. The ranging mechanism operates when the sending and receiving nodes are within communication range. One at the source node and one at the destination node are the only transmission procedures determining the range between every one of the identified nodes and the target node. Those other nodes merely need to be able to listen to broadcasts. Since data receipt necessitates less energy than data transmission, this technique can reduce energy consumption. A back off period also happens when the node being located is given the range request before the sending of the answer message. By doing so, we can avoid the data loss or delay that results from a message collision, and we can reduce the node's overall energy consumption by shortening the retransmission process. The TOA and TDOA location estimation methods discussed in this study improved performance—both in terms of average error and failure rate—when the range estimate error was decreased. The suggested methodology is shown in Figure 2.

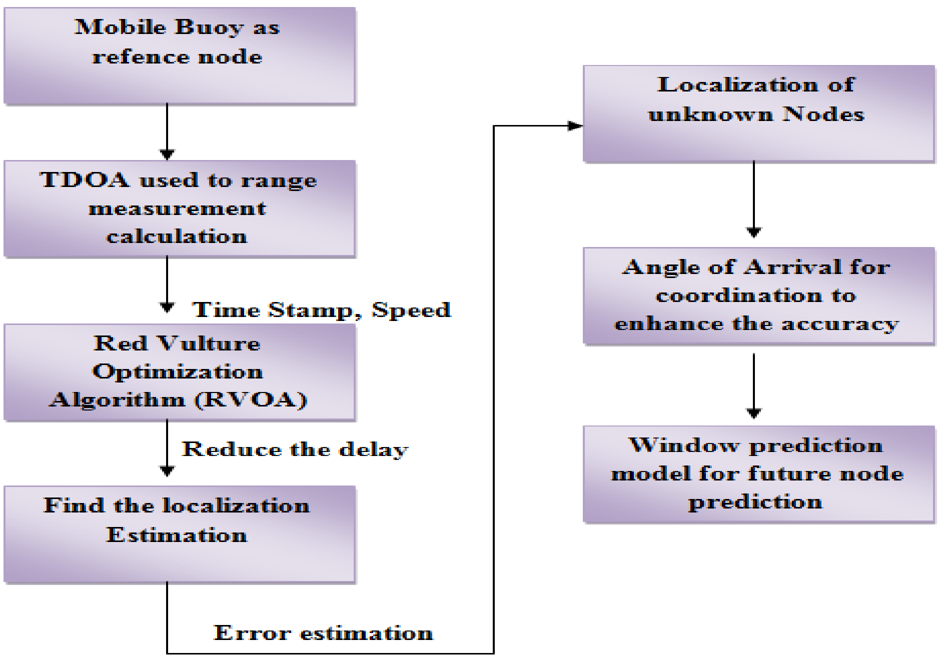


Figure 2. Proposed Methodology.

As a result, we ought to work on achieving a range estimation with higher precision to enhance the location. Two-way ToA and TDoA eliminate the requirement for time synchronization, in contrast to one-way ToA, which only provides one-way ToA. However, more message exchanges are necessary, and a higher amount of energy is used compared to TDOA. When performing localization using TDoA measurements, it is essential to have a sensor network that is correctly synchronized (about the speed at which the signal is propagating). In the TOA method, the TOA of the satellite signal is what is utilized to arrive at an estimate of the satellite's pseudo-range concerning the user. Calculating the amount of time that has passed since the transmission of a signal from one satellite to another is one of the steps involved in the TDOA method. The introduction of optimization algorithms, which mimic the behavior of organisms on the hunt for food, has a wide range of applications for finding optimal solutions to complex functions and provides fresh ideas for the TDOA localization problem, as shown in Figure 3.

After that, the time difference between the unknown node and the anchor nodes can be used to calculate the distance difference between the two sets of nodes. For instance, if we know the distance difference between the unknown node and the known nodes, we know that the unknown node is on the hyperbola with the known nodes as the focal points. Similarly, the novel is on the hyperbola, with the known nodes as the focal points. Furthermore, the coordinates of the unknown node can be determined by solving for the intersection of the hyperbolas following some known conditions.

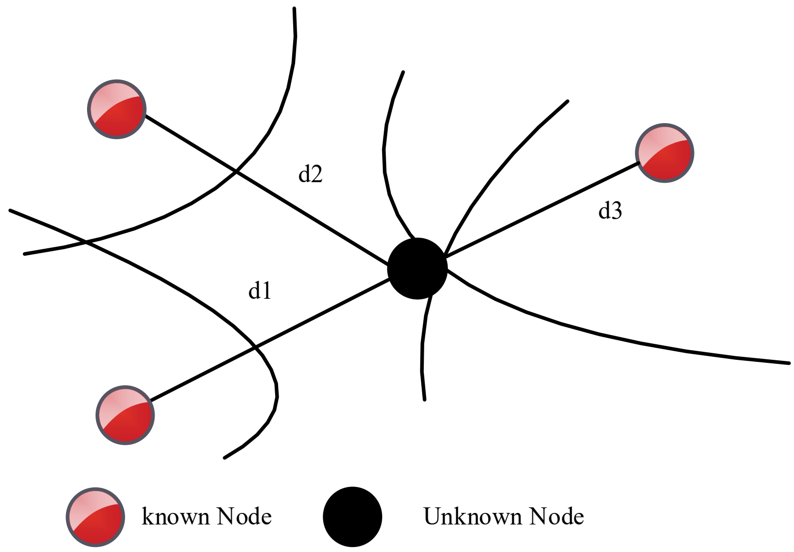


Figure 3. TDOA Localization Strategy.

To measure the TDOA joint localization of the velocity and position of an unknown source by making use of the time and frequency discrepancies between the source and two well-known nodes, collaborative localization of the TDOA is utilized. Assuming there are S sensors located at random throughout the three-dimensional region of the ocean, we can determine the location of the unknown source by$us = [a, b, c]^T$ While the velocity is expressed as $us' = [a', b', c']^T$, the position of the i^{th} the sensor is denoted with$n'_i = [a_i, b_i, c_i]^T$, it is velocity by $n'_i = [a_i', b_i', c_i']^T$ where i = 1,2,3…, S. Given these parameters, the distance between the sensor node and the unknown origin is,

$$d_i^0 = \|us - n_i\| = \sqrt{[us - n_i]^T\,(us - n_i)} \tag{7}$$

It is possible to express the noise-containing distance $r_{i,1}$ as where $d_{i,}$ 10 is the theoretical distance difference between the unknown source with sensor i = (i ≠ 1) and sensor, and $r_{i,}$ 1 is the actual distance difference measured by the sensor in dispute,

$$d_{i,1} = p \times t_{i,1} = d_{i,1}^0 + l_{i,1} = d_i^0 - d_1^0 + l_{i,1}\ (i = 2{,}3{,}\ldots S) \tag{8}$$

In this case, p is the signal propagation velocity, $t_{i,1}$, is the TDOA measurement, $l_{i,}$ 1 is the noise added by the measurement at i=1, and $d_i^0 = \|us - n_i\|$. The equation is where the time data is kept (8). The relationship between I and 1 is analogous to finding the rate of change in the distance between the unknown source and the sensors by utilizing the first sensor as a reference sensor, i and 1 are,

$$d'^0_{i,1} = d'^0_i - d'^0_1 \tag{9}$$

$$d'^0_i = \frac{([us' - n'_i]^T (us - n_i)}{d^0_i} \quad (10)$$

In this way, a matrix provides a convenient way to represent distances and the rates at which they change:

$$d^0 = \left[d^0_{2,1}, d^0_{3,1}, \dots, d^0_{S,1}\right]^T \; and \; [d'^0_{2,1}, d'^0_{3,1}, \dots, d'^0_{S,1}]^T \quad (11)$$

