A ZEBRA Optimization Algorithm Search for Improving Localization in Wireless Sensor Network

Dr. Ajay Rana
Amity University Uttar Pradesh
Greater Noida, India
ajay_rana@amity.edu

Dr. Virender Khurana
Associate Professor
Department of Computer Science
Vaish College, Rohtak, India
drvkkhurana@gmail.com

Amit Shrivastava
Department of CSE,
Chameli Devi Group of Institutions
Khandwa Road
Indore, India,
dean.engineering@liet.in

Dr. Durgaprasad Gangodkar
Department of CSE
Graphic Era Deemed to beUniversity
And Graphic Era Hill University
Dehradun, Uttarakhand, India,
Dr.gangodkar@geu.ac.in

Deepika Arora
Department of CSE
Lloyd Institute of Engineering and
Technology
Greater Noida, Uttar Ptadesh, India
Dean.engineering@liet.in

Anil Kumar Dixit
Division of Research & Innovation,
Uttaranchal University,
Uttarakhand, India,
anil@uttaranchaluniversity.ac.in

Abstract*— Wireless sensor networks (WSNs) make use of an abundance of sensor nodes in order to gain a deeper understanding of the world around them. If the data were not gathered in an open and honest fashion, then no one would be interested in them. In military applications, for instance, the detection of opponent movement relies substantially on the placement of sensor nodes in wireless sensor networks (WSNs). Discovering the locations of all target nodes while utilizing anchor nodes is the major purpose of the localization challenge. This research suggests two adjustments that could be made to the zebra optimization algorithm (ZOA) in order to improve upon its deficiencies, one of which being its tendency to get trapped in the local optimal solution. In versions 1 and 2 of the ZOA, the exploration and exploitation components have been modified to make use of improved global and local search algorithms. In order to assess how effective, the proposed ZOA versions 1 and 2 are, a large number of simulations have been run, each with a different combination of target nodes and anchor nodes and a different number of each. In order to solve the problem of node localization, ZOA, along with a number of other attempted optimization strategies, are employed, and the outcomes obtained by each strategy are compared. Versions 1 and 2 of ZOA perform far better than its competitors in terms of the mean localization error, the number of nodes that are successfully localized, and the computation time. ZOA versions 1 and 2 are proposed, and the initial ZOA is evaluated in terms of how accurately it localizes nodes and the number of errors it generates when provided with a range of possible values for the target node and the anchor node. The simulations prove without a reasonable doubt that the suggested ZOA variation 2 performs better than both the existing ZOA and the original proposal in a variety of ways. The proposed ZOA variation 2 is superior to the proposed ZOA variation 1, ZOA, and other existing optimization methods for determining the location of a node because it performs calculations at a faster rate and has a lower mean localization error. This is due to the fact that the proposed ZOA variation 2 is based on a more accurate probability distribution.

Keywords*— *Localization error, Target nodes, the Bat optimization technique, and computation time.

I. INTRODUCTION

In recent days wireless technology is becoming more advanced, researchers are looking into the vast array of problems that might develop in wireless sensor networks (WSNs). Large sensor nodes that are part of WSNs are often placed in unexpected or prearranged locations with the intention of gathering data and sending it on to other nodes. [1,2] WSNs have been put to use in a wide variety of contexts, one of which is the monitoring of environmental parameters such as temperature, pressure, and levels of pollution. In addition to these applications, they have been utilized in the fields of health and agriculture, as well as for the real-time detection of landslides and fires in forests [3-5]. When carrying out these duties with wireless sensor networks, the location of the sensor nodes is of the utmost importance. In the field of information and network security, wireless sensor networks (WSN) are utilized for a variety of purposes, one of which is to prevent unauthorized access to sensitive data and assaults on that data in virtual private networks (VANETs) and metropolitan area networks (MANETs) [6].

WSNs have been found to have a number of problems [4–6], some of which include difficulty in localization, node placement, routing, energy consumption, and sensor node lifetimes. The second problem with WSN is its lack of longevity. This pertains to the amount of power that sensor nodes consume and can be remedied with clustering-based routing algorithms [7,8]. Another hurdle that wireless sensor networks (WSN) face is coverage problems brought on by a restricted number of sensor nodes [7]. WSNs have a significant obstacle with localization because it is essential to be able to precisely locate the origin of the data that is acquired by the sensor nodes [2]. In WSNs, different nodes are installed in locations that are unknown to the user. The primary focus of the localization problem [8,9] in WSNs is on the process of determining the positions of the individual sensor nodes. The problem of localization can be solved by making use of the global positioning system, also known as GPS. This will allow the location of the sensor nodes to be determined. However, this strategy cannot be used with WSNs since these networks are constructed consisting of huge sensor nodes, and installing a GPS receiver on each one would increase the cost, complexity, and energy consumption of the network [10]. Therefore, this approach cannot be used with WSNs.

