An Anchor-Based Localization in Underwater Wireless Sensor Networks for Industrial Oil Pipeline Monitoring
Une localisation basée sur un ancrage dans les réseaux de capteurs sans fil sous-marins pour la surveillance des oléoducs industriels

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***Abstract*— Industries need solutions that can automatically monitor oil leakage from deployed underwater pipelines and to rapidly report any damage. The location prediction of mineral reservoirs like oil, gas, or metals in deep water is a challenge during the extraction of these resources. Moreover, the problem of ores and mineral deposits on the seafloor comes into play. The abovementioned challenges necessitate for the deployment of underwater wireless sensor networks (UWSNs). Anchor-based localization techniques are segregated into range-free and range-based processes. Range-based schemes depend on various techniques like angle of arrival (AoA), time of arrival (ToA), time difference of arrival (TDoA), and received signal strength indicator (RSSI). In this article, the localization of these leakages is performed by using range-based metrics for calculating the distance among anchor nodes (ANs) and target nodes (TNs). This estimated distance is further optimized to minimize the estimation error. A multilateralism procedure is used to estimate the optimal position of each TN. The results exhibit that the proposed algorithm shows a high performance when compared to previous works, in terms of minimum energy consumption, lower packet loss, rapid location estimation, and lowest localization error. The benefit of using the proposed methodology greatly impacts on identifying the leakage area in mobility-assisted UWSN, where rapid reporting helps to lower the loss of resources.**

***Résumé*— Les industries ont besoin de solutions permettant de surveiller automatiquement les fuites de pétrole des pipelines sous-marins déployés et de signaler rapidement tout dommage. La prédiction de l'emplacement des réservoirs de minéraux comme le pétrole, le gaz ou les métaux en eaux profondes est un défi lors de l'extraction de ces ressources. En outre, le problème des minerais et des dépôts minéraux sur le fond marin entre en jeu. Les défis mentionnés ci-dessus nécessitent le déploiement de réseaux de capteurs sans fil sous-marins (UWSN). Les techniques de localisation basées sur l'ancrage sont classées en deux catégories : les procédés sans portée et les procédés basés sur la portée. Les procédés basés sur la portée dépendent de diverses techniques comme l'angle d'arrivée (AoA), le temps d'arrivée (ToA), la différence de temps d'arrivée (TDoA) et l'indicateur de la force du signal reçu (RSSI). Dans cet article, la localisation de ces fuites est effectuée en utilisant des métriques basées sur la distance pour calculer la distance entre les nœuds d'ancrage (AN) et les nœuds cibles (TN). Cette distance estimée est ensuite optimisée pour minimiser l'erreur d'estimation. Une procédure multilatéralisme est utilisée pour estimer la position optimale de chaque TN. Les résultats montrent que l'algorithme proposé est très performant par rapport aux travaux précédents, en termes de consommation d'énergie minimale, de perte de paquets réduits, d'estimation rapide de la position et d'erreur de localisation minimale. L'avantage de l'utilisation de la méthodologie proposée a un impact important sur l'identification de la zone de fuite dans les UWSN á mobilité assistée, où un signalement rapide permet de réduire la perte de ressources.**

***Index Terms*— Location, mobility, oil and gas wells, optimization, underwater communication.**

Nomenclature

$p(d)$	Signal power loss.
η	Path loss factor.
S_α	Shadow fading.
Δt_{ij}	Time delay between the microphone i, j.
UNODE	Unlocalized node.
LNODE	Localized node.
Pi	% of improvement in fitness value.
AN_j	Anchor nodes.
Ni	Sensor nodes.
$\text{Dist}_{i,j}$	Estimated distance between AN_j and N_i.
Loc_i	Estimated location of N_i.
$F(d)_i$	Fitness function for N_i.
$E_{\text{consumption}}$	Energy consumption.
E_{initial}	Initial energy of a node.

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E_{residual}	Residual energy of a node.
LocalizationErr	Localization error.
$\text{Time}_{\text{req\_msg}}$	Time to broadcast the request message.
$\text{Time}_{\text{get\_loc}}$	Time to get the localization information.

I. Introduction

WITH the increased demand for energy resources across the globe, the extraction industry is more focused on reservoirs under the seafloor, which in itself constitutes 70% of the Earth's surface [1]. The underwater environment is very challenging and it needs for continuous monitoring, such as disaster deterrence, pollution monitoring, offshore exploration, and monitoring oil/gas spills [2]. Several options have been proposed, but underwater wireless sensor network (UWSN) stands out as a potential technology that matches such scenarios [3]. Different forms of nodes work in sync with UWSNs to collect the data under the water and disseminate it to an onshore station for additional processing [4].

To track the UWSNs and the source detection, the localization plays an important role. The shortage of node location information creates the problem of data acknowledgment at the sink node because the area where the data is coming from does not get recognized [5]. If the source is not known, then accumulated information may become useless for protocol management and efficient networking applications to track the source [6]. Underwater pipelines are the main transportation medium for supplying minerals like gas, oil, etc., such as the 23 000 mi of interconnected lines in the Gulf of Mexico [7]. The challenge is to continuously observe the pipelines and rapidly report any leakage. In this proposal, we aim to divide the network into multiple segments so that leakage can be efficiently located. Every segment behaves as a different network that ultimately reports to a surface buoy as a central collection point. Here, sensor nodes that are near the pipeline will sense the leakage (if any) and transfer this information to a surface buoy. To communicate this collected information to the main network station, every surface buoy uses a radio communication system [8], [9]. The anchor-based localization techniques are separated into range-free and range-based strategies. The range-based method uses distance, angle statistics, and an anchor's location to localize a nonlocalized node [10]. The range-free approach uses information like the number of hop counts amid the sensor nodes and area localization to localize the nonlocalized nodes. There is a myriad of factors, such as the number of sensors, the range method, the initial reference position, the position of the anchors in the network, and the number of anchors, on which the implementation of each localization technique depends [11].

