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RESEARCH ARTICLE

Development and Evaluation of RSSI and AOA-Based Localization Methods Utilizing the MVO Algorithm for UWSNs

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Abstract – Underwater Wireless Sensor Networks (UWSNs) play an essential role in aquatic environment monitoring, supporting applications such as oceanographic data collection, underwater resource management and disaster prevention. However, accurate localization in underwater remains a significant challenge due to the unique features of underwater environments, including the reliance on acoustic communication, mobility of sensor nodes and the complexity of three-dimensional topology. Traditional localization techniques, like Received Signal Strength Indicator (RSSI) and Angle of Arrival (AOA) methods, suffer from several limitations, including inaccuracies due to time-varying sound speeds affected by salinity, temperature, and pressure. Additionally, they often exhibit high energy consumption, slow convergence, and poor adaptability to dynamic underwater environment. Existing optimization-based localization approaches, face trade-offs between exploration and exploitation, limiting their effectiveness in achieving optimal position estimates. The primary challenge in UWSN localization is achieving high accuracy while minimizing energy consumption and computational complexity. Many existing methods struggle with adaptability in dynamic underwater conditions, where sensor nodes are mobile and environmental factors significantly affect signal propagation. There is a need for an advanced localization approach that can effectively balance accuracy, efficiency, and robustness in complex underwater environments. This paper presents a novel localization approach utilizing the Multi-Verse Optimization (MVO) algorithm, a physics-inspired metaheuristic technique. MVO enhances RSSI and AOA-based localization by maintaining a balance between exploration and exploitation, leading to improved position estimation. Through extensive simulations, we evaluate performance of MVO in terms of localization accuracy, convergence speed, energy efficiency and resilience to anchor node distribution variations. The results demonstrate that MVO significantly outperforms conventional methods by achieving higher localization accuracy while reducing computational overhead. While AOA-based localization is more precise under ideal conditions, RSSI-based methods offer lower complexity, making them suitable for resource-constrained deployments. By overcoming key limitations such as sensitivity to environmental fluctuations and high computational costs, this work establishes MVO as a robust and efficient localization solution for UWSNs operating in challenging underwater environments.

Index Terms – UWSNs, Positioning, RSSI, AOA, MVO Algorithm, Localization Accuracy, Energy Usage, Coverage, Delivery Rates.

1. INTRODUCTION

In the present age, research on underwater environments has gained great importance as a means to reduce dependence on terrestrial resources. The sea is a vast and unused natural resource, and its need to detect abundant reserves. In addition, it is necessary to deepen understanding of the marine ecosystem to promote practices that contribute to the sustainability to achieve this, an effective monitoring of the underwater media is required and UWSNs play an important role in this field [1]. UWSNs is composed of sensory nodes or mobile vehicles placed in underwater media and cooperates to monitor various marine conditions.

This network includes a variety of applications, considering marine data collection, pollution level monitoring, overseas tool search, strategic observation, detection and measurement of natural disasters [2]. If the sensor is a mobile node, the network is called mobile UWSNs. UWSNs has a similar point with ground Wireless Sensory Networks (WSNs), but it shows a unique problem in some main differences. For example, UWSN relies on sound waves for communication and has a longer delay, error in three -dimensional space and

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causes additional complexity of mobile nodes. These differences cause important problems for the design and distribution of UWSNs. To effectively control the underwater environment, sensors or wireless nodes are strategically placed to collect important data for the environment. This data may include environmental parameters. After data is assembled, it is transmitted to surface shell for further analysis and interpretation. This process is important for disclosure of important information, which can help the management and protection of the marine ecosystem. We can use the technology of the wireless sensor to collect data in real time to improve decision making and support environmental protection efforts [3]. Figure 1 shows the basic architecture of UWSNs.

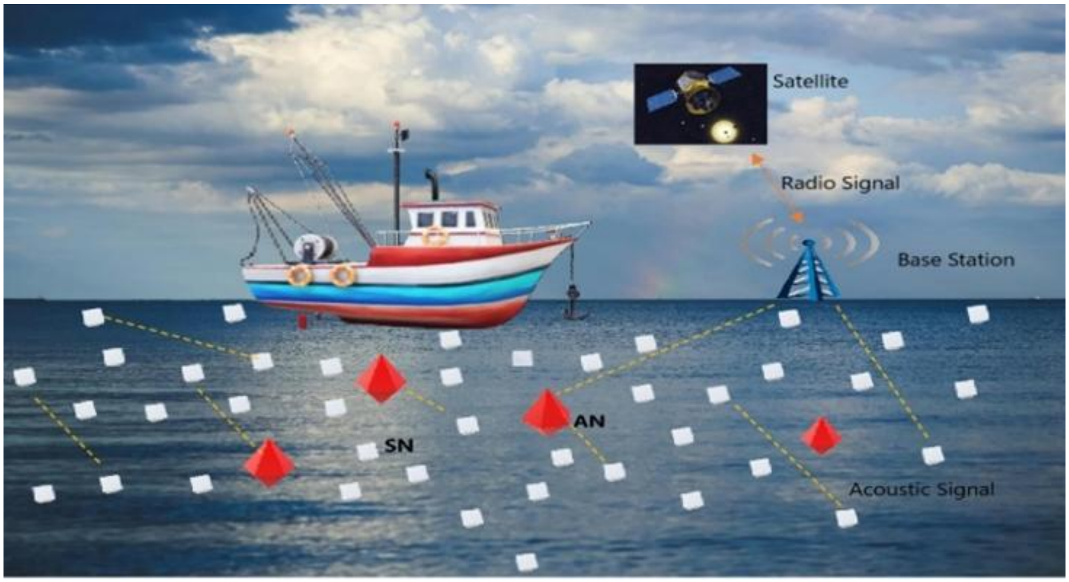

Figure 1 UWSNs Sensors and Base Station

UWSNs sensors are needed to capture actual physical conditions and to detect various changes in the environment, such as temperature fluctuations, pressure changes and sound strengths. The exact understanding of these changes is important for effective response and management strategies [4]. The concept of localization includes the exact position definition of the sensor about the environmental phenomena they detect. Localization plays a decisive role in ensuring accurate interpretation of the data collected from the sensors, which allows researchers and rescue teams to make reasonable decisions according to the exact position of environmental changes [5]. Localization methods provide accurate spatial identification of the sensory node, which is essential for effective observation and monitoring. Knowing the location of each node, the network increases accuracy of data, communication effect and general decision production opportunities.

In addition, localization guarantees that the sensory network is effectively adapted to environmental changes, if the answer is timely and accurate. Without the exact localization, data collected on the loading node is meaningless to the user. Localization is generally achieved using methods like Time of Arrival (TOA), Time Difference of Arrival (TDOA), AOA, RSSI [6]. Localization methods of underwater WSN can commonly be classified into two categories. These are range-based and range-free approaches, each with its subcategories depending on the specific techniques employed [7].

1.1. RANGE-BASED ALGORITHMS

These algorithms depend on ranges or bearing data to estimate the location of sensor nodes. Range-based protocols give more accurate estimates of sensor node location. Additional hardware is needed to measure distances, thus making the network costlier. The receiving end needs propagation time to obtain the signal. Table1 summarized the range-based algorithms.