In order to address these problems, the academic community has created a variety of localization solutions. It is possible to find some of the anchor and sensor nodes in the network even when none of the nodes in the network make use of their GPS capabilities. [9,10] With the assistance of these anchor nodes, it is possible to discover the target nodes that have not been given names. The localization approach [11] takes into account both the position of the anchor node and the data that were measured. There are numerous varieties of localization, the most common of which are range-based and range-free localization, respectively. We make use of connection information as a complementary technique to range-free localization [12]. On the other hand, range-based localization makes use of supplemental data such as the angle of arrival (AOA), received signal strength (RSS), etc.

Researchers have looked into a variety of methods for measuring the distance that separates two sensor nodes [13]. The time of arrival (TOA), the time difference of arrival (TDOA), the angle of arrival (AOA), and the relative speed of sound (RSS) are the terms used to refer to these aspects (TDOA). In recent years, researchers have turned to optimization strategies such as particle swarm optimization, bat optimization, salp swarm, and Fredy algorithms in order to find the best possible configuration for the placement of sensor nodes in wireless sensor networks (WSNs). Additional examples of computations that improve performance include the Fredy method, the bat optimization algorithm, and the particle optimization technique. Each distinct optimization algorithm comes with its own set of advantages as well as drawbacks. There are many different ecological systems, each of which has its own unique way of locating food and preserving life. Observing how others handle a situation can provide you valuable insight into the best way to handle it yourself. Utilizing optimization methodologies allowed for the determination of where the best possible sites for sensor nodes could be found. Ideas for improving one's overall performance can be found in virtually every academic field. Deep learning is used to identify COVID-19 in [13], and in [14], it is used to improve legitimate user reviews while weeding out fraudulent ones. In [13], deep learning is used to identify COVID-19. It is employed in the process of identifying COVID-19 in [15].

In this article, we investigate various different ways in which the bat optimization technique can be used to locate sensor nodes in WSNs. The navigational methods that bat use, notably echolocation, serve as a model for the bat optimization process, which takes its cues from these approaches. Several alternative optimization strategies are available, in addition to the cuckoo search optimization method that was just described. These strategies include the Fredy algorithm (FA), particle swarm optimization (PSO), and genetic algorithms (GA) (CSOA). Nevertheless, the bat algorithm is superior to its competitors in a number of important respects, including the following: Data mining, job scheduling, and pressure vessel design are just a few instances of the many problems for which it may be utilised to generate optimal solutions [16]. There are a great number of issues for which it can be utilised. By utilising it, one might potentially solve a great deal of problems.

This section describes the innovative characteristics of node localization based on the suggested ZOA variations, including but not limited to the following:

- Versions 1 and 2 of the proposed ZOA are superior in terms of both exploration and exploitation. These improvements make the current ZOA's search capabilities more robust.
- The mean localization error, computation time, and the number of nodes that are localized are used to evaluate the proposed ZOA variants 1 and 2 in comparison to the original BOA and other optimization algorithms such as the particle swarm optimization (PSO) algorithm, the grey wolf optimization (GWO) algorithm, the butterfly optimization algorithm (BTOA), the salp swarm optimization (SSO) algorithm, and the frefy algorithm. Other optimization algorithms include the grey wolf optimization (GWO) algorithm (FA).
- Third, when compared to the most recent and cutting-edge methods, both versions 1 and 2 of the proposed ZOA effectively identified all of the target nodes with a considerable decrease in the mean number of mistakes caused by localization and a reduction in the amount of time required for computation. According to the statement, calculations involving time and mean localization error favour ZOA version 2 over BZOA version 1.

The performance of the original ZOA as well as the recommended ZOA variants 1 and 2 are evaluated based on the localization error metrics of average localization error, normalized localization error, root-mean-square error, and localization efficiency for a variety of node situations.

When compared with the original ZOA and the recommended ZOA variation 1, the performance of the proposed ZOA variation 2 is superior in every category of error.

As a consequence of this, the key concerns with range-based localization methods are those pertaining to the cost and accuracy of the process. The existing versions of ZOA, FA, BTOA, PSO, and SSA, as well as GWO, all produce far bigger mean localization mistakes than the proposed versions of ZOA, which are versions 1 and 2. This is due to the fact that these algorithms rely on local search techniques that are more time demanding and global search strategies that are less efficient. By utilizing ZOA versions 1 and 2, it is possible to determine the positions of the WSN's nodes with a greater degree of accuracy. The incorporation of ZOA versions 1 and 2 does not result in an increase in the cost of WSN because these versions do not call for the purchase of any extra hardware. Both Version 1 and Version 2 of ZOA feature a shorter amount of time required for calculations and a faster rate of convergence compared to the usual algorithms.

The rest of the article is divided into these sections: In Section 2, an overview of a number of ways to find the best way to place nodes is given. In Section 3, researchers talk about the proposed ZOA versions 1 and 2. In Section 4, the results and analysis of the simulation are shown, and in Section 5, the conclusion is discussed.

