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Original scientific paper

Enhanced Dwarf Mongoose Optimization Based Node Localization Scheme for Underwater Wireless Sensor Networks

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Abstract: Recently, the Underwater Wireless Sensor Network (UWSN) with movable nodes has been launched because it has a lot of potential uses in aquatic science and is getting a lot of attention from researchers. Because there are so many more possible underwater uses, it is important to make sure that signals can get from one underwater point to another. Because of the long lags in signal transmission and the changing speed of sound underwater, it is hard and not possible to use the usual localization method in UWSN. Node localization (NL) in UWSN tries to figure out where new nodes are by using known nodes. The correctness of location can have a big effect on how well a UWSN works. UWSN has a lot of trouble with precise NL. When it comes to WSN, NL problems mean figuring out where unknown sensor nodes (SNs) are. This shows how important it is to have a perfect NL system. The Enhanced Dwarf Mongoose Optimization based Node Localization Scheme (EDMO-NLS) for UWSN is being worked on in this study. The scout group, the alpha group, and the babysitters are the three social groups of dwarf mongooses that were used in the suggested method. The family hunts as a unit, and the main female starts hunting. This sets the sleeping mounds, the road for hunting, and the distance that is covered. The EDMO-NLS method shown here finds nodes whose locations are unknown in UWSN. The modeling results showed that the proposed model worked better than existing methods. Based on the findings and the discussion, it is clear that the suggested method has shown the best localization success in UWSN.

Keywords: anchor node; node localization sensor node; received signal strength; time of arrival; underwater wireless sensor network

1 INTRODUCTION

Wireless Sensor network (WSN) comprises a massive amount of connected sensor nodes (SNs) that allows to carry out collaborative monitoring task in a provided underwater area [1]. The networking technique opens new possibilities to understand the oceans that could improve the monitoring capability for different applications [2]. To support this application, precise location data of SNs is needed for precisely interpreting and analysing the sampling dataset. To implement precise localization for Under Water Sensor Networks (UWSN), a considerable amount of underwater localization scheme has been developed. Generally, this scheme consists of the subsequent three stages, viz., position estimation, information collection, and distance measurement [3]. Initially, SN collects location-related data like the time of flight (TOF), the positions of anchor nodes, the time difference of arrival (TDOA), the received signal strength (RSS), and the time of arrival (TOA).

Using the gathered dataset, the relative distances amongst anchor nodes (ANs) and the SNs are evaluated in the following phase, where localization estimator is proposed for calculating the position of SNs [4]. For all the stages, the location data leakage is not evitable, because the relative distance is exposed to the network whereas the position of AN has fed into the localization estimator. It should be noted that UWSN is deployed generally in harsh environments, and the disregarding of privacy preservation could simply make localization scheme vulnerable to various attacks [5]. For example, the enemy could be attacking the ANs easily and wreck the whole localization scheme once the location data of ANs have been gathered. One more example is that the enemies could deduce the position of SNs by relating the distance measurement with the monitoring region. Hence, it can be essential to preserve the private position of ANs and SNs in the process of localization [6]. Fig. 1 depicts the structure of UWSN.

Generally, the localization scheme proposed for sensor networks that could accomplish higher accuracy localization depends on time. The time-based scheme employs different models namely TDOA, TOA, or TOF, for measuring distance [7]. Because the distance measurement has been acquired to the time (or time difference), the time-based scheme deeply relies on the clock synchronization model of SNs. But the special features of USN make underwater localization further [8]. For example, radio wave is absorbed strongly in water, and GPS technique is unavailable for USN. Consequently, the time clock in USN is generally asynchronous; that makes them hard to get a precise measurement of the distance [9]. Even though the Received Signal Strength (RSS) technique does not need the assumption of clock synchronization, RSS signal is generally imprecise in water. Then again, the node in water frequently has passive motion driven by water current that leads to the difference in round-trip propagation delays among any 2 nodes [10]. Thus, the localization scheme proposed for terrestrial sensor networks could not be applied directly to USN.

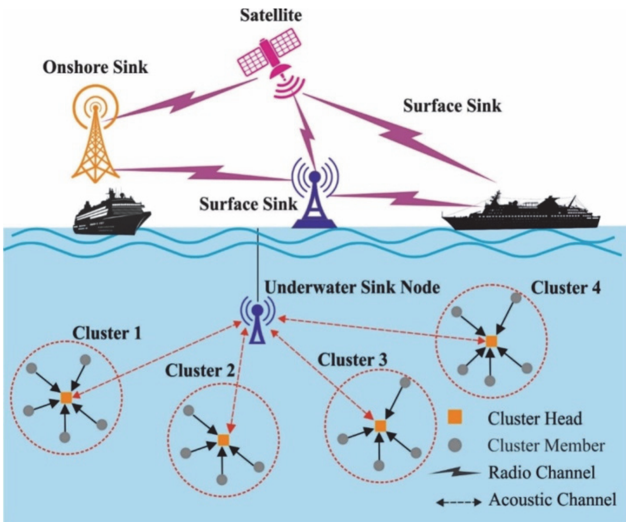

Figure 1 Structure of UWSN

This study develops an Enhanced Dwarf Mongoose Optimization based Node Localization Scheme (EDMO-

NLS) for UWSN. In the proposed algorithm, three social groups of dwarf mongooses were applied namely scout group, alpha group, and babysitters. The family forage as a unit, and alpha female begins foraging, which defines the sleeping mounds, the foraging path, and the distance covered. The presented EDMO-NLS technique determines the unknown position of the nodes in UWSN. The simulation outcome stated the enhanced performance of the proposed model on existing approaches.