We use the following matrices to determine the erroneous values:
$d = [d2,1, d3,1, \dots, dS, 1]^T$ and d'= $[d'2,1, d'3,1, \dots, d'S, 1]^T$. Consequently, we can obtain,

$$d = d^0 + l_i \quad (12)$$

$$d' = d'^0 + l'_i \quad (13)$$

The TDOA measurement error matrix is denoted by n, while the FDOA error matrix is dnoted. Additionally, $[l2,1, l3,1, \dots, lS, 1]^T$ and $[l'2,1, l'3,1, \dots, l'S, 1]^T$. Vectors represent the error in the distance difference and the rate of change in the distance. Furthermore, we can assume that $l_i = l^T, l^T$, and further, assume that l_i is the Gaussian noise distribution with a mean of zero and a covariance matrix of Q. Mobile underwater source localization system diagram is shown in Figure 1.

3.4. Red Vulture Optimization Algorithm

In this research, we offer a localization technique for underwater sensor networks that uses an enhanced version of the red vulture optimization algorithm to pinpoint precisely the locations of in-the-field sources in motion. Recent years have demonstrated nature's prowess as a designer of committed behaviors that optimize actions in conditions that pose different challenges to performers. Animals' abilities as hunters, communicators, breeders, and foragers are displayed for our amusement. Curious occurrences in the natural world of plants and other elements also motivate scientific progress. Furthermore, hybrid optimization is crucial in resolving the optimization problem and significantly enhancing accuracy. To address this location and velocity-based localization estimation mistake, researchers combined the red fox optimization and the African vulture optimization to create the Red Vulture Optimization. A large number of samples allows the suggested method to converge to the global optimum, which is responsible for its enhanced performance. To begin, African Vulture Optimization's limited local search capability is considered. Pre-processing the initial population with the Red Fox method, then improving the search depth with the location and velocity update formulae, yields the hybrid Red Vulture algorithm. The red fox is an effective predator of both domestic and wild small animals. A fox will seize any opportunity for sustenance as it travels across its territory and will sneak up on its victim until it is close enough to make an effective assault. In our method, the fox's territorial exploration of food after spotting its prey in the distance is modeled as a worldwide search. The second stage is a local search that involves moving across the habitat to get as close to the prey as possible before making an assault. Our approach to fixing the localization estimation inaccuracy was similarly informed by how vultures act when finding food and settling down with their prey.

To accomplish this, the Red Vulture Optimization Algorithm (RVOA) is utilized to pinpoint the precise location of the known and unknown nodes, with the ideal first-level nodes serving as reference points. The step by step process of RVOA is shown in Algorithm 1.

Figure 4 depicts the RVOA method flowchart. Survival patterns of foxes and vultures in such hunting situations inspired the RVOA to set such limits. This RVOA technique uses the TDOA's velocity output and the distance between known and unknown nodes based on position as input to achieve an optimal localization estimate. In Table 2, we can see the Red Vulture Optimization Algorithm. In further iterations, RVOA's population will always have the same amount of nodes. A point with their respective coordinates is used to designate each of them.

$$a = (a0, a1,., an-1) \quad (14)$$

We add the notation a_j^k, where k is the population total number of nodes and each node in Iteration w a_k .l denotes coordinates determined by the dimensions of the solution space, to distinguish is identified by a unique set of coordinates, denoted by l, defined by the dimensions of the solution space. We suppose that foxes explore the solution space using the presented equations to discover the optimal values for the criterion function. As each fox in a pack is crucial to the group's continued existence, so are the unknown nodes in this analysis. If food is scarce where they are, or if they want to see the world, members of the herd will travel great distances to find it. They return home and teach their loved ones what they've discovered to increase their chances of survival and success. As we model our way around the neighborhood, we make sure to take everyone's health into account. The proposed strategy assumes that the most qualified individual has visited the world's most interesting locations and can share their insights with others back at home. So, we begin by arranging the population in the order of fitness, and then we calculate the square of the Euclidean distance between each individual as follows,

$$h((\overline{a}^{k})^{w}, (\overline{a}^{best})^{w}) = \sqrt{\|(\overline{a}^{k})^{w} - (\overline{a}^{best})^{w}\|}, \tag{15}$$

and we move individuals in the population toward the best one

$$(\overline{a}^{k})^{w} = (\overline{a}^{k})^{w} + \alpha sign(\overline{a}^{best})^{w} - (\overline{a}^{k})^{w}) \tag{16}$$

Therefore, the optimal solution for locating known nodes and identifying unknown nodes within their communication range may be determined. Using an algorithm inspired by African vultures' behaviors, we can significantly lower the best solution error. When hungry, vultures have low energy and can only fly short distances, but they can cover great distances when they're well-fed.

Table 2. Parameter for proposed model simulation.

Specifications	**Details**
Value of buoy nodes	50
Value of underwater sensor node	12, 200, 320, 400, 600
Range of Communication (R/m)	120
Predicted Window Size (t_m/min)	10, 20, 30, 40, 50, 60
Velocity ($\frac{m}{s}$)	1,500 ($\frac{m}{s}$)
Transmit/receive Node power (W)	35/0.3

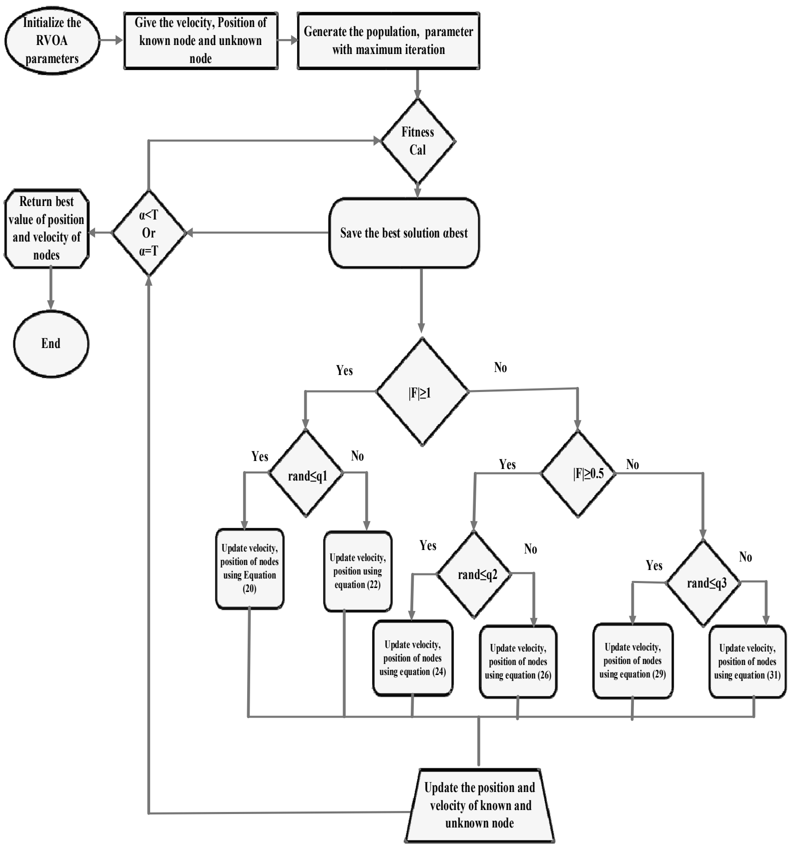


Figure 4. Proposed Red Vulture Optimization Algorithm (RVOA) flowchart.

