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Enhanced seagull optimization based node localization scheme for wireless sensor networks

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Abstract
Wireless sensor network (WSN) has become an emergent paradigm of networking and computing. It uses several application domains like military, healthcare, surveillance, target tracking, etc. Despite the benefits of WSN, node localization (NL) remains a crucial problem. It intends to define the exact place of unknown nodes from the network depends upon the anchor nodes. NL issues may be processed as non-deterministic polynomial-time (NP) hard problems and can be resolved using meta-heuristic optimization techniques. An enhanced seagull optimization-based node localization (ESGOBNL) scheme for WSN was developed in this aspect. The ESGOBNL approach aims to determine the proper location coordinates of the sensor nodes (SNs) in WSN. The proposed ESGBONL technique has been derived by the inclusion of the levy movement (LM) idea into the classification seagull optimization (SGO) algorithm, which is based on the migration as well as the attacking nature of seagulls. A wide range of experiments was implemented in order to report the promising localization efficacy of the ESGOBNL approach. The extensive comparative outcomes highlighted the betterment of the ESGOBNL system on the recent approaches with minimal mean localized error (MLE) of 0.120214. In contrast, the elephant herding optimization (EHO), hybrid elephant herding optimization (HEHO), and tree growth algorithm (TGA) techniques have obtained maximum MLE of 0.793293, 0.333199, and 0.280031, respectively.

Keywords
Network efficiency, Node localization, Anchor nodes, Wireless sensor networks, Seagull optimization algorithm.

1.Introduction
Lately, wireless sensor networks (WSN) are rapidly emerging and commonly utilized in monitoring wide-ranging public housing, medical, environmental, and military applications [1]. Defining the position of an event is a critical problem in WSN applications, and it is worthless when the sensed information has no position data [2, 3]. This necessitates the usage of placement algorithm and mechanism, and thereby, we could attain the node location in WSN [4].

Due to less necessity for hardware, the non-ranging position method is appropriate for largescale wireless adhoc networks and sensor networks [5]. Node localization (NL), coverage, the power consumption of sensor node (SN), data routing problems, etc., are the several problems in WSN applications [6, 7].

Notwithstanding all the problems and challenge, the most crucial one is finding the sensor location. Stimulatingly, the position service of WSN is an assurance of significant services, for example, target tracking, information management, and information collection [8]. Consequently, defining the position, data of sensors becomes predominantly significant in WSN. Global navigation satellite model and global positioning system (GPS) were extensively applied for positioning; nonetheless, it is unfeasible and expensive to incorporate a GPS receiver in all the sensors of whole large-scale sensors [9, 10]. A massive amount of positioning procedures has been presented. The present localization algorithm mostly falls into range-free and range-based approaches, whether the distance amongst nodes is to be estimated beforehand [11]. *Figure 1* demonstrates the process of NL in WSN.

Localization is commonly applied in WSN to find the present position of SNs [12]. A WSN comprise of

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thousands of nodes which create the GPS fixing on every SN expensive and furthermore GPS cannot give proper localization outcomes in an indoor platform. In case of dense networks, manual configuring place reference on every SN is not practical [13, 14]. It causes a problem where the SNs have to define its existing location without manual configuration and without using any hardware like GPS. The localization technique makes the utilization of WSN efficient [15]. Mostly, the localization technique is implemented by using beacon or anchor node (AN), which knows its existing location. This study presents a new enhanced seagull optimization-based node localization (ESGOBNL) scheme for WSN. The ESGO technique was developed by incorporating the models of levy movement (LM) as to migration and attacking strategies of seagulls. The simulation validation of the proposed model occurs under various measures and the outcomes reported the enhanced outcomes of the proposed model.

The rest of the paper was organized as follows. Section 2 offers the literature review, and section 3 introduces the presented method. Next, section 4 and 5 provides performance validation and discussion on the results, and section 5 concludes the study.