This article also discusses a potential application for the intelligent camera system, which would involve the monitoring of traffic and the enforcement of laws. Because of their significance to the INSIGMA research and development effort [12,13], the aforementioned LPR, MMR, and CR features have been incorporated into the system that has been given.

The rest of the paper is organized as follows. The section II presents an extensive literature review within the framework of the subject matter. In Section 3, the proposed system architecture of the presented smart camera system is introduced. In Section 4, the system’s efficiency is reported as results and it has been discussed. Conclusions, with an insight to potential future improvements, are drawn in Section 5.

II. LITERATURE REVIEW

Academics have examined a wide variety of strategies with the goal of improving WSNs and increasing the visibility of node locations. Particle swarm optimization, sometimes known as PSO, is a method that was suggested in [15] to reduce the typical localization mistake that occurs when looking for nodes in WSNs. PSO and the bacterial foraging algorithm are two examples of iterative algorithms that have been offered as potential solutions to the localization problem with multiple goals (BFA). It is a process that builds upon itself, as each of these methods builds upon the previous one. The time and resources required by the proposed approaches for locating the appropriate nodes in WSNs were significantly lower than those required by the status quo. In [17], the Bees optimization was used to close the gap in error rates that existed between the target and anchor nodes. It was absolutely necessary to plan the positions of the anchor nodes in the deployment region with extreme care. There were two potential places under consideration. Each target node is surrounded by more than three nearby anchor nodes, which is the first thing to note. Second, we used careful planning to position beacon nodes at key locations throughout the monitored region [17].

In [18], there is discussion of a three-dimensional deployment space, and it is suggested that stochastic PSO can be used to locate nodes inside that space. The stochastic PSO algorithm has proven to be more successful than any of the other PSO-based techniques in precisely locating the target nodes. The use of a PSO-BFO optimization hybrid yields the findings described in [17], which are an increase in both the precision and speed of the localization process. PSO and BFO utilised far less energy than any of the other algorithms that were investigated while they were looking for sensor nodes. The authors of the study [14] describe a novel application of genetics in the interest of improving optimization through the use of their findings. A key focus of this endeavour will be on finding ways to cut costs during deployment. This strategy is capable of locating any node of interest within a WSN provided that the list of anchor nodes is suitably extensive. The Cuckoo Search Optimization Algorithm (CSOA) is a method that was described in the publication [11] as a way to lessen the required number of iterations, quicken the rate of convergence, and improve the accuracy of target node coordinate specification. The CSOA fared better than any other strategy for optimization in terms of achieving optimal results. In [12], an alternative to the gravitational search optimization approach was offered as a solution to the problem of fip uncertainty in wireless sensor networks (WSNs). It was also revealed that utilising the suggested strategy resulted in a considerable reduction in the usual number of mistakes made during the localization process.

Binary PSO was utilised in order to determine which nodes in the network investigated in [13] were significant. Because of this, we were able to increase the WSNs' productivity and durability (wireless sensor networks). RSS was utilised by sensor nodes in order to save electricity while also accurately determining the distance between the target and anchor nodes. Researchers at [14] devised a two-stage PSO algorithm with a number of different goals in order to improve WSN performance and provide a solution to the flip uncertainty problem. If the two-stage PSO strategy had been utilised, locating all of the nodes that were desired in WSNs might have been a lot less of a problem than it otherwise would have been. It was suggested in [15] that a modified version of the bat technique be used in order to achieve a higher level of precision in the localization process. By utilising the technique that was described, the amount of time spent discovering the required network nodes was cut down significantly. A method that was invented in 1946 to speed up computing while simultaneously improving accuracy has been given the name "parallel frefy." RSS is utilised in the process of attempting to locate the sensors. When the DV-Hop algorithm was altered, the localization process moved along more rapidly and without as much difficulty as it did when using other methods [47]. By using a modified version of the DVHop algorithm, the localization technique was able to be refined, and the approximation error was cut significantly.

