CHAPTER-63

A ZEBRA OPTIMIZATION ALGORITHM SEARCH FOR LOCALIZATION ENHANCEMENT IN WIRELESS SENSOR NETWORK

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ABSTRACT

Massive numbers of sensor nodes are used in wireless sensor networks (WSNs) to gather data about the immediate environment, but this data is meaningless unless the precise location from which it was gathered is made known. In many applications, including spotting enemy movement in military applications, localization of sensor nodes in WSNs is significant. Finding the coordinates of all target nodes with the aid of anchor nodes is the main goal of the localization issue. Two variations of the zebra optimization algorithm (ZOA) are suggested in this study to localize the sensor nodes more effectively and to get beyond the original ZOA's limitations, such as becoming stuck in local optimal solutions. The suggested ZOA versions 1 and 2 modify the exploration and exploitation aspects of the original ZOA by utilizing better global and local search algorithms. Numerous simulations have been run with varying numbers of target nodes and anchor nodes to test the efficacy of the proposed ZOA versions 1 and 2, and the results are compared with those of the original ZOA and other known optimization methods used to solve the node localization problem. When it comes to mean localization error, the quantity of localized nodes, and computation time, the suggested ZOA versions 1 and 2 perform better than the competition. Additionally, given a range of target and anchor node values, the suggested ZOA variants 1 and 2 and the original ZOA are evaluated in terms of different mistakes and localization efficacy. The simulation results show that the proposed ZOA variation 2 has a number of advantages over the proposed ZOA variant 1 and the current ZOA. In comparison to the proposed ZOA variation 1, ZOA, and other current optimization methods, the node localization based on the suggested ZOA variant 2 is more efficient since calculations are completed faster and mean localization error is lower.

Keywords*: Node localization, Bat optimization algorithm, Computation time, Target nodes, Localization error.*

I. INTRODUCTION

Researchers are looking at the many problems that wireless sensor networks encounter because of the modernization of wireless technology (WSNs). In WSNs, the huge sensor nodes are placed at random or at predetermined places to collect data and transmit it to other nodes [1-3]. WSNs have been utilized in a variety of fields, including monitoring different parameters like temperature, pressure, and the amount of air pollutants, detecting landslides and forest fires, and in real-time applications, such as in the medical and agricultural fields [4-6]. In these uses of WSNs, the localisation of sensor nodes is significant. WSN is also utilized for managing electronic waste in [7] and for a number of security applications, including the defense of sensitive information against unauthorized users and assaults in VANET and MANET [8–11].

WSNs encounter a number of issues, including localization, node deployment, routing, energy consumption by sensor nodes, and short sensor node lifetimes [12–16]. A second problem in WSN is extending the network's lifetime, which is related to the energy used by sensor nodes and may be resolved by utilizing clustering-based routing algorithms [16–18]. Using a small number of sensor nodes to achieve enough coverage is another issue that WSN must deal with [19]. One of the main issues with WSNs is localization, as the sensor nodes' data collection is useless unless the place from where it was obtained is identified [20]. In WSNs, several nodes are positioned at arbitrary places whose positions cannot be predicted. Finding the locations of each sensor node in WSNs is the goal of the localization issue [21, 22]. The global positioning system (GPS) can be used to determine the location of sensor nodes as a solution to the localization issue. However, this method cannot be used to WSNs since WSNs are made up of big sensor nodes, and adding a GPS device to each node would make the network more expensive, complicated, and power-hungry [23, 24].

Numerous academics have developed a number of localization strategies to address these issues. The locations of a select few sensor nodes, known as anchor nodes, can be calculated without the requirement to employ the GPS system for all sensor nodes. These anchor nodes allow for the calculation of the position of target nodes, which are unidentified nodes [25, 26]. The localization mechanism receives the position of the anchor node as input, and measuring techniques determine another input [24]. The two categories of localization techniques are range-free localization and range-based localization. Angle of arrival (AOA), received signal strength (RSS), etc., are employed as additional inputs in range-based localization, whereas connectivity data are used as an additional input in range-free localization [27, 28].