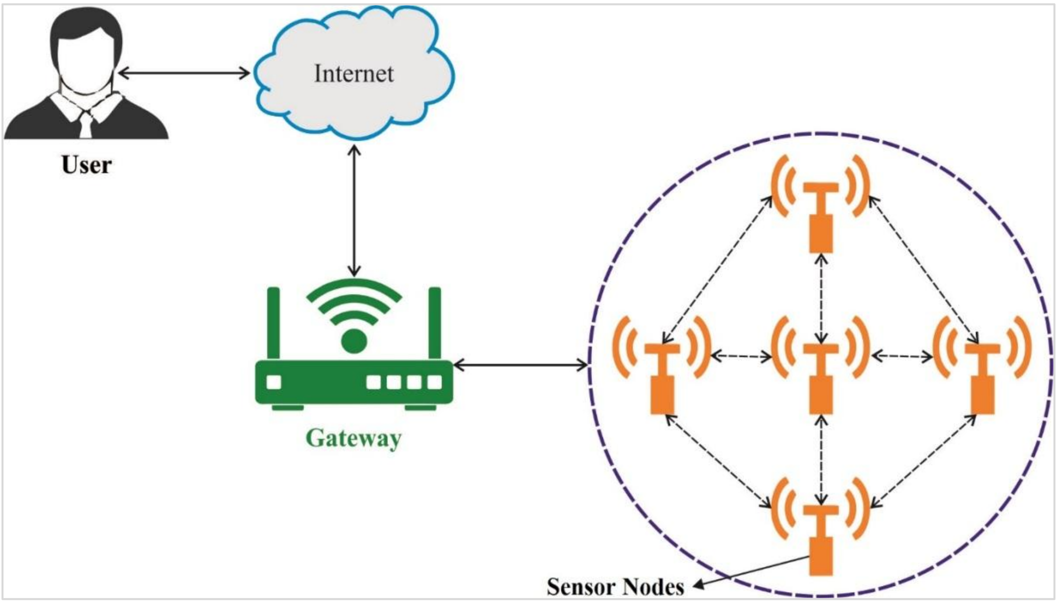

Figure 1 Node localization in WSN

2.Literature review

According to the range-based positioning approaches and the range-free positioning approach, few studies have presented the concept of integrating the heuristic optimization approach using the WSN node positioning techniques. The fundamental of this concept is to create the optimum localization system by attaining the connected topological relations or the distance data among nodes and using the heuristic optimization approach to calculate the optimum solution by iterating the optimal localization method.

Several optimization approaches have been utilized in the realm of heuristic optimization methods. In [16], a particle swarm optimization (PSO) based distance vector (DV)-Hop localization was presented in three-dimensional (3D) WSNs. The projected function was assessed according to the variance, computational time, and average localization error. Strumberger et al. [17] introduced the elephant herding optimization (EHO) approach, adapted for resolving positioning problems in WSN. EHO is a novel swarm intelligence (SI) meta-heuristic that attains promising results while handling non-deterministic polynomial (NP)-hard problems. Node positioning issue in WSN goes to the class of NP-hard optimization, which characterizes the major challenge in this field.

Lv et al. [18] established that the PSO-based backpropagation (PSO-BP) technique could powerfully estimation the coordinate of mobile nodes (MNs) from the indoor 3D space. Also, convergence speed and Estimation accuracy of backpropagation neural network (BPNN) method enriched for PSO are deliberated. The researchers in [19] projected an improvised DV-Hop procedure based dynamic AN set (DANS IDV-Hop). Otherwise, to the current DV-Hop-based algorithm that employs overall ANs, the DANS IDV-Hop of ANs to contribute to positioning. In order to choose proper AN, a fitness function and binary particle coding systems are developed. The researchers in [20] introduced an enhanced DV-Hop positioning with class topper optimization (CTO) for addressing the present shortcoming of the outdated DV-Hop. During the presented technique, a factor to adapt the hop size of beacon node is projected. Although numerous models are available in the works, until there is a need to increase localization efficiency. In addition, the inclusion of multiple parameters for the localization process needs to be developed.

Liang et al. [21] presents an opposition-based learning (OBL) and parallel approaches, artificial gorilla troop optimizer (OPGTO) to reduce the localization error. OBL could considerably higher the global exploration abilities of model and extend the exploration space of the model. Kotiyal et al. [22] introduces an enhanced CS (ECS) technique to minimize the average localization error (ALE) and the amount of time required to localize an unknown node. In this study, an early stopping (ES) mechanism is implemented that significantly enhances the searching procedure with leaving the searching loop when the optimum solution is obtained. In [23], to discover unknown node in 3D environments, only single AN was applied. A new soft computing techniques such as an adaptive plant propagation algorithm (APPA) is presented for attaining the better location of this MN.