Time of arrival (ToA) and time difference of arrival (TDoA), the standard relative distance estimation methods, have disadvantages, such as the Doppler effect and adverse multipath propagation in the underwater acoustic channel, which cause a large estimation error [12]. Similarly, the received signal strength indicator (RSSI)-based procedures show poor performance for underwater node localization. Underwater sensor nodes are expensive and, therefore, they are sparsely deployed. So, the unavailability of direct communication from the anchor node (AN) to ordinary nodes results in low localization coverage. Therefore, few underwater sensors may be short of the actual quantity of reference nodes within their transmission range to support localization. Most of the algorithms mentioned in the literature rely on ANs at immovable positions, which as stated earlier are not a practical approach in many applications. Mobility is an essential factor that must be considered in underwater localization because sensor nodes are mobile due to shipping movements, water currents, and tides. To address distinct challenges encountered by a localization algorithm, the need for a new node localization algorithm has become indispensable.

Several works in the literature address the broad topic of range-based techniques. The accurate node localization can also be estimated by eliminating malicious nodes from the network by using mean square error [13]. However, the authors did not address the energy efficiency of the nodes. In the research work on range-based techniques, the RSS was also targeted for better node localization [14], [15]. However, the authors did not consider the mobility of nodes as well as energy-saving, which is a big requirement for UWSN. Finally, Soares *et al.* [16] addressed the benefit of encoding the dynamic conduct of moving vehicles. However, the authors did not address the range-based metrics to calculate the localization distance between ANs and TNs under energy efficiency requirements.

To fill all these gaps, we propose a range-based metrics method to calculate the localization distance between ANs and TNs, while considering the energy efficiency of the network. The main contributions of the proposed approach are as follows.

1) The proposed algorithm helps in the localization of mobile sensor nodes as localization of these nodes is difficult. The distance between two nodes ANs and TNs is determined by calculating the distance using AoA, ToA, and RSS.
2) The optimal position of the nonlocalized node is calculated by applying the lion optimization algorithm (LOA). An energy efficient localization technique is further developed to determine the accurate position of the leakage area efficiently.
3) Conducted extensive NS2 simulations to evaluate the performance of proposed work, and show its advantages with respect to existing works.

II. Related Works

Localization in UWSN is a critical technology in which plenty of work is yet to be done concerning metal detection, oil leakage, gas leakage, habitat monitoring, etc. For all these applications, it is of paramount importance to know every sensor node's position in UWSN for there to be efficient data transfer, reporting, and analysis.

Previously, the localization problem was formulated with the extraction of received signal strength (RSS) measurements and establishing a correlation between sensor nodes. The nonlocalized sensor nodes estimated their position using some potential ANs. The first-order polynomial is found using a linear regression technique that fits the provided RSS measurement set [10]. This algorithm had less communication overhead, low response time, and low localization error. Cai *et al.* [13] presented a new localization technique robust and cooperative localization (RCL) with a few malicious nodes as well, which resulted in some malicious characteristics. This proposed method uses a distributed reputation voting process within a 1-hop neighboring reference node to find and eliminate the malicious sensors. The exact location is determined using an iterative localization technique that enhances the accuracy and coverage. Furthermore, Chang *et al.* [14] eliminated the noisy ranging error from this RSS-based localization in two cases. In the first case, they derived a new weighted least squares (WLS) estimate when knowledge about the target power transmitter was available. In the second case, reference power is treated as an additional unknown parameter when there is no information regarding the target power transmitter. Furthermore, a range-based localization scheme, using a deep neural network (DNN) considering all ANs and nonlocalized sensor nodes as static was projected [15]. This DNN localization algorithm outperforms other traditional strategies in terms of efficiency and accuracy using generalized least squares (GLS) or least squares support vector machines (LS-SVMs). However, this algorithm works well with a smaller number of ANs only. Soares *et al.* [16] have addressed dynamic localization (DL) algorithm as LocDyn, where the maximum *posteriori* probability (MAP) estimation problem was also removed by using coded DL kinematics information. This method was distributed, fast, and had low computation at each node. However, the problem of self-localization for mobile nodes was still there in UASNs.

Liu *et al.* [17] stated two algorithms to solve this problem of self-localization using the color filtering method. The color-theory based DL (CDL) method and closeness degree are optimized for filtering the samples more accurately. These methods performed well only when the mobile node is of a lower speed, both in terms of robustness and accuracy. Guo *et al.* [18] demonstrated the algorithm with the transformation from a polygonal area into a rectangular area and 3-D coordinates into 2-D. This algorithm improves the localization accuracy and reduces the localization error. But still, the distinction between ANs and multihop sensors was a challenge. Huang and Zheng [19] suggested an AOA-based new localization method, where midway routing nodes are used to estimate the distance amid ANs and unknown sensor nodes. The distance measure is preferred to be calculated through fewer hops due to the accumulation of dimension errors and noise. This proposed algorithm accomplishes distance estimation accurately and is useful when distance estimation error is high. Zhang *et al.* [20] presented the TOA-based movement prediction location (MPL) algorithm, where the algorithm is accomplished in two stages: a mobile prediction and node location phase. This algorithm helps in improving the energy efficiency, localization coverage, and error with overhead network communication.

