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AN OPTIMIZED ALGORITHM DESIGN FOR A TARGET TRACKING IN WIRELESS SENSOR NETWORKS

Haroon Rashid Hammood Al Dallal
Bachelor's degree, Department Engineering in Communication Techniques, Al-Furat Al-Awsat Technical University, Najaf, Iraq.
Master's degree, Department Infocommunication Technologies and Communication Systems, Saratov State Technical University, Saratov, Russia. haroonra1994@gmail.com

Doaa Ashour Sultan
University of Basrah, College of Education for Pure Sciences, Bachelor of Education, Department of Computer Science

Abstract
Due to its sensor technologies, wireless sensor networks have captured the interest of many academics over the past few decades. Several application is a developing approaches in the development of WSNs. In a WSN, numerous sensor nodes are placed throughout a sizable geographic area, and communication happens via wireless technology. Networks having sensors that can electronically detect, analyze, store, and communicate are known as wireless sensor networks (WSNs). Multiple sensors that can detect physical variables like temperatures, light, moisture, and vibrations can be connected in each network terminal. In many applications, including spotting enemy movement in military applications, the positioning of a sensor network in WSNs is significant. Finding the coordinates of all target nodes with the aid of cluster centers is the main goal of the localization algorithm. Two variations of the bat optimization algorithm (BOA) are suggested in this study to more effectively localize the sensor nodes and to get over the basic BOA's limitations, such as becoming stuck in locally optimal solutions. The outcomes of different models for different target nodes and node density counts are compared with the original optimized algorithm and other optimization techniques already in use for the node localization problems. Additionally, given a range of target and node number values, the suggested BOA versions 1 and 2 are compared with the original BOA in terms of different mistakes and localization effectiveness. The model results show that the suggested BOA variation 2 has several advantages over the suggested BOA variant 1 and the present BOA. In comparison to the proposed BOA variation 1, BOA, and other current optimization methods, the node localization based on the suggested BOA variant 2 is more efficient since operations are completed faster and the mean translation error is lower.

Index Terms: Edge intelligence, Node localization, target tracking, Target nodes, WSN, Mobile agent (MA), collaborative computing, target tracking, deep reinforcement learning.

INTRODUCTION

Smart sensors may now be developed due to recent advancements in wireless communication and micro-electromechanical systems technology[1]. Wireless Sensor Networks (WSNs) consequently gain a lot of attention on a global scale [2]. The WSNs are made up of numerous cheap, non-rechargeable, small-capacity sensor nodes with a compact size, lower power consumption, and numerous functions [3]. One of the fundamental uses of WSNs is target tracking system [4]. Its primary objective is to identify a target when it reaches a tracked area of focus using a node. Along with transmitting its position to the base station, it also seeks to estimate the target's location while moving. To provide a more reliable assessment in this situation, at least three sensor nodes' values are necessary[5]. This significance of the object tracking idea can be seen in a variety of situations, including military uses, business applications, and public activities such as monitoring animals in the wild and tracking enemy vehicles [6]. Generally speaking, there are three categories that the targeted tracking algorithms can be divided first is cluster-based tracking and the second prediction-based tracking which is mobocrats message-based tracking, and hybrid-based tracking [4]. Several innovative target tracking procedures and methods have been put out in the research [7]. The accuracy of the tracking process and the decrease in energy consumption are interestingly mentioned as the main issues for any target tracking systems since they work with each other to increase the lifespan of the network. Specialists are examining the multiple problems faced by wireless sensor networks as a result of the modern design advancement in wireless technology (WSNs). The massive sensor nodes are placed either randomly or approximately. Data collection and data transmission to other networks are both necessary in WSNs [8]. WSNs have been utilized in a variety of fields, including real-time applications in the fields of medicine and farming. They were also employed for tracking different factors, including heat, humidity, and the number of air pollutants [9]. Various iterations of the bat optimization technique are suggested in this study to localize the WSNs' wireless nodes. The involuntary movement ability of bats forms the basis of the bat optimization algorithm. Compared to genetic algorithms, the bat algorithm has several benefits. Firefly algorithm (FA), particle swarm optimization (PSO), and due to its simplicity, flexibility, and convergence, the particle swarm optimization algorithm (CSOA). In several applications, including data mining and the scheduling of jobs across time, this method can be utilized to find the best solutions because it is quicker, more reliable, and simple to apply. As well as in compressor engineering[10]. A more effective approach for bat optimization is due to several distinctive characteristics of BOA that are mentioned below.

As a result, price, and reliability are also the two main problems with range-based localization methods. The BOA variations one and two are suggested to use enhanced global and local search algorithms to increase the localization process' efficiency in WSN. The proposed BOA variants 1 and 2 have significantly lower mean localization errors than current algorithms like "BOA, FA, BTOA, PSO, SSA, and GWO". As a result, by employing BOA variants 1 and 2 to localize the WSN nodes, the reliability of the WSN is increased. The suggested BOA variations 1 and 2 do not require any new hardware, hence they don't raise the WSN's cost.

The rest of this essay is organized as follows. In section 3, we outline our proposed algorithm. In Section 4, the simulated results are discussed together with comparisons to relevant past papers. The research study is completed in Section 5.

LITERATURE REVIEW

WSN, situated in Massachusetts, has evaluated itself in terms of the conventional customer model. Mostly in the client and server model, the BS receives the data that each network has collected, while in the MA-based framework, MAs contact networks and gather data, thereby reducing speed and energy utilization. Planning an agenda before visiting sensor nodes is recommended. MA. The problem of route organization has been approached from many various angles up until this point.