2 RELATED WORK

Toky et al. [11] developed a localization system with Angle-of-Arrival (AoA) technology for UWASN. The presented localization system has been classified into Localization, Angle estimation, and Projection Phases. Initially, the location of SNs is evaluated according to the AoA and distance from adjacent node data. Then, the 3D localization problem translates into equal 2D via projecting the SNs to virtual projection plane. Dong et al. [12] designed a scalable asynchronous localization approach with mobility forecasting. During the localization process, the large scale underwater WSN structure. Considered the node mobility, the node movement is constructed on the basis of tidal mobility. As a result of examining the asynchronous transmission among the ordinary nodes and ANs, the earlier location of ordinary node is attained and the forthcoming location of ordinary node is updated and predicted.

Nain and Goyal [13] introduced an energy effective localization system that depends on the prediction of propagation and mobility delay. First, the propagation delay is remunerated to accomplish quick reporting of localization. Precise synchronization time is achieved using prediction of the longer propagation delay. Next, ANs mobility predictive process is proposed to record and analyze its speed at each localization period. The ordinary node makes localization, which utilizes the predicted speed vector attained from the ANs. LN Nguyen and Shin [14] established an RSS-based localization system to define the position of unknown standard sensors in a specific measurement group of possible ANs. Firstly, we presented a real-world path loss method for wireless transmission in underwater acoustic environment whereby ANs are positioned under arbitrary circumstances. TOA provided area of interest, the RSS data assortment was vigorously accomplished, whereby the correlations and the measurement noise amongst themselves are considered.

Choudhary and Goyal [15] developed a dynamic topology control approach for node deployment (DTCND) in mobile UWSN. The study aims at monitoring the node mobility for predicting node position to ensure connectivity and coverage. The SNs are randomly deployed at distinct depths. The ANs observed signal quality index, node density, and energy drain rate at each time intervals and identified node disconnection according to the variation from the observed metrics. Mridula and Ameer [16] handle the challenges of SN localization in the existence of uncertainty in ANplace. The localization in existence of ambiguity in the AN position is highly complicated. As well, the research considers the ray-bending properties of underwater medium because of depth dependent sound speed, for furnishing the precise location estimate of target nodes. Hu et al. [17] developed a novel localization methodology on the basis of variational filtering approach where the spatiotemporal dependency data are exploited for improving the efficiency of localization. In this study, a state evolution method is applied for characterizing the mobility patterns of nodes and capturing the uncertainty of position transition. Next, the measurement system was utilized for reflecting the relationship among the locations and the measurements which consider the dynamics of range noise and acoustic speed.

3 PROPOSED METHOD

In this study, a novel EDMO-NLS approach has been introduced for UWSN. In the proposed algorithm, three social groups of dwarf mongooses have been applied namely the scout group, the alpha group, and babysitters. The family forage as units and alpha female begins foraging, which defines the sleeping mounds, foraging path, and distance covered. The presented EDMO-NLS technique determines the unknown position of the nodes in UWSN.

3.1 Classification of DMO Technique

The novel DMOA scheme has been projected [18]. The proposed DMOA reproduces the dwarf mongoose compensating performance response that is demonstrated as follows.

Alpha Group

The efficacy of all the solutions is computed then the population was established. Eq. (1) computes the probable value, and the alpha female has been selected dependent upon this possibility.

$$\alpha = \frac{fit_i}{\Sigma_{i=1}^{n} fit_i} \tag{1}$$

The t_i refers to the count of mongooses from the α. where *bs* signifies the count of babysitters, *peep* signifies the vocalization of dominant female which maintains the family on way. The solution upgrade process is provided as:

$$X_{i+1} = X_i + ph_i * peep \tag{2}$$

where ph_i denotes the distributed arbitrary number. The sleeping mound (X) has been offered in Eq. (3) however then all the repetitions, whereas phi indicates the uniformly distributed random integer of 1 and 1.

$$si_m = \frac{fit_{i+1} - fit_i}{\max\left[\left|fit_{i+1} - fit_i\right|\right]} \tag{3}$$

Eq. (4) offers the average count of sleeping mounds exposed.

$$\varphi = \frac{\Sigma_{i=1}^{n} si_m}{n} \tag{4}$$

When the babysitting interchange condition was satisfied, this technique developed to scouting phase, if the next food supply/resting mound was assumed [19].