Another challenge is to reduce positioning error, Zhang *et al.* [21] demonstrated the symmetry correction based least square estimation (SC-LSE) to combat this problem. With the help of a distinct symmetrical relationship, this algorithm lessens the indefinite velocity approximation on the localization and positioning error. Shakila and Paramasivan [22] demonstrated a more appropriate range-based localization algorithm using RSSI, where the distance is premeditated between the AN and target node (TN). This estimated distance aids in locating the exact location of the TN. Further, optimization is carried to minimize localization error, energy consumption, delays, and delivery ratio. An algorithm called enhanced autonomous underwater vehicle (AUV)-aided TDoA localization algorithm (EATLA) presented by Hao *et al.* [23] gets completed in four steps. After acquiring their position through the global positioning system (GPS), AUV dives into the predetermined depth and periodically transmits the data packets. Unknown sensor nodes collect these data packets and estimate their coordinates to locate their position, including a time delay system that saves energy. This algorithm enhances the localization coverage and lessens the localization error and time. Lee *et al.* [24] proposed a new range-free localization technique called localization with mobile beacon via motion compensation (LMB-MC) using a geometric constraint elliptical model. LMB-MC improves the localization accuracy and reliability in comparison to other range-free localization techniques. To be more realistic, the use of a mobile AN was still desired. Thoen *et al.* [25] presented a mobile AN assisted localization technique based on region determination. This method helps in reducing energy consumption as well as improving localization accuracy. This localization technique is completed in two steps, in the first step a region is determined and in the second a position is found. Within the first step a region is divided into smaller regions with minimum overlap, this binds the TN to a particular region creating an optimized travel path for the mobile node. This method improves energy efficiency as well as localization accuracy [26].

From the literature review, it is clear that node localization is one of the most significant challenges to accomplish. Table I presents the comparison of related work that was detailed in the section above.

III. Proposed Solution

An anchor-based localization using the LOA approach (ALLOA) is proposed here. The challenging environment of UWSN having sensor's mobility is considered to have an energy-efficient, range-based node localization.

A. Overview

Within the anchor-based localization with LOA approach, we utilize three metrics to calculate the distance between ANs and TNs–RSS, angle of arrival (AoA), and ToA. These estimated distances are analyzed by applying LOA to minimize the estimation errors. The mean square distance is calculated, and the optimum position for each TN is determined.

B. System Model

A deployment scenario model within 3-D UWSN is shown in Fig. 1, the network comprises three central units: an AN, an unknown sensor node, and a base station (BS). ANs are positioned on a surface of the sea and act as buoys that float on the surface with motion due to water current and waves. The AN location is known because it is supported by GPS modules that work only up to a few meters below the water. Unknown sensor nodes are positioned in an unorganized pattern at different profundity to cover the target area. The AN remains in passive motion with its surroundings to detect and communicate the data at the sea surface. The AN accumulates

TABLE I
COMPARISON OF RELATED WORKS

Node Localization Algorithm	Range-based	High Localization Accuracy	Low energy Consumption	Low Computational Complexity	Low Localization Time
LRA [10]	✓	✓	-	✓	✓
SD/SOCP [14]	✓	✓	-	-	-
DNNL [15]	✓	✓	-	-	-
LocDyn [16]	✓	✓	-	✓	-
PCFL & ACFL [17]	✓	✓	-	✓	-
MCBL [18]	✓	✓	-	-	-
MHNL [19]	✓	✓	-	-	-
MPL [20]	✓	✓	✓	✓	-
SC-LSE [21]	✓	✓	-	-	-
IRL-WOA [22]	✓	✓	✓	-	✓
EATLA [23]	✓	✓	-	✓	-
ALLOA (our proposal)	✓	✓	✓	✓	✓

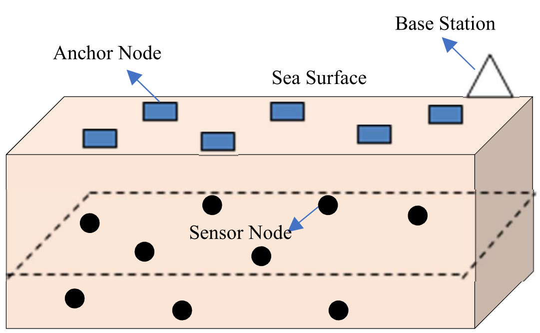

Fig. 1. Deployment state for the 3-D localization.

