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Research Article

A Novel Approach to Node Coverage Enhancement in Wireless Sensor Networks Using Walrus Optimization Algorithm

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ABSTRACT

One of the present field's hotspots for study is the wireless sensor network coverage optimization challenge. By studying coverage optimization challenges, we may make the network more stable, reduce distributed redundancy of sensor nodes, enhance coverage, and use less energy. An approach to node coverage optimization based on WaOA (Walrus Optimization Algorithm) is presented, which aims to address the issues of low coverage and uneven distribution that arise when wireless sensor network (WSN) nodes are randomly distributed. To optimize the coverage of wireless sensor networks, a mathematical model must first be constructed. Next, we solve the WSN coverage optimization issue using the WaOA method. WaOA provides the best results when merging various sub-area network coverages. Based on 23 benchmark functions, simulation results demonstrate that WaOA outperforms several other well-known algorithms in terms of search accuracy and convergence speed. Simultaneously, Butterfly Optimization Algorithm (BOA), Seagull Optimization Algorithm (SOA), and Bald Eagle Search (BES) are the most widely utilized WaOA methods. This indicates that WaOA can attain more coverage than these algorithms in terms of the coverage optimization impact. Empirical findings demonstrate that WaOA may efficiently enhance sensor node coverage and enhance node distribution in WSN coverage optimization issues.

Keywords: wireless sensor network, coverage optimization, WaOA (Walrus Optimization Algorithm), sub-area network, convergence speed.

INTRODUCTION

Wireless Communications, Electrical Technology, Computer Network Technology, and Sensor Methods have all grown rapidly, leading to the development of Wireless Sensor Networks (WSN) [1]. Wireless sensor networks are made up of several energy-constrained sensor nodes that work together to arrange detection in a multi-hop, self-organizing fashion, gather and analyze data about things detected inside the network's coverage area, and then transmit that data to the network's owner. details [2, 3]. As a result, it has a wide range of applications in contemporary urban and military architecture, including smart houses, target tracking, environmental monitoring, and combat monitoring [4]. Unfortunately, sensor nodes are typically dispersed haphazardly throughout the air, leading to haphazard node placement, making it challenging to monitor the whole region. Research on network life cycle, communication quality, and speed are only a few of the challenges that are involved in wireless sensor network coverage optimization. Enhancing the network's coverage performance can lead to better network communications connection, more effective and efficient use of energy, higher-quality network services, and more cooperation amongst sensor nodes [5]. By judiciously distributing network resources, coverage control in WSN may maximize the performance of network coverage. Studying the coverage issue with wireless sensor networks is crucial as a result [6].

Wireless sensor networks have gained widespread industrial use in recent years, effectively displacing wired networks [7]. However, because of the nature of wireless communication, data packets may be lost or delayed over the specified time [9], and interference and collisions may happen during data transfer [8]. Coverage is a critical parameter for assessing attempts to optimize coverage and one of the primary obstacles in wireless sensor networks. Coverage has a significant impact on the service quality of wireless sensor networks as it influences the target monitoring area's monitoring capability [10]. Considering the limited processing power of large-scale wireless sensor network nodes, node coverage optimization technology has been developed to improve the coverage of wireless sensor nodes in big data scenarios [11,12]. However, sensor energy is finite and cannot be refilled, and the operational environment of wireless sensor networks is complicated and variable [13].

Within the subject of wireless sensor networks, one of the main areas of current study is the optimization problem of coverage control. In order to keep an eye on communication blind spots and target area communication availability, real-time network coverage measurement is essential. When a blind area is identified, it may be addressed by expanding the number of sensor nodes or changing the arrangement of the existing ones. To increase monitoring reliability, additional sensor nodes can be placed simultaneously in more crucial monitoring regions [7]. To lessen communication interference, sensor nodes can also be moved. Wireless sensor networks have a range that may be used for both communication and monitoring. In order to reach practical applications, this is crucial [8]. Encourage the growth of practically integrated systems and progressively enlarge and fortify the field of control technology research.

How to cover the largest area with the fewest number of nodes to give precise data gathering information and target tracking services in order to assure the operation of network services? Large-scale static node deployment is the conventional approach to increase network coverage. However, communication conflict will arise from an excessive number of sensor nodes. Swarm intelligence optimization techniques are widely used by academics to maximize the coverage of wireless sensor networks, including artificial bee colonies, ant colonies, and particle swarms.