Scout Group

During the scout group part, once the family forages quite far, it can be derived across an optimum sleeping mound. The scout mongoose was inspired by Eq. (5).

$$X_{i+1} = \begin{cases} X_i - CF*phi*rand\left[X_i - \vec{M}\right], \ if \varphi_{i+1} > \varphi_i \\ X_i + CF*phi*rand\left[X_i - \vec{M}\right], \text{ otherwise} \end{cases} \tag{5}$$

In which, *rand* defines the arbitrary value in range of 0 and 1, *CF* value has been computed by Eq. (6), and $\vec{M}$ value has been computed by Eq. (7).

$$CF = \left(1 - \frac{iter}{\mathrm{Max}_{iter}}\right)^{\left(2*\frac{iter}{\mathrm{Max}_{iter}}\right)} \tag{6}$$

$$\vec{M} = \sum_{i=1}^{n} \frac{X_i * sm_i}{X_i} \tag{7}$$

The babysitters are commonly lesser group members which stay with youngsters and are cycled on regular basis for enabling the alpha female (mother) for conducting the rest of squad on regular hunting journeys. Fig. 2 demonstrates the flowchart of DMOA.

Opposition Based Learning (OBL) is utilized for creating a novel opposing solution dependent upon preceding one. During the OBL, an opposite solution $\left(X^O\right)$ has been projected as a real number. $X \in \left[LB, UB\right]$ is defined as Eq. (8).

$$X^O = UB + LB - X \tag{8}$$

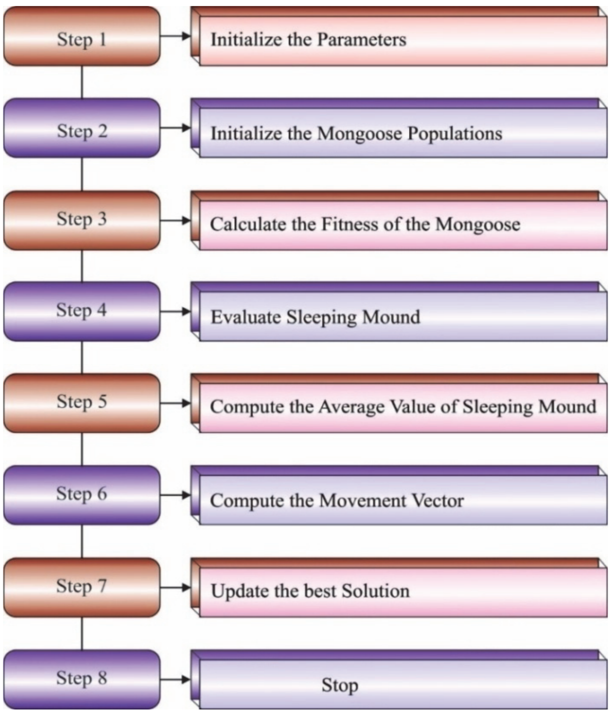

Figure 2 Flowchart of DMOA

Opposite value: $X = \left(X_1, X_2, \ldots, X_n\right)$ is within the provided range, $\left\{X_1, X_2, \ldots, X_D\right\}$ and $X_j\left[UB_j, LB_j\right]$, $j \in 1, 2, \ldots, D$. This mathematical expression was employed in Eq. (9).

$$X_j^O = UB_j + LB_j - X_j, \text{where } j = 1 \ldots D. \tag{9}$$

The FF estimates the 2 solutions (X^O and X) in the optimized procedure. An optimum solution was recognized, and another solution was disregarded.

Algorithm 1: Pseudo-code of the DMOA

Input: Set the condition and solution to this technique.
Initializing the algorithm parameter and solution.
while ($iter < \mathrm{Max}_{iter}$) do
 for ($i = 1$ to Solutions) do
  Compute the Fitness Function (FF) of Mongoose.
  Set time counter (C).
  Define the alpha value by utilizing Eq. (1).
  Conduct a solution employing in Eq. (2).
  Evaluate the sleeping mound by utilizing Eq. (3).
  Define the average of sleeping mounds by utilizing Eq. (4).
  Define the movement vector by employing Eq. (7).
  Imitate the scout Mongoose to the next solution by utilizing in Eq. (5).
 end for
 $t = t + 1$
end while
Output: Return the optimum solution (x).

3.2 Steps involved in Localization Process

The EDMO-NLS localization method is exploited for determining the coordinate point of the sensor. The intention is to compute the coordinate point of desirable node by diminishing the objective function [20]. The localization problems of WSN are considering optimization problem established by numerous metaheuristic techniques. The given model is exploited for locating the sensor in WSN: Place *M* target and *N* ACN in the sensor area. Each ACN is comprised of position attentiveness to recognize the position. Each TN and anchor comprise transmission range *R*.