Several methods, including AOA, RSS, time of arrival (TOA), and time difference of arrival (TDOA), have been utilized by different researchers to calculate the distance between sensor nodes [24, 29]. For localizing the sensor nodes in WSNs, many researchers have utilized a variety of optimization algorithms in recent years, including the particle swarm optimization, bat optimization algorithm, salp swarm algorithm, and frefy algorithm. Every optimization algorithm has advantages and disadvantages. These optimization methods are based on how diverse natural systems behave and look for food sources. The issue of sensor node localisation can be resolved via optimization techniques. The idea of optimization is employed in every field; for instance, deep learning techniques are used in [30] to diagnose the COVID-19 and [31] to enhance the authentic customer rating offered in order to guard against fraudulent reviews.

Various iterations of the bat optimization technique are put forth in this study to locate the sensor nodes in the WSNs. The echolocating behavior of bats is the basis of the bat optimization method. The bat algorithm is superior to the genetic algorithm (GA), particle swarm optimization (PSO), frefy algorithm (FA), and cuckoo search optimization algorithm (CSOA) in a number of ways, including simplicity, flexibility, convergence speed, accuracy, and ease of implementation. It can be used to find the best solutions in a wide range of applications, including data mining, task scheduling in stages, and pressure vessel design [32].

The following is a discussion of the novelty of node localisation based on the suggested ZOA variants:

1. By boosting exploration and exploitation capacities in the suggested ZOA versions 1 and 2, respectively, the present ZOA's searching capabilities are increased.
2. The performance of the proposed ZOA variants 1 and 2 is calculated and compared with the original BOA and other optimization algorithms, such as the particle swarm optimization (PSO) algorithm, the grey wolf optimization (GWO) algorithm, the butterfy optimization algorithm (BTOA), the salp swarm optimization (SSO) algorithm, and the frefy algorithm, in terms of mean localization error, computation time, and number of localized nodes (FA).
3. In comparison to these current methods, the suggested ZOA versions 1 and 2 located each and every target node and had lower mean localization errors and calculation times. In terms of calculating time and mean localization error, the suggested ZOA version 2 is preferable than the proposed BZOA variation 1.
4. In addition to the original ZOA's performance, the suggested ZOA variants 1 and 2 are also evaluated in terms of a variety of error categories, including average localization error, normalized localization error, root-mean-square error, and localization efficiency for various node circumstances.
5. For various sorts of mistakes, the proposed BOA variation 2 is more effective than the proposed BOA variant 1 and original ZOA.

As a result, cost and accuracy are the two main problems with range-based localization methods. The ZOA versions 1 and 2 are suggested to use enhanced global and local search algorithms to increase the localization process' accuracy in WSN. The suggested ZOA versions 1 and 2 have much lower mean localization errors than the current algorithms ZOA, FA, BTOA, PSO, SSA, and GWO. As a result, by employing ZOA versions 1 and 2 to localize the WSN nodes, the accuracy of the WSN is increased. The proposed ZOA versions 1 and 2 do not require any new hardware, hence they do not raise the WSN's cost. Additionally, ZOA versions 1 and 2 converge more quickly and have less computation time than the existing algorithms.

The remainder of the essay is divided into the following sections: The overview of several optimization methods for the node localization problem is presented in Section 2. Section 3 provides an explanation of the suggested ZOA versions 1 and 2. The simulation's findings and analysis are presented in Section 4, and the conclusion is presented in Section 5.

II. RELATED WORK

In order to address the issue of node localisation in WSNs, several researchers have used a variety of optimization strategies. It was recommended in [35] to use particle swarm optimization (PSO) to locate WSN nodes and lower average localization error. PSO and the bacterial foraging algorithm (BFA) were two iterative localization techniques that were suggested in [36] as a solution to the multi-objective localization issue. The recommended techniques took less time to determine the coordinates of the target nodes in WSNs and required less power from nodes. In order to reduce the average error of target nodes from anchor nodes, the bees optimization technique was utilized in [37]. For placing the anchor nodes in the deployment region, two possibilities were taken into consideration. Each target node in the first technique has more than three anchor nodes around it, and in the second way, beacon nodes were placed in the middle of the monitoring zone [37].

