ISSN: 2229-6948(ONLINE)
DOI: 10.21917/ijct.2022.0410

A NODE LOCATION ALGORITHM BASED ON IMPROVED GRASSHOPPER OPTIMIZATION IN WIRELESS SENSOR NETWORK

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Abstract

As the use of swarm intelligence algorithms grows, so does the interest in placing nodes in a Wireless Sensor network. For this reason, the RSSI range model positioning algorithm has been replaced by a more accurate one. With the help of this paper, you can solve complex structural optimization problems with the Grasshopper Optimization Algorithm (GOA). Optimization problems can be solved using this algorithm, which was inspired by the behaviour of grasshopper colonies. CEC2005 is used to test the GOA algorithm quality and quantitative performance. Trusses with a total of 53 and 3 cantilever beams are used to demonstrate the design practicality. It appears that the proposed algorithm outperforms well-known and recently developed algorithms in this area. GOA ability to solve real-world problems with unknown search spaces is demonstrated by its use in the real world.

Keywords:

WSN (Wireless Sensor Network), GOA (Grasshopper Optimization Algorithm), RSSI, Whale Optimization Algorithm

1. INTRODUCTION

Network architecture presents numerous difficulties in monitoring and delivering the required quality data to end-users in the emerging communication and network. Several protocols have been developed to synchronize the operations of network models in wireless sensor networks, which have come a long way. Network performance can be improved by observing and maintaining a linear scale of several factors such as congestion mechanisms, packet delivery, node survival, network lifetime, and optimal path determination. Despite this, wireless sensor networks (WSN) face much greater problems with network congestion because of the high data transfer rates and the rapid rise in the number of people using them [1]. Congestion control and successful packet.

Delivery has been addressed by numerous WSN protocols. To solve this issue, we need to find a solution. At the end-user, a variety of optimization algorithms have been developed to control traffic and route it through multiple paths. The goal of an optimization problem is to find the best possible value and location for a mathematical function. Because it is less likely to get stuck in local optimizations, a modified version of grasshopper optimization has been used. Other possible uses for the proposed method include military operations, weather forecasting, traffic efficiency, cellular changes like intelligent devices, and health infrastructure. Constrained and unconstrained optimization models are widely used in computer science, artificial intelligence, and pattern recognition, as well as energy consumption, structural trusses, engineering areas, and nonlinear time series.

An optimization technique known as GWO [2] has recently been introduced. Based on three optimal samples with zero optimization value, a large-scale search method. Based on ant foraging behaviour, the Ant Colony Optimization Algorithm (ACO) found the shortest route between a colony and its food source. This method worked for a travelling salesman problem. To enhance prediction, selection of features, and running time, this method makes use of cross-validation techniques as well as SVR parameters for hyperparameter optimization [3]. The study of nonlinear time series, constraint-based optimization models, and structural trusses is a common theme in computer science.

Recently, the bionics principle has become more widely accepted, which has prompted researchers to model swarm intelligence algorithms in mathematics. Swarm intelligence optimization, an adaptive AI technology, can be used to solve extreme-value problems. This algorithm is used in a wide range of industries because it is so popular. The Butterfly optimization algorithm (BOA) was used to solve the bolted rim coupling problem in light vehicle design [4]. A robotic clamping mechanism utilizes GOA and Nelder-Mead algorithm [5] techniques in tandem to achieve this result. Industrial structure design issues can be resolved more quickly with a new hybrid Taguchi salt swarm algorithm [6]. The vehicle support shapes can be optimised using the seagull optimization algorithm (SOA) [7]. The Equilibrium Optimization Algorithm (EOA) can be used to solve the structural design optimization of automobile seat supports [8]. Metaheuristic algorithms are used in the design of an automated planetary gear train [9]. Intelligent swarm optimization algorithms can be used to solve these issues [10].

Simple implementation and minimal sensor hardware are required for WSN node positioning using the RSSI (received signal strength indication) [11] range of technology. This paper uses RSSI distance measurement to reduce power consumption and costs. Antenna gain and non-line-of-sight are unavoidable to avoid large RSSI algorithm positioning errors due to wireless signal interference. RSSI values can be corrected using the Gaussian function as a solution to this quandary.