Flower pollination (FP) was used as a tool to assist wireless sensor networks (WSNs) in determining the locations of individual sensor nodes and increasing the total number of sensor nodes that could be included in the study. This was accomplished by increasing the number of sensor nodes that could be pollinated by a single flower (see [18]). When compared to earlier rounds of the PSO method, the FP algorithm represents a significant advancement. In the paper [16], the authors suggest employing a method that is referred to as orthogonal teaching-learning-based optimization, or OTLBO, in order to locate errant nodes. The extraordinarily high degree of intelligence possessed by OTLBO can directly be credited for both the ongoing success and the expansion of the network that it controls. The method of identifying nodes in a three-dimensional environment known as range-free frefy is given a comprehensive explanation in reference [15]. It has been determined through the application of fuzzy logic that there is no linear association between range and RSS. Efforts to reduce the number of computational problems were a main focus. The frefy strategy worked exceptionally well in comparison to the other strategies that were utilised to locate certain sensor nodes. The Artificial Bee Colony (ABC) approach, which is described in [11], was utilised to make the determination of target node locations more precise. ABC was superior to preceding systems in terms of its ability to locate the sensor nodes, but it was more time-consuming to set up because of the improved precision it offered. In order to achieve a higher level of precision, the localization error method described in [12] only took into account two anchor nodes. Increasing the convergence rate was one of the goals of the work presented in [16], which was accomplished by utilising the Chicken Swarm Optimization (CSO) algorithm to locate target nodes. In contrast to the PSO algorithm, the CSO algorithm generated results that were significantly more dependable. In the study, [13] described Grey Wolf Optimization (GWO) as a method for reducing the amount of time spent performing computational tasks. In addition, in comparison to the other methodologies, GWO was successful in locating a greater number of target nodes.

Butterfly Transform is the term given to an optimization technique that was created in [18] to improve the overall performance of wireless sensor networks (WSNs). The method that is described in this article makes the process of locating the nodes of interest more straightforward. By modifying the size of the deployment area in accordance with the sounds that were being played, it was possible to illustrate how effective BTOA is. The findings demonstrated that BTOA was superior to other approaches in terms of both speed and precision. In the article [18], the authors discuss a unique PSO-based method to the problem of detecting missing nodes in WSNs. RSS was used to calculate the number of hops that separated the anchor node and the target node. After that, a few anchor nodes were deliberately placed at oblique angles all across the area that was being observed. Because increasing exposure was the primary objective, we proceeded in this manner. When compared to other approaches, the PSO requires a significantly shorter amount of time to arrive at the best answer.

In the past few years, a multitude of scholars have put their time and energy into attempting to optimise their way out of the WSN localization dilemma. When optimization techniques were used, the amount of time and effort required to find the best possible sites for sensor nodes was significantly reduced. Because of this, we were able to obtain a more accurate result. On the other hand, efficient evolutionary algorithms could cut down on the number of computations that need to be done and the likelihood of making a mistake while determining the location of a target. Scalability, cost, the pace of convergence, and precision are only a few of the many issues that are presented by localization. The capability of a functional wireless sensor network to grow by joining additional nodes is, perhaps, the feature that contributes the most to the network's value. This quality is characterised by its scalability (WSN). The high cost of putting in place the appropriate network infrastructure is a major contributor to the low rate of acceptance of localization, which is one of the primary reasons for this. In spite of the fact that WSN accuracy and cost are inversely connected, the primary purpose of this investigation is to devise a strategy for optimising localization that is both efficient and cost-effective in order to reach the maximum possible value. There is a possibility that the quantity of anchor nodes and target nodes contained within a WSN will have an effect on its selling price. When the number of anchor nodes in a WSN is increased, the level of precision and accuracy of the network's localization is also improved. The cost of a WSN is substantially higher than that of an ANS since it uses GPS to locate anchor nodes. Convergence time is a statistic that may be used to determine how long it takes an optimization process to locate each node in a WSN that serves as a target. Convergence time can be used to determine this. Timing how long it takes for the lines to converge is a straightforward method for accomplishing this goal. The optimization stage of the localization process has one fundamental goal, and that is to pinpoint the exact positions of the target nodes with the maximum possible degree of accuracy. Taking a look at an optimization approach's average localization error is a good way to get a sense of how well it works in terms of localization. Any method that seeks to achieve a higher degree of precision will benefit from a reduction in the overall localization error levels.

In order to satisfy the urgent demand for faster and more exact placement of sensor nodes, new optimization algorithms have been created. In this demonstration, both version 1 and version 2 of the ZOA use improved global and local search algorithms to more effectively detect sensor nodes. Only ten anchor nodes were necessary for BOA versions 1 and 2 to locate all 150 target nodes in the WSN, whereas all of the other optimization approaches required a total of 35 anchor nodes. In BOA versions 1 and 2, to identify 150 target nodes, you only need 20 anchor nodes, which is a huge reduction from the number of anchor nodes that are currently in use.

When applied to a dataset that contains 150 target nodes and 20 anchor nodes, the suggested ZOA variant 2 obtains the lowest localization error when compared to ZOA and the previously published ZOA variant 1.