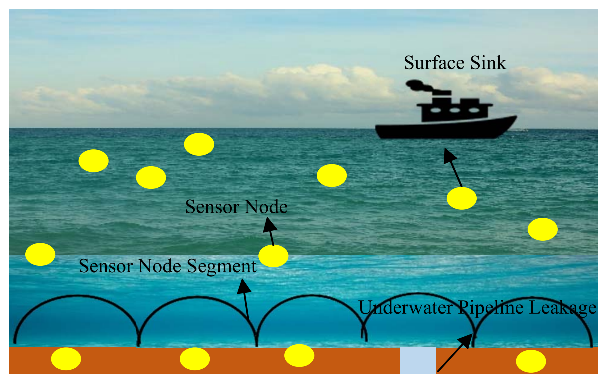

Fig. 2. Arrangement of sensor nodes for detecting leakage or emergency.

the information from the unknown sensors and sends it to the BS, where the data analysis and localization algorithm is executed.

In UWSN, a sensing operation is performed by sensor nodes and AN collects information dependent upon the application, i.e., oil pipeline monitoring. Using this communication between nodes, data is passed on to the surface sink.

The networking protocols like GPRS or cellular satellite services help to upload the sensed data toward the network control center. An application-oriented model is shown in Fig. 2, where surface sinks and sensors are placed below the water in a hierarchical way to cover the whole area in multiple segments. As each sensor node observes its particular segment, if an emergency message like an oil leakage is detected then that segment's sensor node passes this information to the surface sink in the form of data packets. These data packets produced by sensor nodes are transmitted at the sea surface to the AN in a dispersed fashion. The sensor's identity, depth information, and recorded RSS measurements are available in a data packet. The sensor node collects and delivers back to the BS their location while waiting for the data packet to reach a surface AN. Conclusively, the BS accomplishes a centralized localization algorithm to acquire sensor location through acknowledged packets aiding it in taking quick and appropriate actions.

C. ToA-Based Distance Estimation

The ToA is of utmost transparency and intuitive amidst distance assessment approaches. In ToA, the distance among nodes is evaluated through the propagation time of a signal. So, detailed time synchronization is required among the nodes. In ToA, the distance between two nodes a and b is given by correlation between speed and signal transmission time t as $d = \upsilon \times t$. The distance between two nodes and signal propagation time between nodes is directly proportional to each other. The signal start time is recorded at the sender and the reach time is measured at the receiver. If at source node 1, the signal starts at a time t_1 and reaches destination node 2 at time t_2, the interspaces between two sensors are defined as

$$d = \upsilon * (t_2 - t_1) \quad (1)$$

where υ is the tempo of the acoustic signal's propagation (1500 m/s). Therefore, a node must be in a packet at the time when the signal leaves the node.

D. RSS-Based Distance Estimation

The RSS-based distance estimation method is used for calculating the signal strength at the receiver. Mathematically, for distance d between AN and TN, RSS reading is explained by the observed path loss. Equation (2) [9] is used for estimating the distance with respect to, the signal's transmitted power, path loss model, and RSS

$$p(d) = p(d_i) - 10\eta \log_{10}\left(\frac{d}{di}\right) - A(d, f) + S_\alpha[db] \quad (2)$$

where $p(d)$ is signal power loss at the reference distance d_i, η is the path loss factor, and shadow fading is represented by $S_\alpha \sim N\ (0, \alpha^2)$.

The distance between two sensors with an identical method can be derived by taking derivatives of the log-likelihood function L [9], as

$$10(\dot{\eta} + m)\log_{10}\dot{d} + \dot{d}a_f = p(di) - p(d) + 10\dot{\eta}\log_{10}d_i \quad (3)$$

where m is a geometrical spreading coefficient, and its value lies between 1 and 2 ($1 \leq m \leq 2$), e.g., $m = 1$ represents cylindrical geometry and $m = 2$ represents the spherical geometry. a_f is a frequency-dependent absorption coefficient.

Equation (3) can be solved to estimate the distance d_{rss} by applying the graph method. This numerical explanation estimates the corresponding space among the AN and the normal sensor node.

E. AoA-Based Distance Estimation

The AoA, $\emptyset_{ij}$ is estimated as the distance between microphone elements i and j and is represented as d_{ij} [25]. The speed of sound is represented as s_s

$$\sin(\emptyset_{ij}) = (\Delta t_{ij} * s_s)/d_{ij} \quad (4)$$

where Δt_{ij} is the time delay between the microphone i and j. The signal start time is recorded at the microphone i and the reach time is measured at the microphone j.

Thus, the distance (d_{AoA}) can be estimated using (4) as

$$d_{\text{AoA}} = d_{ij} = (\Delta t_{ij} * s_s)/\sin(\emptyset_{ij}). \quad (5)$$

F. Estimation of the Fitness function

The fitness function is derived from the three distance metrics, which are estimated using (1), (3), and (5)

$$F(d) = f\{d_{\text{ToA}}, d_{\text{rss}}, d_{\text{AoA}}\}. \quad (6)$$

This fitness function is then applied by the LOA to accurately estimate the distance between AN and TN, by eliminating the localization errors.

G. Distance Estimation Using LOA

This section explains the basic operations and procedures along with the pseudo-code involved in LOA.

1) Initialization: The LOA is a meta-heuristic population-based algorithm, where the first step is generated randomly over the solution space. Here, each and every single resolution is known as "lion." In a m_{var} dimensional optimization problem, lion $= [y_1, y_2, y_3, y_4, \ldots, y_{m_{\text{var}}}]$.