Distance between the ACN and target is modified and assessed by means of additive Gaussian noise. The TN describes the distance using $\hat{d}_i = d_i + n_i$ but d_i characterizes real distance that is estimated amongst position of beacon $\left(x_i, y_i\right)$ and the location of TN $\left(x, y\right)$ as follows:

$$d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} \tag{10}$$

The n_i parameter describes the noise that affects the assessed distance from $d_i \pm d_i\left(\frac{P_n}{100}\right)$ while P_n represents ratio of noise in the assessed distance. The desirable node is termed a localizable node once it comprises 3 ACN in the transmission radius of TN. A cause afterward this requirement is reliant on the distance between TN d_i and three CAN, trilateral positioning module, coordinates of 3 ACN $(x_1, y_1), B(x_2, y_2)$, and $C(x_3, y_3)$, are recognized. Next, the application of trigonometric laws of sine or cosine, the coordinate of TN is described. Similarly, in multi-alteration TN estimated method, distance metrics of large ACN are exploited for minimalizing error in the estimated and original distance.

For localizable nodes, the EDMO-NLS methodology is accomplished autonomously to recognize the location of TN. The coyote is enforced using the centroid of ACN within communication radius as follows:

$$(x_c, y_c) = \left(\frac{1}{N} \sum_{i=1}^{N} x_i , \frac{1}{N} \sum_{i=1}^{N} y_i \right) \tag{11}$$

Now, N means overall quantity of ACN within the communication range of localizable TN. The EDMO-NLS methodology is suitable for identifying the coordinates (x, y) of the TN that reduce the localization error (LLE). The primitives exploited in localization problems are mean square distance between ACN and target that is minimized using the application as:

$$f(x,y) = 1/N \; (\Sigma\_(i=1)\hat{\ } N \sqrt{((x-x\_i)\hat{\ }2+(y-y\_i)\hat{\ }2)-d\hat{\ }})\hat{\ }2 \tag{12}$$

If $N \geq 3$ it means quantity of ACN within a communication radius of TN. The best measure (x, y) was described using EDMO-NLS approach when the quantity of rounds is constrained. The overall LLEs are described while estimating the localizable TN N_L. This is evaluated as a mean square of distance from the node coordinates (X_i, Y_i) while the actual node coordinates (x_i, y_i) are shown below:

$$E_1 = \frac{1}{N_1} \sum_{i=1}^{N} \sqrt{(x_i - X_i)^2 + (y_i - Y_i)^2} \tag{13}$$

The procedure of two to six is continual until the TN is localized. The localization process depends on the amount of unlocalized nodes N_{N_L} and maximal LLE E_1 are determined in the application of $N_{N_L} = M - N_L$. The minimal scores of E_1 and N_{N_L} enhance an effective localization.

The localized node quantity is increased as the iterative increases. Similarly, it decreases the ANs quantity within the transmission radius of localizable TN, and assessed location of the TN acts as ANs from the consecutive iteration. It can be exploited to constrain the problems of flip uncertainty that makes highest LLE. Consequently, when the iteration is improved, the process duration to localization dataset of the TN progresses.

4 RESULTS AND DISCUSSION

In this section, the node localization performance of the EDMO-NLS model is investigated under distinct measures. Tab. 1 and Fig. 3 provide an overall Number of Localized Nodes (NLLN) investigation of the EDMO-NLS approach with other algorithms under various numbers of ANs.

Table 1 NLLN analysis of EDMO-NLS approach with recent algorithms under distinct count of anchors

No. of Anchors	EDMO-NLS	SS-DE Algorithm	SS-NL Algorithm	CS-NL Algorithm	GWO-NL Algorithm
10	156	142	139	128	119
20	170	158	145	135	128
30	179	169	155	142	136
40	184	168	171	154	140
50	196	182	177	165	147

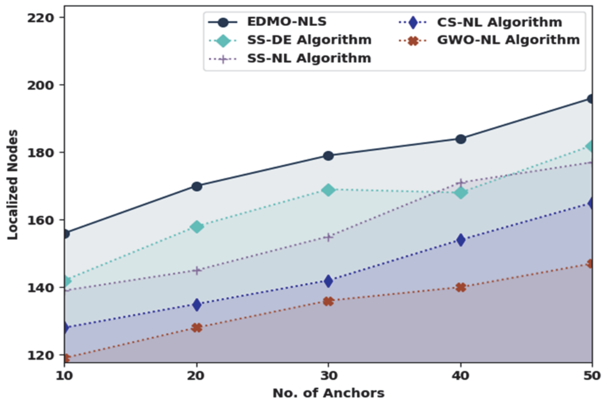

Figure 3 NLLN analysis of EDMO-NLS approach under distinct count of anchors

The outcomes implied that the EDMO-NLS system has offered improved NLLN values under all ANs. For example, with 10 ANs, the EDMO-NLS model offered higher NLLN of 156 whereas the Spherical Search Algorithm with Differential Evolution (SS-DE), Slap Swarm Algorithm for Node Localization (SS-NL), Cuckoo Search for Node Localization (CS-NL), and GWO-NL models have obtained decreased NLLN of 142, 139, 128, and 119 respectively. Also, with 20 ANs, the EDMO-NLS approach has provided superior NLLN of 170 whereas the SS-DE, SS-NL, CS-NL, and GWO-NL systems have acquired lesser NLLN of 158, 145, 135, and 128 correspondingly. Finally, with 30 ANs, the EDMO-NLS technique has provided maximal NLLN of 179 whereas the SS-DE, SS-NL, CS-NL, and GWO-NL methodologies have acquired reduced NLLN of 169, 155, 142, and 136 correspondingly.