- ToA: This is the simplest and most effective distance estimation technique compared to other techniques. The algorithm calculates time taken for a signal to send between nodes in order to find the distance that separates nodes. In UWSNs, accurate time synchronization between two nodes is required if acoustic speed is used. In this case, it takes more time for the signal to propagate between two nodes as the distance between them increases. Because the acoustic channels in the underwater environment have asymmetric properties, the ToA may lead to an inaccurate calculation of the propagation time. Considering all its disadvantages, ToA is recognized as the most effective method for locating underwater nodes [8].

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- TDoA: This technique is mostly used to evaluate difference in arrival time between two packets that are received from two different media, such as acoustic and radio waves. However, radio signals are reduced underwater. Bent path of underwater waves is because of the unevenness of underwater environment. Therefore, localization in UWSNs by mean of TDoA becomes more challenging compared to ground-based networks [8-9].
- AOA: This algorithm computes the angle between the signal's propagated path and a reference direction which is predefined. AOA is not largely employed in underwater because the directional antennas are expensive and large. Recent research on underwater positioning shows the feasible nature of using AOA methods [9].
- RSSI: This algorithm determines sender-receiver distance by evaluating the signal's transmission loss. This process distinguishes the difference between the power sent and received by the signal. It then forms a correlation with a propagation loss model. RSSI incurs minimal overhead. In UWSNs, this is not considered ideal because of the loss of an acoustic signal with transmission is temporary. fading effects and Multipath also have an influence on the acoustic signal, which causes distance measurements to be inaccurate [10].

Table 1 Range Based Algorithms Analysis

Localization Algorithm	Selection Methodology	Localization Accuracy	Computational Cost	Issues
TOA [8] (Distance based)	Ensure that Acoustic/target is synchronized	Moderate	More Expensive	Need of Time Synchronization
TDOA [8] (Distance based)	Transmission time is known	Good	More Expensive	High Energy consumption makes it costly
AOA [9] (Angle based)	Depends on arrival angle	Good	More Expensive	Complex and less accuracy at large scale
RSSI [10] (Signal based)	Based on the strength of the received signal and the impact of route failure	Moderate	Less Expensive	Moderate accuracy and signal loss due to fading of multipath

1.2. RANGE-FREE ALGORITHMS

These algorithms rely on different information to infer the positions of nodes, other than the range and bearing data. No additional hardware is needed for these schemes. These techniques can provide a very basic approximation of the node's position. These algorithms are broadly classified into different algorithms as below:

- Hop-count based algorithm: The square grid has beacon nodes at each corner. The DV-Hop algorithm, the Robust Positioning method, and the DHL algorithm are the three main algorithms. By tallying the number of hops and calculating the average hop distance, we may approximate the distance between the anchor nodes. This method is simple and does not suffer from errors in distance measurement. However, this algorithm is feasible only for isotropic networks [11]. The incorporation of an extra refinement phase helps to strengthen DV-Hop by using a robust positioning algorithm [12]. The DHL algorithm is used to bound the limitation of DV-Hop for the non-uniformly distributed network. The DHL algorithm uses density awareness to make dynamic predictions of distance [13].
- Area-based algorithm: In UWSNs, it might be almost impossible or not necessary keeping track of location of each sensor node. Vague idea of location of sensor node is often sufficient to deliver overall applications. Two major algorithms that are based on area approaches are Area Localization Scheme [14] and Approximate Point in Triangle [15].
- Centroid- based algorithm: This is a proximity-based algorithm that does not rely on range information. In this case, position is determined by employing the equation (1) given below:

$$(a_{est}, b_{est}) = \left(\frac{a_1+a_2+\ldots\ldots+a_n}{n}, \frac{b_1+b_2+\ldots\ldots+b_n}{n}\right) \quad (1)$$

Where, (a_{est}, b_{est}) represents approximate location of receiver [16].

In a typical underwater sensor network, hundreds of nodes are wirelessly connected to underwater gateways and affixed to

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the bottom. Collectively, these nodes gather information and send it to station located on the sea surface via several intermediate relays. The vertical transceivers of the gateways connect to sensor nodes, and horizontal transceivers transmit data to terrestrial surface. In water with more depth, vertical communication is usually based on modems of acoustic and radio for the transfer of data over long distances [17]. The sensor selection method improves estimation performance by formulating the selection problem as an optimization task that minimizes Cramér-Rao Lower Bound (CRLB) while considering correlated measurement noise. It utilizes semidefinite programming (SDP) for convex relaxation, which allows for a more efficient solution compared to exhaustive search methods. To further improve the SDP solution and therefore the localization accuracy, a randomization approach is used [18]. Using measurements of both the received signal intensity and the angle of arrival, 3D cooperative wireless sensor networks are able to tackle the problem of real-time target localization. This approach overcomes the non-convexity of the maximum likelihood estimator by providing a quadratic closed-form solution with linear computational complexity relative to several connections. The proposed estimator achieves superior accuracy compared to existing methods across all evaluated scenarios, providing robust and efficient solution for target localization in complex sensor network environments [19].

1.3. Motivation

The rapid proliferation of wireless sensor networks, particularly underwater WSN has created an urgent need for accurate and efficient localization techniques. The complexity of underwater environment presents several critical challenges that existing solutions struggle to address effectively. While various optimization-based localization schemes have been proposed, many fail to adequately account for node mobility, which is inherent in underwater deployments due to environmental factors such as currents. Furthermore, the emergence of three-dimensional UWSNs deployments has introduced additional complexities, while the growing demand for energy-efficient solutions necessitates new approaches that can balance localization accuracy with power consumption.

These challenges motivate our research to develop an integrated solution that advances state-of-art in underwater sensor node localization. Research explores MVO algorithm, which has demonstrated superior performance in handling complex optimization problems. Unlike other optimization techniques like Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Whale Optimization Algorithm (WOA) and MVO provides more balanced exploration and exploitation mechanism, ensuring better convergence to find optimal solution while avoiding premature stagnation. Additionally, MVO's ability to handle multi-model optimization problems makes it particularly well-suited for dynamic underwater environments. Its unique mechanisms of white, black and wormhole operators allow it to efficiently search solution space, adapting to changing underwater conditions and achieving higher localization accuracy with lower computational complexity. This work aims to create a robust, efficient and practical approach that can perform reliably across diverse deployment scenarios while minimizing both time consumption and computational overhead, ultimately achieving precise localization of sensor nodes in challenging underwater environments.

1.4. Contribution

This research paper presents several significant contributions to the field of UWSNs through the integration of the MVO algorithm with RSSI and AOA techniques. The key contributions are as follows:

- By incorporating the MVO algorithm, the paper demonstrates a marked improvement in localization accuracy within UWSNs. The MVO algorithm effectively balances exploration and exploitation, minimizing localization errors in underwater environments, which are traditionally challenging to analyze.
- The study provides a comparison of RSSI and AOA techniques in terms of various metrics such as accuracy, coverage, energy usage, and delay. It highlights the superior accuracy of AOA due to direct measurements and the better coverage performance of RSSI at shorter distances.
- The paper lays groundwork for future research by proposing the incorporation of additional environmental parameters, like water density and salinity into the optimization process. It also suggests exploring hybrid optimization techniques to further enhance localization accuracy and robustness in UWSNs.