III. PROPOSED METHODOLOGY

The optimization of bats starts with the search for a sufficient number of sensor nodes. The Bat optimization method boasts superior average localization accuracy and significantly increased calculation speed in comparison to alternative approaches. ZOA has a lower success rate compared to other methods because it is unable to discover all of the nodes that are sought inside a network. ZOA is unable to adequately search the entire area being looked for. It is required to make adjustments to the optimization strategy used by the bat in order to resolve these challenges and achieve additional reductions in the mean localization error and computation time. These findings illustrate two different ways that the bat optimization method can be used. In order to make wireless sensor networks (WSNs) more effective, numerous modifications of the zebra optimization algorithm are applied to the conventional bat algorithm. This is done in order to improve the bat algorithm's exploration and exploitation capabilities. A successful move would be to improve the bat optimization algorithm's exploration phase by introducing a more efficient global search method into ZOA variation 1. This would result in a positive outcome. The exploitation function is improved by ZOA variation 2, which implements a local search method that is more effective. An exhaustive discussion of these differences is presented as follows:

3.1 ZOA variant 1 based on improved global search strategy

If the zebra optimization strategy becomes stuck on the local optimum solution, it will be difficult to move it to a state where it can find the global optimal solution. As a result, it is essential not to settle for a solution that is less than ideal but rather to work toward achieving the best possible outcome. The enhanced global search technique has been incorporated into the proposed ZOA variation 1 in order to improve ZOA's existing capabilities in terms of global searches. A superior global search strategy looks at more of the search area and uses a variety of various methods in order to obtain the most accurate response possible for the entire planet.

There are N target nodes and M anchor nodes present in the area that has to be investigated. Due to the fact that there are P people in the population, there are also P different solutions to consider. In the first prototype of the intended ZOA, the speeds of bats are updated at a couple of different frequencies. Ith sensor nodes operate at two distinct frequencies, referred to as Fi(1) and Fi (2). When Equations 1 and 2 are used together, one can determine the following frequencies:

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

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

F_i (1) and F_i (2values)'s depend on, F_{min}, and F_{max}. Two random numbers with values between 0 and 1 are and are. The following equations are then used to update bat velocity and position:

$$V_i^T = V_i^{T-1} + \left(X^b - X_i^T\right) * F_i(1) + \left(X^w - X_i^T\right) * F_i(2) \quad (3)$$

$$X_i^T = X_i^{T-1} + V_i^T \quad (4)$$

The initial optimization process for ZOA, known as bat, will eventually converge on the solution that represents the global optimal state by constructing new solutions centred on the best values. In the first strategy, the bats will just circle the best possible answer, as opposed to the entire area. In the first proposed version of ZOA, the search space for bats is broadened in order to identify the value that is best for the world as a whole. In the initial presentation of ZOA, the bats were tasked with analyzing all of the possibilities, ranking them from best to worst, in order to determine which of the options was the most advantageous. The following are the values that should be used for X^b and X^w if the optimization problem being solved is a minimization problem:

$$X^b = \min(f(X)) \quad (5)$$

$$X^w = \min(f(X)) \quad (6)$$

where f(X) stands for the objective function of the problem. When the bats' positions have been changed, the objective function is computed for each one of them, and at the end of the first iteration, the worst and best solutions are found. The speeds of the bats are adjusted based on the best and worst values in the following iteration of the process.

3.2 ZOA variant 2 based on improved local search strategy

When compared to other algorithms that are used to solve the problem of determining the position of a node, the ZOA variation 1 that was proposed was the one that was successful in discovering all of the target nodes in the wireless sensor network with the lowest average level of error. In comparison to the other techniques now in use, the time needed to locate all of the nodes can be found much more quickly using the ZOA variation 1 that has been recommended. When it comes to changing the speed of the bat, the majority of people go for the option that is the slowest. This is the problem. ZOA version 2 is being considered as a potential solution because of its capacity to significantly cut down on both the typical amount of localization error and the amount of time needed for calculations. ZOA's performance in local search is improved because to the implementation of a method that is proven to be more efficient in the suggested ZOA variation 2, which can be found here. The primary objective of this revised regional strategy is to identify novel approaches to bat conservation by making use of the best available regional data and the most effective existing solution. This goal will be accomplished by utilising the best available regional data and the most effective existing solution. The new regional plan, which incorporated both the best-case and the worst-case scenarios, resulted in a change in the flying velocity of the bats. The ZOA 2.0 interface is presented. It eliminates all of the other potential candidates and only considers those who are at the top of the search results. For ZOA Variation 2, the following equation is used to determine how much the bats' speed should be altered:

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

The node localization problem can be divided into four primary categories: convergence time, average localization error, computation time, and the number of nodes that have been successfully localized. In comparison to ZOA and other algorithms such as FA, BTOA, PSO, GWO, and SSA, both the mean localization error and the amount of time needed to calculate it are significantly lower in ZOA versions 1 and 2. The currently used methods and ZOA discovered all of the target nodes after a total of one hundred iterations, whereas ZOA versions 1 and 2 discovered all of the target nodes after a total of only twenty-five iterations.

3.3. Node localization using the proposed ZOA variants 1 and 2

In order to discover the nodes of interest, a range- and single-hop-based distributed technique is utilised. In order to precisely locate the location of the desired nodes, a small number of anchor nodes are utilised, the locations of which may be determined using GPS. The basic goals of the localization problem are to precisely locate the locations of the target nodes and to reduce the magnitude of the objective function. Figure 1 depicts the schematic that should be used in order to pinpoint nodes in light of the proposed alterations to the ZOA. The following is a list of the many steps that need to be taken in order to locate N target nodes making use of the suggested ZOA modifications.