A detailed localization error (LLE) rate examination of the EDMO-NLS model with other existing models under various ANs is given in Tab. 2 and Fig. 4. The outcome stated that the EDMO-NLS algorithm has exhibited effectual outcome with minimal values of LLE.

Table 2 LLE analysis of EDMO-NLS approach with recent algorithms under distinct count of anchors

No. of Anchors	EDMO-NLS	SS-DE Algorithm	SS-NL Algorithm	CS-NL Algorithm	GWO-NL Algorithm
10	0.241	0.319	0.461	0.477	0.563
20	0.185	0.333	0.414	0.527	0.566
30	0.149	0.302	0.447	0.493	0.524
40	0.083	0.205	0.352	0.425	0.463
50	0.073	0.281	0.344	0.356	0.445

For sample, with 10 ANs, the EDMO-NLS model has gained minimal LLE of 0.241 whereas the SS-DE, SS-NL, CS-NL, and GWO-NL models have obtained enhanced LLE of 0.319, 0.461, 0.477, and 0.563 respectively. Besides, with 20 ANs, the EDMO-NLS system has reached lesser LLE of 0.185 whereas the SS-DE, SS-NL, CS-NL, and GWO-NL models have achieved maximal LLE of 0.333, 0.414, 0.527, and 0.566 correspondingly. Similarly, with 30 ANs, the EDMO-NLS technique has reached lower LLE of 0.149 whereas the SS-DE, SS-NL, CS-NL, and GWO-NL methodologies have accomplished maximal LLE of 0.302, 0.447, 0.493, and 0.524 correspondingly.

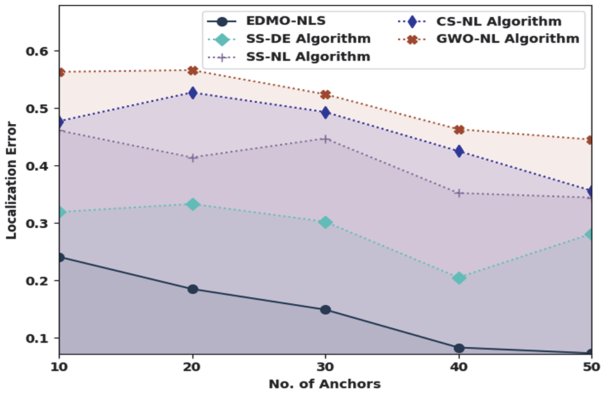

Figure 4 LLE analysis of EDMO-NLS approach under distinct count of anchors

A brief LLE rate investigation of the EDMO-NLS approach with other existing techniques under distinct range errors (RER) is provided in Tab. 3 and Fig. 5. The outcome exposed that the EDMO-NLS approach has demonstrated effectual outcome with decreased values of LLE.

Table 3 LLE analysis of EDMO-NLS approach with recent algorithms under distinct range error

Range Error / %	EDMO-NLS	SS-DE Algorithm	SS-NL Algorithm	CS-NL Algorithm	GWO-NL Algorithm
10	0.295	0.414	0.437	0.527	0.635
15	0.059	0.165	0.418	0.421	0.690
20	0.091	0.120	0.471	0.347	0.649
25	0.072	0.088	0.384	0.283	0.535
30	0.026	0.121	0.154	0.205	0.509

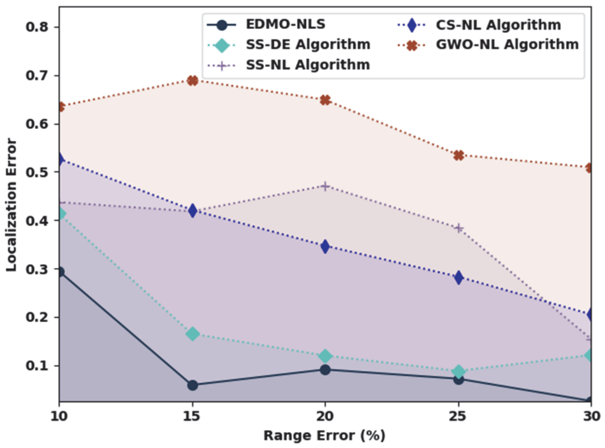

Figure 5 LLE analysis of EDMO-NLS approach under distinct range error

For instance, with 10% RER, the EDMO-NLS methodology has gained minimal LLE of 0.295 whereas the SS-DE, SS-NL, CS-NL, and GWO-NL approaches have attained increased LLE of 0.414, 0.437, 0.527, and 0.635 correspondingly. Also, with 15% RER, the EDMO-NLS system has gained reduced LLE of 0.059 whereas the SS-DE, SS-NL, CS-NL, and GWO-NL models have reached superior LLE of 0.165, 0.418, 0.421, and 0.690 correspondingly. At last, with 20% RER, the EDMO-NLS algorithm has gained minimal LLE of 0.091 whereas the SS-DE, SS-NL, CS-NL, and GWO-NL techniques have achieved superior LLE of 0.120, 0.384, 0.283, and 0.535 correspondingly.