Stochastic PSO was proposed in [38] as a method for localizing the nodes over three deployment (3D) regions. Compared to other PSO-based techniques, the stochastic PSO algorithm has more correctly positioned the target nodes. In [39], a hybrid bio-inspired optimization strategy based on PSO and BFO was applied to improve localization accuracy and convergence rate. Compared to other algorithms, the PSO and BFO method had localized a greater number of sensor nodes and used less energy by nodes. Using a sufficient number of anchor nodes to locate each target node in WSNs, a unique genetic optimization approach was proposed in [40] to reduce deployment costs. The cuckoo search optimization algorithm (CSOA) was suggested in [41] as a way to achieve convergence with fewer iterations and define the target nodes' coordinates more precisely. In order to find the overall ideal results, the CSOA outperformed other optimization algorithms. In [42], the gravitational search optimization technique was modified to address the fip uncertainty problem in WSNs. The findings indicated that the suggested technique also decreased the typical localization error.

Binary PSO was used in [43] to locate the target nodes in the network in order to prolong the life of WSNs and reduce calculation time. In addition to conserving sensor node energy, RSS was employed to calculate the distance between the target and anchor nodes. [44] devised a multi-objective two-phase PSO algorithm to boost WSN performance and solve the fip uncertainty problem. All of the target nodes in WSNs might have been localized faster with the two-phase PSO technique. To identify the ideal degree of error and to improve the accuracy of the localization process, a modified version of the bat method was proposed in [45]. The recommended approach located all target nodes in the network with reduced computing time. Using RSS for sensor node localization, the parallel frefy method was created in [46] to speed up computation and find the overall best answers. The revised DVHop approach was utilized in [47] to decrease approximation error and increase localization accuracy. In comparison to existing localization techniques, the modified DV-Hop algorithm reduced the localization error.

Fower pollination (FP) technique was used in [48] to address the localization issue in WSNs and to locate additional sensor nodes. Compared to previous PSO approaches, the FP algorithm was more precise. The orthogonal teaching-learning-based optimization (OTLBO) methodology was proposed in [49] as a method for localizing mobile nodes. OTLBO increased network life and coverage while being more sophisticated. The range-free frefy technique was presented in [50] to locate the nodes in the 3D environment. The nonlinearity between distance and RSS was established using fuzzy logic to minimize the computation-related problems. The frefy algorithm took less time than other algorithms to find the coordinates of every sensor node. Artificial bee colony algorithm (ABC) was utilized in [51] to more accurately determine the locations of target nodes. Compared to previous strategies, ABC localized the sensor nodes more precisely but required more time for processing. Only two anchor nodes were taken into account while modifying the localization error algorithm in [20] to improve accuracy. In [52], the placements of target nodes were determined using chicken swarm optimization (CSO) to achieve a higher convergence rate. The CSO algorithm was more accurate than the PSO algorithm. Grey wolf optimization (GWO) algorithm was proposed in [53] to shorten computation time and GWO localized more target nodes than previous techniques.

The Butterfy Optimization Algorithm (BTOA) was developed in [54] to enhance the performance of WSNs by more precisely localizing target nodes. In order to demonstrate the effectiveness of BTOA, the deployment area's dimensions were changed and affected by various sounds. The findings showed that BTOA was more effective in terms of accuracy and calculation time. For identifying random mobile nodes in WSNs, a unique PSO-based approach was proposed in [55]. A few anchor nodes were then placed in the monitoring zone at various angles after first computing the distance of the anchor nodes from the target nodes using RSS. Compared to other algorithms, the PSO exhibited a quicker mean convergence time.