Algorithm 1: AVOA Algorithm

1. Define: the number of iterations T, the maximum of the population n, velocity, position, fitness function $f(\cdot)$, size of search space solution
2: Input velocity, position
3: Generate a population consisting of n nodes at random within the search space,
4: t:= 0,
5: while $t \leq T$ do
6: Define coefficients for Iteration: RVOA approaching change a,
scaling parameter α,
7: for each known node in the current population, do
8: Sort individuals according to their fitness function,
9: Select $(best)t$,
10: Calculate the reallocation of individuals according to Equation (15),
10: Update the F using Equation (16)
11: if (|F| ≥ 1) then
12: if (P1 ≥ randq1) then
13: Update the velocity and location of nodes using Equation (20)
14: else
15: Update the velocity and location nodes using Equation (22)
16: if (|F| < 1) then
17: if (|F| ≥ 0.5) then
18: if (P2 ≥ randq2) then
19: Update the velocity and location nodes using Equation (24)
20: else
21: Update the velocity and location nodes using Equation (25)
22: else
23: if (q3 ≥ randq3) then
24: Update the location, and velocity nodes using Equation (27)
25: else
26: Update the location and velocity of Vulture using Equation (29)
Return Best location, velocity1$best)t$,

When hungry, though, vultures can't fly as far and must fight other vultures for scraps. Vultures can also become aggressive when they are hungry. This phenomenon has been mathematically modeled using Equation (17). Vulture hunger and satiety rates have also been used to gauge when to transition from discovery to exploitation. Since the satiety rate tends to decrease over time, Equation (17) has been used to represent this phenomenon.

$$S = d \times (sin^{i}\left(\frac{\pi}{2} \times \frac{iter_k}{\max iters}\right) + cos\left(\frac{\pi}{2} \times \frac{iter_k}{\max iters}\right) - 1) \tag{17}$$

$$S = (2 \times rand_1 + 1) \times z \times \left(1 - \frac{iter_k}{\max iters}\right) + w \tag{18}$$

In Equations (17) and (18), S denotes that the vultures are at total capacity, Iteration indicates the number of iterations currently in progress, and masters are the maximum number of iterations.

Phase 3: Research The AVOA's discovery phase is dissected here. Vultures have keen eyesight, a fantastic sense of smell, and an innate ability to find food in the wild. It can be pretty tricky for vultures to find food. Before venturing far in search of food, vultures expend significant effort inspecting their immediate vicinity. Vultures in the AVOA can employ one of two methods to randomly select one of several possible exploration destinations; this strategy selection is controlled by a parameter named Q1. This parameter's value, which should be set before the search operation begins and can take on values between 0 and 1, will determine which of the two methods will be used.

In the ransQ1 exploration phase, a random number between 0 and 1 is generated and utilized to select a strategy. If this value is more than or equal to the Q1 parameter, then Equation (20) is used. The usage of Equation (8) occurs, however, if the value of rand Q1 is less than Q1. Each Vulture here is scouring the area for meals in a completely random fashion. This is shown as an example in Equation (19).

$$Q_{(K+1)} = \begin{cases} Eq(6) if Q_1 \geq rand_{Q1} \\ Eq(8) if Q_1 < rand_{Q1} \end{cases} \tag{19}$$

$$Q_{(K+1)} = C(k) - V(k) \times S \tag{20}$$

$$V(k) = |X \times C(k) - Q(K)| \tag{21}$$

Consistent with Equation (20), vultures will forage for food at random distances from one of the two groups' finest cultures, where F is the rate of vulture satiation in the current Iteration and $Q(i + 1)$ is the subsequent vulture position vector. $C(i)$ is one of Eq's finest vultures. Equation (21). Moreover, X's vultures migrate randomly to protect prey from other vultures. Using the formula $X = 2$ rand, where a rand is a random number between 0 and 1, X is employed as a coefficient vector to increase the random motion, which changes with each Iteration. Q represents the current vector location of the Vulture (i).

$$Q_{(K+1)} = \text{C(k)} - \text{S} + rand_2 \times \left((\mu e - le) \times rand_3 + le\right) \tag{22}$$

$C(k)$ is one of the best-selected vultures in the current Iteration and is utilized in Equation (22). F is the rate of vulture satiation for the current Iteration, as obtained by applying Eq. mand2 has a random number between 0 and 1 and is equal to 18. The upper bound and lower bound of variables are displayed. Equation generates a simple model for the random production of solutions in the range. In the AVOA (22), by utilizing mand3, the randomness coefficient is increased. A random motion is added to the le if mand3 is given a number close to 1, resulting in a similar distribution of responses.

$$Q_{(K+1)} = \begin{cases} Eq(10) if Q_2 \geq rand_{Q2} \\ Eq(11) if Q_2 < rand_{Q2} \end{cases} \tag{23}$$

Equations (10) and (11) are used to model this step.

$$Q_{(k+1)} = V(k) \times (S + rand_4) - d(w) \tag{24}$$

$$d(w) = C(k) - Q(k) \tag{25}$$

Using Equations (26) and (27), the rotational flight is expressed (27).

$$\begin{gathered} G_1 = C(k) \times \left(\frac{rand_5 \times Q(k)}{2\pi}\right) \times cos\left(Q(k)\right) \\ G_2 = C(k) \times \left(\frac{rand_6 \times Q(k)}{2\pi}\right) \times sin\left(Q(k)\right) \end{gathered} \tag{26}$$

$$Q_{(k+1)} = C(k) - (G_1 + G_2) \tag{27}$$

where Eq. is used to derive G1 and G2 (26); finally the location of the vultures is updated using Equation (27).

$$Q_{(K+1)} = \begin{cases} Eq(16) if Q_3 \geq rand_{Q3} \\ Eq(17) if Q_3 < rand_{Q3} \end{cases} \tag{28}$$

Equations (29) and (30) have been utilized to model this vulture movement.

$$\begin{gathered} J_1 = best\ vul_1(k) - \frac{best\ vul_1(k) \times Q(k)}{best\ vul_1(k) - Q(k)^2} \times S \\ J_2 = best\ vul_2(k) - \frac{best\ vul_2(k) \times Q(k)}{best\ vul_2(k) - Q(k)^2} \times S \end{gathered} \tag{29}$$

$$Q_{(k+1)} = \frac{J_1 + J_2}{2} \tag{30}$$

This motion is modeled using Equation (31).

$$Q_{(K+1)} = C(k) - |d(w)| \times S \times Levy\ (d) \tag{31}$$

The equation is used to calculate the US (32).

$$US_{(x)} = 0.01 \times \frac{\mu \times \sigma}{|D|^{1/\beta}}, \sigma = \left(\frac{\gamma(1+\beta) \times sin\left(\frac{\pi\beta}{2}\right)}{\gamma(1+\beta_2) \times \beta \times 2\left(\frac{\theta-1}{2}\right)} \right)^{1/\beta} \quad (32)$$

In Equation (18), d represents the number of dimension's problem, u &D are random numbers between 0 and 1is always set to 1.5 as a default.