A detailed LLE rate investigation of the EDMO-NLS model with other existing approaches under various transmission ranges (TRR) is given in Tab. 4 and Fig. 6.

Table 4 LLE analysis of EDMO-NLS approach with recent algorithms under distinct transmission range

Transmission Range / m	EDMO-NLS	SS-DE Algorithm	SS-NL Algorithm	CS-NL Algorithm	GWO-NL Algorithm
10	0.184	0.205	0.286	0.397	0.518
15	0.238	0.320	0.317	0.377	0.578
20	0.098	0.115	0.238	0.295	0.521
25	0.054	0.113	0.153	0.271	0.394
30	0.031	0.116	0.200	0.224	0.471

The outcome stated that the EDMO-NLS algorithm has outperformed effectual outcome with lower values of LLE. For instance, with 10m TRR, the EDMO-NLS technique has gained minimal LLE of 0.184 whereas the SS-DE, SS-NL, CS-NL, and GWO-NL systems have achieved enhanced LLE of 0.205, 0.286, 0.397, and 0.518 correspondingly. Moreover, with 15m TRR, the EDMO-NLS model has gained lesser LLE of 0.238 whereas the SS-DE, SS-NL, CS-NL, and GWO-NL methodologies have gained higher LLE of 0.320, 0.317, 0.377, and 0.578 correspondingly. Finally, with 20m TRR, the EDMO-NLS technique has attained lesser LLE of 0.098 whereas the SS-DE, SS-NL, CS-NL, and GWO-NL approaches have achieved higher LLE of 0.115, 0.238, 0.295, and 0.521 correspondingly.

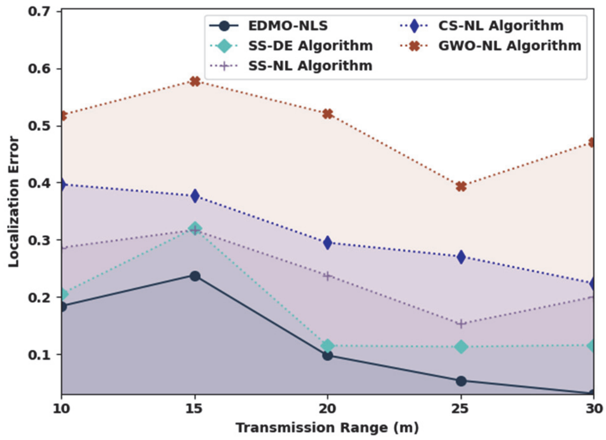

Figure 6 LLE analysis of EDMO-NLS algorithm under distinct transmission range

Tab. 5 and Fig. 7 determine an overall Packet Delivery Ratio (PDR) inspection of the EDMO-NLS approach with other techniques under various ANs. The outcomes represent that the EDMO-NLS system has offered improved PDR values under all ANs. For sample, with 10 ANs, the EDMO-NLS system has offered maximal PDR of 98.78% whereas the SS-DE, SS-NL, CS-NL, and GWO-

NL systems have obtained minimal PDR of 97.81%, 97.43%, 96.99%, and 92.90% respectively.

Table 5 PDR analysis of EDMO-NLS approach with recent algorithms under distinct count of anchors

No. of Anc.	EDMO - NLS	SS-DE Algorithm	SS-NL Algorithm	CS-NL Algorithm	GWO-NL Algorithm
10	98.78	97.81	97.43	96.99	92.90
20	99.50	98.34	96.82	95.07	92.43
30	96.84	95.40	94.42	92.18	89.59
40	95.66	94.35	93.99	91.12	89.51
50	96.30	95.11	91.13	89.22	86.46

Followed by, with 20 ANs, the EDMO-NLS method has provided higher PDR of 99.50% whereas the SS-DE, SS-NL, CS-NL, and GWO-NL techniques have obtained reduced PDR of 98.34%, 96.82%, 95.07%, and 92.43% correspondingly. Lastly, with 30 ANs, the EDMO-NLS algorithm has provided higher PDR of 96.84% whereas the SS-DE, SS-NL, CS-NL, and GWO-NL models have obtained minimum PDR of 95.40%, 94.42%, 92.18%, and 89.59% correspondingly.

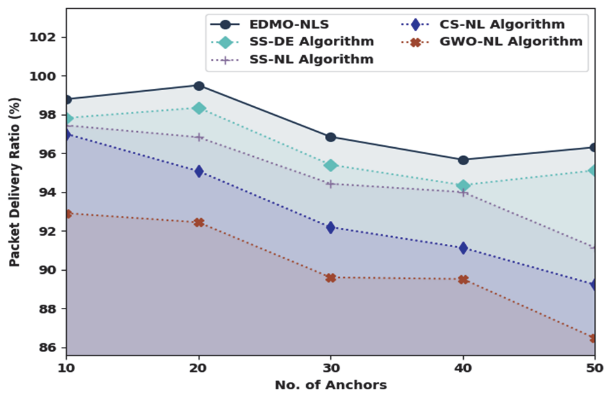

Figure 7 PDR analysis of EDMO-NLS approach under distinct count of anchors

A brief packet loss ratio (PLR) rate investigation of the EDMO-NLS system with other existing algorithms under various ANs is presented in Tab. 6 and Fig. 8.