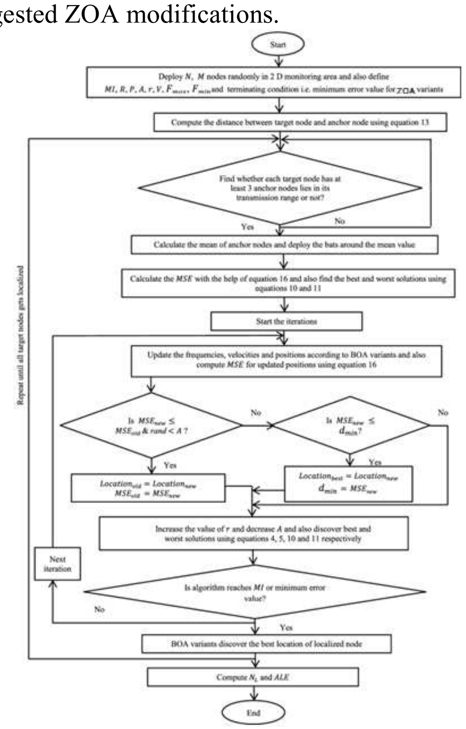

Fig. 1 Flow chart for node localization based on ZOA variants in WSNs

Step 1: Anchor nodes and target nodes are distributed at random all through the observing zone. There are M anchor nodes and N target nodes. By utilizing a global positioning system, the anchor nodes are able to ascertain their precise locations. In addition to the transmission range R between the target and anchor nodes, we also supply the values for additional parameters such as A, r, V, MI, R, P, Fmax, and Fmin. The transmission range R is the distance between the target and anchor nodes. It is essential to establish the level of mistake that signals the end of the process.

Step 2: The distance to each target node is determined using each anchor node as a starting point. Take into account the fact that the required coordinates for the target node are (x, y), and that the desired coordinates for the anchor node are (xi, yi).

Step 3: If the target node is within the transmission range of at least three anchor nodes, then it is assumed that the target node can be localized. It is recommended that each target node be located in close proximity to three anchor nodes. When applying the distances from three or more anchor nodes, it is possible to bring the difference between the expected and actual distances closer to being in line with one another.

Step 4: One of the several optimization strategies will be in charge of conducting the hunt for the coordinates of each target node.

Step 5: Each strategy for optimizing a system works to pinpoint the exact location of the node that is being sought while also lowering the localization error that is connected with that search. The mean square error between the anchor node and the target node is going to be used as the goal function for the node localization problem. Following is an explanation of the mean square error, also known as MSE; this error tends to get smaller whenever an efficient optimization process is used.

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

Step 6: In 6th step, you will update the settings for the frequency, speed, and placement of the bats so that they match the changes made by the ZOA. The next thing that needs to be done is to work out the MSE for the new locations of the bats.

Step 7: Mean squared error (MSE) should be less than or equal to the previous MSE, and the loudness parameter should be a lower value than the random number (rand) (A). If you answered yes, proceed to step 9 to update the files with the updated location of the bat file and the MSE value. In the event that this is not the case, go to Step 8.

Step 8: Check to see if the newly calculated MSE is more than or equal to the minimum distance (dmin). If that is the case, then the current location of the bat ought to be regarded as the most viable alternative, and the MSE ought to be reverted to its minimum value. If that is the case, go on to step 9.

Step 9: Adjusting Eqs. 4 and 5 will result in an increase in the pulse emission rate (r) and a decrease in the loudness parameter (l), respectively (A).

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

Step 10: Check to see if the ZOA versions that are recommended can be utilized to locate all of the target nodes. If this is the case, continue on to Step 11. Proceed to step 11 if any of the nodes are found to be located beyond the boundary; otherwise, go back to step 3.

Step 11: Calculating the average localization error (ALE) and the number of unlocalized nodes (NNL) with equation 9 is a good way to determine whether or not a method of optimization was successful in achieving the desired result of successful node localization. The performance of the algorithm will improve if the ALE and NNL of the optimization technique used to determine node positions are lowered. This technique is used to determine node locations.