Thenmozhi et al. [24] presents a sparrow search algorithm with doppler effect (SSA-DE) for NL in WSN. Generally, the SSA was motivated by the anti-predation, group wisdom, and foraging performance of sparrows. In addition, the Doppler Effect is integrated as to SSA for improving performance of the NL. Dao et al. [25] develops a node place detection in WSN dependent upon ant lion optimiser (ALO) with the standard model of localized. The updating solution of the population is analysed for location amending to enhance the accuracy of the node positioning.

Lakshmi et al. [26] purposes for developing a novel and precise localized systems for WSNs. This effort provides localize utilizing 2-hybrid localization technique such as ensemble learning PSO (ELPSO) and PSO-BPNN. Bacanin et al. [27] concentrations on establishing the deep learning technique termed as graph long short-term memory (GLSTM) NN for predicting the air quality features. Then, the evolutionary algorithm, termed as a Dragon fly optimizer was utilized for localizing the node depends on the forecast. Punithavathi et al. [28] examines a novel multi-objective manta ray foraging optimized (MRFO) related NL with intrusion detection (MOMRFO-NLID) approach for WSN. The objective of the MOMRFO-NLID system is to optimum localizing the unknown node and define the presence of intrusions from the network.

In [29] a new node location technique dependent upon proximity-distance mapping (PDM) and Jaya optimizer has been presented. During this method, proximity and Euclidean distance can be extracting in connection of ANs for constructing a mapping matrix with utilizing the knowledge of PDM. In [30], an enhanced localization technique named as MAOA DV-Hop dependent upon the modified Archimedes optimization algorithm (MAOA) and DV-Hop is presented that can obtain the balancing betwixt the localization precision as well as localization speed. Though several NL techniques are available in the literature, it is still needed to improve the localization performance.

3.Methods

In this study, a novel ESGOBNL method has been established to determine the proper location coordinates of SNs in WSN. The proposed ESGBONL technique has been derived by the inclusion of LM idea into the classification seagull optimization (SGO) technique that is dependent upon the migration as well as the attacking nature of seagulls.

3.1Design of ESGO algorithm

Now, the SGO algorithm is developed for selecting the routing or cluster development leader. A complete description of SGO is available. Seagulls belong to the Laridae family and are seen in the wider biosphere [31]. There are several kinds of sea birds; nonetheless, seagulls have attractive features; for example, their prey drive is stronger and persistent. Hence, the seagulls are represented as clever birds and show the behaviors of hunting and specific migration. The SGO procedure has two significant procedures, namely, attacking and migration that are described below [32]:

Migration

Here, the seagull should recompense the following conditions. In the SGO, to avoid the impacts among neighbors, additional limitations are prepared for the estimation of the exploration agent setting as given in Equation 1:

$$Cs = A \times Ps(X) \quad (1)$$

Whereas the drive feature of the searching agent is considered as A, current iteration is specified as X, the searching agent's existing position is quantified as Ps, and remaining agents don't influence Cs. The searching agent movement pattern is available in Equation 2:

$$A = Pc - (X \times \left(\frac{Pc}{\max iteration}\right) \quad (2)$$

Whereas $X = 0,1,2, \ldots \max iteration$.

Pc is chosen as 2; A is linearly labelled and condensed from Pc to 0; Fc is utilized for regulating the constraint frequency. Once collision among neighbors is removed, the exploration agent is distinguished in the direction of optimum neighbor movement as in Equation 3:

$$Ms = B \times (Pb(X) - PS(X)) \quad (3)$$

Here the searching agent and their location are quantified by PS (X) & Ms; B is labelled as an arbitrary agent that is responsible for effective calculation among manipulation and examination; the exploration agent with optimum fitness is specified by $Pb(X)$,· and the arbitrary value estimated is formulated in Equation 4:

$$B = 2 \times S = A^2 \times RD \quad (4)$$

In which RD is elected as an arbitrary quantity available in range among [0, 1]. Eventually, the position of upgraded searching agent is associated with the searching agent [33], as provided in Equation 5:

$$DS = |Cs + Ms| \quad (5)$$

DS is determined as the distance between the best-fit and the actual searching agents. *Figure 2* exhibits the procedure flow of SGO technique.