1.5. Paper Organization

Section 2 provides a comprehensive review of existing localization strategies, with a focus on optimization-based techniques. Section 3 explains basis of MVO algorithm. Section 4 introduces the proposed MVO-based localization method, including theoretical foundation and implementation. Section 5 discusses experimental setup and results, offering a comparative analysis of MVO with alternative localization approaches. Last but not least, Section 6 summarizes important results and suggests avenues for further study.

2. RELATED WORK

Several localization techniques have been proposed in literature to improve accuracy and efficiency of UWSN. In this section, we review significant contributions that leverage

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optimization algorithms and advanced methodologies for localization in UWSNs.

A 3D- localization technique for wireless sensor networks based on PSO is introduced in [20]. This approach utilizes swarm intelligence to enhance localization accuracy by iteratively updating particle positions based on global and local best positions. PSO-based algorithm demonstrates improved convergence speed and localization precision. However, its performance deteriorates in highly dynamic underwater environments due to the sensitivity of PSO to initial conditions and local optima. Improved range-based localization technique using WOA in UWSNs is presented in [21]. This method employs WOA's bubble-net hunting mechanism to optimize sensor positions for enhanced localization accuracy. The results indicate better precision compared to conventional range-based techniques. A localization scheme based on MAP estimation and PSO for drifting-restricted UWSN is discussed in [22]. The MAP method is used to estimate the most probable sensor positions, while PSO further refines these estimates for reduced localization error. The approach effectively addresses sensor node drift issues and improves robustness. However, the dependency on prior knowledge of drift patterns limits its applicability in highly unpredictable underwater conditions. Three-dimensional localization in underwater optical wireless networks is analysed in [23], considering uncertain anchor positions. A probabilistic model is developed to address anchor position uncertainty, using a hybrid optimization framework combining Bayesian inference with convex optimization. Proposed work reduces localization errors. However, it requires high computational resources, making real-time implementation challenging in resource-constrained UWSNs. Analysis of localization and time synchronization in UWSNs is conducted in [24], categorizing existing methodologies into range-based and range-free approaches. Study emphasizes the need for hybrid solutions that integrate multiple techniques for enhanced accuracy. Various localization techniques and their challenges in UWSNs are reviewed in [25]. A comparison is made between range-based methods like TOA and AOA and range-free methods like centroid-based and DV-hop algorithms. The study identifies power consumption and propagation delays as major constraints in underwater environments. However, no novel solution is proposed to mitigate these issues. Performance of range-free localization techniques in WSNs is evaluated in [26], focusing on Monte Carlo-based and centroid localization techniques. Their accuracy is assessed under different node densities. The results show that Monte Carlo-based methods provide higher accuracy at the cost of high computational overhead. A major limitation of this work is the exclusion of real-world underwater scenarios in the evaluation process.

Time synchronization-free localization schemes in UWSNs are reviewed in [27]. Algorithms such as LSE and MLE techniques, which do not require time synchronization between nodes are analysed. While these methods reduce synchronization overhead, they exhibit lower accuracy compared to time-based techniques. A hybrid approach combining range-based and range-free methods is suggested to achieve a balance between accuracy and efficiency. A ToA-based localization algorithm for UWSNs is proposed in [28], utilizing the time delay of acoustic signals to estimate sensor positions. Improved localization accuracy in static underwater is demonstrated. However, ToA techniques suffer from signal attenuation and multipath interference, limiting their effectiveness in dynamic underwater conditions. MVO-based technique is introduced in [29]. This algorithm models universes competing for optimal solutions, thereby improving exploration and exploitation capabilities. MVO based technique shows superior performance in optimization problems compared to traditional algorithms. However, its computational complexity remains challenge for large-scale underwater deployments. Table 2 shows summary of localization techniques.

Table 2 Summary of Localization Techniques in UWSNs

Ref	Methodology	Advantages	Disadvantages
[20]	PSO	Improved convergence speed and accuracy	Sensitivity to initial conditions, local optima issues
[21]	Range-based localization with WOA	Enhanced precision	Retraction raises validity concerns
[22]	MAP estimation with PSO refinement	Addresses sensor drift, improved robustness	Dependency on prior knowledge of drift patterns
[23]	Bayesian inference with convex optimization	Reduced localization error	High computational resource requirements
[24]	Range-based and range-free approaches	Highlights key challenges and hybrid solutions	Lacks experimental validation

[25]	ToA, AOA, DV-hop, centroid-based	Identifies constraints like power and delay	No novel mitigation strategies proposed
[26]	Monte Carlo, Centroid-based	Monte Carlo provides higher accuracy	Computational overhead, lacks real-world testing
[27]	LSE, MLE	Reduces synchronization overhead	Lower accuracy than time-based methods
[28]	ToA-based	Improved accuracy in static environments	Affected by attenuation and multipath interference
[29]	MVO	Superior performance in optimization tasks	High computational complexity

3. MVO ALGORITHM

MVO draws inspiration from astronomy principles, specifically nature of black, white, and wormholes. Cosmological theory puts white holes down as sources of new universes, while black holes have an enormous gravitational attraction, pulling in objects within their vicinity. Wormholes, by contrast, are theoretical structures that link far-off areas of space, having the possibility of facilitating instant movement between other points [30].

The mechanism of search within MVO is divided into two phases, that are, exploration and exploitation, both of which are oriented towards cosmological events. Exploration is enabled through white holes, which inject new solutions into the search space, and black holes, which consume better solutions to provide a diverse and wide-ranging search. Exploitation, on the other hand, is undertaken through wormholes that facilitate efficient jumping from one solution to another, ensuring quick refinement. Every candidate solution is given a status as an independent universe, where the rate of growth in its variables is proportional to its performance. Instead of repetition of search patterns, the algorithm evolves dynamically with time, enabling solutions to communicate, share information, and converge to best results [31]. Optimization follows these basic principles:

An inflation rate that is higher raises the chances of the creation of white holes, lowering the chances of the appearance of black holes.

Objects tend to move out through white holes in areas with higher inflation rates, while objects will gravitate toward black holes in areas of lower inflation rates.

Objects in various universes can travel randomly towards the universe with the highest rate of inflation.

Transition happens when there's tunnel formation that allows transfer from white holes with higher rates of inflation to black holes with lower inflation rates. The process of exchange is very essential for optimizing overall optimization, allowing solutions to transfer from one universe to another and promoting an interactive, dynamic search process. With time, the mechanism causes the distribution of inflation rates to be more balanced across universes as outlined in equations (2) and (3).