Based on beginning values and interference settings, a new localization model is created with localization error as the objective function to retrieve the source's initial value. The localization error is used as the objective function to estimate the unknown source parameter under the assumption that each measurement has Gaussian noise and does not account for other error components. The new localization model uses the target parameter error and the original target position and velocity estimates. We then utilize weighted least squares to locate and speed up the source.

Possibly the AOA seen by the receiver is not the direct path. In this case, the data have little to no relationship to the accurate AOA of the transmitter and can be treated as a normally distributed random variable. It is possible to express the likelihood of AOA mistakes using a mixture of the Gaussian and uniform distribution functions. A device's location can be determined without outside interference by finding where the line segments connecting at least two reference nodes connect. More than two directional lines can't follow at a single point. When there's background noise. As a result, further processing is needed to ascertain the best possible position estimation. All the unidentified nodes can talk to the known ones. Because of the reference nodes, the locations of all the blind nodes may be calculated. With information on the angles measured from several unknown nodes and reference nodes, the below equation 33 can be used to determine where precisely the node in question should be positioned.

$$a = +n \quad (33)$$

where n is the accurate AOA, n is the noise in the AOA data, and is the matrix representing all the AOA readings. However, there are always some unavoidable inaccuracies in the measured data in the real world. Since the locations of the nodes in the excited area (reference nodes and unknown nodes) can be used to determine both, it follows that the unknown locations play a role in determining. Thus, we can get a better idea of the blind nodes' locations by bringing them closer together $\theta - \alpha$.

The current location data is used to anticipate future mobile models, estimating the future location. Given that the algorithm for movement prediction treats each prediction window as a separate prediction unit, the algorithm splits the total positioning time into several prediction windows, each of which has a length of Tm. The node then executes actual positioning every other Tm.

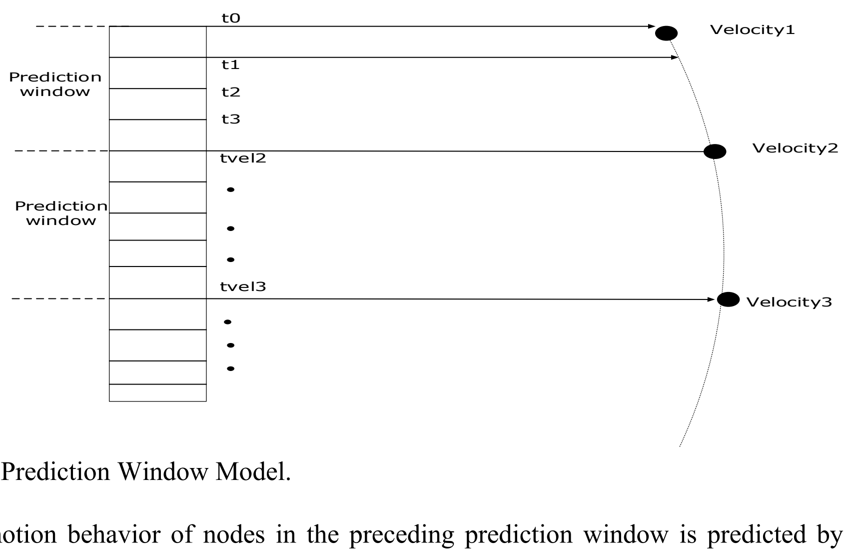


Figure 5. Prediction Window Model.

The motion behavior of nodes in the preceding prediction window is predicted by the algorithm utilizing the velocity data from the most recent prediction period as shown in figure 5. This is done under the assumption that the motion behaviors of nodes do not suddenly change between successive prediction periods in the prediction window. By comparing the node's actual location to its anticipated location in the kth period, we can calculate the RVOA algorithm's location inaccuracy. Once one prediction window is finished, the process continues to the next.

4. Result and Discussion

4.1. Experimental and Simulation

For node localization prediction, the Angle Time of the Red Vulture Arrival Approach (ATRVA) approach that was just

Proposed is simulated and evaluated with the help of MATLAB software. MATLAB is the software that is used to run the simulations. Several presumptions are made concerning the capabilities of the modems and the communications channel. The assumption is that autonomous underwater vehicles (AUVs) can transfer information effectively with active and passive sensor nodes and that data packets sent during communication can be received appropriately. The simulation parameters are listed in Table 2.

We take into account the timing estimate noises at the receiver nodes so as not to lose the generality of the statement. In the simulation, 20 sensors, 50 reference sensors, and 30 source sensors spread across an area of 1,000 meters on each side.

4.2. Performance Analysis

The algorithm's performance is analyzed in this work from two different vantage points: the location error and the energy consumption of the nodes. In this way, an Angle Time of the Red Vulture Arrival Approach (ATRVA) is studied to evaluate a system's accuracy, location coverage, energy consumption, propagation delay, transmission delay, average delay, execution delay, and prediction error.

In the beginning, we investigate how the accuracy of the localization is affected by the error(s) introduced by the measured transmission error and the transmission speed/velocity. As a result of errors in error localization estimation and prediction, there is also an increase in the amount of energy consumed. The error distribution pattern of the measured distance is determined by how drifting patterns of time and velocity interact. Although the speed of sound in water exhibits some degree of variability, this factor has a negligible effect on the accuracy of distance measurements, provided that accurate time synchronization can be preserved. In these situations, it can be quite difficult to locate the sensor nodes in the most advantageous areas to maximize the coverage and their lives. At this point, monitoring underwater acoustic sensor networks in coastal monitoring is the top priority for sustainable development. Accurate localization of mobile node discovery is the appropriate way to handle the issue. Because deploying sensors in water resources, particularly underwater resources, and replacing their batteries come with a substantial financial burden, it is essential to implement UASN using the fewest possible sensors while maximizing both coverage and the sensors' lifetimes. According to this, the Red Vulture Optimization Algorithm (RVOA) that we have presented can be utilized to cut down on the location estimation inaccuracy in an effective manner by picking the best solution possible based on the most accurate function value shown in Figure 6.

As shown in Figure 6, an innovative optimization approach is used to find the optimal point and value for the function to minimize inaccuracy. The fitness value, also known as the function value, is determined using 32 variables to assess the current state. As a direct consequence of this, the value of 434.709 is achieved. The hybrid red fox and African vulture methods assist with the estimate error by attaining the best value, 338.607, by assessing the best point among 32 variables. This helps out with the estimation error. When the searching distance of the better-using behavior of fox was increased through 600 iterations, the fitness values did not improve; on the other hand, when the searching distance of the best vulture behavior was increased through those same iterations, the fitness values changed in the direction of a better deal. In direct correlation with this, the 600 iterations with optimization are utilized to significantly reduce the amount of errors made and the amount of energy consumed.