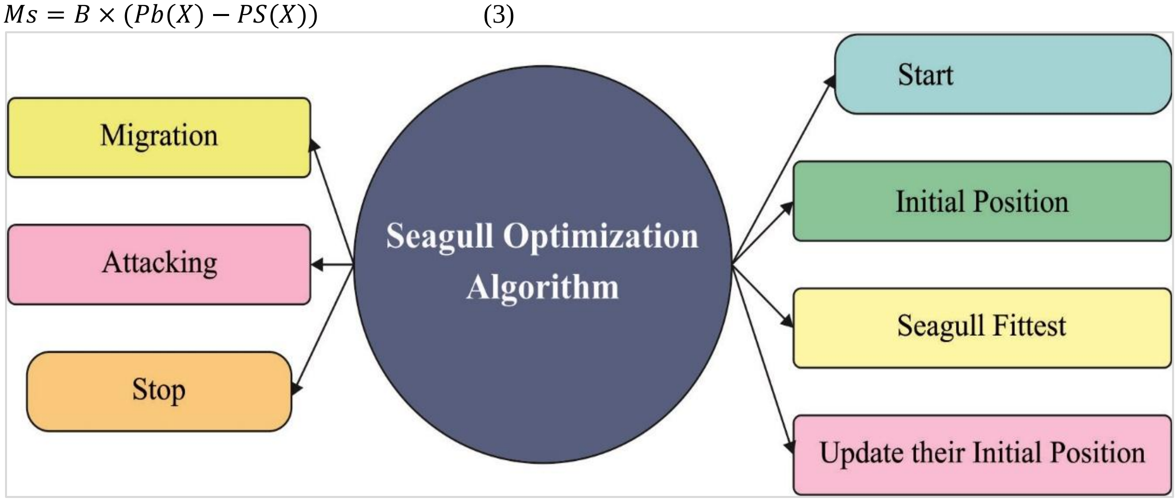

Figure 2 Flowchart of SGO

Attacking the prey

The reduced quantity of estimation is included in the exploration stage. In the attacking process, seagulls adapt to the migration state, where the motivation is on conserving their altitude-based weight and air currents. During attacking, the prey might implement twisting movements in the air and it can be shown in the Equation 6 to Equation 9 as given below:

$$X = R \times \cos K \quad (6)$$

$$Y = R \times \sin K \quad (7)$$

$$Z = R \times K \quad (8)$$

$$R = U \times e^{KV} \quad (9)$$

Whereas the actual logarithm base is denoted by e, spiral shape quantity is determined by u and v, k is labelled by an undiscriminating number with the interval $[0 \leq k \leq 2\pi$ and the extension of spirals are indicated by R. The upgraded development of the searching agent is estimated in Equation 10:

$$Ps(X) = (DS \times X \times Y \times Z) + Pbs(X) \quad (10)$$

In the equation, $Pbs(X)$ represents an optimal response and defines the location of the residual searching agents.

To improve the ESGO algorithm's performance, the ESGO approach was resultant by utilizing of LM model. LM is an arbitrarily search path substituting amongst short and irregularly long walks subsequent the Levy distribution [34]. The position upgrade formulation of LMis determined in Equation 11 to Equation 13:

$$x_{ij}(t+1) = x_{ij}(t) \times \ Levy\ (d), \quad (11)$$

$$Levy\ (\beta) = 0.01 \times \frac{(r_1 \times \sigma)}{|r_2|^{\beta^{-1}}} \quad (12)$$

$$\sigma = \left(\frac{\left(\Gamma(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)\right)}{\left(\Gamma\left(1+\frac{\beta}{2}\right) \times \beta \times 2^{\left(\beta-\frac{1}{2}\right)}\right)}\right)^{\beta^{-1}} \quad (13)$$

$i$refers the i^{th} individual and $j$signify the number of individuals. $\Gamma(\beta) = (\beta-1)!$. $t$stands for the existing algebra. $d$implies the dimensional of optimized objects, $r_1, r_2 \in rand\ (0,1)$. β define the partial real constant. If the fitness value has been judged as optimum or worse depending on the recently produced individual place vector, an original individual from the SGO technique is substituted by optimum.