2. RELATED WORK

Using the RSSI positioning algorithm, you can improve your positioning accuracy. Low power consumption and the absence of additional hardware facilities make RSSI a popular algorithm [12]. Even though RSSI ranging errors can be caused by multipath propagation and obstacles, a better antenna can make a significant difference. Using this technology, mobile nodes can save energy and improve their location accuracy [13]. Poor positioning accuracy is one of the drawbacks of this iterative method in noisy environments [14]. A few examples include hierarchical analysis and the weighted nearest neighbour algorithm for indoor location, which utilizes deep learning (see [15]). By increasing the weights' influence on RSSI differences between reference points, the hierarchical analysis method improves location accuracy.

Adaptive Kalman filtering also improves noise reduction by accounting for RSSI measurement deviations. As a result of improvements in localization accuracy, the algorithm has become unmanageable. Improved node location was achieved using a fuzzy C-mean clustering algorithm [16]. The learning regression tree method and RSSI filtering have been proposed as new target tracking algorithms. This method is both practical and effective, according to the results [17].

Two methods for locating WSN nodes have been proposed: an RSSI ranging model and a 3D weighted centroid algorithm [18]. Improved node localization accuracy has been achieved using this DV-Hop improvement algorithm. These algorithms help to improve the accuracy of the nodes that need to be placed [19] to some extent. The positioning nodes are identified using a trilateral centroid location algorithm.

3. NODE OPTIMIZATION ALGORITHM

WSN use range-based positioning algorithms that use spatial geometry to calculate the distance or angle between nodes to locate nodes. Localizations such as minimum-maximum, maximum likelihood, and trilateral localizations are all examples. There is a good chance that trilateral localization will happen because of its low power use, low cost, and low complexity. It is accurate when three anchor nodes cross, but if there are no crossovers, the accuracy of their position estimation is typical [20]-[24]. For this reason, an adaptive swarm intelligence optimization algorithm is employed. The placement of nodes is treated as an optimization problem in a swarm intelligence algorithm. Particle swarm optimization (PSO) has been used to improve the accuracy of swarm intelligence algorithms such as the whale optimization algorithm (WOA), slime mould algorithm (SMA), hunger games search (HGS), and Harris Hawks optimizer [25]-[28].

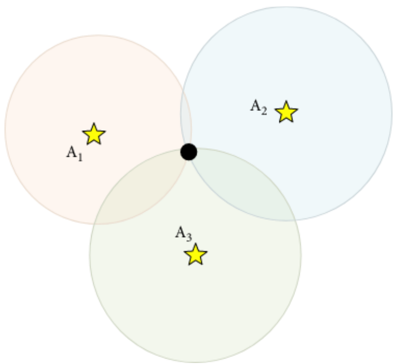

Fig.1. Three anchor nodes cross

Different methods are used to solve the problem of localization on an approximate or actual line based on the estimation error for each hop [29]. Monte Carlo and particle swarm optimization are two methods for locating mobile nodes. In a variety of situations, the algorithm prioritizes accuracy, efficiency, and speed. An algorithm called particle swarm optimization was used to improve the localization accuracy. The particle swarm algorithm convergence conditions and initial search space characteristics in WSN localization [30] are the reasons for this. No additional time or complexity was added by the new particle swarm algorithm. According to other algorithms, this one has lower average positioning errors and faster calculation times, which is good news for the user. Network traffic and energy consumption are reduced by the EFPA, which provides a better routing mechanism. Cluster intelligence optimization-based location algorithms must be simple to implement, with minimal parameter tuning and minimal time and space complexity. There has been a dynamic reduction of the search space [31] [32]. To improve WOA global search ability and development trends, a new communication method (CM) could be used. The exploration and development trends are then coordinated using a BBO algorithm, which considers biogeographically considerations. To improve the efficiency of exploration and development and to ensure more stable development trends, additional strategies are added to the original method. As a result of chaos, the optimizer incorporates a chaotic initialization phase. Gaussian variation can be used to increase the diversity of an evolutionary population. In [33] the shrinkage and chaotic local search strategies boost the development tendency of the basic optimizer. Improved positioning accuracy is achieved in this stage by optimizing the positioning nodes.