The fitness cost of each lion is calculated by evaluating the value function, as

$$f(\text{lion}) = f(y_1, y_2, y_3, y_4 \ldots, y_{m_{\text{var}}}). \quad (7)$$

In a given search space, the population generated is represented as m_p. Some percentage m (in our case $m = 40\%$) is randomly taken from the generated population as nomad lions, and the residual population is divided into k points prides. In this algorithm, each solution has a definite number of genders and these remain the same throughout the optimization process. For every pride, the entire population formed in the preceding step, p (in our case $p = 50\%$) is taken as females, and the remaining are taken as males. Vice versa, the percentage taken for nomad lions is $(1 - p)$. During the search process, the best visited location is marked by every lion. Each pride's region is formed with the help of these marked locations by its members' best marked position.

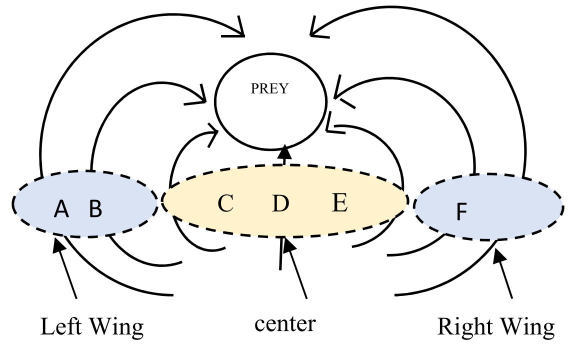

Fig. 3. Diagram of generalized lion hunting behavior.

2) Chasing: During the localization process, localized nodes help in finding the location of the unknown sensor nodes. These localized sensor nodes form clusters to find the position of unknown sensor nodes. Nodes are split into three subcategories arbitrarily. The cluster having maximum (C, D, and E), and the remaining two clusters are deliberated as two wings on the left (A and B) and the right (F and G) shown in Fig. 3.

During localization, if the node enhanced its fitness, the UNODE will not be localized and the new position of an unlocalized node can be obtained as

$$\begin{aligned}\text{UNODE}' = {} & \text{UNODE} \\ & + \text{rand}(0, 1) * Pi * (\text{UNODE} - \text{LNODE}) \quad (8)\end{aligned}$$

where UNODE denotes the current location of the unlocalized node, LNODE is the new place of localized nodes who search the UNODE, and Pi the percentage of improvement in fitness value of LNODE.

The succeeding methods are suggested to copy the surrounding victim by the declared hunter clusters. The new positions of hunters which belong to both the left and the right wings are created as follows:

$$\text{LNODE}' = \begin{cases} \text{rand}((2 * \text{UNODE} - \text{LNODE}), \text{UNODE}), \\ \quad (2 * \text{UNODE} - \text{LNODE}) < \text{PREY} \\ \text{rand}(\text{UNODE}, (2 * \text{UNODE} - \text{LNODE})), \\ \quad (2 * \text{UNODE} - \text{LNODE}) > \text{PREY} \end{cases} \quad (9)$$

where LNODE' denotes the new location of the unlocalized node.

Novel locations of Center localized nodes will be calculated as follows:

$$\mathrm{LNODE}' = \begin{cases} \mathrm{rand}(\mathrm{LNODE}, \mathrm{UNODE}), & \mathrm{LNODE} < \mathrm{UNODE} \\ \mathrm{rand}(\mathrm{UNODE}, \mathrm{LNODE}), & \mathrm{LNODE} > \mathrm{UNODE}. \end{cases} \quad (10)$$

In the function of (10), rand (a, b) generates the random number amid a and b, of upper and lower bounds, respectively.

3) Moving Toward Safe Place: Few nodes from every group help with localization and others remain in a silent state. So, silent nodes' new position is given as

$$\begin{aligned} \mathrm{SNODE}' &= \mathrm{SNODE} + 2D * \mathrm{rand}(0,1)\{R1\} \\ &\quad + U(-1,1) * \tan(\theta) * D * \{R2\}\{R1\} \cdot \{R2\} = 0 \\ ||\{R2\}|| &= 1 \end{aligned} \quad (11)$$

where SNODE′ is the silent node's present location; D denotes the distance amid the SNODE's place and the designated point chosen by tournament selection among the silent nodes. The distance between the silent node's areas is selected by tournament selection. $\{R1\}$ is a vector perpendicular to $\{R2\}$ where $R1$ is the starting point of the female lion's previous position, with its direction toward the designated position.

$\tan(\theta)$ denotes the angle of direction toward the position.

The tournament strategy is as follows: localization of a node is described if it improves its best position in the last iteration of the LOA. In a group g during iteration i the success of node l is defined as

$$s(l,i,g) = \begin{cases} 1, & \mathrm{Best}^{i}_{l,g} < \mathrm{Best}^{i-1}_{l,g} \\ 0, & \mathrm{Best}^{i}_{l,g} < \mathrm{Best}^{i-1}_{l,g}. \end{cases} \quad (12)$$

Till iteration i, best location or position of node l in a group g is represented by $\mathrm{Best}^{i}_{l,g}$.

4) Roaming: Owing to certain motives, every AN wanders in its localization area. To imitate this nature of nodes, R in our case $R = 30\%$) of the localized area is chosen randomly and inspected by that AN. If the node visits a novel location during wandering, which is better than its present best place, it informs its top-visited resolution.