Numerous researchers have employed a variety of optimization strategies over the past few years to address the WSN's localization issue. The benefit of utilizing optimization techniques for sensor node localization is that the computation time and localization error were both significantly decreased. However, efficient evolutionary algorithms might still be utilized to further reduce the computation time and localization error. In localization, there are a number of problems, including scalability, expense, convergence speed, and accuracy. Scalability is the ability to expand the WSN by adding more nodes, and it plays a significant role in determining how well the WSN performs. The price of the network is another problem with localization. Although the accuracy and cost of WSN are trade-offs, the researchers' main objective is to provide a cost-effective optimization approach for localization. Another element that affects the cost of the WSN is the ratio of anchor to target nodes. As the number of anchor nodes rises, the localization error lowers and the accuracy of the WSN rises. But because GPS is needed to pinpoint the locations of anchor nodes, it also raises the price of WSN. The optimization algorithm's time to locate each target node in the WSN is measured by the convergence time. The primary goal of the localization algorithm's optimization step is to precisely determine the position of the target nodes. The average localization error is a measure of how accurate an optimization approach is for localization. The accuracy of an optimization process increases with decreasing average localization error values.

These problems lead academics to propose innovative optimization techniques to more quickly and accurately position sensor nodes. The suggested BOA variations 1 and 2 increase the searching capabilities by applying better global and local search algorithms, respectively, to find the sensor nodes more precisely in less time. While the aforementioned optimization techniques used 35 anchor nodes, the proposed BOA versions 1 and 2 localized all 150 target nodes in the WSN using just 20 anchor nodes. Because the suggested BOA versions 1 and 2 require just 20 anchor nodes to locate 150 target nodes, their cost is therefore lower than that of the current methods. For 150 target nodes and 20 anchor nodes, the proposed BOA variation 2's localization error is less than that of all other methods, BOA, and the proposed BOA variant 1.

III. PROPOSED METHODOLOGY

The initial method for bat optimization located a sufficient number of sensor nodes. Bat optimization algorithm's mean localization error and computation time are lower than those of other current methods, but ZOA's success rate is lower since it doesn't locate all of the network's target nodes. ZOA is unable to thoroughly explore every angle in the search area. In order to solve these problems and further minimize mean localization error and calculation time, it is required to tweak the bat optimization method. Two different iterations of the bat optimization technique are put forth in this study. The zebra optimization algorithm variations are made available to improve the exploration and exploitation properties of the basic bat algorithm and to offer WSNs with efficient performance. The introduction of a better global search strategy in ZOA variation 1 improves the exploration feature of the bat optimization algorithm. In ZOA variation 2, a better local search approach is used to increase the exploitation feature of ZOA. The following is a detailed discussion of these variations:

BOA variant 1 based on improved global search strategy

It is impossible to acquire the global optimal solution when the zebra optimization method is stuck in the local optimum solution. Therefore, it is vital to steer the current solution in the direction of the final, ideal solution. The proposed ZOA variation 1 uses the enhanced global search technique to increase ZOA's global search capabilities. The basic idea behind an enhanced global search strategy is to explore a greater portion of the search area and use various techniques to discover the global optimal answer.

In the search region, N target nodes and M anchor nodes are randomly distributed, and the population size is P, meaning that P potential solutions will exist. Two frequencies are created in the proposed ZOA version 1 to update bat velocity, and these frequencies are designated as Fi(1) and Fi(2) for ith sensor nodes. Using Eqs. 1 and 2, the values of these frequencies are calculated:

$$F_i(1) = F_{min} + (F_{max} - F_{min})\delta \quad (1)$$

$$F_i(2) = F_{min} + (F_{max} - F_{min})\varepsilon \quad (2)$$

Fi(1) and Fi(2values)'s depend on,, Fmin, and Fmax. Two random numbers with values between 0 and 1 are and are. The following equations are then used to update bat velocity and position:

$$\mathrm{V}_\mathrm{i}^\mathrm{T} = \mathrm{V}_\mathrm{i}^{\mathrm{T}-1} + \left(\mathrm{X}^\mathrm{b} - \mathrm{X}_\mathrm{i}^\mathrm{T}\right) * \mathrm{F}_\mathrm{i}(1) + \left(\mathrm{X}^\mathrm{w} - \mathrm{X}_\mathrm{i}^\mathrm{T}\right) * \mathrm{F}_\mathrm{i}(2) \quad (3)$$

$$\mathrm{X}_\mathrm{i}^\mathrm{T} = \mathrm{X}_\mathrm{i}^{\mathrm{T}-1} + \mathrm{V}_\mathrm{i}^\mathrm{T} \quad (4)$$