Hairong et al.[11] proposed a global nearest first and a localized nearest first optimal route for MA. During route optimization in LCF, nodes closer to the MA are chosen up until the last sensor cluster is approached. The approach planning's first sensor network is the network that is nearest to the MA, while the route planning's last sensor node is the node that is most distant from MA. GCF, on the other hand, plans routes by investigating nodes that are near the ground station. High migration costs are this situation's main problem. Wu et al. [12] introduced an evolutionary approach for calculating a portable device's path operator. The output of the experiment demonstrates that the GA technique outperforms LCF and GSF. Both route computing and transmission latency are problems for the suggested technique. It is extremely large, it makes time-related applications uncomfortable. Multi-agent route management utilizing a shortest spanning tree was suggested by Chen et al. [13]. The name of this strategy is BST-MIP. The system in question is created as a networked graph. The map's drain and come from various serve as its edges, from which the sequence number weight of each edge is determined. The disadvantage of this strategy is that there were only a few routes available. Xu et al. [14] suggested ISMAP and IDMAP for distributed application movement. Before sending out the MA, the path is chosen in ISMAP. While in IDMAP, the next hop of MA is determined according to the current wireless configuration. When clustered develop as well as how to choose the first component for MA dispatched are not explained by the writer there. Three methods for the implementation of target detection were put out by Xu et al.[15] Here, MA contacts the sensor nodes because they have accurate location information. After gathering the necessary data, MA returns to BS. This strategy takes a lot of time, and MA encounters numerous difficulties while going back to BS.

First, Shakshuki et al. [16] use two categories of operators.

One is a permanent operator that keeps track of an SN's related communication that takes place and increases its information, while a distributed application moves from node to node and engages with the static agents connected to each networking component. Utilizing a distributed algorithm and static device increases the cost and network's electricity consumption. In their presentation of TBID, Konstantopoulos et al. [17] employed a tree-based method. It operates in two phases: The detection system is separated into transition zones in the first stage, and the MA migration path is chosen in the latter. Here, costs rise as a result of updated tree facilities. which employs a tree-based technique, was introduced by Mpitziopoulos et al. [18]. For figuring out the MAs' almost ideal routes. It sends out many MAs to visit the sensor.

Nodes of a tree structure in order. When going to a node with two or more child nodes, to access kid vertices, master MAs create a copy of themselves known as a slave MA. Slave Nodes collect information and send it back to the SN, where it is sent to the master. These methods have such a scalability issue. Two route methods and IEMA—were suggested for MAs by Chen et al [19]. To give each node a chance to serve as a source node, IEMF employs round and technique. In the event, if that base station is left off, LCF is then employed. The incremental iteration of the IEMF is IEMA. Aloui and others

[20] Proposed a GIGM-MIP approach for MIP that lowers energy usage by relying on geographic data and the volume of information produced from each sensor network.

Usage of the sensor nodes. Below, the k-means method divides the entire network into Clustering is employed in K clusters, so it determines the acceptable number of MA based on the data volume and path. Within each cluster. This approach's path construction is dependent on the LCF approach LCF rises in the amount of energy used. It was recommended in [21] to use particle swarm optimization (PSO) to locate the vertices in WSNs and to decrease averaged localization failure. The forage technique and PSO are examples of repeated localization methods. In [22], (BFA) was suggested as a solution to multi-objective localization issues. The proposed methods also decreased the amount of electricity that networks used. Defining the locations of target nodes in WSNs is quicker.[23] Employed the Bees optimization technique to reduce the mean inaccuracy of target nodes from anchor nodes. For placing the anchor nodes in the transmission range, two possibilities were taken into consideration. Every targeting network in the first technique has more than three anchor nodes surrounding it, and in a second way, light nodes are placed in the middle of the monitored area. Tamizharasi et al [24]. Compared to other PSO-based techniques, the stochastic PSO algorithm had more correctly positioned the design processes. Using a hybrid bio-inspired optimization technique based on PSO and BFO, the localization accuracy and fast convergence were improved. In the order to extend the lifespan of WSNs as well as reduce calculation time, binary

PSO was employed to pinpoint the target nodes in the network. RSS was employed [25]. To calculate the separation between object points and base stations, as well as to store energy by detector clusters. [26] devised a multi-objective two-phase PSO method to WSN efficiency should be improved, and the flip ambiguity problem should be resolved. All of the target nodes in WSNs might have been localized faster with the 2 different PSO techniques. The modified algorithms were recommended in [27] to find the ideal value of inaccuracy and to improve the localization procedure' precision. For the duration of calculation, all target nodes in the network were localized by the less approach that was proposed. The duration of the computations all target nodes in the network were localized by the less technique that was proposed. To lessen parallel flexible technique to reduce computation time and get the general best solutions was created in [28] and utilized RSS to locate sensor nodes. The modified DVHop approach was utilized in [29] to reduce approximations error and increase localization accuracy. In comparison to existing localization techniques, the modified DV-Hop algorithms reduced the generalization error. To order to localize more sensors and overcome the localization problem in WSNs, Goyal et al., [30], the fewer pollination (FP) algorithm was employed.