When optimizing network coverage, these algorithms are prone to slipping into local optima, which lowers the accuracy of network data transmission and node redundancy. They also have low solution accuracy and sluggish convergence speeds. In order to properly position sensor nodes in the monitoring region, enhance coverage, lessen sensor node redundancy, and increase network life cycle, this study suggests the WaOA (Walrus Optimization Algorithm). In this paper, we provide a coverage optimization approach for wireless sensor networks based on the hippocampal optimization technique Raja etal., [28]. The primary contributions of this study, as compared to currently accepted selection techniques, can be summed up as follows.

- Describe the problems with a coverage control approach for wireless sensor networks (WSNs) and construct the coverage control algorithm's problem.
- Provide a unique coverage optimization approach based on the technique for walrus optimization. The usefulness and effectiveness of the suggested coverage optimization approach should be illustrated using comprehensive simulation data.
- Assess the suggested algorithms' performance by contrasting it with the BOA, SOA, DOA, AOA, and BES coverage optimization methods.

LITERATURE SURVEY

Improved network coverage, reduced distributed redundancy of sensor nodes, reduced energy consumption, extended network life, and overall network stability are all achieved via research on coverage optimization. Certain specialists and researchers employ current algorithms to enhance the coverage effectiveness of wireless sensor networks. A boundary-based coverage optimization protocol (PeCO) for wireless sensor networks was suggested by the authors in [9]. This method's innovation basically resides in creating a brand-new mathematical optimization model to maintain sensor activity in response to ambient coverage levels. Tests demonstrate that the PeCO algorithm can extend sensor network coverage and offer a longer life cycle. In [10], we put up an expanded strategy for distributing mobile sensor nodes at random to cover predetermined areas and keep base station connectivity in case of WSN failure. In order to increase network coverage, the authors of [11] address redundant nodes in wireless sensor networks via mesh partitioning. A traversal approach was utilized in the literature [12] to ascertain the combination of sensor nodes and radius, and the suggested wireless sensor network node structure was predicated on dynamic sensing distance. The authors of [13] suggested a traveling path planning technique called TRP-MC, which uses mobile collectors to locate shortcuts in wireless sensor networks with the greatest number of sensors. The algorithm has a long network life and good coverage. Numerous studies on the optimization of coverage for this kind of wireless sensor network are now underway, and the field as a whole has produced several significant discoveries and insightful study findings.

PSO (Particle Swarm Optimization) has been developed over twenty years, and it has several clear benefits over other intelligent optimization techniques, including easier iteration rules and faster convergence. Many technical sectors have successfully used the PSO approach. Co-evolutionary PSO algorithm-based WSN dynamic deployment optimization was covered by Wang et al. [1]. A better global PSO technique was presented by Sun et al. [2] using hybrid hybrid leapfrog optimization. Wang et al. Based on combinatorial mathematics and the PSO algorithm, we provide a covering method

[2]. In order to maximize the K-barrier coverage, Zhang et al. [3] included the immune approach into the PSO algorithm. By using an enhanced PSO algorithm, Bai et al. [5] were able to increase the k coverage of WSN under restricted mobility. For WSN range optimization, Xu et al. [6] used a novel hybrid MOEA/D-II method with a single particle swarm algorithm. Wang et al.'s [7] combination of the PSO algorithm with simulated annealing led to energy-saving WSN coverage.

While conventional algorithms have shown significant advancements in coverage optimization and produced decent results, they still have several glaring flaws. To fulfill real-time requirements, for instance, certain algorithm structures are too complicated and the total computation performance is too sluggish. Some algorithms perform too poorly, have a poor coverage impact, and have a big user base in terms of distance and business demands. A network model that has too many parameters for a given algorithm is frequently too complicated to be used in practice. An innovative approach to the wireless sensor network coverage optimization problem is put forth by the cluster intelligence algorithm. Numerous academics have examined the effectiveness of cluster intelligence algorithms and soft computing techniques in a number of domains recently, including airport clustering, corrosion imaging, WSN coverage control, classification algorithms, and more. For instance, the author of the literature [16] optimizes the coverage problem in WSN using the Firefly method. The whole methodology is quite intricate, and although the optimization impact is good, the convergence pace is slow. In order to address the coverage problem of wireless sensor networks, a novel approach based on particle swarm optimization (PSO) was presented [17].