5) Coupling: Coupling is a necessary procedure that offers a chance to interchange data among the associates. Some percentage is taken as $\%F$ (here $F = 30$) of the localized nodes, coupled with one or numerous ANs in every area. For producing the new results, coupling is used which is a linear combination of ANs and localized nodes. New results began as AN, and localized nodes are selected for the coupling process as per the following equations:

$$c^{1}_{d=}\gamma * \mathrm{LNODE}_d + \sum \frac{(1-\gamma)}{\sum_{l=1}^{N} s_l} * \mathrm{ANODE}^{l}_{d} * S_l \quad (13)$$

$$c^{2}_{d=}(1-\gamma) * \mathrm{LNOD}E_d + \sum \frac{(\gamma)}{\sum_{l=1}^{N} s_l} * \mathrm{ANODE}^{l}_{d} * S_l \quad (14)$$

where d is a dimension.

S_l is taken as 1, if AN, and l is selected for mating else, S_l equals to 0. N is the total number of nodes. γ is a randomly produced figure with normal distribution containing a standard deviation of 0.1 and a mean value of 0.5. One node is randomly chosen from these produced offspring as AN and another as LNODE. M is the probability (%) of the mutation applied on every result of the node from both nodes, as information is shared between genders with LOA's help, through mating while characters are inherited in new cubs from both genders.

6) Migration: Based on lions behavior in nature and their dependence on lioness as focal points in the pride, and lions can be expelled from the pride, similarly in this localization process, nodes are mobile and they can move from one place to another but using ANs position of these unlocalized nodes can be found. Conversely, the node's relocation and shift figure the link for data interchange. $S\%$ of the node's population deceives AN' population in every group. Some females chose randomly to become nomads for the migration operator. In every pride, the migrated female's size is excess to the female in every pride plus $\%I$ of the extreme quantity of females. When designated females transfer from egotisms and turn out to be wanderers, novel wanderers females and old wanderer females are fixed based on their health. The finest female is then nominated arbitrarily and disseminated to egotisms to block up the unfilled area of voyaged females. This approach preserves the divergence of the entire population and shares data amidst the pride. In the same way ANs help in finding the position of an unlocalized node that is chosen as the best node.

7) Pseudo-Code of LOA: The steps involved in LOA listed in the pseudo-code [27] are given in Algorithm 1.

8) Distance-Based Localization: This research aims to approximate the position of sensor node X with the help of distance measurement from ANs M. In a 3-D space, the multilateration procedure requires $M = 4$. Using distance measurement from M ANs, the location of sensor X is estimated. As the localization process commences, every AN broadcasts a HELLO beacon message along with its location information. These sensors then determine their positions with the aid of measured distances through RSS, ToA, and AoA, as described in Section III. Using the estimated distance from LOA, to produce a single location approximation, a range-based multilateration technique is applied. Precisely, the calculated position can be measured as the intersection of the areas generated by the calculated distance dˆ from the numerous ANs. Algorithm 2 presents the localization process by applying LOA and multilateration.

The abbreviations used in the algorithm are as follows.

AN_j	Anchor nodes, $j = 1, 2, \ldots, m$.
Ni	Sensor nodes, $i = 1, 2, \ldots, N$.
$\mathrm{Dist}_{i,j}$	Estimated distance between AN_j and N_i.
Loc_i	Estimated location of N_i.
$F(d)_i$	Fitness function for N_i.

IV. Results and Analysis

This section presents the results of our proposed localization algorithm based on LOA and helps in evaluating the performance of the proposed algorithm.

A. Simulation Settings

The suggested localization algorithm ALLOA is simulated using the Aqua-Sim toolkit of NS2 [28]. Aqua-Sim efficiently handles the diminution of the acoustic signal, circulation model, and packet collisions. Furthermore, we have used an energy-efficient UWAN-MAC protocol and some other simulation parameters are summarized in Table II.

Algorithm 1 Steps in LOA

1. Develop random space of Lions X_{pi} (X_{pi} is an indicator of the preliminary populace)
2. Launch points of pride and nomad lions
   - Arbitrarily select %X as nomad lions and remaining lions divided into y prides, and form each pride's territory.
   - In every pride %P is taken as females and (1-P) % as males. This rate is inversed in nomad lions.
3. For every pride,
   - Few arbitrarily chosen female lions go for withdrawing network traffic data
   - $Leftover_{female}$ lions in pride goes in the direction of one of the best-selected locations.
   - In a pride, for every resident male, $\%W$ (Roaming percent) of the territory is arbitrarily chosen and analyzed.
   - $\%Q_{female}(Pride)$ mate with one or several resident males. ($\%Q$: Mating probability)
   - $Weakest_{male}$ is driven out from the pride and becomes a nomad.
4. For Nomad
   - $Nomad_{male+female}$ move arbitrarily in the search space
   - $\%Q$ of the nomad Female mate with most excellent nomad males
   - The $Nomad_{male}$ arbitrarily assails prides.
5. For each pride Do
   a) Few females with rate I migrate from pride and become a nomad. (I: rate of females becoming nomad)
6. Do
   - Based on fitness value sort each gender of the normal lions.
   - After that, $finest_{female}(pride)$ is chosen and circulated to points of pride in place of migrated females
   - Min fitness ($Nomad_{lion}$) will be detached.
7. If a close standard is not fulfilled, then go to step 3

Algorithm 2 Anchor-Based Localization Algorithm

```
For each AN_j
        For each N_i
                Estimate d_ToA (i)
                Estimate d_rss (i)
                Estimate d_AoA (i)
                Estimate F(d)_i
                Dist_i,j = LOA(F(d)_i)
        End For
End For
For each AN_j
        For each N_i
                Estimate Loc_i using Multilateration
        End For
End For
```

B. Performance Results

The proposed ALLOA is compared with the LocDyn approach [16] and RCL [13]. The associated localization error is measured to analyze localization precision, average energy consumption metric to analyze the overhead involved in the localization process, and localization delay to analyze the algorithm's robustness.