3.2Steps involved in the ESGOBNL technique

The ESGBONL technique's aim in WSN is to calculate the coordinates of unknown target sensor arbitrarily dispersed in the surveillance platform, intending to minimalise the main function [35]. The target node (TN) assessment was defined by the range-based distributed positioning method that can be implemented in two stages: the ranging stage and the location assessment stage. In a two-dimensional (2D) WSN observing platform, M (TN) and N (AN) are arbitrarily positioned, with the broadcast range R. Calculated distance amid anchor and TNs are studied using the Gaussian noise variable. For all the TNs, the distance among ANs is estimated as $\hat{d} = d_j + n_j$, in which n_j denotes the additive Gaussian noise, and d_j indicates the actual distance in Equation 14:

$$d_i = \sqrt{(x-x_i)^2 + (y-y_i)^2}, \quad (14)$$

Here the location of TN is represented by (x, y), and the location of AN is characterized by (x_i, y_i).

The variance of n_i, as the noise affecting the estimated distance betwixt the AN and TN, is shown in Equation 15:

$$\sigma_d^2 = \beta^2 \cdot P_n \cdot d_{j,} \quad (15)$$

P_n denotes the percentage noise from the distance measurement $d_i \pm d_i(\frac{P_n}{100})$, and β indicates a variable that value was commonly fixed to 0.1 in a real-world implementation. During this trilateration technique for assessing the location of the unknown sensors, the TN is determined as localized when there are minimal 3ANs with the known coordinate$(x_a,\ y_a), B(x_b, y_b)$, and (x_c, y_c) in its broadcast range R, and with distance d_i in TNn. Through the trigonometric principle of sines and cosines, the place of TNs is estimated. This reduces the error among estimated and actual distances.

The SI metaheuristic is independently executed for all the localized TNs to attain the location. The agent is initialized with centroid of AN has positioned with the range of localized TN as given in Equation 16:

$$(x_{c'} y_c) = \left(\frac{1}{N}\sum_{i=1}^{N} x_{i'} \frac{1}{N}\sum_{i=1}^{N} y_i\right), \quad (16)$$

Whereas N presents the overall amount of ANs within the broadcast range of TN that is subjected to positioning.

Moreover, the ESGOBNL technique aims to find the coordinate (x, y) of the TN to minimise the positioning error. The main function $f(x, y)$ of the node positioning issue is expressed as the mean square distance among the AN as well as TN, as provided in Equation 17:

$$f(x,y) = \frac{1}{N}\left(\sum_{i=1}^{N}\sqrt{(x-x_i)^2 + (y-y_i)^2}\right)^2, \quad (17)$$

In which $N \geq 3$ (the trilateration rule needs minimum 3ANs within broadcast range R of localized TN).

Localization error E_L is defined afterwards, determining the position of each TNN_L. It can be estimated as mean of the square of distances among the real (x_j, y_i) node co-ordinates and the assessed $(X_i,\ Y_i)$ node coordinates as given in Equation 18:

$$E_L = \frac{1}{N_L}\sum_{i=1}^{N}\sqrt{(x_i-X_i)^2 + (y_i-Y_i)^2} \quad (18)$$

The efficacy of localization method can be estimated using the average positioning error E_L and the amount of nodes that haven't been positioned N_{NL}, whereas $N_{NL} = M - N_L$. The less the value of $E_L$and N_{NL}, the greater the efficiency and performance of the model.

4.Results

The proposed model can be simulated by using the MATLAB tool. The parameter setting is provided as follows: network size-100×100m^2, node count-100, initial energy-0.5J, communication range-10m, and packet size 4000 bits. In this section, the localization performance of ESGOBNL technique is investigated with varying numbers of TN and AN. *Table 1* provides a brief number of localized nodes (NLN) assessment of the ESGOBNL model with existing techniques and with distinct numbers of TNs and ANs. The outcomes implied that the ESGOBNL approach has led to in efficient outcomes under all TNs and ANs. For example, under run-1 with 25TNs and 10Ns, the ESGOBNL model has offered a higher

NLN of 23, while the EHO, hybrid elephant herding optimization (HEHO), and tree growth algorithm (TGA) techniques have reached lower NLN of 19, 21, and 22, correspondingly.