This method can easily slip into local optimization following optimization, despite its great capacity to converge globally and its ability to identify a deployment model that is generally applicable to wireless sensor networks fast. The best coverage plan for wireless sensor network nodes was proposed by a literature study [18] using an enhanced genetic algorithm and binary ant colony algorithm. There have been advancements. The suggested method has great coverage and efficiently prolongs the network life, with a high computation efficiency. A WSN coverage optimization technique for artificial fish swarms was proposed in literature [19]. Although the node coverage redundancy is large, this approach has produced strong optimization results in WSN coverage optimization and enhanced network coverage. The authors of [20] suggested an improved technique for distribution that was based on Artificial Bee (ABC). By restricting the total number of deployed relays and improving network characteristics, ABC-based deployment provides longer lifetime. The authors of [21] suggested a fuzzy-based process for clustering airports using fuzzy geometry that was based on the unit hypercube idea. To acquire pictures that recreate corrosion profiles, an evolutionary computation-based normalizing technique has been suggested Vinayakan et al., [22]. The authors published a wireless sensor network coverage optimization model in Vinayakan et al., [23] that was based on the improved whale approach. In order to maximize the population's initial distribution, a mathematical model of wireless sensor network node coverage was developed. Additionally, the original whale swarm optimization technique was modified to incorporate dynamic concepts. This approach may enhance network performance and efficiently increase the coverage of wireless sensor network nodes.

These algorithms, however, fall short in certain areas when it comes to maximizing wireless sensor network coverage. For instance, inadequate particle optimization optimization parameters will result in inadequate network coverage [24]. The ant colony method creates a multi-parameter, intricate network model that causes issues during real deployment. In response to these issues, this study successfully resolves the wireless sensor network sensor node coverage optimization problem by optimizing wireless sensor network coverage through the use of the enhanced gray wolf optimization method from the preceding chapter.

In addition to analyzing the mathematical model of wireless sensor network node coverage and summarizing previous research, this study suggests a coverage optimization approach based on the Walrus optimization method.

METHODS

WSN Node Coverage Model

Assume that q sensor nodes are dispersed at random over a M×N·m2 two-dimensional WSN monitoring region. (xi, yi) is a representation of the coordinates of each node Si, where i = 1, 2,... q. The node set in this instance may be expressed as S={S1, S2,...Si,...Sq. }. The two-dimensional WSN monitoring region's network model looks like this:

(1) Since every sensor node has the identical characteristics, structure, and communication capacities, they are all homogenous sensors.

(2) Every sensor node is equipped with enough energy, can communicate normally, and can get data quickly.

(3) Every sensor node has the freedom to travel and the ability to promptly update its position data.

(4) Every sensor node has a detecting radius of Rs and a communication radius of Rc, both expressed in meters, with Rc ≥2Rs.

A sensor node's detection range is a circular region with the node at its center and a detection radius of Rs. The set of target monitoring points may be written as T={T1, T2,...Tj,...Tn}, with its position coordinates representing each target point to be observed, assuming that there are n target monitoring points in such a two-dimensional WSN monitoring region. Tj is made up of (xj,yj). In this case, j = 1, 2,...n. It may be concluded that a sensor node covers a target monitoring point Tj if the distance between it and one of the nodes is less than or equal to the sensing radius Rs. The following defines the Euclidean distance between the goal monitoring point Tj and the sensor node Si.

This article uses a Boolean detection model as its node detection model. That is, the chance of detecting the target is one if the detection radius Rs is more than or equal to dSi, Tj. If not, there is no chance that the target will be noticed. The following is the likelihood that the sensor node Sibep will cover the target point Tj to be monitored:

Sensor nodes in this two-dimensional WSN monitoring region can cooperate with one another. In other words, the likelihood that a monitoring point Tj is jointly detected is as follows since all target monitoring points may be examined simultaneously by numerous sensors:

Coverage may be defined as the ratio of each sensor node's coverage area to the monitoring area's overall area. As a result, the following describes the suitable range of this two-dimensional WSN monitoring region.

The following integer linear programming model may be used to characterize the wireless sensor network node coverage optimization issue, according to the study presented above.

At this point, Si stands for the i-th sensor node, Tj for the j-th monitoring point, and Cov for the aim function that seeks to attain maximum coverage. M×N is the size of the monitored area. Constraint 1 is the combined detection probability constraint for all monitoring sites Tj. The monitoring area cannot be larger than the total area occupied by all of the sensor nodes inside it, which is the second constraint. Thirdly, in order to fully cover the target monitoring point, the Euclidean distance between the sensor node Si and the target monitoring point Tj must be smaller than the detection radius Rs. It takes time to use integer linear programming to solve the coverage problem and identify the best solution while installing a large number of sensor nodes. Metaheuristic algorithms are appropriate for effectively resolving this challenging issue. because metaheuristic algorithms are capable of producing acceptable outcomes in a reasonable amount of time. Therefore, in order to address the coverage optimization issue with wireless sensor networks, this research suggests an enhanced version of the duck method.