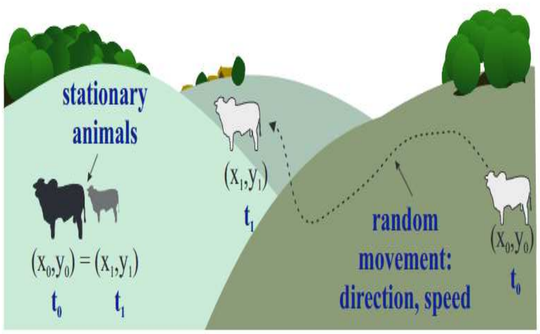

Fig 2. Camera surveillance system

IV. RESULT AND DISCUSSION CONCLUSION

MATLAB R2016a is the software that is used to run the simulations. It is now possible for us to assess the relative benefits of ZOA versions 1 and 2 in terms of the utility they provide. Each sensor node has the ability to broadcast data up to 30 meters distant, which allows them to monitor an area that is 100m on each side. Any part of this region can serve as either the starting point or the final destination of the journey. In this study, we compare the results of ZOA versions 1 and 2 to those obtained using the traditional zebra optimization approach in order to assess the effectiveness of these versions (ZOA).

The first and second versions of ZOA that were proposed are evaluated using standard metrics such mean localization error (MLE), average localization error (ALE), computation time (T(s), normalized localization error (NLE), root-mean-square error (RMSE), and localization efficiency (LE). In the next paragraphs, we will continue our consideration of all ALE, computation time, MLE, RMSE, NLE, and LE arguments.

The typical length of an error that can be found on this website (ALE) One technique for determining how accurate the optimization method that was used to discover the target nodes was is to find the error that existed between the estimated and actual coordinates of the target nodes, add up the errors that existed for each target node, and then take the average of all of the errors that existed. This is done in order to determine how accurate the optimization method was. Take a look at the localization error that occurs the most frequently if you want to evaluate how effectively the process of optimizing localization is working. In order to perform the calculation, authors will refer to the time period denoted by T. (s) The amount of time, denoted by the symbol T, that an optimization method needs to compute a solution is referred to as the computation time of the optimization method. This time is measured in seconds. The amount of time required by the optimization method to pinpoint the exact positions of all WSN targets is known as the computational effort (s). The tic-toc timer is utilized so that no important moments are overlooked at any cost (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%

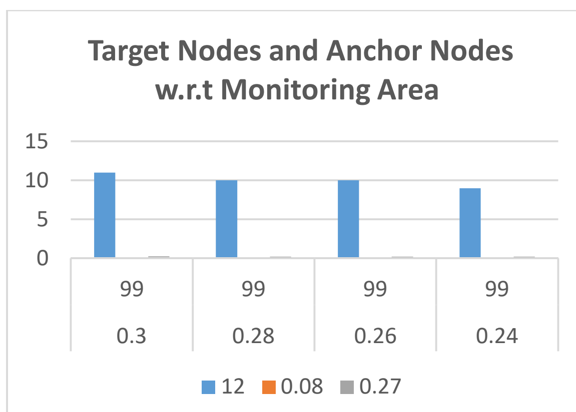

Fig 3. Target Nodes and Anchor Nodes w.r.t Monitoring Area

Table 2. Effect of anchor nodes on localization efficiency 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

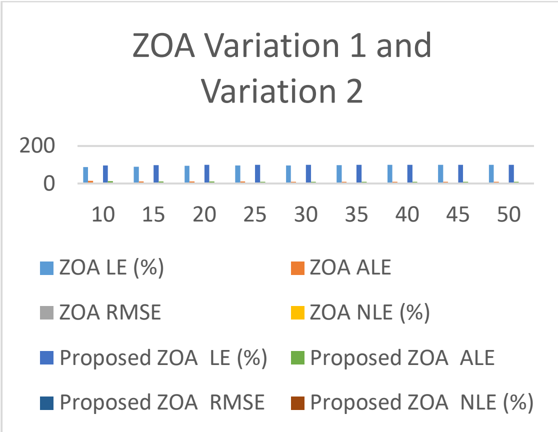

Fig 4. ZOA Variation 1 and Variation 2

V. CONCLUSION

It is frequently essential to recognise the originating source of the information gathered while using wireless sensor networks. The location of a WSN's sensor nodes has a direct bearing on the effectiveness of the network as a whole. The bat optimization strategy has been shown to provide lower average localization errors and to be computationally more efficient than alternative approaches. The problem is that it has a poor localization efficiency and has a tendency to stay stuck on the settings that are ideal for the current location. This study suggests two modifications to the regular ZOA in an effort to alleviate the deficiencies that are associated with it. Both the first and second suggested versions of ZOA have been modernised to make use of search engines that are both more effective globally and locally. Because of this advancement, it is now possible to discover and make use of them without any difficulty. The suggested variants of ZOA, both 1 and 2, along with BTOA, FA, PSO, GWO, SSA, and the original ZOA are put through their paces in a number of scenarios employing anchor nodes and target nodes. The results of these tests are compared to those obtained from the original ZOA. According to the findings, the suggested ZOA variants 1 and 2 converge more quickly, identify more target nodes, and have fewer mean localization errors when compared to other algorithms that are currently in use as well as the original ZOA. After twenty-five iterations, one may make the case that the two approaches get the same outcomes and are equally efficient. ZOA variation 2 achieves better results in terms of both the average localization error and the processing time when compared to ZOA variation 1. (computation time).