TABLE II
SIMULATION PARAMETERS

Parameters	**Values**
Number of Nodes	25, 50, 75, 100 and 125
Area Size	1000m x 1000m x10m
Simulation Time	100 seconds
Channel	Underwater Channel
Range	100m
Routing Protocol	Vector based Forward
Antenna Type	Omni Directional
Initial Energy	10000 Joules
Transmission Power	2.0 Watts
Receiving Power	0.75 Watts
Idle Power	0.008 Watts
Frequency	25KHz
Packet Size	25 bytes
Interval	100 Sec
Position Update Interval	0.3 Sec

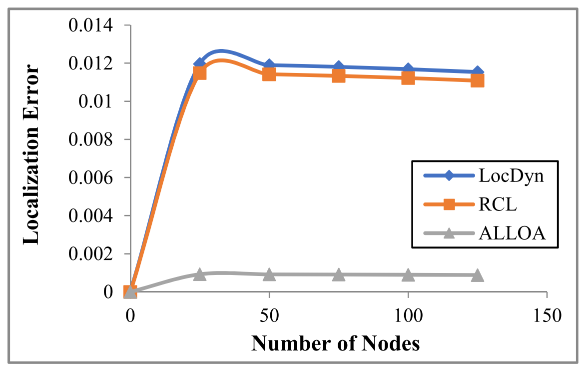

Fig. 4. Number of nodes versus localization error for varying number of nodes.

1) Localization Error: This is the mean of the differences between the true position and the estimated position. It is calculated as

$$\text{LocalizationErr} = \sqrt{(x_{\text{est}} - x_{\text{true}})^2 + (y_{\text{est}} - y_{\text{true}})^2} \quad (15)$$

where

x_{est} estimated x coordinate;
y_{est} estimated y coordinate;
x_{true} true position or actual x coordinate;
y_{true} true position or actual y coordinate.

The graphical presentation of the results of localization error for variable number of nodes is shown in Fig. 4. The localization error of ALLOA is 31% less than LocDyn and 28% less than RCL. The existing schemes RCL uses only ToA metrics for localization, and LocDyn requires prior knowledge of node locations; therefore, the localization error is a little high in these techniques. However, in the proposed scheme, the distance between nodes is calculated using mean square and then it is optimized, resulting into reduced localization error.

2) Energy Consumption: Energy consumption by a node is defined as the energy consumed during network operations or the difference in the energies between the node's initial and present stages.

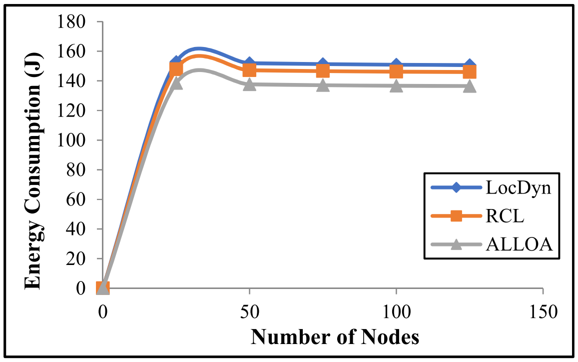

Fig. 5. Number of nodes versus energy consumption for varying number of nodes.

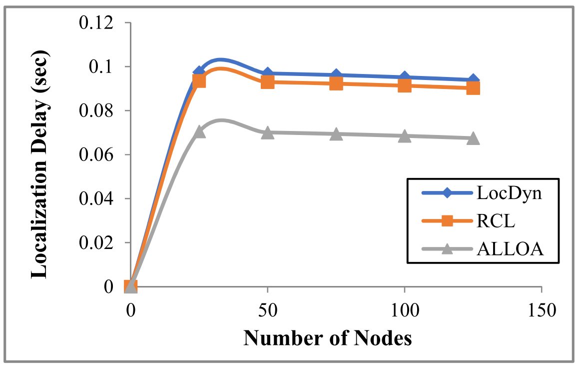

Fig. 6. Number of nodes versus localization delay for varying number of nodes.

It is also expressed as the energy consumption of all the nodes during networks operations.

The graphical presentation of energy consumption is directly proportional to the number of sensors as shown in Fig. 5 where the energy consumption of ALLOA is 9% less than that in LocDyn and 7% less when compared to RCL. Overall energy consumption in existing schemes is more because RCL has to eliminate malicious anchors and LocDyn uses iterative localization. However, in the proposed scheme, nonlocalized sensor nodes do not send any message until these nodes receive any message from the AN so energy consumption is less.