Mathematical Model

In this research, network coverage is computed using a probabilistic identification modelEach sensor node's coverage area in a wireless sensor network is seen as a circle with a predetermined sensing center and communication radius [24, 25]. As such, it is challenging for any sensor node to officially ascertain the whole monitoring area's boundaries. The monitoring region can be split up into m×n pixels to ease the coverage issue with wireless sensor networks. The coverage of the wireless sensor network may be expressed as x/(m×n) if x pixels are covered. Assume that each sensor node in a WSN has a measurement radius (r) equal to the communication radius (r), and that each sensor node's coverage area is a circle with a radius of r. The sensor network's measurement area is assumed to be a two-dimensional plane M in this research, discretized into m×n pixels. N sensor nodes make up a wireless sensor network. The i-th sensor node, gi, is located at (xi, yi). The collection of sensor nodes in the measured region is G={g1,g2,......,gN}. The following represents the distance between pixel H and sensor node gi where pixel H's coordinates are (xH, yH):

Two-dimensional perception model is used to calculate the likelihood that sensor node gi will detect pixel H.

The joint probability[23] that the sensor node at pixel H is seen by the sensor node set G of wireless sensor network is because several sensor nodes may detect a single sensor node at the same time.

As stated in reference [23], the coverage rate of all sensor nodes to be detected is the ratio of the total number of pixels covered by all nodes to the complete monitored region. Equation (9) states that the largest value of the coverage function is the optimization goal of the WSNs coverage model.

Walrus Optimization Algorithm

The essential idea and theory of the proposed Walrus Optimization Algorithm (WaOA) are presented in this part, along with a mathematical model of each stage. Source of inspiration for WaOA Large aquatic creatures with wings that are specifically found in the Arctic Ocean and subarctic seas near the North Pole 42 are known as marine mammals. The distinctive features of adult walruses are their enormous beards and tusks. Social creatures, walruses spend a lot of time searching for and consuming graphite bivalves on sea ice. The elongated teeth of the hippocampal species are its most remarkable characteristic. Males and

females may weigh up to 5.4 kg and reach a maximum length of 1 meter. They also have enlarged fangs.

Males utilize their longer, somewhat thicker tusks for display, fighting, and dominance. The group's leader and most powerful male with the longest tusks commands and mentors the others. The picture of the sea state is shown in Figure 1. When the weather warms and the ice melts in the late summer, walruses often go to rocky beaches and outcrops. There are several aquatic phenomena included in these striking movements44. The only two natural adversaries of walruses, due to their size and strong tusks, are killer whales (orcas) and polar bears. Based on observations, walrus and polar bear battles are prolonged and physically taxing, with polar bears frequently leaving the fight after sustaining injuries from walruses. But the walrus hurts the polar bear with its tusks during their struggle. Killer whales may hunt walruses successfully and deal little to no damage in their battles45. Walrus social interactions and instinctive behavior are examples of intelligent activity. The most evident of these clever actions are three. (i) Tell the person to consume while being supervised by a tusking member. (ii) Marine creatures move to rocky beaches; (iii) the major source of inspiration for the development of the suggested WaOA approach came from mathematical modeling of these behaviors.

Algorithm initialization

The WaOA algorithm is a type of metaheuristic swarm search where the searchers inside the swarm are actual ocean phenomena. Every sea condition in WaOA indicates a potential fix for the optimization issue. The location of each sea state in the search space therefore determines possible values for the problem variables. As a result, all ocean phenomena may be represented mathematically using what are known as population matrices, which allow for the modeling of ocean populations. Initialization of the walrus population was done at random at the start of WaOA deployment. The WaOA population matrix is established by means of (1).

The number of sea phenomena is denoted by X, the candidate for the $\boldsymbol{X}$th sea phenomenon is represented by, the value of the jth choice variable suggested by the th sea phenomenon is represented by j, and the number of sea states is denoted by N. As previously stated, every hippocampal cell is a potential solution to the problem, and the values suggested for the decision variables may be used to assess the problem's objective function. (2) specifies the estimate of the goal function that was derived from the hippocampus.

The objective function vector is denoted by F, and the objective function value, Fi, is determined by the sea state. The most accurate way to assess a prospective solution's quality is to look at its objective function value. The best member is the candidate solution that determines the objective function's best value. The worst member is instead the candidate solution that produces the lowest value of the target function. With every iteration, the value of the goal function is updated, along with the best and worst members. WaOA computational simulations.

Three stages make up the modeling process for updating walrus positions in the WaOA, which is based on the animals' natural activities.