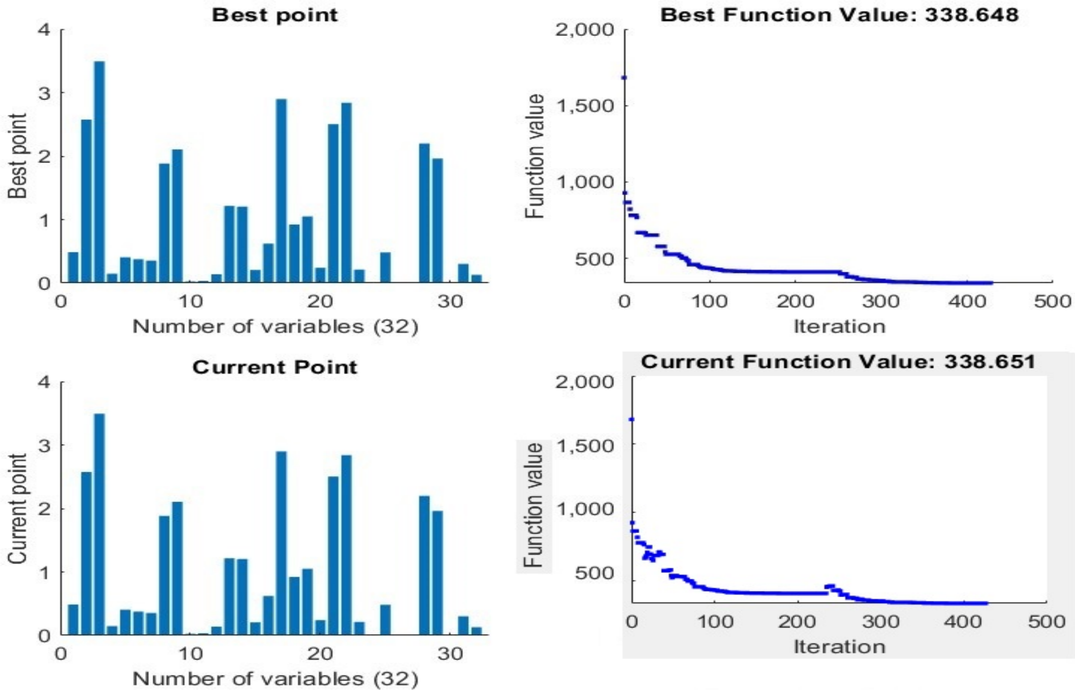


Figure 6. Novel Optimization Analysis.

4.3. Delay Based on Iteration

As seen in Figure 7, the Angle Time of the Red Vulture Arrival Approach (ATRVA) can reduce the average delay compared to other algorithms. Furthermore, as we get closer to the end of the iterations, the performance of ATRVA improves. This is because the interaction between nodes decreases with time, and as a result, the nodes become more familiar with one another. Therefore, individuals make decisions regarding the importance of trust with greater awareness. As a consequence, our suggested method is superior to others such as MPL, GA-SLMP, SLMP, and LSLS in that it can reduce the delay while simultaneously increasing the number of iterations.

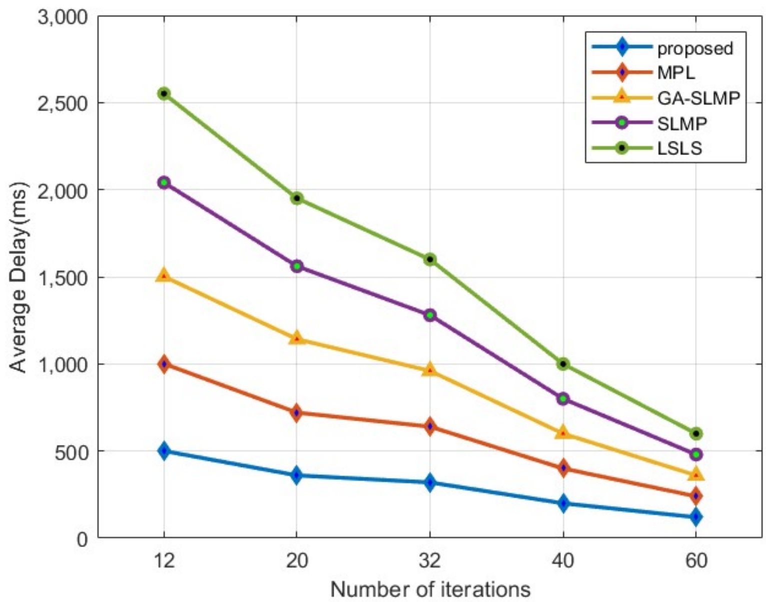


Figure 7. Analyzing the Average Delay. X axis iteration = 10 iteration, Y axis 1ms =1 ms.

A comparison of the amount of energy used by the Angle Time of the Red Vulture Arrival Approach (ATRVA) algorithm can be seen in Figure 8. In light of this, a high- iteration analysis consisting of 5000 iterations was carried out to investigate energy use. As has been demonstrated, ATRVA has the lowest energy consumption and helps us extend networks' lifetime by tuning the weight of consumed energy during data transmission through accurate node location detection in 400 iterations. This allows us to adjust the weight of consumed energy in a way that will enable us to extend the lifetime of networks.

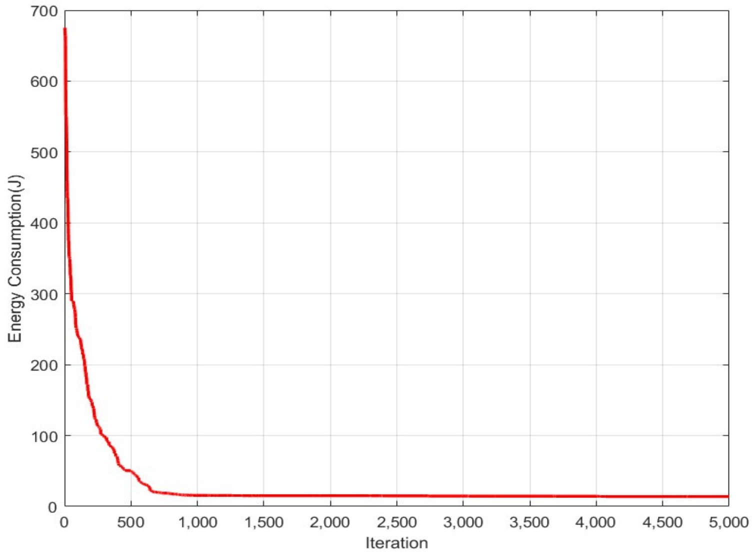


Figure 8. Energy Consumption based on Iteration.

4.4. Location Coverage

The research community has placed substantial emphasis on area coverage due to its status as an essential performance parameter for UASN. The primary purpose of the model that has been developed is to address the issue of how to handle the possibility of having coverage holes when the placements of the sensors are wrong. This is because the coverage confidence might be reduced when the location inaccuracy is ignored or estimated imprecisely. This is what sparked this idea. To accomplish this, the suggested model is contrasted with several other methods already in use, including MPL, GA-SLMP, SLMP, and LSLS. As a direct consequence, the comparison of location coverage can be seen in Figure 9.

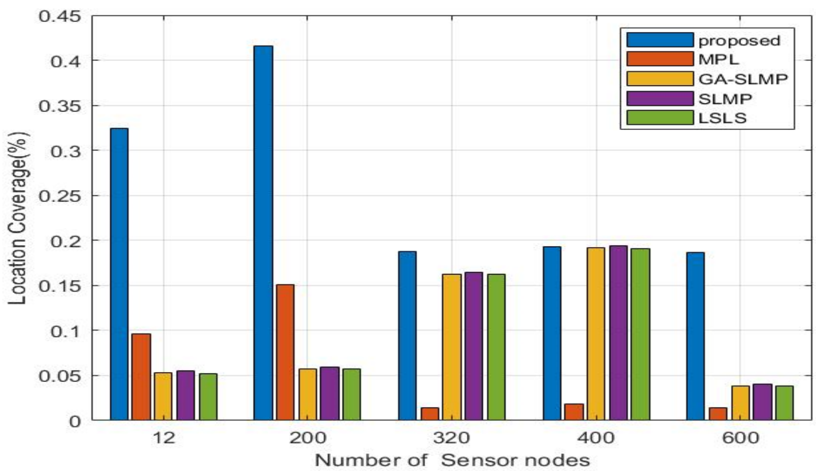


Figure 9. Localization Coverage vs. Number of sensors.