3) Localization Delay: This is the sensor node's time difference between broadcasting the "Request" message and obtaining its location

$$\text{Localization delay} = \text{Time}_{\text{req\_msg}} - \text{Time}_{\text{get\_loc}} \tag{16}$$

with $\text{Time}_{\text{req\_msg}}$ as the time to broadcast the request message, while $\text{Time}_{\text{get\_loc}}$ is the time to obtain the localization information.

The graphical presentation of localization delay varying with the number of nodes is shown in Fig. 6 where the localization delay of ALLOA is 27% lesser than LocDyn and 33% lesser than RCL. This is because RCL has to eliminate malicious anchors and LocDyn uses iterative localization, whereas it is not so in the proposed scheme. The simulation outcomes infer that the suggested algorithm ALLOA provides improved performance than LocDyn and RCL algorithm with regards to energy consumption, localization delay, and localization error.

4) Localization Error With Transmission Range: Fig. 7 shows the localization error for transmission range. Localization error for LocDyn varies from 0.011966 to 0.011537, RCL varies from 0.0112 to 0.01090, and ALLOA varies from 0.00828 to 0.00788. It shows that localization error of ALLOA is less than other two techniques as it uses a combination of ToA, RSS, and AoA for distance estimation and then distance is optimized using LOA method.

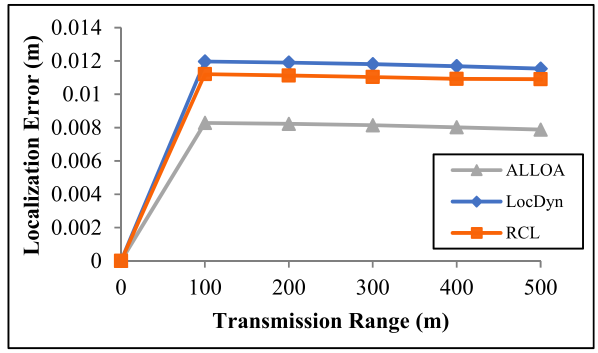

Fig. 7. Number of nodes versus localization error for varying transmission range.

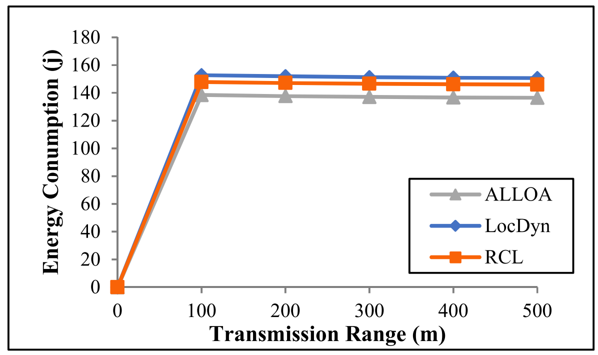

Fig. 8. Number of nodes versus energy consumption for varying transmission range.

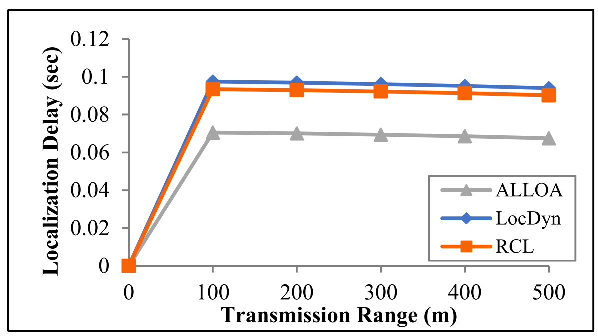

Fig. 9. Number of nodes versus localization delay for varying transmission range.

5) Energy Consumption With Transmission Range: For longer network lifetime energy consumption should be less as it is very tough to replace the sensors below the water. Fig. 8 shows the transmission range and energy consumption for RCL, LocDyn, and the proposed technique ALLOA. It is observed that energy consumption is less in ALLOA than other two Techniques as nonlocalized sensor node does not participate in any communication.

6) Localization Delay With Transmission Range: This is defined as time period when a node broadcast the request message to when it got its position. Fig. 9 shows the localization delay varying with transmission range. Localization delay of LocDyn varies from 0.097427 to 0.093915 s, RCL localization delay varies from 0.093421 to 0.090187 s and for ALLOA it varies from 0.070506 to 0.0674471 s.

V. Conclusion

In this manuscript, we design, implement, and evaluate the performance of an anchor-based localization that is helpful to locate the oil/gas pipeline leakage below the water, where continuous manual monitoring is not possible. The use of mobility assisted UWSNs makes it possible where sensor nodes monitor for emergency conditions such as oil leakage and pass on this information rapidly to the surface station. The proposed scheme ALLOA measures the distance among ANs and TNs using three range-based metrics RSS, AoA, and ToA. Furthermore, to diminish the estimation errors, the estimated distances were optimized by applying LOA. Compared to existing schemes, LocDyn and RCL, the proposed scheme ALLOA lowers the localization error by 28%, energy consumption by 7%, and localization delay by 27%. With these great benefits, it is derived that ALLOA is a good candidate scheme to be used for mobility assisted UWSN where no special AUV is required. Furthermore, the proposed scheme is applicable where automatic monitoring and rapid oil pipeline leakage is to be communicated. In future work to extend the proposed localization techniques, we can consider the dynamic environmental changes, by including the learning strategies. By considering these changes, we can try to find zero error localization techniques. The various abbreviations used in the manuscript are summarized in the Nomenclature.

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