Assume that,

$$u = \begin{bmatrix} a_1^1 & a_1^2 \cdots & a_1^d \\ a_2^1 & a_2^2 \ldots & a_2^d \\ \vdots & \vdots & \vdots \\ a_n^1 & a_n^2 \ldots & a_n^d \end{bmatrix} \quad (2)$$

where n is universes and d is parameters.

$$a_i^j = \begin{cases} a_k^j R1 < NI_r(u_i) \\ a_i^j R1 \geq NI_r(u_i) \end{cases} \quad (3)$$

Where a_i^j is j[th] number in i[th] universe, u_i is i[th] universe, $NI_r(u_i)$ is standardized inflation rate of i[th] universe *R1* is random variable in [0, 1] and a_k^j indicates j[th] parameter of k[th] universe [32]. Reducing inflation enhances the likelihood of objects being moved across tunnels produced by white and black holes, which is essential in optimization situations where the rate of inflation must be positive. This positive approach helps in exploration by forcing universes to exchange objects and experience abrupt changes. To maintain a balance between exploring and exploiting, it is considered that universe has wormholes allowing for random exchange of objects. This introduces uncertainty to improve the variety of solutions. Moreover, wormholes connect a certain universe to the best universe found so far. This mechanism allows universes to seize superior solutions, improves small changes within the particular domain, and helps to increase overall growth rates by ensuring that the algorithm remains adaptive as well as efficient. As portrayed in equation (4).

$$y_i^j = \begin{cases} \begin{cases} y_j + T_D \times \left(\left(U_j - L_j \right) \times r_d + lb_j \right) r_a < 0.5 \\ y_i - T_D \times \left(\left(U_j - L_j \right) \times r_d + lb_j \right) r_b \geq 0.5 \end{cases} & r_a, r_b < P \\ x_i^j r_c \geq P \end{cases} \quad (4)$$

Where, y_j is j[th] variable of best universe created, U_j and L_j are upper and lower boundaries of jth variables, y_i^j is j[th] variable of i[th] universe and r_a, r_b, r_c and r_d are random numbers in [0, 1]. P is existence probability of wormholes, and T_D is distance traveling rate, these are two aspects that cannot be negated in any processes optimization of the algorithm MVO. P represents the presence of a wormhole in universe, and straight-line improvement of such enhances the efficiency of the transfer of objects between universes much more frequently. Similarly, T_D is a measure of the distance from an object that is teleportable through a wormhole compared to the most optimal universe so far found. The algorithm increases the accuracy of local searches by improving T_D. That helps objects move closer to the best solutions possible. All of those together make a big difference in the general efficiency and success of the process of optimization. The formula is provided in equation (5).

$$P = m_{min} + i \times \left(\frac{m_{max} - m_{min}}{I}\right) \tag{5}$$

Where m_{min} and m_{max} represents the minimum and maximum values respectively. Let i be present iteration and I be maximum iterations [33].

4. PROPOSED MVO-BASED LOCALIZATION METHOD

Accurate localization is crucial for efficient operation of UWSNs. Traditional methods such as RSSI and AOA suffer from significant limitations including environmental interference, multipath effects, and high energy consumption.

This paper proposes an enhanced localization approach that leverages the MVO algorithm to improve accuracy, minimize localization errors, and ensure energy-efficient operation in dynamic underwater environments.

4.1. Working Model of MVO-Based Localization

This section describes the working model of the MVO-based localization approach in UWSNs. The proposed model integrates MVO with RSSI and AOA methods to enhance localization accuracy, minimize computational complexity and improve energy efficiency.

The model consists of multiple stages including network deployment, signal measurement, optimization and localization estimation. The flowchart of working model is shown in Figure 2.

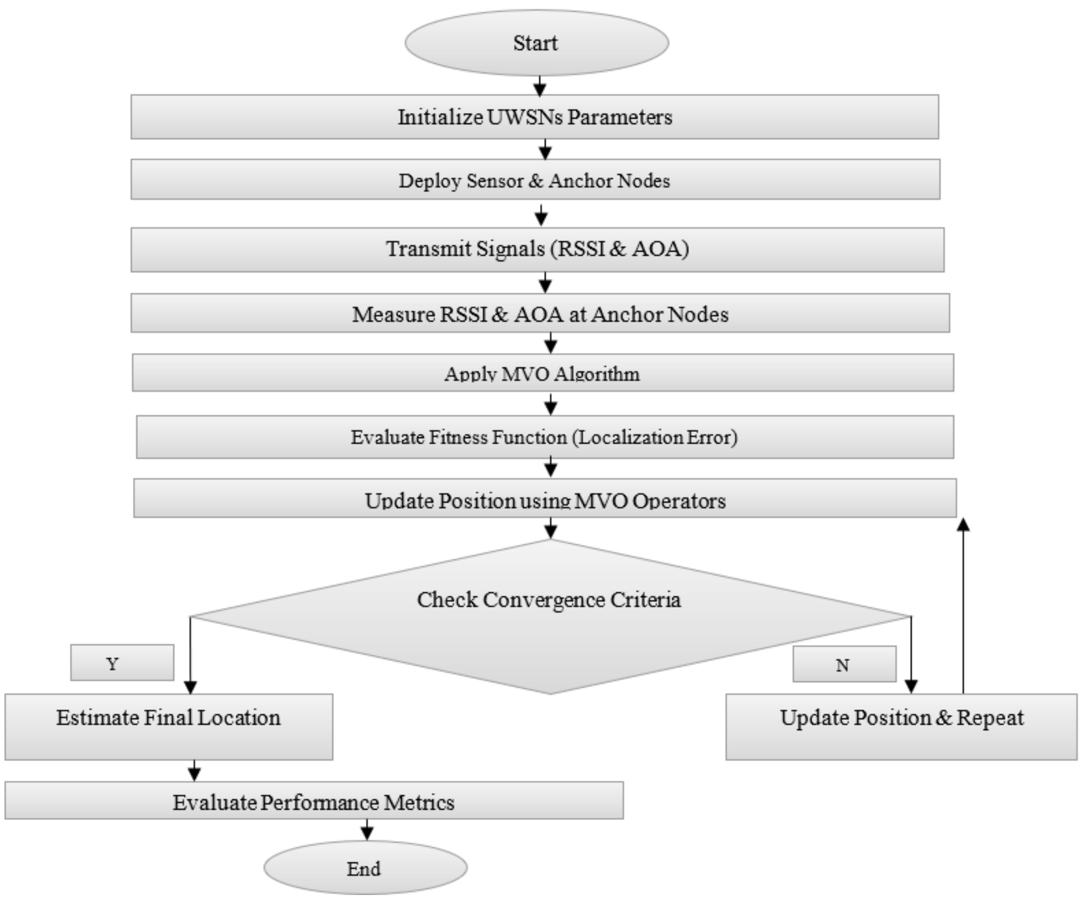

Figure 2 Flowchart of Working Model

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4.2. RSSI-Based Localization with MVO

In this deployment, RSSI method is used, where location of a sensor node is calculated based on RSS sensed by surrounding anchor nodes. Every sensor node is connected to several anchor nodes directly and its position in the network is estimated based on the received signal strength from anchors, provided that they are in the transmission range. This approach relies on correlation between transmitting power of sensor nodes and signal strength at anchor nodes, which is the basis for position estimation [21]. The mathematical definition of RSS is given by equation (6).

$$RSS(g) = 10 \times h \times log\left(\frac{g_o}{g}\right) + S \qquad (6)$$

Where, S is strength of signal at g_0 which signifies reference distance in decibels. h is path-loss exponent, constant that indicates rate of signal degradation, while g is actual distance between sensor and anchor node. Ratio among reference distance (g_0) and actual distance (g) is expressed using logarithmic term. With increase in g, log ratio decreases. Hence, this gives a lower RSS(g).