The coverage rate is the area covered by the sensor nodes in the region, as shown in Figure 9, which illustrates that this is the case. The coverage rate of the proposed ATRVA is compared with the coverage rates of other existing research works, taking into account the number of sensor nodes as 12, 200, 320, 400, and 600, respectively. The work presented has a reasonable coverage rate thanks to 200 sensor nodes. The currently implemented results execute location coverage. However, they are inefficient and cannot reach a greater coverage rate.

4.5. Prediction Error

According to Figure 10, when the forecasting interval increases, the predicting error also increases. This is because many unknown components are involved in the wireless sensor network monitoring system. To analyze the accuracy of the prediction, a total of 30 sensor nodes are used. When only a few data points are used to make the model and the prediction (which results in a larger forecasting interval), the model cannot effectively reflect the system, which results in a more significant prediction error.

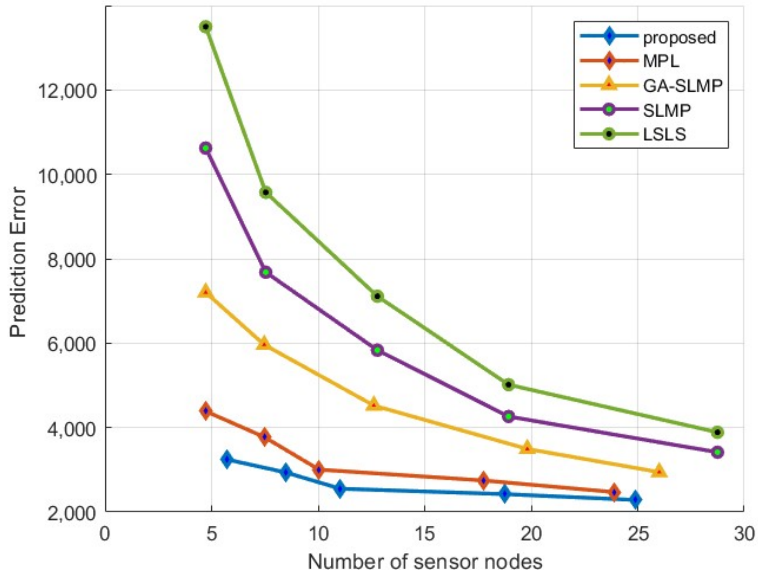


Figure 10. Prediction Error Analysis.

4.6. Propagation Delay

When used for mobile node localization procedures, there is a significant delay in the time it takes for messages from sensor nodes to propagate across an Underwater Acoustic Sensor Network. The wait has been significantly cut down through the proposed method, as shown in Figure 11.

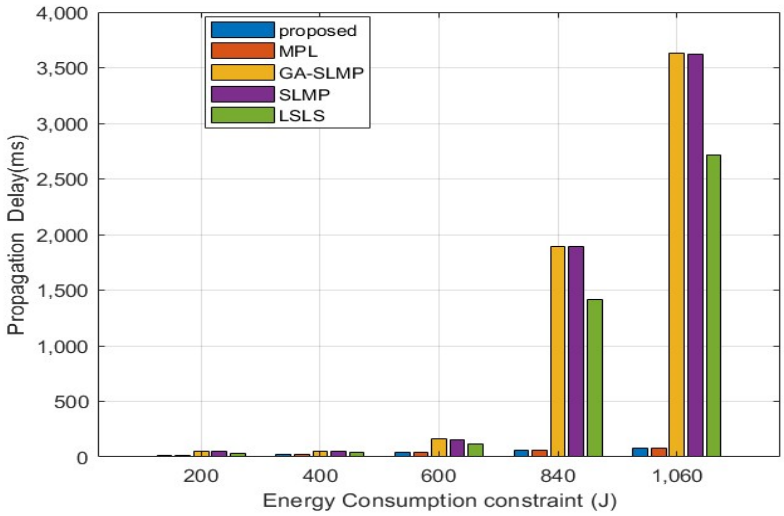


Figure 11. Analysis of Propagation Delay and Energy Consumption

Figure 11 illustrates the discernible correlation between the length of the propagation delay and the rise in the amount of energy. It has been noticed that the Angle Time of the Red Vulture Arrival Approach (ATRVA) performs better than its competitors when minimizing the propagation delay while simultaneously modifying the energy consumption limits. As a result, ATRVA offers superior performance over the other four algorithms—MPL, GA-SLMP, SLMP, and LSLS—regarding Variable propagation delay. This is the case even though all four algorithms deal with delay variance.

4.6. Transmission Delay

During the data transmission process, the proposed Angle Time of the Red Vulture Arrival Approach (ATRVA) can be utilized in UASN to help limit the consumption of needless energy. The visual presentation of the transmission latency for different configurations of the nodes is shown in Figure 12.

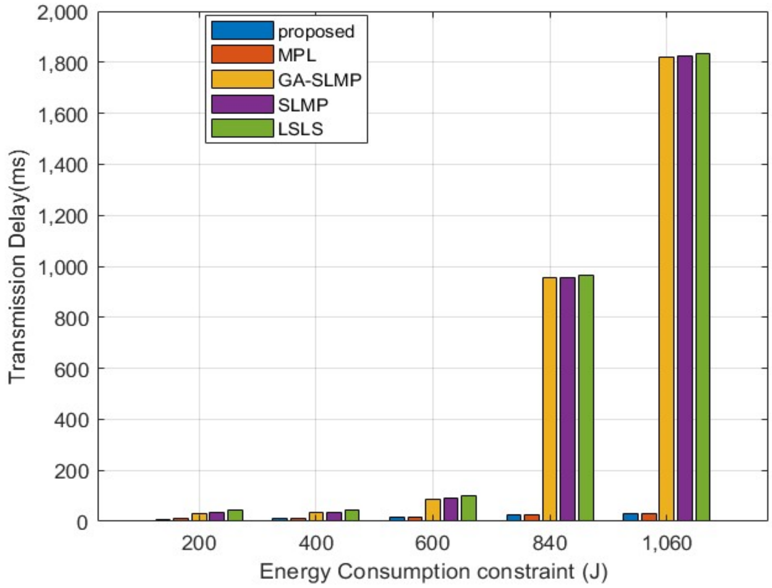


Figure 12. Performance of Transmission Delay and Energy Consumption.

Figure 12 is a comparison table for energy usage with varied transmission delays for each of the three localization algorithms. If the criterion of ensuring no delay in the data transmission is met, ATRVA can lower the amount of energy consumed by each node to the least possible value. The diagram illustrates the transmission delay for a range of possible numbers of energy consumption limits, from 200 to 1060. ATRVA has a significantly shorter localization delay than MPL, GA-SLMP, SLMP, and LSLS.

4.7. Execution Delay

The time it takes for ATRVA and MPL to carry out their operations is reduced when more nodes are used. Compared to MPL, the results produced by existing methods such as GA-SLMP, SLMP, and LSLS are considered reasonably satisfactory. Compared to ATRVA, it makes substantial delays despite having a relatively small number of nodes as shown in Figure 13.