New solutions are developed around the best values in the original bat optimization method, and ZOA is progressively imprisoned in the local optimal solution. The bats in the original method just fly around the best answer and don't scout the full area. The search space for bats is expanded in the first suggested ZOA version 1 in order to identify the global optimal value. The bats in the proposed ZOA variation 1 would search the whole space, from best to worst options, until they find the overall best solution. The values of Xb and Xw are established as follows if the optimization issue is one of minimization:

$$\mathrm{X}^\mathrm{b} = \min\,(\mathrm{f}(\mathrm{X})) \quad (5)$$

$$\mathrm{X}^\mathrm{w} = \min\,(\mathrm{f}(\mathrm{X})) \quad (6)$$

Where f(X) is the optimization problem's objective function. The objective function is computed for each bat after updating their locations, and at the conclusion of the first iteration, the values of the worst and best solutions are determined. The bats' velocities are updated in the following iteration using these best and worst values, and so on.

ZOA variant 2 based on improved local search strategy

In comparison to other current algorithms used to solve the node localization problem, the suggested ZOA variation 1 located all of the target nodes in the wireless sensor network and had the minimum mean localization error. In comparison to existing algorithms, the proposed ZOA variation 1 converges more quickly and requires less time to locate all the nodes. But when updating the bat velocity, there is a propensity to use the worse option. ZOA version 2 is recommended as a solution to this issue in order to significantly reduce the mean localization error and calculation time. In the proposed ZOA variation 2, an improved local search approach is applied to raise ZOA's local search performance. The main rationale for an enhanced local approach is to create new solutions for bats using the best data currently available locally and the best existing solution. The updated local approach updated the bat velocity using the best solution currently known as well as the worst solution. The second iteration of ZOA is being presented, and it searches a smaller region that is closer to the greatest answer so far found while excluding the worst. The suggested ZOA variation 2 uses the following equation to modify bat velocity:

$$V_i^T = V_i^{T-1} + \left(X^b - X_i^T\right) * F_i(1) + \left(X^w - X_i^T\right) * F_i(2) \tag{7}$$

Convergence rate, mean localization error, calculation time, and number of localized nodes are the four main problems in the node localization problem. The suggested ZOA versions 1 and 2 have mean localization errors and calculation times that are lower than those of ZOA and current algorithms like FA, BTOA, PSO, GWO, and SSA. The above-mentioned current algorithms and ZOA localized all target nodes and converged at 100 iterations, whereas the suggested ZOA versions 1 and 2 localized all target nodes and converged at 25 iterations.

Node localization using the proposed ZOA variants 1 and 2

The distributed single hop range-based technique is used to estimate the target nodes' coordinates. A small number of anchor nodes, which can pinpoint their location using GPS, are used to calculate the locations of the target nodes. Discovering the position of target nodes and minimizing the objective function are the main objectives of the localization problem. Fig. 1 displays the flow chart for node localisation based on the suggested ZOA variations. Following is a discussion of the many stages involved in utilizing the suggested ZOA variations to determine the coordinates of N target nodes:

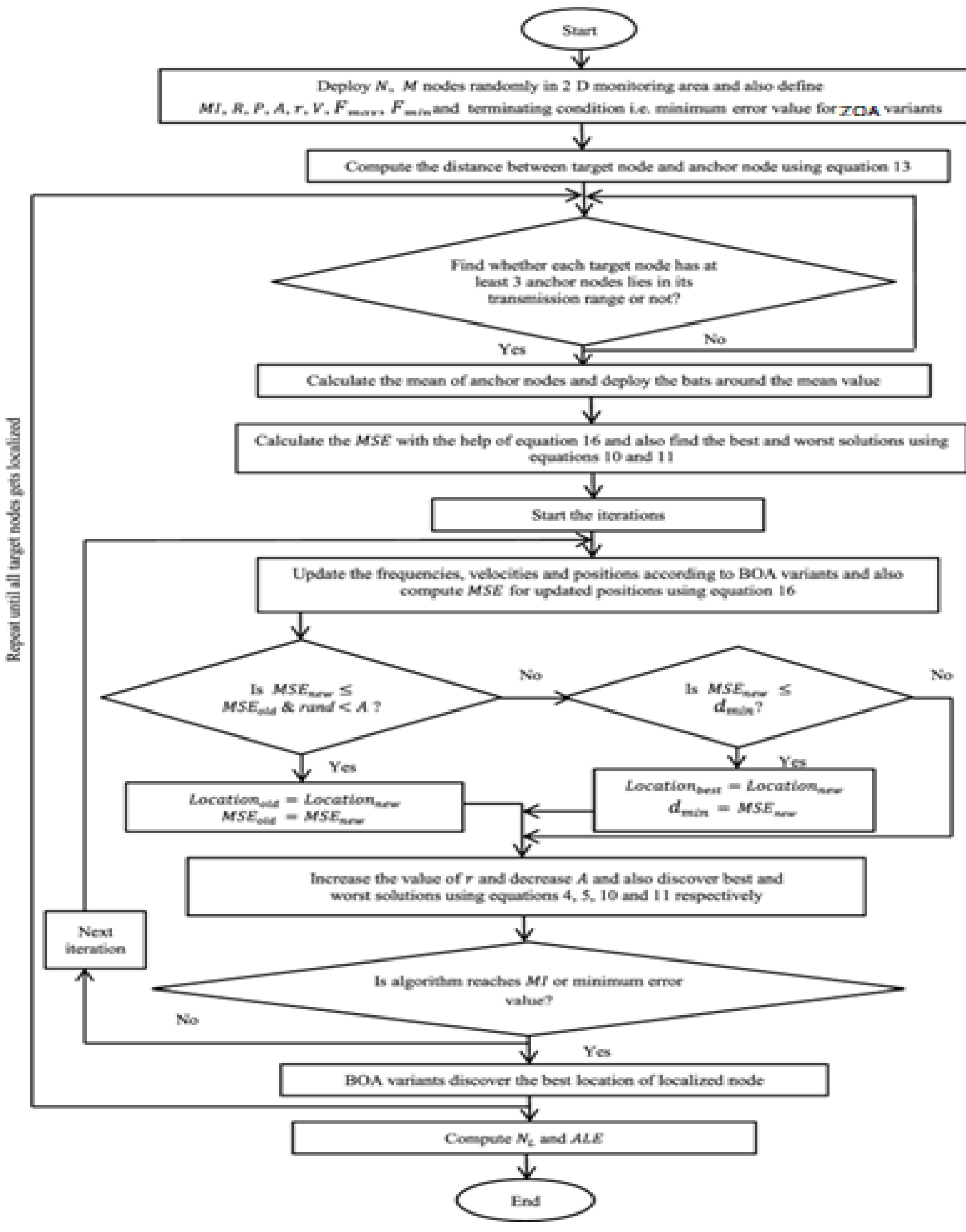


Figure. 1 Flow chart for node localization based on ZOA variants in WSNs

Step 1: First, M anchor nodes and N target nodes are randomly placed in the monitoring region. Through a GPS device, the anchor nodes may determine their location. The transmission range R of the target and anchor nodes, as well as the values of other parameters including A, r, V, MI, R, P, Fmax, and Fmin, are all described. The terminating condition, or minimal value of error, should be defined.

Step 2: From all anchor nodes, the distance to each target node is calculated. Assume that (x, y) represent the coordinates of the target node that has to be found and (xi, yi) represent the location of the ith anchor node.
Step 3: If the target node has at least three anchor nodes that are located within its transmission range, it is presumed to be a localizable node. Check to see if each target node has three or more anchor nodes within reach. It is possible to reduce the localization error between the predicted distance and the real distance by using the distances derived from three or more anchor nodes.
Step 4: Each optimization method is run independently to determine the coordinates of each target node that must be localizable.
Step 5: Every optimization method determines the target node's coordinates and lowers the localization error. The goal function of the node localization issue is the mean square error between the anchor node and the destination node. The following is a description of the mean square error (MSE), which is decreased by applying an efficient optimization algorithm:

$$\text{Objective function} = \text{MSE} = f(x, y) = \frac{1}{M}\left(\sum_{i=1}^{M} \sqrt{(x-x_i)^2 + (y-y_i)^2} - \hat{d}_i\right)^2 \quad (8)$$