A total of c nodes forms the sensor network. The network also comprises anchor nodes represented with t whose locations are known as well as sensor nodes represented with $(c - t)$ whose locations are unknown. For the determination of positions $c - t$ sensor nodes, we changed the position of a sensor to each $(c - t)$ locations. These take several readings of the signal strength at the designated position. The distances are calculated among anchor nodes and the mobile sensor node at each of (c-t) locations using RSS data, as shown by equation (7)

$$v_{i,i=1\ to c-t} \qquad (7)$$

In the grid, if the absolute locations of the mobile sensor is (a_i, b_i), $i = 1\ to (c - t)$ and locations of anchor nodes are (A_j, B_j), $j = 1\ to\ t$, then Euclidean distance between sensor and anchor nodes is given by equation (8)

$$V_{ij} = \sqrt{(A_j - a_i)^2 + (B_j - b_i)^2} \qquad (8)$$

Its aim is to reduce error between actual and estimated distance. Thus, objective function is represented as below by equation (9)

$$\sum_{j=1}^{t} \sum_{i=1}^{c-t} \left(V_{ij} - v_{ij}\right)^2 \qquad (9)$$

MVO improves solutions by a systematic method involving exploration, exploitation, and wormhole-based transitions. At the beginning, a variety of universes is created where every universe corresponds to a potential solution. The algorithm starts with the evaluation of these universes in terms of their performance as solutions. If a universe is satisfactory according to the specified requirements and is found to be a good solution, it is kept. But if a universe does not meet the criteria, it is refined through a series of processes made possible by major operators: white holes, black holes, and wormholes. This refining process repeats itself until the most optimal solution based on RSS values is found, thus providing accurate position determination.

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1. Input: Anchor nodes, Target nodes, Universes, White holes, Black holes, Wormholes, Inflation Rate, Area, Dimension.

2.Output: Optimal sensor node position represented by (a_{best}, b_{best})

3.Objective Function:

Minimize localization error by reducing difference among estimated and actual positions:

$$f(x) = \sum_{j=1}^{t} \sum_{i=1}^{c-t} \left(V_{ij} - v_{ij}\right)^2$$

4. Population initialization

5. For each universe u:

Randomly assign initial positions (a_u, b_u) in a defined search space

6. Set up the necessary parameters, including universes and optimization constraints

7. Iterative optimization:

Compute RSSI

Create new position (a_{new}, b_{new})

For each universe:

Recompute RSSI

Evaluate $f(a_{new}, b_{new})$

8. Replace $(a_u, b_u,)$ to (a_{new}, b_{new})

9. Enhance exploration and exploitation through MVO

10. Return the optimal positions (a_{new}, b_{new}) that yield the minimum localization error $f(x)$

Algorithm 1 MVO Based Method for RSSI Localization

The RSSI based localization with MVO optimization method (as shown in Algorithm 1) is designed to optimize sensor node location in UWSNs by minimizing localization errors. The algorithm starts by taking input parameters like anchor nodes, sensor nodes, universes, white holes, black holes, wormholes, inflation rate, area and dimensions. It initializes a population of sensor node positions randomly within defined search space. Each universe represents potential solution and its fitness is evaluated based on the difference between

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estimated and actual node positions. Algorithm iteratively improves localization accuracy by computing RSSI values, generating new sensor positions and evaluating their accuracy. The best-performing positions are retained while poorly performing ones are replaced using white, black, and wormhole mechanisms of MVO. White hole effect enhances solutions by sharing high-quality positions, while the black hole effect eliminates suboptimal solutions. The wormhole effect introduces random jumps, ensuring global exploration and preventing premature convergence. This iterative optimization continues until the algorithm converges on the best possible sensor node positions. By leveraging MVO, the approach enhances localization accuracy, reduces computational overhead and ensures robust performance in dynamic underwater environments.

4.3. AOA-Based Localization with MVO

UWSN is system consisting of anchor (M) and sensor nodes (N) that are deployed in a target area. They are wirelessly connected, and one of the sensor nodes traverses monitoring region at velocity less than velocity of signal propagation. Anchor nodes are provided with omnidirectional antennas and make use of carrier frequencies to send monitoring signals. The reflected signals from the mobile node are then received by sensor nodes.

Sensor nodes quantify two significant parameters from the observed signals:

Doppler Shift: It is caused by the alteration in frequency between the received and transmitted signals.

AOA: This is elevation and azimuth angles at which reflected signal arrives at sensor nodes.

Sensor nodes send Doppler Shift and AOA information to an onshore monitoring, which can analyze this data to calculate position of mobile node. Calculations are all done within a specified reference frame using signals broadcast by anchor nodes.

AOA algorithm determines equation of sensor node j when reflected signal arrives anchor node i is represented by equation (10)

$$\mu_{i,j} = \mu_c\left(1 + \frac{\rho}{\eta}\left(cos\gamma_{i,\rho} + cos\gamma_{j,\rho}\right)\right) \quad (10)$$

Where, μ_c is carrier frequency of the signal, ρ is mobile node velocity, η is sound speed in water, $\gamma_{i,\rho}$ is angle among anchor node and direction of mobile node. $\gamma_{j,\rho}$ is angle between ordinary node and mobile node's movement direction.

By solving the eq. (10), we get to equation (11)

$$\mu_{i,j} = \mu_c - \frac{\mu_c}{\eta}\left(\varepsilon_0^i + \varepsilon_0^j\right) \quad (11)$$

Where, ε_0^i and ε_0^j are the components of Doppler frequency influenced by distances and relative velocities.

Relative velocity components ν_i, ν_j among mobile node and anchor node i and j as seen in equation (12) and equation (13)

$$\nu_i = (k_o - K_i)^T m_o \quad (12)$$

$$\nu_j = \left(k_o - K_j\right)^T m_o \quad (13)$$

Where, k_o represents mobile node, K_i and K_j represents anchor node and ordinary node respectively, m_o represents the velocity vector.

The distances among the mobile node$u_o and$ anchor node s_i and also mobile node s_i and the ordinary node n_j is illustrated in equation (14) and equation (15)

$$\omega_o^i = \sqrt{(a + a_i)^2 + (b + b_i)^2 + (c + c_i)^2} \quad (14)$$

$$\omega_o^j = \sqrt{\left(a + a_j\right)^2 + \left(b + b_j\right)^2 + \left(c + c_j\right)^2} \quad (15)$$

The angles at which the signal reaches the sensor nodes are determined by the AOA and is given in equation (16) and equation (17).

$$\theta_o^j = tan\left(\frac{b - b_j}{a - a_j}\right) \quad (16)$$

$$\varphi_o^j = sin\left(\frac{c - c_j}{\omega_o^j}\right) \quad (17)$$

Modified azimuth and elevation angles by taking into account the minor inaccuracies in measurements can be given by equation (18) and equation (19).

$$\theta_o^j = \theta_o^j + \Delta\theta_j \quad (18)$$

$$\varphi_o^j = \varphi_o^j + \Delta\varphi_j \quad (19)$$

Where, $\Delta\theta_j$ is error in azimuth and $\Delta\varphi_j$ represents error in elevation.