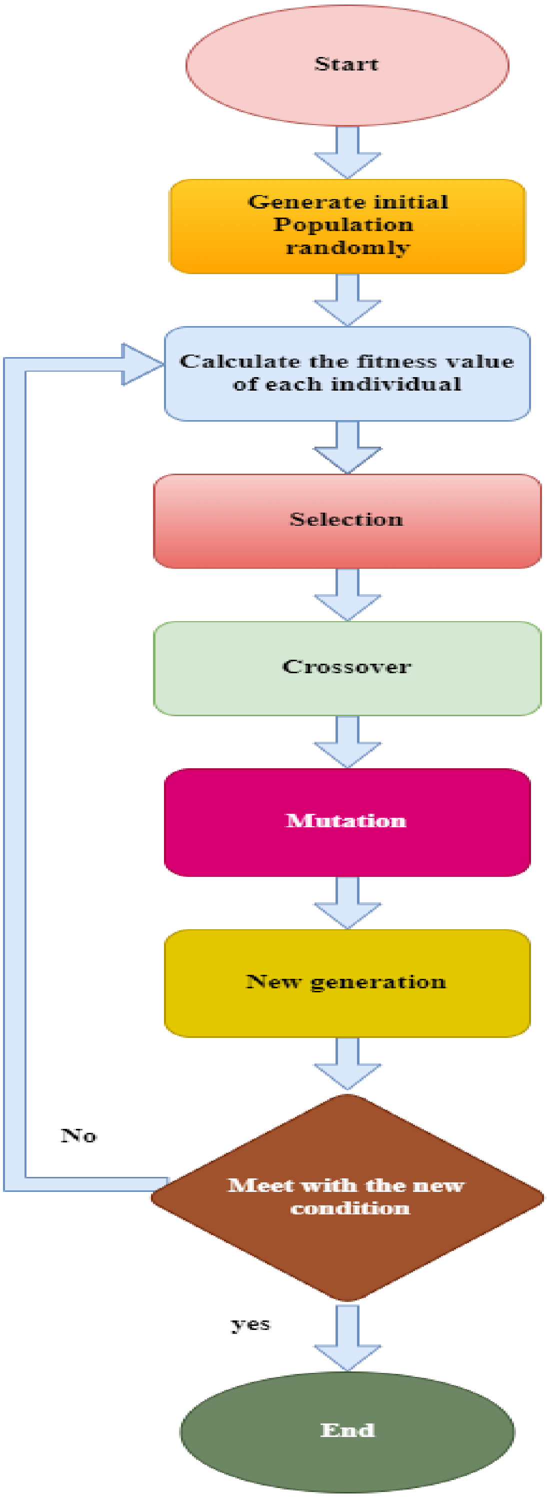

Figure 1: Peng, B, and L. Li

The Butterfly Optimization Algorithm (BTOA) was developed by Arora et al, [21]to enhance the performance of Wireless sensing network applications by more precisely translating object points. To prove the efficiency of BTOA, the distribution area's parameters were changed and affected by different sounds. The findings showed that BTOA was more advantageous in terms of precision and computational efficiency. In identifying random mobile nodes in WSNs, a unique PSO-based approach was proposed by Singh et al [31]. Just few anchor networks were placed in the observation area at different angles after first determining the distances of the base stations from the edge points using RSS. Compared to another method, the PSO showed a quicker average time complexity.

D.Y [32] proposes a new set of intelligent distributed collaborative rules (EIDCA) based on the endocrine system for target tracking, inspired by the structural regulation mechanism of human hormones in this study. EIDCA allows nodes in wireless sensor networks to self-prepare without centralized operations for object detection. A probability-based hormone transfer scheme is also proposed to mitigate network fluctuations due to node sharing switches. Wireless sensor networks (WSNs) are widely accepted as resourceful frameworks with self-contained size and control capabilities. The main contributions of this literature review include the creation of the AESN moderation principle and the randomness-based statistical variation mechanism within WSNS. These mechanisms facilitate the creation of a fully distributed cooperative operational scheme and statistical alternation between nodes, which gives the proposed algorithm the ability to efficiently and reliably maintain community monitoring objectives.

Our work on the goals will affect the parameters within EIDCA, the WSN configuration and the goal to monitor performance, for example you can control the range of nodes in WSNs, the distribution of nodes, and how they have modified the objectives.

[33]in this article, the researcher supports a multi-objective optimization framework to solve the problem of sensor selection in uncertain Wi-Fi sensor networks (WSNs). Uncertainty in wireless sensor networks generates a series of sensor observations but insufficient statistics on the target. They support a new full sensor selection scheme based on mutual terrain reality (MIUB) with low computational complexity, the same as the Fisher data-based full sensor selection scheme (fi) and provide very good estimation performance similar to mutual registration Sensor-based options.

In this paper, researchers were interested in finding the sensor selection strategy with a multi-objective optimization technique on uncertain WSNs. The target boxes will consider: 1) the application of the multi-target optimization technique for annoying multi-target monitoring on uncertain WSNs; 2) the estimation of sensor detection probabilities, and three) some alternative multi-objective optimization algorithms that require much less computational complexity.

[34]Wireless sensor networks are becoming increasingly important in many civil and military applications. Sensor nodes can be used extensively in large-scale sensing disciplines to gather information on bodily phenomena of interest. Densely dispersed nodes provide overlap insurance, which improves robustness and anomaly detection, and accuracy. This paper introduces the hassle of using distributed Wi-Fi sensor networks to monitor targets across large areas, a hobby for many software packages such as security and surveillance, battlefield data tracking, visitor management, and wildlife tracking. And more environmental monitoring.

There are many worthy subjects for future paintings. First, the framework can be extended to tracking systems, where sensors can better collect the simplest and most efficient measurements. Second, by incorporating an appropriate form of energy penalty into communication and calculation, community energy savings can be explicitly reflected in the sensor allocation formula.

[35]in this article, researchers propose a new method to monitor moving objects in wireless sensor networks, mainly based on hybrids. Irregularly ordered genetic rule set ii (NSGA-ii) and generalized extended Kalman filter (GEKF) (NGEKF).

GEKF is one of the big precise rules, but using all sensors in target tracking and high intensity intake is your defect. To overcome these shortcomings, the problem of programming the sensors is considered to find the most ideal sensor array to estimate the objective function.

In this article, a new tracking algorithm called NGEKF has been derived using a dimensional multiplicative noise model for tracking moving objects. In this technique, NSGA-ii is used to select the correct sensor at each stage. To evaluate the overall performance of the proposed algorithm, the tracking of low and high noise cases of deflected targets is simulated. It turns out that the proposed rule set improves tracking accuracy over GEKF and MLE and KF. Furthermore, the service life of WSN can be increased due to lower energy consumption.

[36] One utility for the Wi-Fi sensor community (WSN) is localization and medicalization, an ever-evolving goal. Recommending an effective protocol for monitoring targets is a formidable challenge. As with any monitoring scheme, the main challenge is keeping the current draw to a minimum and achieving excellent tracking accuracy.

This phase includes the results of the proposed plan. The results are obtained by simulating the proposed scheme using MATLAB. The overall performance of the proposed scheme is compared to a technique called Hybrid Cluster Target Based Monitoring (HCTT).

In which observe that the accuracy for the proposed scheme is 8.6% better than HCTT in this scenario.