Update the bats' frequency, velocity, and location values in accordance with BOA variations in step 6. Next, calculate MSE for the new bat locations.
Step 7: Verify that the new MSE value is lower or equal to the old MSE value and that the value of the random number (rand) is lower than the loudness parameter (A). If so, proceed on to step 9 and save the new bat location and MSE value in the old and new, respectively. If not, go back to step 8.
Step 8: Calculate if the new value of the MSE is less than or equal to the value for the minimum distance (dmin). If so, choose the temporary position of the bat as the new best location and set the new MSE value to dmin; if not, move on to step 9.
Step 9 Using Eqs. 4 and 5, increase the value of the pulse emission rate (r) and reduce the value of the loudness parameter (A).

$$N_{N_L} = N - N_L \quad (9)$$

Step 10: Using the suggested BOA variations, verify that all target nodes are localized. If so, move on to step 12; if not, repeat steps 3 through 11 until each node is localized inside the monitoring region.

The average localization error (ALE) and number of unlocalized nodes (NNL), which are determined using Eq. 18, affect the effectiveness of node localization when applying an optimization technique. If the ALE and NNL of the optimization method used for node localization are lower, the algorithm will work better.

IV. RESULTS AND DISCUSSION

The simulations are run on a laptop with an Intel Core i3 processor, 64 GB of RAM, and a 2.40 GHz CPU while using the MATLAB R2016a software to check the performance of the suggested BOA versions 1 and 2. The transmission range of all sensor nodes is set to 30 m, and the anchor and target nodes are arbitrarily placed in the monitoring region of 100 m 100 m. The effectiveness of the suggested ZOA versions 1 and 2 is evaluated by comparing their results to those of the original zebra optimization method (ZOA).

Mean localization error (MLE), average localization error (ALE), calculation time T(s), normalized localization error (NLE), root-mean-square error (RMSE), and localization efficiency are used to assess the performance of the proposed ZOA versions 1 and 2. (LE). The following explanations apply to the ALE, computation time, MLE, RMSE, NLE, and LE:

Localization error on average (ALE) By determining the difference between the estimated coordinates and the real coordinates of the target nodes, adding the errors for each target node, and then taking the average of the total errors, the accuracy of the optimization technique used for localizing the target nodes may be determined. The average localization error indicates the precision of the localization optimization procedures. Calculation Period T (s) The computation time T(s) is defined as the entire amount of time required by the optimization method to complete all calculations necessary for the localisation of each target node in the WSN. The tic toc function is used to calculate the calculation time T(s).

Table 1. Parameters of ZOA and Proposed ZOA variants 1 and 2 for various of monitoring area.

Monitoring area	Transmission range R	Target nodes N	Anchor nodes M	Ranging error (noise)
100mx100m	30m	150	35	2%
200mx200m	60m	300	70	4%
300mx300m	90m	450	105	6%
400mx400m	120m	600	140	8%