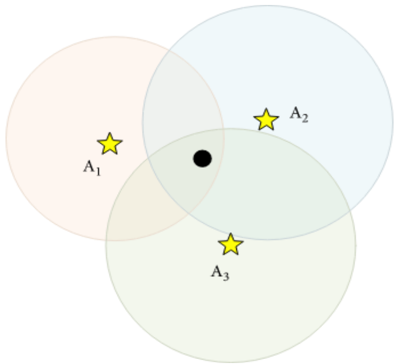

Fig.2. Three anchor nodes do not cross

3.1 RSSI RANGING MODEL

Based on transmission loss, RSSI calculates the transmitter-to-receiver distance using one of two models: theoretical or empirical. The RSSI location accuracy is greatly affected by the channel attenuation. Here is an example of the log-distance distribution model that was used:

$$PL(d) = PL(d_0) + 10n \log(d/d_0) + \varepsilon \tag{1}$$

$PL(d)$ and d_0, the anchor node, and the node distance from the base station can all be used to estimate the strength of the signal at the node in question (d_0). d_0 is the distance between the anchor node and the base station; d is the distance between the node and the base station, and d is random noise with a mean less variance of d. Equation is used to estimate the distance between the anchor node and the node to be located (1).

$$d = 10PL(d) - PL(d_0) - \varepsilon/10n \tag{2}$$

3.2 WHALE OPTIMIZATION ALGORITHM

The term WOAs refers to algorithms based on the whale feeding process in the field of artificial intelligence. For the algorithm to find and converge on an optimal solution, individual whales use a variety of strategies. Hunters can use WOA surround, random, or spiral search methods to keep track of their prey. First, we initialize the position W (i = 1, 2, n) and fitness values for each whale in the population, and then we evolve each individual whale separately, calculating the coefficient vectors *A* and *C* and generating a random p^{th} decision with a uniform distribution. This is done to create the p^{th} decision random number.

$$\vec{A} = 2a\vec{r}_1 - a\,;\ \vec{C} = 2\vec{r}_2 \tag{3}$$

The number of iterations increases the decrease from 2 to zero. Random vectors (r_1) and (r_2) on the [0, 1] plane.

3.3 FRAMEWORK OF GOA

There are a wide variety of grasshoppers, and they'll eat just about anything that comes their way. Farmers are terrified of these tiny pests because of the devastating impact they have on their crops. When a swarm of millions of grasshoppers gathers in the wild, it creates one of the largest natural swarms ever seen. The larval and adult stages of the grasshopper life cycle are distinct from those of other insects. Grasshopper swarming can be observed in both stages, but the behaviors are distinct. Because they lack wings, grasshoppers crawl slowly across the ground in their larval stage. As an example, a swarm of adult grasshoppers in the air moves quickly with large steps. [34][35].

There are two types of swarming behavior, and the GOA is primarily motivated by the differences between them. A mathematical model of swarm dynamics is shown in the following:

$$X_i = S_i + G_i + A_i \tag{4}$$

There is a relationship between the location of a grasshopper and its social interaction and its gravitational pull on the surrounding environment, as illustrated in this figure: X_i - location for each grasshopper, S_i - its social interaction, G_i is its gravity force, and A_i is its wind advection.

$$S_i = \sum_{\substack{i=1 \\ j\neq 1}}^{N} s\left(d_{ij}\right)\hat{d}_{ij} \tag{5}$$

$$d_{ij} = |X_j - X_i| \tag{6}$$

$$\hat{d}_{ij} = (X_j - X_i)/d_{ij} \tag{7}$$

For example, each grasshopper has a d_{ij} and cd_{ij} distance from its neighbor; this distance is referred to as d_{ij} cd_{ij}. There are an infinite number of grasshoppers in this model, so N_i represents the total number of grasshoppers.

$$s(r) - fe^{\frac{-d}{l}} - e^{-d} \tag{8}$$

F - object intensity of attraction, *l* - attractive length scale. There are distinct zones of repulsion, attraction, and comfort between two grasshoppers (where there is neither attraction nor repulsion). For example, the grasshopper-per shifts its position because it is attracted to or repulsed by something. The i-th grasshopper gravity and wind advection can be determined using the following equations:

$$G_i = -g\hat{e}_g \tag{9}$$

$$A_i = -u\hat{e}_w \tag{10}$$

Constants *g* and *u* are referred to as constants here, $\hat{e}_w$ and $\hat{e}_g$ represent the direction of the earth centre and the wind direction, respectively, as the unity vector.