Table 1 NLN outcome of ESGOBNL system with other algorithms under different TN and AN

No. of localized nodes (NLN)								
No. of Runs	**EHO**	**HEHO**	**TGA**	**ESGOBNL**	**EHO**	**HEHO**	**TGA**	**ESGOBNL**
Target Node = 25, Anchor Node = 10					Target Node = 100, Anchor Node = 25			
1	19	21	22	23	93	94	95	97
2	19	22	22	23	94	94	94	96
3	17	20	21	22	93	93	98	100
4	19	19	22	23	93	94	97	97
5	20	22	23	23	96	94	96	96
Target Node = 50, Anchor Node = 15					Target Node = 125, Anchor Node = 30			
1	44	45	46	49	118	118	122	122
2	45	44	44	49	121	118	120	122
3	42	47	46	49	121	122	120	123
4	45	45	46	46	119	119	123	124
5	45	47	46	48	119	119	119	123
Target Node = 75, Anchor Node = 20					Target Node = 150, Anchor Node = 35			
1	67	70	73	74	143	145	144	149
2	71	72	73	75	144	147	146	148
3	69	72	71	72	146	146	146	150
4	67	69	71	71	145	146	148	150
5	70	68	73	73	142	143	146	149

Similarly, under run-2 with 25TNs and 10Ns, the ESGOBNL model has provided an increased NLN of 23, while the EHO, HEHO, and TGA techniques have attained decreased NLN of 19, 22, and 22, correspondingly. Likewise, under run-3 with 25TNs and 10Ns, the ESGOBNL model has obtained an improved NLN of 22, while the EHO, HEHO, and TGA methods have depicted reduced NLN of 17, 20, and 21, correspondingly. Eventually, under run-4 with 25TNs and 10Ns, the ESGOBNL model has reached an enhanced NLN of 23, while the EHO, HEHO, and TGA approaches have resulted in the decreased NLN of 19, 19, and 22, correspondingly. Moreover, under run-5 with 25TNs and 10Ns, the ESGOBNL model has offered a higher NLN of 23, while the EHO, HEHO, and TGA techniques have reached lower NLN of 20, 22, and 23, correspondingly.

Table 2 provides a detailed mean localized error (MLE) assessment of the ESGOBNL method with existing approaches and with distinct numbers of TNs and ANs. The outcomes exposed that the ESGOBNL method has resulted in efficient outcomes under all TNs and ANs. For a sample, under run-1 with 25TNs and 10Ns, the ESGOBNL approach has obtained lesser MLE of 0.247859 while the EHO, HEHO, and TGA method have reached higher MLE of 0.741273, 0.277096, and 0.314733 correspondingly.

Table 2 Mean localized error analysis of ESGOBNL technique with recent approaches under varying TN and AN

Mean localized error (MLE)								
No. of Runs	**EHO**	**HEHO**	**TGA**	**ESGOBNL**	**EHO**	**HEHO**	**TGA**	**ESGOBNL**
Target Node = 25, Anchor Node = 10					Target Node = 100, Anchor Node = 25			
1	0.741273	0.277096	0.314733	0.247859	0.605807	0.331595	0.345654	0.237042
2	0.737506	0.253678	0.238396	0.227037	0.599010	0.273772	0.236402	0.235867
3	0.701727	0.346203	0.313086	0.193068	0.521375	0.359145	0.429527	0.211351
4	0.793293	0.333199	0.280031	0.120214	0.516527	0.534826	0.302804	0.229372
5	0.653573	0.193560	0.194456	0.178643	0.722203	0.386361	0.493982	0.115613
Target Node = 50, Anchor Node = 15					Target Node = 125, Anchor Node = 30			
1	0.560929	0.298701	0.285712	0.272253	0.805779	0.656487	0.514151	0.493411
2	0.401729	0.280618	0.301321	0.214213	0.611791	0.676752	0.698035	0.510337
3	0.593232	0.399374	0.358882	0.276520	0.898072	0.951882	0.650667	0.442557
4	0.417187	0.237576	0.302604	0.208411	0.721057	0.740375	0.539573	0.526028
5	0.608073	0.467109	0.343067	0.340670	0.656361	0.679698	0.603613	0.441152