Phase 1: Feeding strategy (exploration)

Over sixty different kinds of marine creatures, such as sea cucumbers, tuna, shrimp, and different mollusks, are consumed by walruses. Nonetheless, walruses have a preference for bivalve mollusks, particularly shellfish, and they graze on the bottom, detecting and locating food with the help of faint vibrations and vigorous fin movements. The walrus with the biggest tusks and most strength leads the other walruses in the group in their hunt for food. The lengths of the hippocampal canines and the objective function values of potential solutions are qualitatively comparable. As a result, the strongest sea state in the group is determined by selecting the candidate solution that has the highest objective function value. WaOA's navigation skills in global searches are enhanced as a result of the search behavior of various ocean phenomena, which results in distinct scan zones of the search space. The most significant group members provided direction for the mathematical modeling of the feeding mechanism-based hippocampus location updating process, which was done using equations (10) and (11). According to (10), the initial step in this process is the generation of new hippocampus locations. This new location will take the place of the prior position as the goal function's value grows. In (11), this concept is modeled.

In this case, jP1 is the j-th dimension, XiP1 is the position of the i-th newly generated hippocampal according to step 1, xi, $F\ P1$ is the objective function value, $rand$lv, j is a random number in the interval [0,1], and the value is the best and most Strong hippocampal, $\boldsymbol{U}$, j is a randomly selected integer between 1 and 2.

Phase 2: Migration

Seahorses go to rocky beaches and nodules in late summer as part of their normal activity to enjoy the warm weather. WaOA uses this migration method as a reference for search space oceanography in order to identify appropriate search space areas. Assuming that you relocate each sea event to the position of another sea event (randomly chosen) in a different part of the search space, (12) and (13) provide a mathematical model for this behavioral process. Consequently, in accordance with (12), suggested new places are first created. Then, in accordance with (13), if the new location of the walrus increases the value of the goal function, the old position is substituted.

In this case, $XP2$ is the objective function value X, $N\}$, $jP2$ is the j-th dimension, and $X\ P2$ is the newly formed ∞-th hippocampal location based on step 2. The vth hippocampal location is determined by $k\neq$, the jth dimension is represented by j, and the objective function's value is represented by Fk.

Phase 3: Escaping and fighting against predators (exploitation)

Killer whales and polar bears regularly attack seahorses. The walrus's surroundings alter as a result of its escape and defense tactics against these predators. By mimicking these innate hippocampal activities, WaOA is better able to take advantage of local search in the troubleshooting space around potential answers. It is assumed that every ocean state has neighbors in WaOA in order to mimic this occurrence. Equation (14), when the objective function's value rises, causes this new position to take the place of the old one.

$P3$ $XiP3$. The permissible local lower limits of the jth variable are Partial and the $lblocal$, ndon, respectively.

Repetition process, pseudocode, and flowchart of WaOA

The hippocampus position is updated depending on the first, second, and third phases, and the first WaOA loop is then completed along with the new hippocampal location and objective function value. Iterative updates and improvements to potential solutions are made using WaOA equations and steps. From (3) until the last iteration (9). When the algorithm has finished running, WaOA presents the top candidate solution discovered during the run as a fix for the particular issue. Algorithm 1 contains the specifications for the associated pseudocode, whereas Figure 1 displays the WaOA implementation flow chart.

Algorithm 1: Pseudocode of WaOA

Start WaOA.