According to [36] [37], to solve the optimization problem, an altered version of Eq.(4) is proposed, but it is not possible to use the mathematical model presented thus far:

$$X_i^d = c\left(\sum_{\substack{i=1 \\ j\neq 1}}^{N} C\,\frac{ub_d - lb_d}{2}\,s\left(\left|x_j^d - x_i^d\right|\right)\frac{x_j - x_i}{d_{ij}}\right) + T_d \tag{11}$$

The d^{th} dimension has upper and lower limits, and T_d is the best value. The comfort zone, repulsion zone, and attraction zone all shrink in the outer c is as the number of iterations rises.

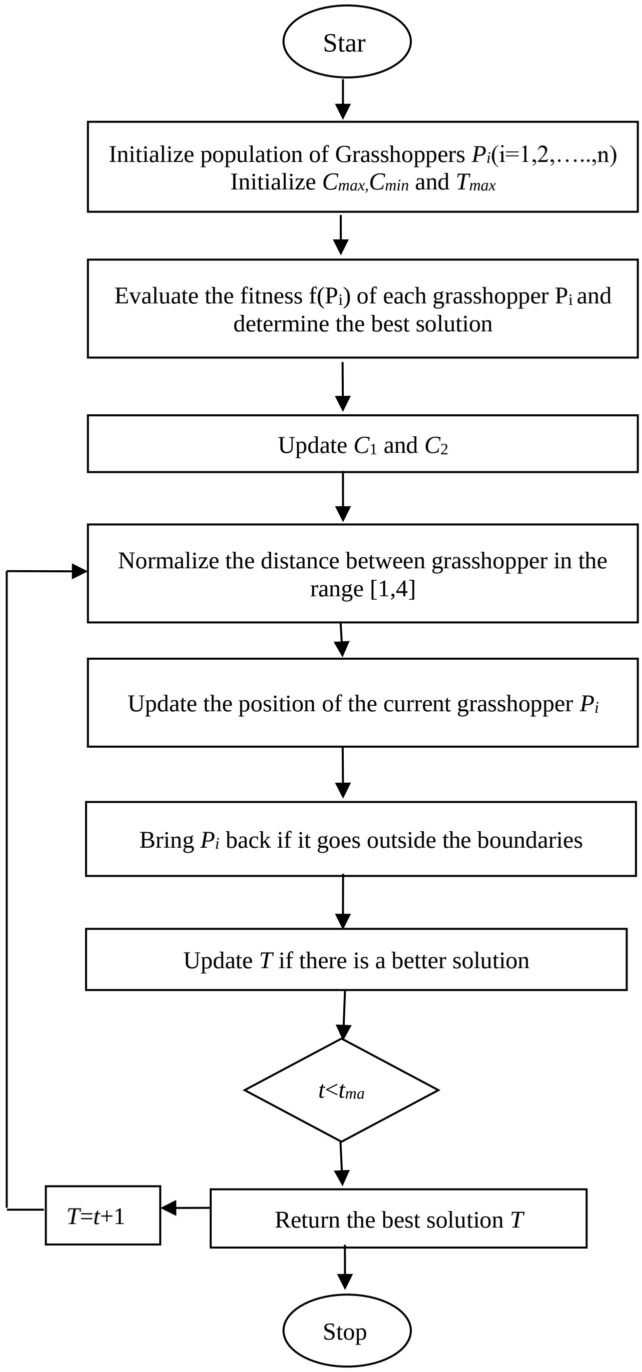

Fig.3. Flowchart Grasshopper Optimization Algorithm

The parameter c is can be calculated using the equation below:

$$c = c_{\max} - l\frac{c_{\max} - c_{\min}}{L} \tag{12}$$

For each iteration, l denotes how many times it has already been done, and L represents the maximum number of times it can be done. A value of 1 is the default for Cmax and Cmin, respectively. Assuming the target Td wind direction, gravity is not considered in the modified equation.