In the future, a scheme could also be devised to form clusters of different shapes based on sensor distribution and target motion characteristics.

[37]Target monitoring (TT) is an important application of wireless sensor networks. The TT is mainly based on the signal intensity indication (RSSI) obtained using the most economical and unique technique, but suffers from low stability and accuracy due to different paths, occlusion effects and miscalibration. To address this problem, they propose a revolutionary set of T.T rules called the SVM and KF method, which combines bootstrap vector devices (SVM) and advanced Kalman cleanup (KF). SVM to get an initial estimate of the target location based solely on RSSI. This complements the ability of our algorithm to register nonlinear systems.

In this inspection, the researcher suggests a new technique, called SVM called the KF method, for WSN applications. This approach avoids the status quo of missing versions of classes. Instead, it uses the SVM method to establish a link between the target location and the RSSI value obtained through the nodes in the WSN to estimate the target function. This estimate is then revised for higher accuracy using an improved KF technique based entirely on innovative revisions. Experimental and simulation results confirm that the proposed method effectively improves tracking accuracy and stability compared to other applicable algorithms.

[38]the above properties and advances in microelectromechanical structures have made it possible to provide and use small battery-powered nodes in Wi-Fi communications. A network that includes such nodes that can measure is called a wireless sensor network (WSNs). The

initial purpose of using a node is associated with an internal application. Preliminary nodes are capable of sensing scalar data, including temperature, humidity, pressure, and proximity to surrounding devices. However, power for the sensor nodes is provided by batteries with limited capacity. Therefore, due to limited resources, a balance must be struck between the accuracy and power optimization of these networks. In this article, a new approach is proposed to solve the problem of optimal energy consumption in WSNs. Therefore, using the FSN swarm optimization rule set, we propose a routing protocol capable of recognizing the power in WSNs that optimizes power consumption. In this paper, power intake becomes the biggest problem in WSNs. Bundling becomes the right way to optimize energy consumption. Here, we propose a new clustering method by exploiting the FSH artificial swarm optimization algorithm. The performances of the proposed algorithm and the technical protocol were simulated by the OPNET simulator and compared. Analyze the effect of the simulation and identify the following parameters: sensor node current consumption, stop-to-stop delay, media access delay, signal-to-noise ratio, the statistical probability of successful transmission to the receiver, and throughput charges.

[39, 40]Wireless sensor networks (WSN) are used to capture and collect facts in battle, communicating important facts to face. Wireless sensor networks (WSN) have been widely deployed and have become an important part of the sensing layer in recent years. Wireless sensors have some advantages, small range, low cost, and high sensitivity.

Therefore, Wireless sensors have become an important factor and are used in various situations. This article studies the problem of force protection in wireless sensor networks for defensive combat. Power plays a fundamental role in the WSNs. Once the power runs out, the sensing layer stops working. Therefore, it is important to save power to prolong the operation of the WSNs. Buildings with networks and wireless sensor nodes are added first. Next, optimization metrics on target tracking are proposed, including power consumption, detection ability, and tracking accuracy. After that, the sensor planning objective function was embedded. Future work will focus on the following aspects. First, others would be an energy-efficient way to extend the working day study; second, the application of the proposed energy Save methods will be extended from 2D to 3D environment ambient; finally, the suggested approach will be experimental count and external environment.

[41]this paper focuses on the target tracking problem of a class of wireless tracking facilities with unknown but limited noise. By focusing on the reason for insufficient power for wireless sensor nodes, an element-based contingency mechanism is adopted to reduce the symbol rate by discarding meaningless log transmissions. The goal of the troubleshooting was to design an event-driven set club filter for goal tracking and performance assurance.

In this paper, they were focused on the problem of tracking moving targets from wireless locators, hopefully. Enhance the safety disclosure ability of personnel in the industrial field. While the wireless statistical transmission is susceptible to unknown but limited noise in complex industrial environments, an ellipsoidal state estimation method is used to provide steady-state estimates within the region of the actual country state carried by the system.

METHOD AND DATA

Yang proposes the Bat Optimization Algorithm (BOA) to find the worldwide ideal outcomes [42]. The community optimization approach known as BOA is attracted by the engaging behaviors of the bat group, such as locating food and Identifying and classifying a wide variety

State object function f (Z), X = (Z1, Z2, Z3, Z4……… Zd)^t

Start

Define the size of group, Initial starting value Z_i and velocity W_i i =(1, 2, 3, 4….n)

Starting frequency bats B_i at Z_i

Set the value of loudness S_i and the pulse emission rate is m_i.

While T < Maximum Iteration

Using the 1, 2, 3 equations, create the solution of velocity, frequency and positions.

If rand > m_i

Exposed the best value of solution by using these equestrians

End IF

New solution are generated

If (rand <S_i) &(f Z_i < f $X^{\$}$)

of bugs in a pitch-black. The researchers are inspired to examine. The wings are move speeds during the preparation stage and then scattered around the investigated area at different spots. The VT speeds frequency I, Fi locations, and ZT. The mathematical more represents the updating of the number I of bats at time T Ingredient and to avoid obstacles. The bat group can locate the area. Delivering pulse of low- and high-frequency sound toward the food source, and all these pulses striking and coming back to the bats for bats. The whole bat colony uses sound waves, or Sound, to find food. The position of the feed the bats novel infrastructure technique. The algorithm[43] environments.

Step by Step procedure the or bat optimization algorithm

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$$Bi = B_{Min} + (B_{Max} - B_{Min})a \qquad (1)$$

$$W_i^t = W_i^{t-1} + \left(X_i^t - X\right) F i \qquad (2)$$

$$Z_i^t = Z_i^{t-1} + W_i^t \qquad (3)$$

The above equation is used to show the frequency, velocity and destination such as $W^t{}_I$, F_i and $Z^t{}_i$.