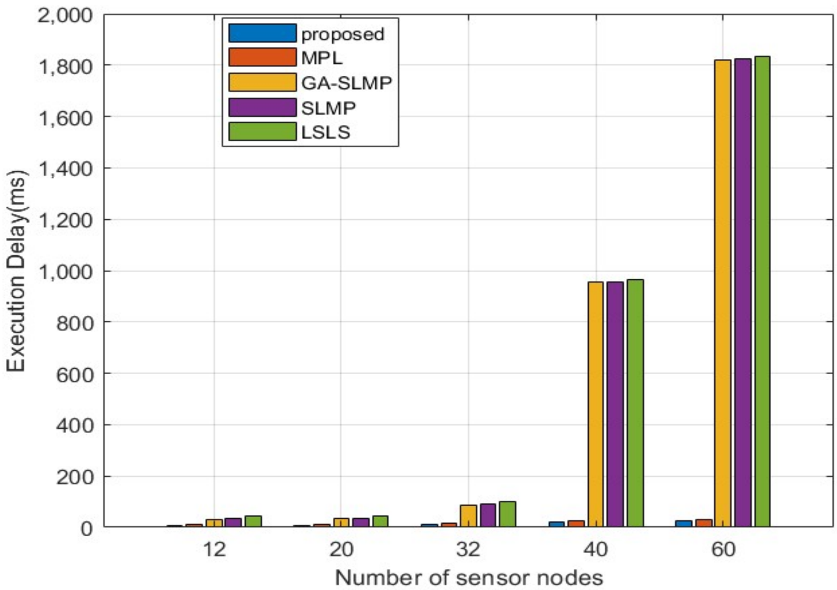


Figure 13. Analysis of Execution Delay.

4.8. Cost

The cost to locate the sensor des is referred to as this here. When calculating it, we consider communication overhead, power usage, and the time it takes to localize a sensor node, and so on. The visual presentation of the localization cost is shown in Figure 14. This depiction takes into account a range of different numbers of nodes.

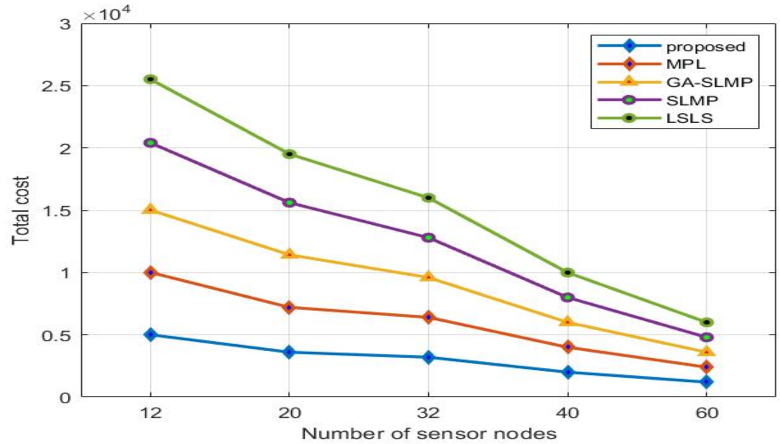


Figure 14. Comparison of performance of cost.

Figure 14 illustrates that the proposed localization cost can range anywhere from 12 to 60 regarding the number of sensor nodes. As a consequence, the simulation results indisputably confirm that the proposed method excels in terms of cost.

4.9. Energy Consumption

In UASN, having accurate information about nodes' locations can help increase the effectiveness of the Network's use of energy. This article makes a trade-off between the amount of energy consumed and the number of sensor nodes shown in Figure 15 to improve the overall performance of ATRVA.

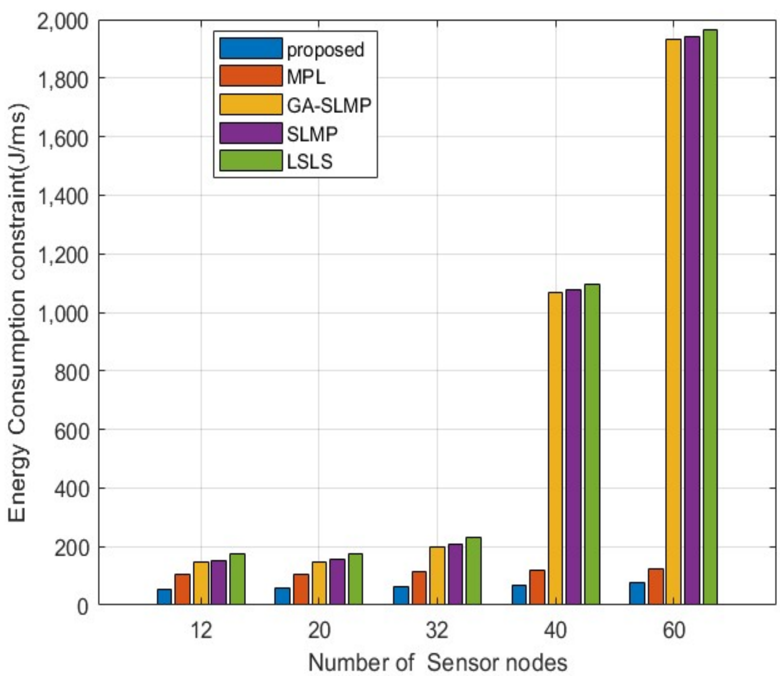


Figure 15. Comparison analysis of Energy Consumption.

The amount of energy that a network with a large number of sensors consumes is depicted in Figure

15. The energy consumption of the suggested ATRVA was higher than the existing approaches as MPL, GA-SLMP, SLMP, and LSLS algorithms based on the number of sensors. The number of nodes protocol increases, and the number of times the nodes are required to communicate with each other also increases. In addition, the required quantity of requests for distance measurements as frequently as required, increases the energy consumed. It demonstrates that the overall awake period of a node was decreased for the suggested approach when compared to existing algorithms such as Movement Prediction Localization (MPL), Genetic Algorithm -Scalable Localization with Mobility Prediction (GA-SLMP), Scalable Localization with Mobility Prediction (SLMP), and Localization Scheme for Large Scale (LSLS).

5. Conclusions

The angle Time of the Red Vulture Arrival Approach (ATRVA) is described in this study as a means of resolving the problems associated with the mobility of UASN and the high amount of energy required by these nodes. Whereas the node in question is a method of estimation founded on TDOA ranging, the Red Vulture Optimization Algorithm is strongly recommended for application. The window prediction method is incorporated into the Euclidean distances strategy to reduce estimation errors and delays significantly. The node mobility model is applied to forecast each time point of velocity and position. This model enables the calculation of the location of the node underwater, which is necessary for accurate forecasting. The node mobility model is applied to forecast each time point of velocity and position. This model enables the calculation of the location of the node underwater, which is necessary for accurate forecasting. It was proven that the proposed method has a superior delay, cost, energy consumption, and accuracy performance compared to other currently used techniques, such as Movement Prediction Localization (MPL), Genetic Algorithm -Scalable Localization with Mobility Prediction (GA-SLMP), Scalable Localization with Mobility Prediction (SLMP) and localization Scheme for Large Scale (LSLS). These comparisons were carried out after the proposed method was analyzed and compared to other currently used methods.