3.4 VARIANTS OF GOA

Fig.4 depicts a variety of GOA modifications and hybrids that have been proposed in the literature. In the following sections, you'll find all the information you need to know about these versions.

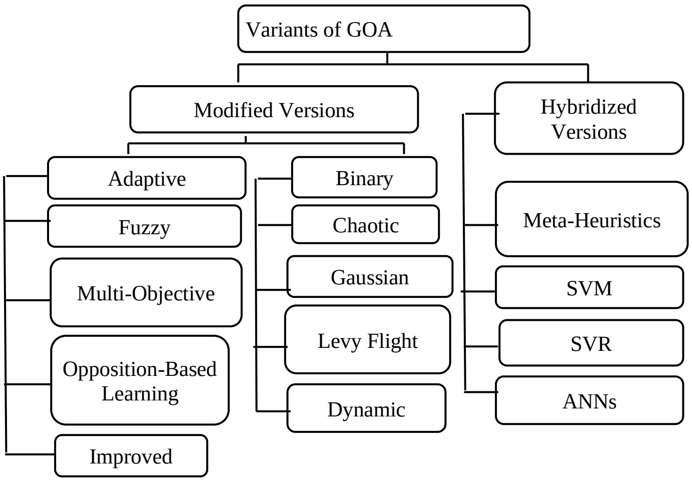

Fig.4. Variants of GOA

3.5 BINARY GOA

The Multidimensional Knapsack Problem was addressed by [38], who developed BGOA, a binary GOA based on the percentile notion (MKP). KMTR compared the performance of BGOA to BAAA and K-Means Transition Ranking with OR-Library benchmarks. BGOA excelled both the BAAA and KMTR models in comparison to other tests.

As a solution to the problem of set coverage, [39] presented a Binary GOA (BGOA) (SCP). Using the percentile principle, GOA binary version was created. When it comes to the SCP, BGOA answers are more precise and high-quality thanks to simulations.

To tackle the difficulty of feature selection, Hichem et al. [40] recommend adopting a novel binary GOA (NBGOA). Twenty datasets from the UCI dataset collection were used to evaluate NBGOA against five well-known feature selection optimization approaches. NBGOA has a superior fitness function and a greater average classification accuracy than the other programmes tested.

3.6 CHAOTIC GRASSHOPPER OPTIMIZATION ALGORITHM

Some variations of enhanced chaotic GOA for the construction of three-bar trusses and the estimate of frequency-modulated sound synthesis parameters (ECGOAs) [41]. It was found that ECGOA with the Singer map outperforms the normal GOA and nine different variations of ECGOA.