Focus of objective function is to minimize localization error for mobile node. Accurate localization requires aligning calculated angles with real angles as seen in equation (20).

$$\sum_{i,j}\left(\hat{x}_{i,j} - x_{i,j}\right)^2 + \left(\hat{\theta}_{i,j} - \theta_j\right)^2 + \left(\hat{\varphi}_{i,j} - \varphi_j\right)^2 \quad (20)$$

Where, $\hat{x}_{i,j}$ and $x_{i,j}$ are estimated and measured Doppler shift among anchor node i and sensor node j respectively. $\hat{\theta}_{i,j}$ and θ_j estimated azimuth angle and measured azimuth angle respectively. $\hat{\varphi}_{i,j}$ and φ_j are estimated and measured elevation angle of arrival at the sensor node j.

The error rate is represented in equation (21):

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$$E_u = \sqrt{\frac{1}{G}\sum_{g=1}^{G}\left(p_o - \hat{p}_l\right)^2} \qquad (21)$$

Where, p_o and $\hat{p}_l$ are the true position and estimated position of mobile node at iteration g respectively. G is total iterations [31].

---

1. Input: Number of anchor nodes, number of target nodes, Number universes, Number white holes, Number black holes, Number wormholes, inflation rate, area, dimension

2. Output: optimal sensor node position represented by $(a_{best}, b_{best}, c_{best})$

3. Objective Function:

Minimize localization error by reducing difference between estimated and actual positions:

$$f(x) = \sum_{i,j}\left(\hat{x}_{i,j} - x_{i,j}\right)^2 + \left(\hat{\theta}_{i,j} - \theta_j\right)^2 + \left(\hat{\varphi}_{i,j} - \varphi_j\right)^2$$

4. Initialize population

5. For each universe (u):

Randomly assign initial positions (a_u, b_u, c_u) in a defined search space

6. Set up the necessary parameters, including universes and optimization constraints

7. Iterative optimization:

Compute AOA

Create new position $(a_{new}, b_{new}, c_{new})$

For each universe:

Recompute AOA

Evaluate $f(a_{new}, b_{new}, c_{new})$

8. Replace (a_u, b_u, c_u) to $(a_{new}, b_{new}, c_{new})$

9. Enhance exploration and exploitation through MVO

10. Return the optimal positions $(a_{new}, b_{new}, c_{new})$ that yield the minimum localization error $f(x)$

Algorithm 2 MVO for AOA Localization

The AOA-based localization with MVO method (as shown in Algorithm 2) optimizes sensor node position in UWSNs by minimizing localization error in angle estimation. It starts with initializing sensor node positions within a defined search space and computing AOA values. Iteratively, new positions are generated, and AOA is recalculated to refine accuracy. White, black, and wormhole mechanisms of MVO enhance exploration and exploitation, ensuring optimal sensor location. Poor solutions are replaced while high performing ones are retained to improve accuracy. The process continues until the best sensor node positions are obtained with minimal localization error.

5. RESULTS AND DISCUSSION

The MATLAB 2023 software, running on an Intel Core i5 processor with Operating System that is 64-bit Windows10, is utilized to check the efficiency of the algorithms RSSI and AOA in combination with the MVO technique. In the experiment, a 2D area is used for RSSI while the area for AOA is 3D along with 100 randomly dispersed sensor nodes. The MVO algorithm starts with a random solution in the space of search and reduces the parameter fitness function. The MVO performs at most 100 iterations. More detail on the values of parameters is given in below Table 3.

Table 3 List of Simulation parameters

Parameters	Value
Area of Localization	(500 x 500) m^2
Depth	500 m
Sound Speed	1500 m\s
Anchor Node	20
Target Node	30
Sensor Node	100
Transmission Power	35 W
Received Power	0.3 W
Universe	5
Black Hole	3
White Hole	2
Worm Hole	4
Inflation Rate	1.2

In the context of evaluating the MVO algorithm along with RSSI and AOA techniques for localization in UWSNs, several performance criteria can be considered. Evaluation is conducted using essential performance matrices referenced in [34].

Results indicate that integration of MVO algorithm improves accuracy of sensor node placement, minimizes localization errors, and provides reliable performance in underwater environments. The comparative analysis of RSSI and AOA techniques reveals distinct advantages and limitations for each method, offering valuable insights for their application in different underwater scenarios.

5.1. Localization Error

Localization error is difference among sensor's actual position and estimated position by a system using equation (9) and equation (21).

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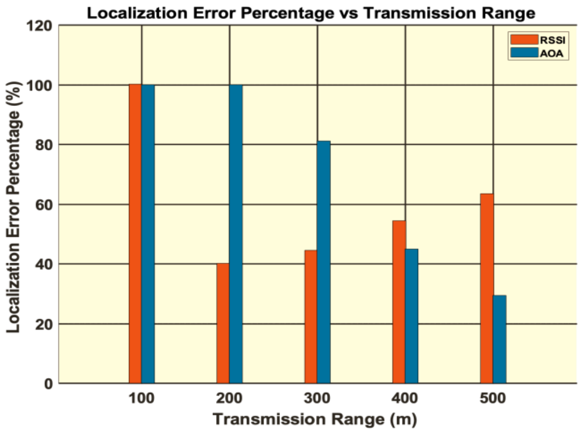


Figure 3 Localization Error vs Transmission Range

Figure 3 illustrates a comparative evaluation of localization error in AOA andRSSI methods over transmission distances from 100 to 500 meters. Both techniques have equally high localization errorsnearing 100% at near distances (~100m), which indicates that neither method has an advantage in near-proximity applications.

As the range of transmission goes from 200–300 meters, the performance of the both methods starts to drift apart. AOA shows greater accuracy or lower error percentages, while RSSI continues to produce growing error rates. But with 400–500 meters, this trend inverts. RSSI produces more accuracyand AOA performs worse. When the range goes to 500 meters, RSSI performs way better than AOA, whose error rate grows to about 30% in contrast to AOA's 60%.

These performance differences can be explained by several factors. AOA's degradation in accuracy at farther distances is probably caused by greater signal reflections and multipath effects, wherein small angular variations result in high error rate as distance grows. Environmental interference also affects AOA measurements more significantly over longer distances. On the other hand, RSSI's better performance at longer distances could be due to the Multi-Verse Optimization algorithm, which efficiently utilizes signal strength fluctuations, making them more pronounced and reliable for localization at longer distances.

Figure 4 is a comparative evaluation of percentages of localization errors using AOA and RSSI methods with MVO in Underwater WSNs with different anchor nodes. Notable observations from figure is uniform trend wherein RSSI has greater localization errors (~70%), while AOA shows relatively lower error rates (~60%) in all anchor node setups (1 to 10). This difference in performance remains fairly consistent with little fluctuation as anchor nodes increases.

In underwater environment, there are key factors that affect performance of both localization methods. AOA exhibits higher accuracy due to the fact that underwater conditions naturally improve angle-based measurements. The greater density of water than air ensures more stable signal paths and underwater acoustic waves which are widely employed in UWSNs suffer less scattering than radio waves. Consequently, AOA provides more reliable angular measurements even with changing numbers of anchor nodes.