Table 6 PLR analysis of EDMO-NLS approach with recent algorithms under distinct count of anchors

No. of Anchors	EDMO - NLS	SS-DE Algorithm	SS-NL Algorithm	CS-NL Algorithm	GWO-NL Algorithm
10	1.22	2.19	2.57	3.01	7.10
20	0.50	1.66	3.18	4.93	7.57
30	3.16	4.60	5.58	7.82	10.41
40	4.34	5.65	6.01	8.88	10.49
50	3.70	4.89	8.87	10.78	13.54

The outcomes expose that the EDMO-NLS algorithm has exhibited effective outcome with lesser values of PLR. For example, with 10 ANs, the EDMO-NLS system has obtained decreased PLR of 1.22% whereas the SS-DE, SS-NL, CS-NL, and GWO-NL methodologies have accomplished maximum PLR of 2.19%, 2.57%, 3.01%, and 7.10% respectively.

Besides, with 20 ANs, the EDMO-NLS model has gained minimal PLR of 0.50% whereas the SS-DE, SS-NL, CS-NL, and GWO-NL models have obtained maximal PLR of 1.66%, 3.18%, 4.93%, and 7.57% correspondingly. Similarly, with 30 ANs, the EDMO-NLS system has gained reduced PLR of 3.16% whereas the SS-DE, SS-NL, CS-NL, and GWO-NL models have reached higher PLR of 4.60%, 5.58%, 7.82%, and 10.41% respectively.

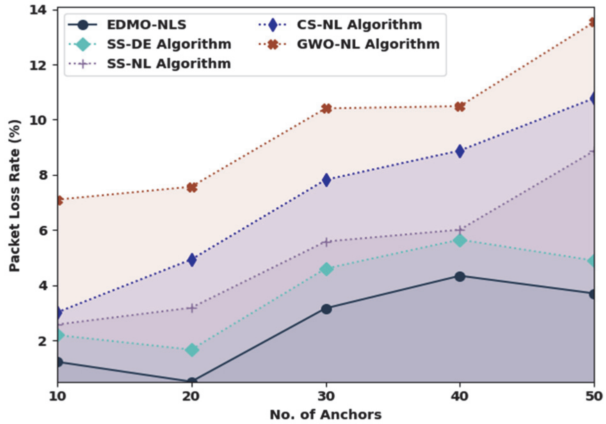

Figure 8 PLR analysis of EDMO-NLS approach under distinct count of anchors

From these results and discussion, it can be clear that the proposed methodology has exhibited maximum localization performance in UWSN.

5 CONCLUSION

In this proposed method, a novel EDMO-NLS methodology was introduced for UWSN. In the proposed algorithm, three social groups of dwarf mongooses have been applied namely the scout group, the alpha group, and babysitters. The family forages as a unit, and alpha female begins foraging, which defines the sleeping mounds, foraging path, and distance covered. The presented EDMO-NLS technique determines the unknown position of the nodes in UWSN. The simulation analysis stated the enhanced performance of the proposed model on existing approaches. Therefore, the EDMO-NLS technique has been developed for effectual node localization in the NLS model. In future, the performance of the EDMO-NLS technique will be extended to the use of lightweight cryptographic techniques for accomplishing secure UWSN communication.

6 REFERENCES

[1] Yun, H., Song, W., Huibing, K., & Yanzhu H. (2022). Iterative Virtual Force Localization Based on Anchor Selection for Three-Dimensional Wireless Sensor Networks. *Technical Gazette*, *29*(3), 813-817. https://doi.org/10.17559/TV-20220219093303

[2] Toky, A., Singh, R. P., & Das, S. (2020). Localization schemes for underwater acoustic sensor networks-a review. *Computer Science Review*, *37*, 100241. https://doi.org/10.1016/j.cosrev.2020.100241

[3] Saha, S. & Arya, R. (2022). An evolved algorithm for underwater acoustic sensor node localization enhancement using reference node. *Physical Communication*, *34*, 101827. https://doi.org/10.1016/j.phycom.2022.101827

[4] Kumar, M., Goyal, N., & Khullar, V. (2022). Emerging Node Localization State-of-Art Techniques Classification with Comparative Analysis in UWSNs. *Proceedings of 2nd International Conference on Advance Computing and Innovative Technologies in Engineering,* 1824-1828. https://doi.org/10.1109/ICACITE53722.2022.9823574