- **Gaussian GOA:** GOA was enhanced by [42] to predict financial stress (IGOA). In GOA, Opposition-based learning, Gaussian mutation, and Levy-flight were employed in GOA to establish a fair balance between exploitation and exploration. For the years 1995 to 2009, data from Japanese financial statements were used to compare IGOA to other accounting measures such as GA and FA. IGOA is more accurate than other methods when it comes to classifying items.
- **Levy-Flight GOA:** Based on Levy flight in GOA, Developed an improved approach (LGOA) for visual tracking [43]. LGOA was compared to other GOAs in a series of comparisons. The LGOA algorithm outperformed the more typical GOA, PSO, CS, and ALO algorithms in tests.
- **Dynamic GOA:** For feature selection, an evolutionary population dynamic (EPD) and selection operator GOA (GOA EPD) was proposed [44]. Real-world datasets from the UCI machine learning library were utilized to assess GOA EPD performance. GOA EPD was found to be extremely long-lasting when compared to other materials such as GA, PSO, BGSA, BBA, and bGWO.
- **Adaptive GOA:** For solar-powered unmanned aerial vehicles (SUAVs) in urban contexts, an adaptable GOA (AGOA) has been proposed [45]. Natural selection, dynamic feedback, and democratic decision-making procedures were employed to improve AGOA performance. GOA, GWO, and GOA outperform AGOA in simulations, according to the statistics.
- **Fuzzy-Based GOA:** GOA and the Fuzzy approach [46] were used to construct this model to find the best locations for distributed generation, shunt capacitors, and charging stations for electric vehicles. Fuzzy GOA beat the conventional technique and Fuzzy GA and PSO in distribution networks with 51 and 69 buses, respectively.
- **Opposition-Based Learning GOA:** To deal with benchmark optimization functions and engineering difficulties, [47] presented a better version of GOA, OBLGOA, which incorporates the OBL mechanism into GOA. With 23 benchmark functions and four engineering issues, OBLGOA was compared against normal GOA and GA, as well as GA, BA, DE, and DA. In comparison to the most cutting-edge optimization techniques, OBLGOA surpasses.
- **Multi-Objective GOA:** Path planning for robots in stationary contexts has been proposed using GOA [48]. (MOGOA). It was in MOGOA that we looked at the length of a path, costs, smoothness, and computation time.
- **Other Improved GOA:** A combined approach (LWSGOA) [49] proposed to address the issue of energy management. This approach combines GOA with Linear Weighted Sum (LWS). The effectiveness of LWSGOA was evaluated using an optimal model consisting of three interconnected heat exchangers (EH) to represent the Multi-Integrated Energy System (MIES). Because of its scalability and flexibility, LWSGOA outperformed other methods in terms of multi-carrier energy consumption, peak power, and heat demand.

4. METHODOLOGY

The deployment of sensor nodes and reference nodes in a random pattern gives rise to a WSN. To obtain the desired level of coverage, great consideration should be given to the selection of the node density.

4.1 LOCALIZATION OF NODES

After the first deployment, nodes utilize the GOA approach to self-localize. The initial step is comparable to a hop-based algorithm, but communication ranges replace hop counts. This modification helps mitigate the effect of variability on distance calculations.

Here, each reference node broadcasts its location data (x, y) and communication range CR to its neighboring nodes. The neighboring nodes store this data and add their CR to the received CR. If this sum of CR is less than a predefined CR threshold, nodes broadcast them together with reference node location information. The CR threshold aids in identifying only the closest reference nodes, hence minimizing the effect of curved pathways on distance calculations.

After receiving this information, neighbor nodes determine whether the obtained reference node information is already stored in their neighbor information. If it is a new node, the neighbor information is updated using the received position of the reference node and the sum of CR. If the collected node information is already recorded, the received CR sum is compared to the stored value, and the smaller of the two CR values is saved with the location information. At the conclusion of this process, each node will possess the location information of reference nodes and the minimum value of the sum of CR from the reference node to itself.

After localization, each node knows its position inside the field. Next, this location data is used to identify coverage gaps. This is accomplished by ensuring a uniform distribution of neighboring nodes with overlapping sensing ranges surrounding each node. Each node identifies a small number of locations evenly spread around it at a distance of SNi. The identified number of points can be any number greater than 1.

After recognizing the points, the nodes determine whether or not they are within the sensing range of any of the neighbor nodes contained in the neighbor matrix. If any of a node identified points do not exist inside the sensing range of a neighboring node, the node is identified as a border node with the Border parameter set to 1.

By selecting additional locations, it is possible to find coverage gaps with smaller sides. However, since every point must be examined for neighboring nodes that overlap, this raises the computational burden. Therefore, a suitable amount of points must be determined based on the application requirements.

5. SIMULATION RESULTS AND ANALYSIS

Most benchmark functions, such as unimodal and multimodal operations, are derived from the literature [50]. The comparison indices for the standard deviation of each experiment are shown in Fig.5, Fig.6, Fig.7 describes the lowest (the best value), median, maximum, and average values. The novel whale method outperformed HPSO and WOA-QT compared to ten unimodal functions in addition to its improved local search performance. With 3 multimodal operations, the grasshopper algorithm has an absolute advantage in ranking all metrics.