B max and B min variables are used to define the highest and lowest frequencies of the bit optimization algorithms. Maximum frequency and minimum frequency are shown by a B min and B max variable. The emission rate will change if the value of loudness change is denoted by the following variables and questions.

$$S_i^{T+1} = \beta S_i^T \quad (4)$$

$$r_i^{T+1} = r_i^0 \left[1 - e^{-rt}\right] \quad (5)$$

The starting value of loudness and the emission rate is specified with β, y and S^t_i.

The method for bat optimization's exploring characteristics better global searching technique is added to BOA variation 1 to improve. In BOA version 2, the exploiting feature of BOA is enhanced by adopting an improvement research methodology. The following is a detailed discussion of these variations:

Of the bat algorithms.

The main motive is to improve the global optimum solution by using the different algorithms. (B) Variable denotes the number of base stations and (A) variable use is d to show the number of target nodes placed at random. The total population within the target region is P, thus there will be P numbers there. Several potential answers. The suggested BOA version 1 generates two frequencies. To update the bats' speed, these frequencies are designated as Fi (1) and Fi (2) using network devices.

In comparison to existing methods, the suggested BOA variation 1 conforms more quickly and takes less time to localize all the clusters. But when changing the bat frequency, there is a temptation to use the worse option. In order to solve this issue and reduce mean localization error and computation

BOA variation 2 is advised at this time. A better local search approach is employed to the BOA's global search functionality in the second suggested BOA model.

f_(i) (1)=B_min+(B_max-B_min)δ (6)

f_(i) (2)=B_min+(B_max-B_min)Ɛ (7)

Fi (1) and Fi (2values)'s depend on δ and Ɛ , B min, and B max and are arbitrary in the range of numbers between 0 and 1.

Z^b = min (f (Z)) (8)

Z^w = max (f (Z)) (9)

Where f (Z) is the independent function of optimization problematic. Afterward changing the positions of all rackets, the objective function is calculated for every racket and then again the values of worst and best resolutions are calculated at the end of the first iteration.

W_i^t= W_i^(t-1) +(Z^b 〖-Z〗_i^t)*f_i (1)-
(Z^w 〖-Z〗_i^t) *f_i (2) (10)

The updated local approach updated the bat frequency using the optimal answer currently known as well as the worst approach. The BOA version 2 that is being suggested explores a limited area that is closer to the best solution so far found and excludes the very worst solution. The suggested BOA variation 2 utilizes the following equations to modify bat velocity:
W_i^t=W_i^(T-1)+(Z^b-Z_i^t)*B(1)-(Z^w-Z_j^t)*B_i(2)
(11)

Table1: Basic symbols and list of abbreviations

Symbol	*No of iteration*
A	Goal Node
B	Presenter nodes
M	Frequency
P	Minimum distance
$r^0{}_i$	initial value of loudness
W	Velocity
Z$	Global optimization solution
S	Loudness
m	Pulse emission rate
B min	Maximum frequency
B max	Minimum frequency
rand	random number between 0 and 1
MLE	Mean localization error
NLE	Normalized localization error
D min	Minimum distance

The first part of equation number 11is W_i^t=W_i^(T-1)+(Z^b-Z_i^t)*B (1) in this equation specifies that the response is moving in the direction of the optimal method, i.e., the new approach that is formed is coming closer to the optimal value. The second term in the equation, B(1)-(Z^w-Z_j^t)*B_i(2) (2), shows that the solution avoids the very worst value. Employing Equations 11 and 12, the values of Fi(1) and Fi(2) are calculated. The enhanced local search approach only fully explores the tiny area immediately surrounding the best option.
Several iterations, average localization error, calculation time, and amount of localized nodes. There are 4 main problems in the localization challenge. The suggested BOA versions 1 and 2 have calculation times and mean localization errors that are fewer than those of BOA and known methods like" FA, BTOA, PSO, GWO, and SSA".

Following is a discussion of the many stages involved in using the suggested Bit optimization algorithm variations to get the coordinates of N target nodes:

Step :1

First, B anchor nodes and A target nodes are randomly placed in the observing region. Throughout a GPS device, the base station may determine its location. The communication range R of the targeted its and base stations, as well as the quantities of other variables including S, m, W, MI, M maximum value, and M minimum value, are all described. The critical level, such as the lower limit of error, should read defined.