1. Input all optimization problem information.

2. Set the number of walruses (N) and the total number of iterations (T).

3. Initialization process of walruses' locations.

4. For t=1:T

5. Update strongest walrus based on objective function value criterion.

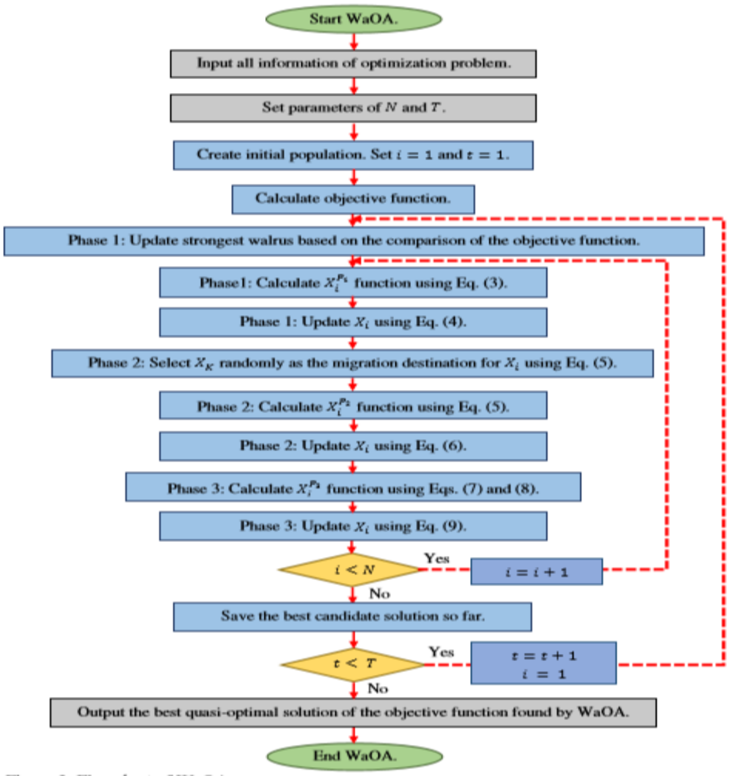
6. For i=1:N

7. Phase1: Feeding strategy (exploration)

8. Calculate new location of the jth walrus using (3).

9. Update the ith walrus location using (4).

Figure1: Flowchart od WaOA



10. Phase 2: Migration

11. Choose an immigration destination for the ith walrus.

12. Calculate new location of the jth walrus using (5).

13. Update the ith walrus location using (6).

14. Phase 3: Escaping and fighting against predators (exploitation)Figure: Flowchart od WaOA

15. Calculate a new position in the neighborhood of the ith walrus using (7) and (8)

16. Update the ith walrus location using (9).

17. end

18. Save the best candidate solution so far.

19. end

20. Output the best quasi-optimal solution obtained by WaOA for given problem.

End WaOA.

Computational complexity of WaOA

We examine WaOA's computational complexity in this subsection. The complexity of WaOA's initialization is equal to that of (Nm), including the creation of the population matrix and the objective function computation. The number of hippocampi in this case is N, while the number of issue variables is m. There are three phases in the WaOA updating process, and each step's complexity is equal to (Kjkl). T represents the algorithm's iteration count in this case. As a result, WaOA's overall computational complexity equals ((1 + 3T)).

Coverage Optimization Strategy

This paper focuses on the coverage problem of wireless sensor networks and computes network coverage using a probabilistic discriminant model. utilizing the enhanced seahorse optimization technique to optimize wireless sensor network coverage deployment. In this study, the WaOA algorithm's optimization goals are to solve the wireless sensor network coverage optimization objective function's maximum value, produce the WaOA optimal coverage, and determine the distribution location of each sensor node in the network. Its objective is. Optimize regions for post-deployment testing.

The enhanced sea state algorithm's coverage optimization makes the assumption that there are M different types of sea states. The formula Xi= (xi1, yi1, xi2, yi2, ..., xiN, yiN) provides the location of the hippocampal regions. Each hippocampus represents a node placement plan with N nodes. The location coordinates of each sensor are represented here by the parameters (x, y). Every sea state has a varied location, and the area range that corresponds to the location arrangement varies as well. The oceanographic algorithm serves as the foundation for enhancing the coverage optimization of the algorithm; the fitness function is the wireless sensor network's coverage range, and the input value is the sensor node's position information. (Quadruple). α represents the person with the greatest fitness value, β and δ represent the people who correspond to the second and third fitness values, and Ω represents the people who remain. The algorithm's α determines the prey's location. A group of marine items is made up of several sea objects with identical size. The measurement area is a two-dimensional plane, and the ocean object's size is twice the number of sensor nodes. The ordinate of the d-th sensor node is represented by the 2d dimension, whereas its abscissa is represented by the 2d-1 dimension.