REFERENCES

[1] Poongodi M, Vijayakumar V, Al-Turjman F, Hamdi M, Ma M (2019) Intrusion prevention system for DDoS attack on VANET With reCAPTCHA controller using information based metrics. IEEE Access 7:158481–158491.

[2] Poongodi M, Hamdi M, Sharma A, Ma M, Singh PK (2019) DDoS detection mechanism using trust-based evaluation system in VANET. IEEE Access 7:183532–183544. https://doi.org/10.1109/ ACCESS.2019.2960367

[3] Poongodi M, Sundan B (2015) Stochastic model: reCAPTCHA controller based co-variance matrix analysis on frequency distribution using trust evaluation and re-eval by Aumann agreement theorem against DDoS attack in MANET. Clust Comput 18:1549–1559. https://doi.org/10.1007/ s10586-015-0496-y

[4] Bizagwira H, Toussaint J, Misson M (2016) Synchronization protocol for dynamic environment: design and prototype experiments. In: 23rd International Conference on Telecommunications (ICT), pp 1–7.

[5] Kalnoor G, Agarkhed J (2016) QoS based multipath routing for intrusion detection of sinkhole attack in wireless sensor networks. In: International Conference on Circuit, Power and Computing Technologies (ICCPCT), pp 1–6.

[6] Khan AA, Agrawal H (2016) Optimization of delay of data delivery in Wireless Sensor Network using Genetic Algorithm. In: International Conference on Computation of Power, Energy Information and Communication (ICCPEIC), pp 159–164.

[7] Mohar SS, Goyal S, Kaur R (2021) Optimized sensor nodes deployment in wireless sensor network using bat algorithm. Wirel Pers Commun 116(2):2835–2853. https://doi.org/10.1007/ s11277-020-07823-z

[8] Singh H, Singh D (2021) Hierarchical clustering and routing protocol to ensure scalability reliability in large-scale wireless sensor networks. J Supercomput.

[9] Singh H, Singh D (2018) Multi-level clustering protocol for load-balanced and scalable clustering in large-scale wireless sensor networks. J Supercomput 75:3712–3739. https://doi.org/10.1007/ s11227-018-2727-5

[10] Singh H, Singh D (2019) An energy efcient scalable clustering protocol for dynamic wireless sensor networks. Wireless Pers Commun 109:2637–2662.

[11] Priyadarshi R, Gupta B, Anurag A (2020) Deployment techniques in wireless sensor networks: a survey, classifcation, challenges, and future research issues. J Supercomput. https://doi.org/10.1007/ s11227-020-03166-5.

[12] Shrivastava, A.; Prakash Arul Jose, J.; Dilip Borole, Y.; Saravanakumar,R.; Sharifpur, M.; Harasi, H.; Abdul Razak, R.K.; Afzal, A., A study on the effects of forced air-cooling enhancements on a 150 W solar photovoltaic thermal collector for green cities, Sustainable Energy Technologies and Assessments, 2022, DOI: 10.1016/j.seta.2021.101782.

[13] Anurag Shrivastava; Ali Rizwan; Neelam Sanjeev Kumar; R. Saravanakumar; Inderjit Singh Dhanoa; Pankaj Bhambri; Bhupesh Kumar Singh; Samarendra Nath Sur, VLSI Implementation of Green Computing Control Unit on Zynq FPGA for Green Communication,Wireless Communications and Mobile Computing2021-11-30, DOI: 10.1155/2021/4655400.

[14] D. Haripriya; Keshav Kumar; Anurag Shrivastava; Hamza Mohammed Ridha Al- Khafaji; Vishal Moyal; Sitesh Kumar Singh; Mohammad R Khosravi, Energy- Efficient UART Design on FPGA Using Dynamic Voltage Scaling for Green Communication in Industrial Sector, Wireless Communications and Mobile Computing, 2022-05-05, DOI: 10.1155/2022/4336647.

[15] Anurag Shrivastava; D. Haripriya; Yogini Dilip Borole; Archana Nanoty; Charanjeet Singh; Divyansh Chauhan, High performance FPGA based secured hardware model for IoT devices, International Journal of System Assurance Engineering and Management,2022-03,DOI: 10.1007/s13198-021-01605-x

[16] J. Banfield, “Challenge in artistic flow experiences: an interdisciplinary intervention,” Qualitative Research in Psychology, vol. 18, no. 1, pp. 104–125, 2021.

[17] R. Bonatti, W. Wang, C. Ho et al., “Autonomous aerial cinematography in unstructured environments with learned artistic decision-making,” Journal of Field Robotics, vol. 37, no. 4, pp. 606–641, 2020.

[18] “Features of professional training of primary school teachers in the field of artistic and graphic activities in the context of digital education,” Science and School, vol. 1, no. 1, pp. 104–115, 2021.