6. Future Enhancement

In subsequent studies, an expanded focus will be placed on developing an algorithm for tracking the mobile node, which is being monitored. The primary idea behind the proposed algorithm is to enhance the capabilities of UASNs in the areas of surveillance, defense, and control. In addition, our activities in the future will concentrate on improving the method's robustness by utilizing the data from each node and introducing a new optimization strategy focused on localization.

Author Contributions

Conceptualization, K.K.G. and G.K.; methodology, K.K.G.; software, G.K.; validation, K.K.G., and G.K.; writing—original draft preparation, K.K.G. and S.G.; writing—review and editing, S.G. and G.K. All authors have read and agreed to the published version of the manuscript.

Funding

This research received no external funding.

Conflict of Interest Statement

The authors declare no conflicts of interest.

Data Availability Statement

No new data were created.

References

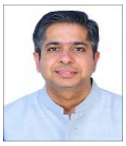
1. Gola, K.K. and Arya, S. (2023) ‘Underwater Acoustic Sensor Networks: Taxonomy on applications, architectures, localization methods, deployment techniques, routing techniques, and threats: A systematic review’, Concurrency and Computation: Practice and Experience, 35(23). doi:10.1002/cpe.7815.
2. Gola, K.K. and Arya, S. (2024) ‘Optimal localization prediction using Red Vulture arrival approach in underwater sensor networks’, Proceedings of the 25th International Conference on Distributed Computing and Networking. doi:10.1145/3631461.3631482.
3. Sharma, Amit, and Pradeep Kumar Singh. (2021).Localization in wireless sensor networks for accurate event detection. *International Journal of Healthcare Information Systems and Informatics (IJHISI)* 16.3: 74-88.
4. Yogeshwary, B. H., K. S. Shivaprakasha, and N. Yashwanth. (2022). Node Localization Techniques in Underwater Sensor Networks. 2022 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS). IEEE.

5. Gola, K.K. and Gupta, B. (2021) ‘Underwater Acoustic Sensor Networks: An energy efficient and void avoidance routing based on grey wolf optimization algorithm’, Arabian Journal for Science and Engineering, 46(4), pp. 3939–3954. doi:10.1007/s13369-020-05323-7.
6. Shakshuki, Elhadi, et al. (2019). Comparative study on range free localization algorithms. *Procedia Computer Science*151 : 501-510.
7. Kumar Gola, K. et al. (2021) ‘Sea lion optimization algorithm based node deployment strategy in Underwater Acoustic Sensor Network’, International Journal of Communication Systems, 34(5). doi:10.1002/dac.4723.
8. Pan, Jeng-Shyang, et al. (2020). A node location method in wireless sensor networks based on a hybrid optimization algorithm. *Wireless Communications and Mobile Computing 2020*.
9. Ansari, Keyvan. (2019). Cooperative position prediction: Beyond vehicle-to-vehicle relative positioning. *IEEE Transactions on Intelligent Transportation Systems* 21.3 : 1121-1130.
10. Yan, Jing, et al. (2017) .Asynchronous localization with mobility prediction for underwater acoustic sensor networks.*IEEE Transactions on Vehicular Technology*67.3 : 2543-2556.
11. Ullah, Inam, et al. (2019) .Localization and detection of targets in underwater wireless sensor using distance and angle based algorithms. *IEEE Access 7*: 45693-45704.
12. Saeed, Nasir, Tareq Y. Al-Naffouri, and Mohamed-Slim Alouini. (2018) .a low-rankmatrix approximation method which can accurately estimatethe missing inter-node distances in transmission distance of underwater optical sensors.*IEEE Transactions on Communications*67.1 : 611-622.
13. Saeed, Nasir, et al. (2019). Localization of energy harvesting empowered underwater optical wireless sensor networks. *IEEE Transactions on Wireless Communications*18.5 : 2652-2663.
14. Shams, Rehan, et al. (2021). Joint Algorithm for Multi-Hop Localization and Time Synchronization in Underwater Sensors Networks Using Single Anchor. *IEEE Access 9*: 27945-27958.
15. Han, Guangjie, et al. (2019) .Prediction-based delay optimization data collection algorithm for underwater acoustic sensor networks. *IEEE Transactions on Vehicular Technology*68.7 : 6926-6936.
16. Zhang, Wenbo, et al.(2020). A node location algorithm based on node movement prediction in underwater acoustic sensor networks.*IEEE Transactions on Vehicular Technology*69.3: 3166-3178.
17. Rao, Madhuri, and Narendra Kumar Kamila. (2021). Cat Swarm Optimization based autonomous recovery from network partitioning in heterogeneous underwater wireless sensor network. *International Journal of System Assurance Engineering and Management* 12, no. 3 : 480-494.
18. Datta, A. and Dasgupta, M., (2021). On accurate localization of sensor nodes in underwater sensor networks: A Doppler shift and modified genetic algorithm based localization technique. *Evolutionary Intelligence*, 14(1), pp.119-131.
19. Sun, Yujiao, et al. The coverage optimization method for underwater sensor network based on VF-PSO algorithm. 2020 Chinese control and decision conference (CCDC). IEEE, 2020.
20. Shah S, Khan A, Ali I, Ko KM, Mahmood H. 2018 Oct 15. Localization free energy efficient and cooperative routing protocols for underwater wireless sensor networks. Symmetry. 10(10):498.
21. Shanthi, M. B., and Dinesh K. Anvekar. Secure localization for underwater wireless sensor networks based on probabilistic approach. 2018 Second International Conference on Advances in Electronics, Computers and Communications (ICAECC). IEEE, 2018.

Author Biographies

Kamal Kumar Gola is an Assistant Professor at COER University, Roorkee, India. He completed his B.Tech. Degree in Computer Science and Engineering from Moradabad Institute of Technology and his M.Tech. Degree in Computer Science and Engineering from Uttarakhand Technical University. He is pursuing a Ph.D. in Computer Science and Engineering from Indian Institute of Technology, Jodhpur. With over 14 years of university teaching experience and six months of industrial experience, Kamal Kumar Gola is a seasoned educator with a wealth of knowledge in his field. He has published more than hundred papers in international journals and has participated in various international and national conferences where he has presented his research. He kept himself updated by attending various professional development programs, workshops, and training courses organized by esteemed institutions such as IIT, NIT, IIIT, and others. His main research interests lie in Underwater Acoustic Sensor Networks, Algorithms and Security.

Dr Gulista Khan, 17+ yrs of Academic & Research Experience. Currently Associate Professor at FoE,Teerthanker Mahaveer University. Did .B.Tech from Kurukshetra University, Kurukshetra, Haryana in 2009, after that did M.Tech from MMEC, Mullana , ambala, Haryana in 2009, PhD. from Teerthanker Mahaveer University, Moradabad, UP, India in 2019. Working domain are Mobile Computing, Cryptography and security, networks, UWSN and VANET etc. Official Member of different Scientific Societies like IEEE, IAENG. Published research papers in international referred journals including SCI, SCOPUS,WoS, UGC Listed, UGC Care Listed also some articles under communication with SCI, Scopus journals. Attended various FDPs ,FTPs, Workshops organized by different National Importance Institutions. Delivered Expert Sessions at different organizations.



Dr Sagar Gulati, presently working as Director School of CS and IT at JAIN Deemed to be University is a resilient academic leader with over fifteen years of experience in Institution building, Academic Governance, Programme Excellence, Curriculum Engineering, Student success and Team Management. He is a proud Lifelong learner, as he strives to keep himself updated as per developments around technology. His area of research includes Artificial Intelligence, Wireless Networks and Distributed Systems.