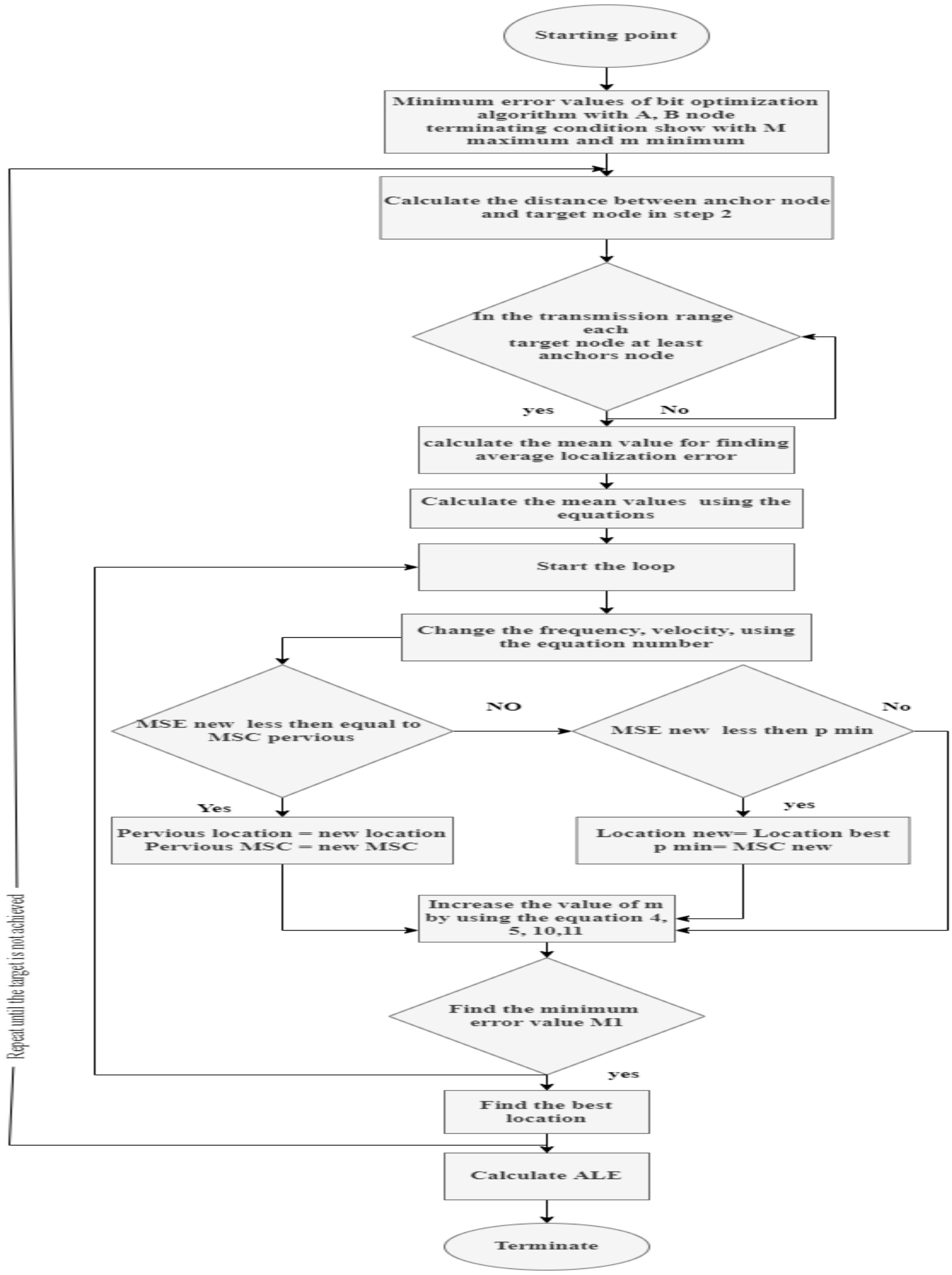

Figure 2: Flow chart of Proposed Algorithm

Step 2:

Each target node's width from each anchored node is calculated. Assume that (a, b) represent dimensions of the destination point that has to be found and (ai, bi) represent the location of the anchor node. The following formula is used to determine how far (pi) the destination node is from the anchor node:

$$p_i=\sqrt{(a-a_i)^2+(b-b_i)^2} \qquad (12)$$

Step 3:

If the target node has at least three anchor nodes that are located within its communication range, it is considered to be a localizable network. Check to see if each target node has three or more anchor nodes within reach. To reduce the localization error—the difference between the predicted range and the actual measurements determined from three or more anchor nodes are used.

Step 4:

Each optimization algorithm performs independently to determine the locations of each destination point that must be localizable. At first, bats are distributed by calculating the mean of anchor nodes that are located within the communication range of a destination point that is localizable, wherein M represents the number of cluster centers that also are located within that communication range.

$$(a_m, b_m)=\left(\frac{1}{B}\sum_{i=1}^{B} a_i,\ \frac{1}{B}\sum_{i=1}^{B} b_i\right) \qquad (13)$$

Step 5:

Every optimization algorithm finds the targeted node's positions and minimizes the prediction error. The goal variable of the node localization issue is the mean square error between the anchor node and the goal node. The following is a description of the mean square error (MSE), which is decreased by applying an efficient optimization technique:

Mean Square error:

$$f(a,b)=\frac{1}{B}\left(\sum_{i=1}^{B}\sqrt{(a-a_i)^2+(b-b_i)^2}-d_i\right)^2 \qquad (14)$$

Step 6 :

Changing the values of "frequency, velocity and position" of bats according to BOA variants. Then, calculate MSE for efficient locations of bats.

Step 7:
The old value of MSE is greater than the new value of MSE. Loudness parameters (S) value is greater than the and value. If so, proceed on to process 9 and save the new sensor position and MSE values in the old and new, respectively. If not, go back to step 8.

Step 8:
The minimum distance value (pmin) is greater than the new value of MSE. If yes, then choose the impermanent position of the bat as the new best place and the new MSE value as pmin, then go back to step 9.

Step 9:
Only with aid of Equations 4 and 5, raise the value of the pulse emission rate (r) and reduce the amount of the volume variable (A). Find the best and worst solutions by applying Equations 10 and 11.

Step 10 :
The optimum value of (x, y) is exposed
by optimization, procedure after successively the algorithm for number of repetitions and by decreasing the value of objective function.

Step 11:
Using the suggested BOA variations, verify that all target nodes are localized. If so, move on to process 12, if not, perform processes 3 through 11 until each node is localized inside the sensing region.

Step 12:
Finding the positions of each goal node is followed by calculating the overall localization error. It is calculated by averaging the numerator of the difference between the true node positions (Ai, Bi) and the localized node positions (Ai, Bi).

Average localization error =

$$\frac{1}{A_L}\sum_{i=1} A \sqrt{(A_i - a_i)^2 + (B_i - b_i)^2} \qquad (15)$$

RESULTS AND DISCUSSION

To check the accuracy of the suggested BOA alternatives 1 and 2, the execution on MATLAB a2018a application using a computer having Intel Core i5CPU, 32 GB RAM, and 2.60 GHz .
The size of the population is 20 optimization algorithms.
Each methodology has its parameters that control the performance of the system. M maximum (m max) and m minimum (m min) variables are used in the suggested algorithms with variant one and two. The pulse and loudness rates of the optimization algorithms are set at the starting points of 0.3 and 0.6.

Evaluation parameters:

The ALE, calculation time, “MLE, RMSE, NLE and LE” are explained as follows:

Average Localization Error (ALE):

To find the accuracy errors between the actual goal node and the estimated node using the optimization algorithms. After that calculate the total errors from the target node and average nodes errors. The calculation of the Average Localization error has already been discussed in equation number 15.