Mean localized error (MLE)								
No. of Runs	**EHO**	**HEHO**	**TGA**	**ESGOBNL**	**EHO**	**HEHO**	**TGA**	**ESGOBNL**
Target Node = 75, Anchor Node = 20					Target Node = 150, Anchor Node = 35			
1	0.595582	0.383067	0.358891	0.156612	0.916915	0.660396	0.868803	0.657907
2	0.567570	0.360868	0.306377	0.276627	0.639588	0.957253	0.691624	0.612986
3	0.663044	0.355431	0.256531	0.225162	0.783153	0.699844	0.778107	0.685397
4	0.541911	0.380674	0.283232	0.272987	1.002330	0.896610	0.576893	0.569038
5	0.827393	0.264674	0.348117	0.185418	0.766274	0.804646	0.772542	0.730322

Likewise, under run-2 with 25TNs and 10Ns, the ESGOBNL system was offered a minimal MLE of 0.227037, while the EHO, HEHO, and TGA techniques have attained higher MLE of 0.701727, 0.346203, and 0.313086 correspondingly. In addition, under run-3 with 25TNs and 10Ns, the ESGOBNL model has obtained a reduced MLE of 0.193068, while the EHO, HEHO, and TGA systems have demonstrated improved MLE of 0.701727, 0.346203, and 0.313086 correspondingly. At the same time, under run-4 with 25TNs and 10Ns, the ESGOBNL technique obtained decreased MLE of 0.120214, while the EHO, HEHO, and TGA techniques have resulted in enhanced MLE of 0.793293, 0.333199, and 0.280031 correspondingly. Finally, under run-5 with 25TNs and 10Ns, the ESGOBNL model has offered the lower MLE of 0.178643, while the EHO, HEHO, and TGA methods have reached higher MLE of 0.653573, 0.193560, and 0.194456 correspondingly.

5.Discussion

Table 3 presented a brief execution time (ET) assessment of the ESGOBNL technique with existing approaches with various TNs and ANs. The outcomes revealed that the ESGOBNL technique has resulted in effectual outcomes under all TNs and ANs. For sample, under run-1 with 25TNs and 10Ns, the ESGOBNL technique has offered least ET of 0.71s while the EHO, HEHO, and TGA techniques have reached higher ET of 1.55s, 1.29s, and 0.81s correspondingly. In addition, under run-2 with 25TNs and 10Ns, the ESGOBNL approach has offered reduced ET of 0.57s, while the EHO, HEHO, and TGA methods have reached increased ET of 1.39s, 0.95s, and 0.61s, correspondingly.

Table 3 ET outcome of ESGOBNL technique with recent methodologies under varying TN and AN

Execution time (sec)								
No. of Runs	**EHO**	**HEHO**	**TGA**	**ESGOBNL**	**EHO**	**HEHO**	**TGA**	**ESGOBNL**
Target Node = 25, Anchor Node = 10					Target Node = 100, Anchor Node = 25			
1	1.55	1.29	0.81	0.71	3.67	2.93	2.85	2.58
2	1.39	0.95	0.61	0.57	3.14	3.49	2.88	2.52
3	1.30	1.04	0.97	0.84	4.02	4.06	2.29	2.05
4	1.30	1.07	0.99	0.85	3.61	3.17	3.09	2.49
5	1.42	1.02	0.87	0.71	4.07	3.58	3.02	2.74
Target Node = 50, Anchor Node = 15					Target Node = 125, Anchor Node = 30			
1	1.93	1.88	1.31	1.13	4.98	5.16	3.84	3.51
2	2.15	1.83	1.20	1.06	5.06	4.34	3.26	3.14
3	1.97	1.55	1.35	1.11	5.67	5.07	3.33	3.19
4	1.97	1.92	1.60	1.32	4.49	4.46	3.72	3.15
5	2.26	1.62	1.12	1.02	5.75	4.89	3.73	3.24
Target Node = 75, Anchor Node = 20					Target Node = 150, Anchor Node = 35			
1	2.59	2.24	1.69	1.45	7.45	6.82	4.65	3.69
2	2.94	2.82	2.02	1.05	6.22	5.79	4.48	3.28
3	2.74	2.32	1.81	1.54	6.23	6.84	4.94	4.39
4	2.53	2.61	1.75	1.54	7.40	5.86	4.33	4.17
5	2.63	2.21	2.29	1.87	6.81	6.66	4.69	4.27