[5] Ahmad, I., Rahman, T., Zeb, A., Khan, I., Ullah, I., Hamam, H., & Cheikhrouhou, O. (2021). Analysis of Security Attacks

and Taxonomy in Underwater Wireless Sensor Networks. *Wireless Communications and Mobile Computing*, *2021*(1), 1-15. https://doi.org/10.1155/2021/1444024

[6] Kumar, M., Goyal, N., Qaisi, R. M. A., Najim, M., & Gupta, S. K. (2022). Game Theory based Hybrid Localization Technique for Underwater Wireless Sensor Networks. *Transactions on Emerging Telecommunications Technologies*, *33*(11), e4572. https://doi.org/10.1002/ett.4572

[7] Luo, J., Chen, Y., Wu, M., & Yang, Y. (2021). A Survey of Routing Protocols for Underwater Wireless Sensor Networks. *IEEE Communications Surveys & Tutorials*, *23*(1), 137-160. https://doi.org/10.1109/COMST.2020.3048190

[8] Luo, J., Yang, Y., Wang, Z., & Chen, Y. (2021). Localization Algorithm for Underwater Sensor Network: A review. *IEEE Internet of Things Journal*, *8*(17), 13126-13144. https://doi.org/10.1109/JIOT.2021.3081918

[9] Choudhary, M., Goyal, N., Benslimane, A., & Aswathy, L. K. (2021). Underwater Wireless Sensor Networks: Enabling Technologies for Node Deployment and Data Collection Challenges. *IEEE Internet of Things Journal*, *99*. https://doi.org/10.1109/JIOT.2022.3218766

[10] Gupta, O., Kumar, M., Mushtaq, A., & Goyal, N. (2020). Localization Schemes and its Challenges in Underwater Wireless Sensor Networks. *Journal of Computational and Theoretical Nanoscience*, *17*(6), 2750-2754. https://doi.org/10.1166/jctn.2020.9116

[11] Toky, A., Singh, R. P., & Das, S. (2021). A Localization Scheme for Underwater Acoustic Wireless Sensor Networks using AoA. *Recent Advances in Computer Science and Communications (Formerly: Recent Patents on Computer Science)*, *14*(3), 690-699. https://doi.org/10.2174/2666255813666191210143537

[12] Dong, M., Li, H., Yin, R., Qin, Y., & Hu, Y. (2021). Scalable Asynchronous Localization Algorithm with Mobility Prediction for Underwater Wireless Sensor Networks. *Chaos, Solitons & Fractals*, *143*(1), 110588. https://doi.org/10.1016/j.chaos.2020.110588

[13] Nain, M. & Goyal, N. (2022). Energy Efficient Localization through Node Mobility and Propagation Delay Prediction in Underwater Wireless Sensor Network. *Wireless Personal Communications*, *122*(3), 2667-2685. https://doi.org/10.1007/s11277-021-09024-8

[14] Nguyen, T. & Shin, Y. (2019). An efficient RSS localization for underwater wireless sensor networks. *Sensors*, *19*(14), 3105-3122. https://doi.org/10.3390/s19143105

[15] Choudhary, M. & Goyal, N. (2022). Dynamic Topology Control Algorithm for Node Deployment in Mobile Underwater Wireless Sensor Networks. *Concurrency and Computation: Practice and Experience*, *34*(5), e6942. https://doi.org/10.1002/cpe.6942

[16] Mridula, K. M. &Ameer, P. M. (2018). Localization under Anchor Node Uncertainty for Underwater Acoustic Sensor Networks. *International Journal of Communication Systems*, *31*(3),e3445. https://doi.org/10.1002/dac.3445

[17] Hu, K., Sun, Z., Luo, H., Zhou, W., & Guo, Z. (2018). STVF: Spatial-Temporal Variational Filtering for Localization in Underwater Acoustic Sensor networks. *Sensors*, *18*(7), 2078. https://doi.org/10.3390/s18072078

[18] Agushaka J., Ezugwu, A. E., & Abualigah, L. (2022). Dwarf Mongoose Optimization Algorithm. *Computer Methods in Applied Mechanics and Engineering*, *391*(10), 114570. https://doi.org/10.1016/j.cma.2022.114570

[19] Aldosari, F., Abualigah, L., & Almotairi, K. H. (2022). A Normal Distributed Dwarf Mongoose Optimization Algorithm for Global Optimization and Data Clustering Applications. *Symmetry*, *14*(5),1021. https://doi.org/10.3390/sym14051021

[20] Ponni, R., Jayasankar, T., & Vinoth Kumar, K. (2023). Investigations on Underwater Acoustic Sensor Networks Framework for RLS Enabled LoRa Networks in Disaster Management Applications. *Journal of Information Science & Engineering*, *39*(2), 389-406. https://doi.org/10.6688/JISE.202303_39(2).0009

[21] Ahmad, M. F., Isa, N. A. M., Lim, W. H., & Ang, K. M. (2022). Differential Evolution with Modified Initialization Scheme using Chaotic Oppositional based Learning Strategy. *Alexandria Engineering Journal*, *61*(12), 11835-11858. https://doi.org/10.1016/j.aej.2022.05.028

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