Execution Time :

The execution time calculate as the maximum time taken by the proposed algorithms. In wireless sensing devices the total time to reach the target node

The execution time T(s) is calculated with the help of some function.

Mean Localization Error (MLE):

The total communication tare of wireless sensing devices is measured by MLE.

MLE is also called regular location error per meter and it’s calculated by the following equations.

$$\frac{1}{A_L}\sum_{i=1} A \sqrt{(A_i - a_i)^2 + (B_i - \frac{b_i)^2}{R}} \qquad (16)$$

Table 2: Means Localization v

Target nodes	Anchor node	Total Iterations	BOA	SSA	GWO	FA	Suggested Approach
145	36	25	0.353	0.512	0.559	0.199	0.308
		55	0.342	0.522	0.554	0.189	0.307
		70	0.332	0.514	0.523	0.156	0.306
		100	0.312	0.132	0.516	0.162	0.345

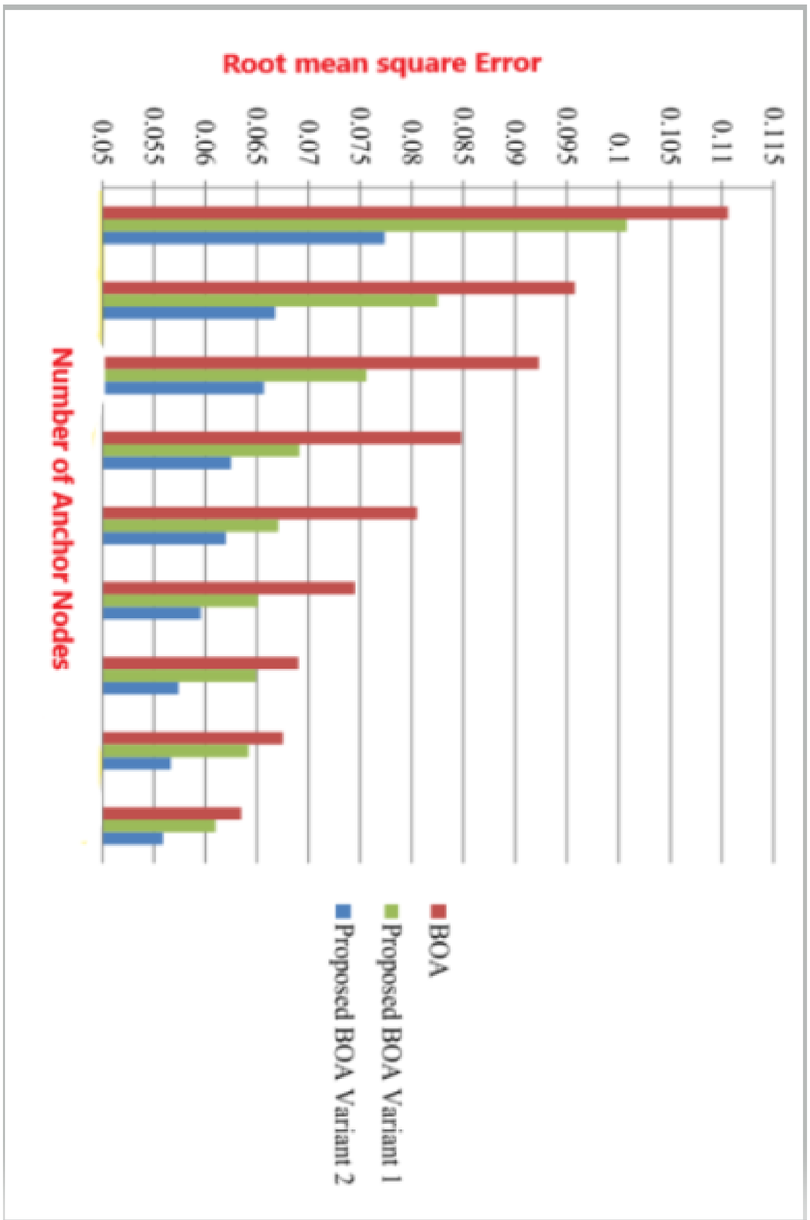

Figure 3: Localization efficiency of the Proposed algorithm

CONCLUSION

Various application Wireless Sense network used the location information from where the data have been obtained. Hence, The performance of wireless sensing networks relies on the localization of sensor nodes. The optimization algorithm has less mean localization error rate and smaller computation time also as compared to other current algorithms. But the optimization algorithm that is the efficiency of localization is not 100% and it is also difficult to compute optimization values. To overcome these problems faced by the original BOA, it's variants optimization algorithms 1 and 2 are prepared in this paper. These variant modifications have been seen by using improved global and local search strategies for the batter exploration and exploitation abilities to discover the best optimum solutions.

References:

1. Darabkh, K. and R. Aygün, TCP traffic control evaluation and reduction over wireless networks using parallel sequential decoding mechanism. EURASIP Journal on Wireless Communications and Networking, 2007. 2007: p. 1-16.
2. Hawa, M., et al., A self-learning MAC protocol for energy harvesting and spectrum access in cognitive radio sensor networks. Journal of Sensors, 2016. 2016.
3. Darabkh, K.A., et al. A new cluster head replacement protocol for wireless sensor networks. in 2017 European Conference on Electrical Engineering and Computer Science (EECS). 2017. IEEE.
4. Darabkh, K.A., et al., Performance evaluation of selective and adaptive heads clustering algorithms over wireless sensor networks. Journal of Network and Computer Applications, 2012. 35(6): p. 2068-2080.
5. Darabkh, K.A., W.Y. Albtoush, and I.F. Jafar, Improved clustering algorithms for target tracking in wireless sensor networks. The Journal of Supercomputing, 2017. 73(5): p. 1952-1977.
6. Shurman, M.M., et al. Hierarchical clustering using genetic algorithm in wireless sensor networks. in 2013 36th international convention on information and communication technology, electronics and microelectronics (MIPRO). 2013. IEEE.
7. Ismail, S.S., E.I. Al Khader, and K.A. Darabkh, Static clustering for target tracking in wireless sensor networks. Global Journal on Technology, 2015.
8. Aldeer, M.M. A summary survey on recent applications of wireless sensor networks. in 2013 IEEE Student Conference on Research and Developement. 2013. IEEE.
9. Fakilidz, I., Wireless sensor network: a survey. Computer Networks, 2002(38): p. 393-422.
10. Yang, X.-S., Bat algorithm: literature review and applications. arXiv preprint arXiv:1308.3900, 2013.
11. Qi, H. and F. Wang, Optimal itinerary analysis for mobile agents in ad hoc wireless sensor networks. Proceedings of the IEEE, 2001. 18(5): p. 147-153.
12. Wu, Q., et al., On computing mobile agent routes for data fusion in distributed sensor networks. IEEE Transactions on Knowledge and Data Engineering, 2004. 16(6): p. 740-753.
13. Chen, M., et al. Balanced itinerary planning for multiple mobile agents in wireless sensor networks. in International conference on ad hoc networks. 2010. Springer.
14. Xu, Y. and H. Qi, Dynamic mobile agent migration in wireless sensor networks. International Journal of Ad Hoc and Ubiquitous Computing, 2007. 2(1-2): p. 73-82.
15. Xu, Y. and H. Qi, Mobile agent migration modeling and design for target tracking in wireless sensor networks. Ad Hoc Networks, 2008. 6(1): p. 1-16.
16. Shakshuki, E., H. Malik, and M.K. Denko, Software agent-based directed diffusion in wireless sensor network. Telecommunication Systems, 2008. 38(3): p. 161-174.
17. Konstantopoulos, C., et al., Effective determination of mobile agent itineraries for data aggregation on sensor networks. IEEE transactions on knowledge and data engineering, 2009. 22(12): p. 1679-1693.

18. Mpitziopoulos, A., et al., CBID: a scalable method for distributed data aggregation in WSNs. International Journal of Distributed Sensor Networks, 2010. 6(1): p. 206517.
19. Chen, M., et al., Itinerary planning for energy-efficient agent communications in wireless sensor networks. IEEE Transactions on Vehicular Technology, 2011. 60(7): p. 3290-3299.
20. Aloui, I., et al., A new itinerary planning approach among multiple mobile agents in wireless sensor networks (WSN) to reduce energy consumption. International Journal of Communication Networks and Information Security (IJCNIS), 2015. 7: p. p. 116-122.
21. Gopakumar, A. and L. Jacob. Localization in wireless sensor networks using particle swarm optimization. in 2008 IET International Conference on Wireless, Mobile and Multimedia Networks. 2008. IET.
22. Kulkarni, R.V., G.K. Venayagamoorthy, and M.X. Cheng. Bio-inspired node localization in wireless sensor networks. in 2009 IEEE International Conference on Systems, Man and Cybernetics. 2009. IEEE.
23. Moussa, A. and N. El-Sheimy. Localization of wireless sensor network using bees optimization algorithm. in The 10th IEEE International Symposium on Signal Processing and Information Technology. 2010. IEEE.
24. Tamizharasi, A., R. Arthi, and K. Murugan. Bio-inspired algorithm for optimizing the localization of wireless sensor networks. in 2013 Fourth International Conference on Computing, Communications and Networking Technologies (ICCCNT). 2013. IEEE.
25. Zain, I.F.M. and S.Y. Shin. Distributed localization for wireless sensor networks using binary particle swarm optimization (BPSO). in 2014 IEEE 79th Vehicular Technology Conference (VTC Spring). 2014. IEEE.
26. Li, D. and X.b. Wen, An improved PSO algorithm for distributed localization in wireless sensor networks. International Journal of Distributed Sensor Networks, 2015. 11(7): p. 970272.
27. Goyal, S. and M.S. Pattern, Modified bat algorithm for localization of wireless sensor network. Wireless Personal Communications, 2016. 86(2): p. 657-670.
28. Lin, S.-Y. and T.-M. Chou. Numerical analysis of the Pennes bioheat transfer equation on the skin surface. in 2015 Third International Conference on Robot, Vision and Signal Processing (RVSP). 2015. IEEE.
29. Peng, B. and L. Li, An improved localization algorithm based on genetic algorithm in wireless sensor networks. Cognitive Neurodynamics, 2015. 9(2): p. 249-256.
30. Goyal, S. and M.S. Patterh. Flower pollination algorithm based localization of wireless sensor network. in 2015 2nd International Conference on Recent Advances in Engineering & Computational Sciences (RAECS). 2015. IEEE.
31. Singh, P., et al., A novel approach for localization of moving target nodes in wireless sensor networks. International Journal of Grid and Distributed Computing, 2017. 10(10): p. 33-44.
32. ·, D.Y., An endocrine-based intelligent distributed cooperative algorithm. 2014.
33. Nianxia, C., Sensor Selection for Target Tracking in Wireless. 2016.
34. YINFEI, F., Distributed Sensor Allocation. 2012.

35. ehsan, F., Target tracking in wireless sensor networks using NGEKF algorithm. 2019.
36. Ahmad, T., EEAC: An energy efficient adaptive cluster-base. 2020.
37. Wang, X., SVM+KF Target Tracking Strategy Using the Signal. 2020.
38. Gorgich, S., Proposing an Energy-Aware Routing Protocol by Using Fish. 2021.
39. Pang, C., A new energy efficient management approach for wireless sensor. 2020.
40. Lv, C., et al., An improved target tracking scheme based on MC-MPMC method for mobile wireless sensor networks. EURASIP Journal on Wireless Communications and Networking, 2022. 2022(1): p. 1-26.
41. Bai, X., Target tracking for wireless localization systems using. 2021.
42. Yang, X.S. and A.H. Gandomi, Bat algorithm: a novel approach for global engineering optimization. Engineering computations, 2012.
43. Mohar, S.S., S. Goyal, and R. Kaur, Optimized sensor nodes deployment in wireless sensor network using bat algorithm. Wireless Personal Communications, 2021. 116(4): p. 2835-2853.