Likewise, under run-3 with 25TNs and 10Ns, the ESGOBNL system has obtained a reduced ET of 0.84s, while the EHO, HEHO, and TGA methods have depicted improved ET of 1.30s, 1.04s, and 0.97s correspondingly. Besides, under run-4 with 25TNs and 10Ns, the ESGOBNL algorithm has reached decreased ET of 0.85s, while the EHO, HEHO, and TGA models have resulted in enhanced ET of 1.30s, 1.07s, and 0.99s correspondingly. Finally, under run-5 with 25TNs and 10Ns, the ESGOBNL technique has offered lower ET of 0.71s, while the EHO, HEHO, and TGA methodologies have reached highest ET of 1.42s, 1.02s, and 0.87s correspondingly. From the results mentioned above and discussion, it can be confirmed that the ESGOBNL algorithm can be utilized as an effective tool for NL in WSN. The enhanced performance of the proposed model is due to the integration of LM concept in the design of ESGO algorithm.

Although the proposed model offers maximum benefits, few limitations are still needs to be addressed. Initially, the computational efficiency of the proposed model is yet to be examined in detail. In addition, the performance of the proposed model on the large-scale network is yet to be explored.

A complete list of abbreviations is shown in *Appendix I.*

6.Conclusion and future work

In this study, a novel ESGOBNL technique has been established for identifying the proper location coordinates of the SNs in WSN. The presented ESGBONL approach has been derived by the inclusion of LM idea into the classification SGO algorithm, which is based on the migration as well as the attacking nature of seagulls. A wide range of experiments is implemented in order to report the promising localization efficacy of the ESGOBNL methodology. The extensive comparative results highlighted the betterment of the ESGOBNL algorithm on the existing approaches with respect to different measures. Therefore, the ESGOBNL method can be considered as an effectual tool for NL process. In the future, the efficiency of the proposed model was enhanced by using multihop route selection protocols. Besides, the data aggregation concept needs to be incorporated to improve the energy efficacy of the presented technique. Furthermore, the presented system should be tested in large-scale real-time environment.

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Conflicts of interest

The authors have no conflicts of interest to declare.

Author’s contribution statement

D. Lubin Balasubramanian: Conceptualization, investigation, data curation, study conception, design, data collection, supervision, investigation on challenges, writing – original draft. **V. Govindasamy:** Writing – review and editing, data collection, conceptualization, analysis and interpretation of results.

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Appendix I

S. No.	Abbreviation	Description
1	ALE	Average Localization Error
2	ALO	Ant Lion Optimiser
3	AN	Anchor Node
4	APPA	Adaptive Plant Propagation Algorithm
5	BPNN	Backpropagation Neural Network
6	CTO	Class Topper Optimization
7	DANS IDV-Hop	Improved Distance Vector-Hop Procedure Based Dynamic Anchor Node Set
8	DV	Distance Vector
9	ECS	Enhanced Cuckoo Search
10	EHO	Elephant Herding Optimization
11	ELPSO	Ensemble Learning Particle Swarm Optimization
12	ES	Early Stopping
13	ESGOBNL	Enhanced Seagull Optimization-Based Node Localization
14	ET	Execution Time
15	GLSTM	Graph Long Short-Term Memory
16	GPS	Global Positioning System
17	HEHO	Hybrid Elephant Herding Optimization
18	LM	Levy Movement
19	MAOA	Modified Archimedes Optimization Algorithm
20	MLE	Mean Localized Error
21	MN	Mobile Node
22	MRFO	Manta Ray Foraging Optimized
23	NL	Node Localization
24	NLN	Number Of Localized Nodes
25	NP	Non-Deterministic Polynomial
26	OBL	Opposition-Based Learning
27	OPGTO	Opposition-Based Learning And Parallel Approaches, Artificial Gorilla Troop Optimizer
28	PDM	Proximity-Distance Mapping
29	PSO	Particle Swarm Optimization
30	PSO-BP	Particle Swarm Optimization-Based Backpropagation
31	SGO	Seagull Optimization
32	SI	Swarm Intelligence
33	SN	Sensor Nodes
34	SSA-DE	Sparrow Search Algorithm With Doppler Effect
35	TGA	Tree Growth Algorithm
36	TN	Target Node
37	WSN	Wireless Sensor Network