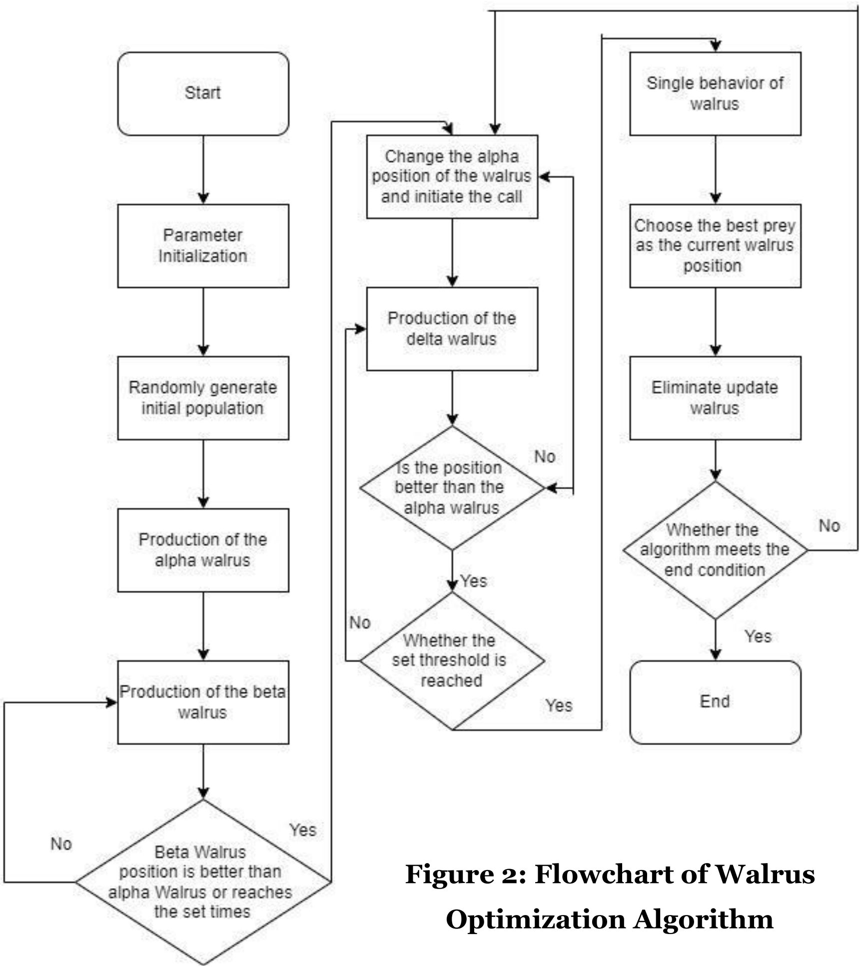


Figure 2: Flowchart of Walrus Optimization Algorithm

The following are the stages involved in putting WSNs' coverage optimization algorithm into practice:

(1) Determine the method's parameters, such as the population size (N), dimension (d), maximum number of iterations (tmax), control parameter (a), swing factor (C), convergence factor (A), and other specifics.

(2) First, initialize the population X (x1, x2, ..., xD); in other words, produce N intelligent people at random and apply the fitness function (4) to determine each walrus's fitness value throughout the population.

(3) For each individual walrus in the original population, ascertain their fitness level. After that, select the three most physically fit people and label them $X\alpha$, $X\beta$, and $X\delta$, respectively.

(4) By using equations (13) and (14), you may update the walrus's location, compare the adaptive value again, determine the control parameter α's value, and use equations (8) and (9 to update the convergence factor A and the swing factor C).

(5) Recalculate each walrus's fitness value, update $X\alpha$, $X\beta$, and $X\delta$, and choose the individuals with the highest fitness value.

(6) Ascertain if the last requirement has been met. The number of iterations is raised by 1 if it is not satisfied, and step (3) is then repeated. It stops and Xa terminates if it is pleased.

Figure 2 illustrates the WaOA algorithm-based coverage optimization procedure for a wireless sensor network.

Results and Discussion

WaOA for WSN Coverage Optimization Problem

We examined the suggested method with a number of alternative collective intelligence algorithms in order to confirm WaOA's effectiveness in WSN coverage optimization situations. The goal function for solving the WSN coverage optimization model is the combination of equations (4) and (5). We discovered throughout the testing that WaOA was not able to solve the wireless sensor coverage optimization problem with optimal performance. We revised formulae (19) to (20) for the wireless sensor coverage optimization problem after conducting various tests.

In this case, the vector -→cand has a size of (ub-lb+r)/r and is bounded by (lb, ub+r), following a rectangular distribution. The wireless sensor's node radius is denoted by r. Equation (20), which represents the exponential coefficient ind, provides the formula for calculating it.

$$ind = \begin{cases} j\%r + 1 \; if \; j \; is \; odd \\ [-\cos\frac{\pi j}{2} * \left(\left[\frac{j}{r}\right]\%2\right) + \left|1 + \left|\cos\left(\frac{\pi j}{4}\right)\right| + [\frac{2j-2}{r}]\right|] \; if \; j \; is \; even \end{cases} \tag{20}$$

where % is the mod operator and j is the whale object's dimensional index. The purpose of this experiment is to assess and test the compatibility between the modified WOA algorithm and the five previously mentioned techniques. The evaluation metric is variance, which expresses the average overall coverage and the stability of the method. A 100 m by 100 m area was used to test the coverage of 27 target points, with an 11 m coverage radius for each target point. We carried out 30 experiments, each of which was repeated 200 times, in order to strengthen the validity of our experimental conclusions. Table 1 displays the experimental parameter settings.

Table 1: Parameters of WSN coverage optimization problem

Parameters	Values
Region size	100 m×100 m
Sensing Range	11m
Sensor Node Number N	27
Individual Number	50
Iteration	200
Test time	30

Comparison of WaOA with Other Basic Algorithms

This section compares WaOA's efficiency to that of BOA, DOA, AOA, SOA, and BES. The comparison algorithms' parameter configurations are all derived from this body of research. The algorithm suggested in this article was tested against the five collective intelligence algorithms mentioned above. Table 2 and Figure 3 display the outcomes of the program's calculations.