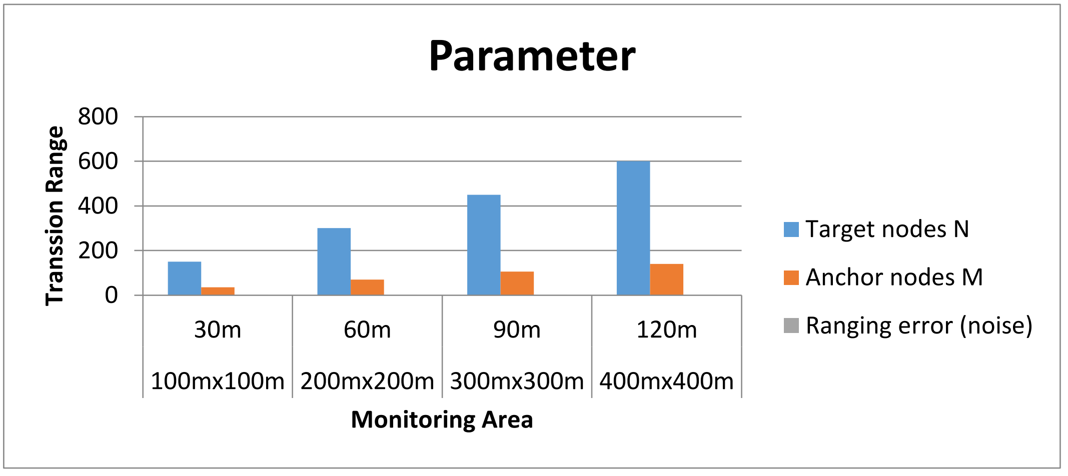
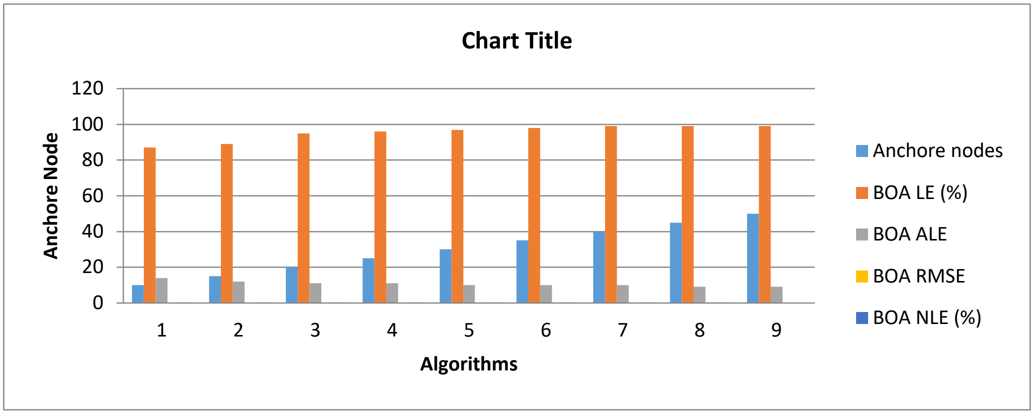


Table 2. Efect of anchor nodes on localization efciency and various errors of ZOA and proposed ZOA.

Anchore nodes	ZOA				Proposed ZOA			
	LE (%)	ALE	RMSE	NLE (%)	LE (%)	ALE	RMSE	NLE (%)
10	87	14	0.11	0.36	96	13	0.10	0.33
15	89	12	0.09	0.31	98	12	0.08	0.27
20	95	11	0.09	0.30	99	11	0.07	0.25
25	96	11	0.08	0.28	99	10	0.06	0.23
30	97	10	0.08	0.26	99	10	0.06	0.22

35	98	10	0.07	0.24	99	9	0.06	0.21
40	99	10	0.06	0.22	99	9	0.06	0.21
45	99	9	0.06	0.22	99	9	0.06	0.21
50	99	9	0.06	0.21	99	9	0.06	0.20



V. CONCLUSION

In many wireless sensor network applications, the location information from whence the data were acquired is necessary. As a result, the location of sensor nodes affects WSN performance. Compared to other methods, the original bat optimization technique has a lower mean localization error and takes less time to compute, but its localization efficiency is lower than 100% and it tends to become stuck at local optimum values. In this study, two ZOA variations are offered to address the issues with the original ZOA. Improved global and local search techniques are used to modify the suggested ZOA versions 1 and 2 in order to increase their capacity for exploration and exploitation in quest of the most optimal solutions. For several situations involving anchor nodes and target nodes, the performance of the proposed ZOA versions 1 and 2 is compared with that of other optimization algorithms as BTOA, FA, PSO, GWO, SSA, and conventional ZOA. In comparison to other existing algorithms and the original ZOA, the results showed that the proposed ZOA variants 1 and 2 have less mean localization error, localized more target nodes, and better convergence speed. In other words, both algorithms converge at 25 iterations and require less computation time. In terms of mean localization error and speed, the suggested ZOA variation 2 performs better than the proposed ZOA variant 1. (computation time).

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