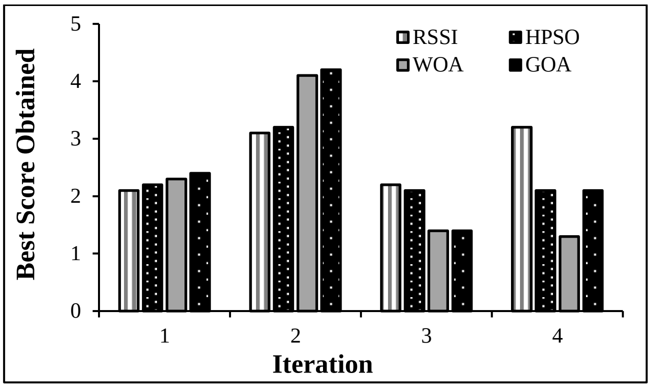

Fig.5. Iteration

Fig.5 describes compared to the original RSSI algorithm, HPSO algorithm, WOA algorithm, and WOA positioning error, the node placement algorithm in this study has a positioning error compared to the other algorithms. It has been demonstrated that this paper localization algorithm grasshopper algorithm outperforms the other three.

Fig.6 describes the average positioning error of the four methods falls as communication distance grows and then increases when communication distance increases more than it decrease. Compared to the original RSSI, HPSO, and WOA algorithms used in this study, GOA, the average positioning errors of the node location algorithm and the positioning errors of this algorithm have been minimized.

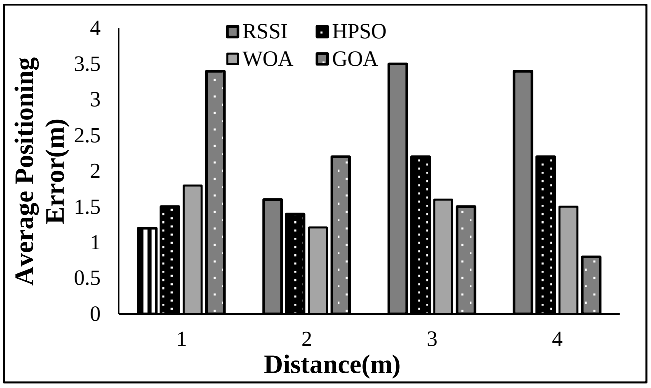

Fig.6. Communication Distance

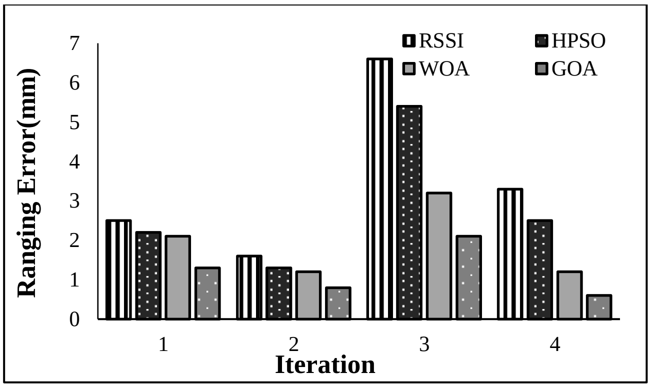

Fig.7. Ranging Error

Fig.7 describes although this approach has a less average positioning error than either RSSI or HPSO or WOA or even the original WOA algorithm, it still has a larger positioning error than the node location technique GOA described in this study. The average placement error of the four algorithms rises dramatically when the range error is high. But the algorithm in this paper localization grasshopper algorithm error is always smaller than that of the original RSSI, HPSO, and WOA algorithm, regardless of how the ranging error changes.

6. CONCLUSION

Based on enhanced whale optimization, this work develops an algorithm for finding WSN node locations that takes environmental aspects into account. As a starting point, the RSSI-ranging model is altered using a Gaussian fitting function. Positioning precision can be further increased by utilizing the newly developed grasshopper optimization technique. The first step is to draw a boundary around the search region. The real distance between the anchor and target nodes is omitted in favour of an estimated distance, resulting in a more objective fitness metric hierarchies and feedback mechanisms can be introduced throughout the algorithm, including during random walks, to hasten convergence and enhance search accuracy. Convergence and node positioning accuracy are superior to RSSI and HPSO algorithms under the same hardware conditions. Researchers will study the grasshopper algorithm performance in future studies.

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