In contrast, RSSI has greater error rates given the complicated nature of measuring underwater signal strength. The underwater communication channel impacts signal propagation greatly by absorbing, scattering, and causing multipath effects due to changes in water density, temperature gradients, and salinity. Such environmental factors introduce higher instabilities to RSSI-based localization and render signal strength measurements less accurate and more erroneous in underwater environments.

This evaluation indicates that, in underwater conditions, the fundamental limitations of each localization method especially RSSI are more controlled by underwater channel properties rather than anchor nodes. Therefore, increasing reference points is not always going to increase accuracy of localization. Rather, choosing proper localization method is more essential to achieve better performance in underwater WSNs.

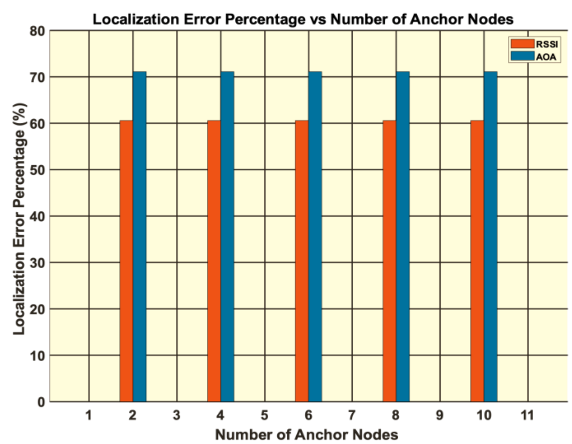


Figure 4 Localization Error vs No. of Nodes

5.2. Localization Coverage

Localization Coverage Ratio (LCR) can be determined by quotient of localized nodes and total nodes in network as represented in equation (22).

$$LCR = \frac{Numberofdetectedsensornodes}{Totalnumberofsensornodes} \quad (22)$$

Figure 5 is a comparative overview of localization coverage percentages of AOA and RSSI methods over transmission ranges of 50 meters to 550 meters. The outcomes show a significant difference in performance, with AOA always showing better coverage than RSSI over all distances. At shorter ranges of transmission (50–100m), AOA starts with around 20% coverage, while RSSI shows minimal coverage. With increasing transmission range, AOA's coverage increases considerably, to 55% at 200m, 85% at 300m, and almost 100% at 500–550m. On the other hands, RSSI shows gradual improvement, only starting to show significant coverage 15%at 300m and reaching a maximum of 40% coverage at 550m.

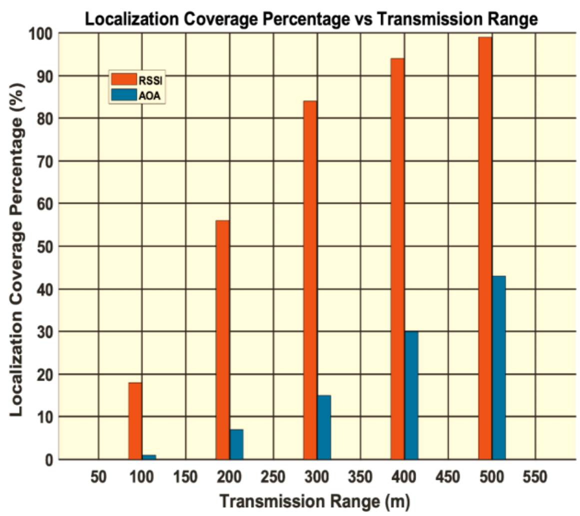


Figure 5 Coverage vs Transmission Range

The trend in performance can be attributed to the inherent properties of each method within an underwater channel. The higher performance of AOA stems from its usage of angular measurements, which are more immune to signal attenuation than RSSI. Weaker performance from RSSI is understandable as it uses signal strength measurements, which are sensitive to underwater absorption, scattering, and multipath propagation. This discussion emphasizes the need to consider environmental factors in choosing localization method in UWSN. Though AOA gives higher coverage, its accuracy could be compromised under underwater propagation conditions, while RSSI with lesser coverage has a more stable measurement mechanism over longer distances.

Figure 6 shows comparison of localization coverage percentage and anchor nodes for AOA and RSSI methods in Underwater Wireless Sensor Networks. The outcome indicates a noticeable performance difference, with AOA consistently outperforming higher localization coverage with different numbers of anchor nodes.With only 2–3 anchor nodes, AOA is already able to provide around 70% coverageand this is further improved as more anchor nodes are added, with almost 100% coverage with 8–9 anchor nodes. RSSI has a relatively linear increase in coverage, beginning at about 10% with 2–3 anchor nodes and gradually improving to nearly 80% coverage with 10 anchor nodes.

AOA’s performance superiority is based on its angle-based measurement that is more stable in the environment of water due to the fact that acoustic waves travel more uniformly in the denser medium. Moreover, AOA is advantaged more with more anchor nodes because each node acts as a solid angular reference point that will increase the precision of geometric triangulation. On the other hand, RSSI's poor performance is due to the inherent difficulties of signal strength-based localization in water environments. Parameters like variations in water density, temperature gradients, salinity variations and underwater currents have considerable effects on signal strength readings.One key observation is that AOA achieves close-to-optimal coverage with fewer anchor nodes (approximately 8–9), while RSSI needs more anchor nodes to match the performance. This observation indicates the resourcesaving nature of AOA-based localization and the fact that it is a more efficient and scalable solution for underwater WSN deployments, especially in situations where deployment of large anchor nodes is impractical or prohibitively expensive.

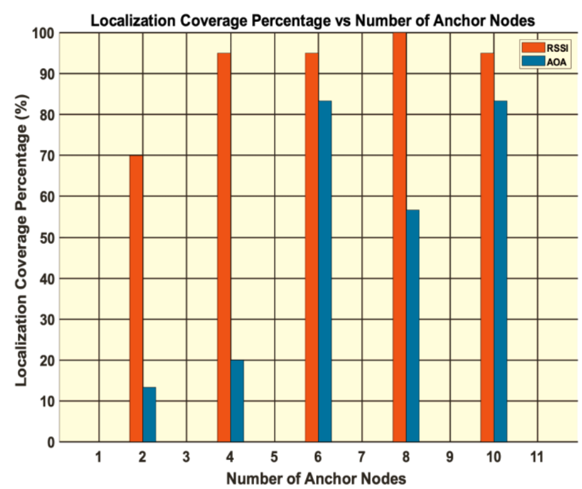


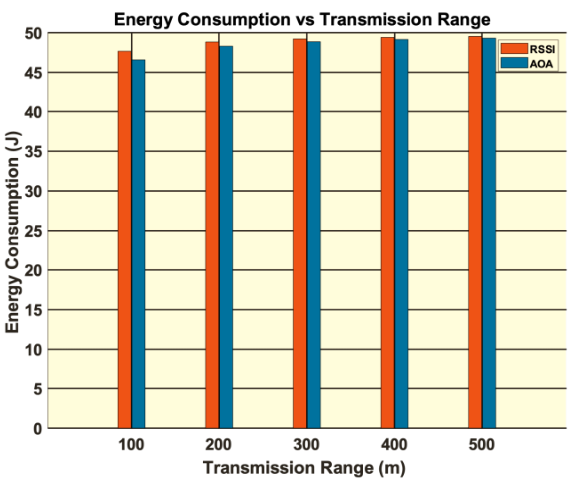
Figure 6 Coverage vs No. of Nodes

5.3. Energy Consumption

The amount of energy used by a node while forwarding it is known as its definition. Alternatively, it can be stated as the difference in the amount of energy between the present and initial state of the node. The measurement unit for consumption of energy is Joules(J) as represented in equation (23).

Energy cons.= initial energy – current energy (23)

Figure 7 illustrates energy consumption by AOA and RSSI methods for various transmission ranges (100m to 500m) in UWSNs. The graph presents very similar patterns of energy consumption for both methods, with merely insignificant variations for all transmission ranges. Both AOA and RSSI exhibit uniform patterns of energy consumption of about 45-50 Joule with mere slight increases as the transmission range increases.This is due to various reasons in underwater settings. The similar energy consumption indicates that the fundamental power demands for signal transmission and reception in underwater acoustic communication are the driving force behind the overall energy expenditure, whether it is angle-basedor strength-basedmeasurements. The acoustic channel in the underwater environment is very power-demanding for the propagation of the signal because of water resistance and high density, which seems to be the major energy expense instead of either localization method's specific processing requirements.



The minor rise in energy usage with growing transmission distance is probably the result of stronger signal transmission necessary to bridge the extra distance and attenuation of the underwater channel. The riseis smalland it indicates that the baseline power demands for underwater acoustic communication largely surpass the excess power required for longer range transmission. Both methods equally demand comparable amounts of energy resources, suggesting energy efficiency might not be a driving factor in either selecting AOA or RSSI for underwater localizations.

5.4. Delivery Ratio

Packets received successfully to total packets that have been sent as represented in equation (24).

$$\text{Delivery Ratio} = \frac{\text{No. of Packets recieved}}{\text{No. of Packets transmitted}} \qquad (24)$$

Figure 8 illustrates the delivery ratios of RSSI and AOA techniques at varying transmission distances. Both techniques exhibit the increase in delivery ratios with the growth in the transmission range, but RSSI is always better than AOA. At 100m transmission range, RSSI delivery ratio is approximately 0.15, whereas a gradual increase is noticed up to a point where it approaches nearly 0.95 at 500m transmission range. In contrast, AOA starts with a delivery ratio of about 0.02 at 100 meters and then approximately 0.80 at 500 meters. The principal cause RSSI performs better than is because it has the ability to effectively handle signal propagation across greater distances. It handles signal strength measurements to continue working properly even when communication is in reflection. In general, the trend is upwards for both methods, as increasing transmission ranges enhances signal coverage and allows for more reliable communication paths. This is likely due to the possibility of having alternative paths for effective packet forwarding even when there is signal loss or degradation in some routes. Large transmission ranges are very helpful in underwater wireless networks as they guarantee reliable data delivery with minimal variation over all transmission ranges.

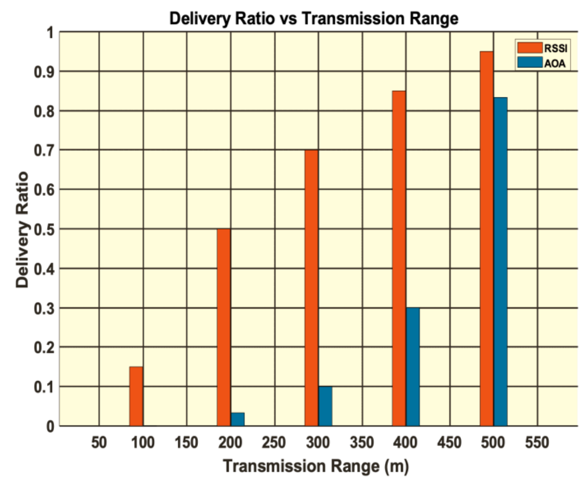


Figure 8 Delivery Ratio vs Transmission Range

5.5. Delay

System delay is the time required for data transmission from source node to target node within the network. This measurement is expressed in seconds(s).

Figure 9 compares delay exhibited by RSSI and AOA methods for transmission distances ranging from 100m to 500m. In all the ranges, AOA indicates increased delay of approximately 4.2x10^-6 seconds whereas delay in RSSI is approximately 2.6×10^−6 seconds. In both of these approaches, the delay is independent of the transmission range, delay appears to be highly dependent on the processing time of the localization techniques and not the signal distance. The reduced delay in RSSI can be explained by its dependence on simple signal strength readings that are less processor-intensive. Conversely, AOA involves more complicated calculations to achieve angles of arrival, resulting in increased processing time and thus greater delays. This inherent trade-off highlights the point that, AOA can be more precise in specific situations, it incurs a performance cost in

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terms of increased delay. The uniform behavior for various ranges highlights that the delay is algorithm dependent and reasonably independent of the transmission distance.

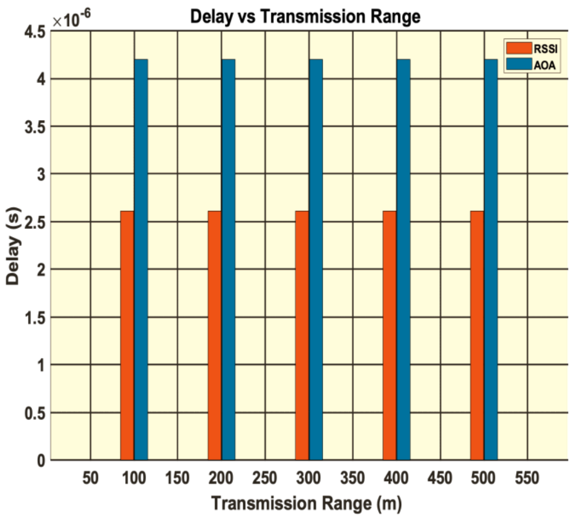

Figure 9 Delay vs Transmission Range

6. CONCLUSION

The incorporation of MVO algorithm with RSSI and AOA significantly increases the accuracy and shows reliable nature of sensor node placement in UWSNs. The MVO technique balances effective exploration and exploitation that minimizes localization errors within the underwater environment, a region that is challenging to analyze where traditional techniques may fail. This paper tested RSSI and AOA techniques about localization in UWSNs in terms of various metrics. The performance of AOA is better than that of RSSI in term of accuracy, mainly because it directly measures the angle of arrival. However, the RSSI-based approach demonstrated better coverage at shorter distances, when there are fewer anchor nodes. Energy consumption remains consistent at 45-50 Joules for both methods, while in delivery ratio RSSI outperforms reaching 0.95 at 500m compared to AOA's 0.80 and shows lower delay at 2.6×10^-6 seconds versus AOA's 4.2×10^-6 seconds. In term to delay, RSSI is found to be performing better than AOA because it has more complex processing requirement. This advancement is particularly important in UWSNs where accurate location helps in different applications like observation of environment, underwater exploration, operations of military and so forth. Future work may focus on improving the MVO algorithm by incorporating additional environmental parameters, such as different densities of water and salinity values in the optimization process. Investigating hybrid approaches that combine different optimization techniques might provide stronger and more powerful localization alternatives for UWSNs. Possible utilization of the MVO-enhanced localization method in real-world scenarios is also taken into account, pointing to its applicability in different underwater conditions.

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