Table 2: Coverage ratio comparison of WOA-LFGA with other basic algorithms

Method	Avg	Std	C
BOA	69.237%	0.0284	0.7826
DOA	77.457%	0.0294	0.7630
AOA	69.437%	0.0248	0.7760
SOA	65.613%	0.0316	0.7362
BES	80.813%	0.0342	0.8874
WaOA	92.814	0.0017	0.9974

As seen in Table 3, WaOA considerably enhances the coverage optimization of WSN when compared to BOA, DOA, AOA, SOA, and BES. In this experiment, BOA, AOA, and BES can all have greater optimization effects overall, and the average application rate is less than 70%. The other three algorithms' target point ranges are comparatively high and exhibit little variations, suggesting their potential utility in optimizing wireless sensor ranges. In particular, the optimization effects of BES and DOA are comparable at 75% and 80%, whereas BES has a little larger optimization impact at 79.68%.

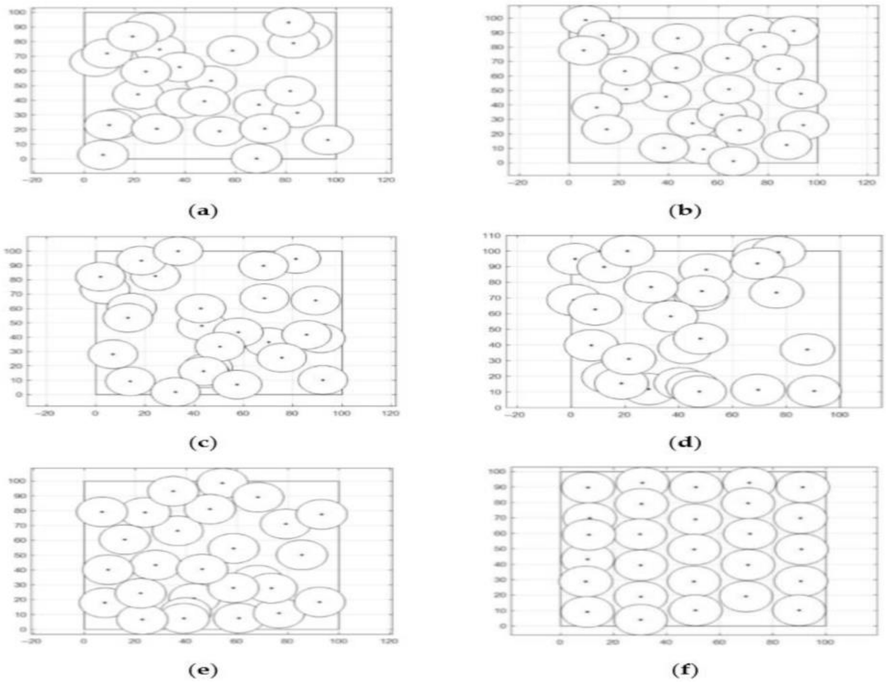


Figure 3: Node coverage distribution diagram. (a) BOA, (b) DOA, (c) AOA, (d) SOA, (e) BES, (f) WaOA

With a coverage rate of 90.97%, however, the enhanced BES in this article obtained the best optimization performance to date, surpassing the initial second-place result. At 0.0019, the difference between WaOA and the second assessment index is the lowest. Put differently, the highest stability is possessed by this algorithm. By merging the two assessment indicators, the revised BES algorithm offers apparent improvements in performance compared with the other five methods. WaOA is the optimization technique that delivers the maximum node coverage efficiency in terms of coverage efficiency. This suggests that the method has a more uniform node distribution and less redundant nodes in this region.

An ideal scenario is reached when the number of iterations approaches around 30% of the maximum number possible. Although SOA is a good approach, it might not work well for the problems this paper outlines. AOA and SMA have comparable optimization effects. Calculating the coverage age: Throughout iterations, not much changes. Although BES and DOA may reach around 80% final coverage, they will require more than 60% of iterations to attain the maximum coverage because to slower convergence rates than WaOA. This article's enhanced BES has strong practicability and efficiency in real-world applications, and it converges faster than previous algorithms.

Table 3: Iteration vs Coverage Ratio

Iteration	BOA	DOA	AOA	SOA	BES	WaOA
25	0.58	0.64	0.7	0.72	0.75	0.8
50	0.61	0.67	0.7	0.74	0.77	0.82
75	0.64	0.7	0.7	0.77	0.79	0.82
100	0.65	0.73	0.7	0.8	0.82	0.87
125	0.65	0.74	0.7	0.82	0.83	0.90
150	0.65	0.74	0.7	0.84	0.85	0.93

This minimal spanning tree is then utilized to define the communication network between monitoring nodes as seen in Figure 4.

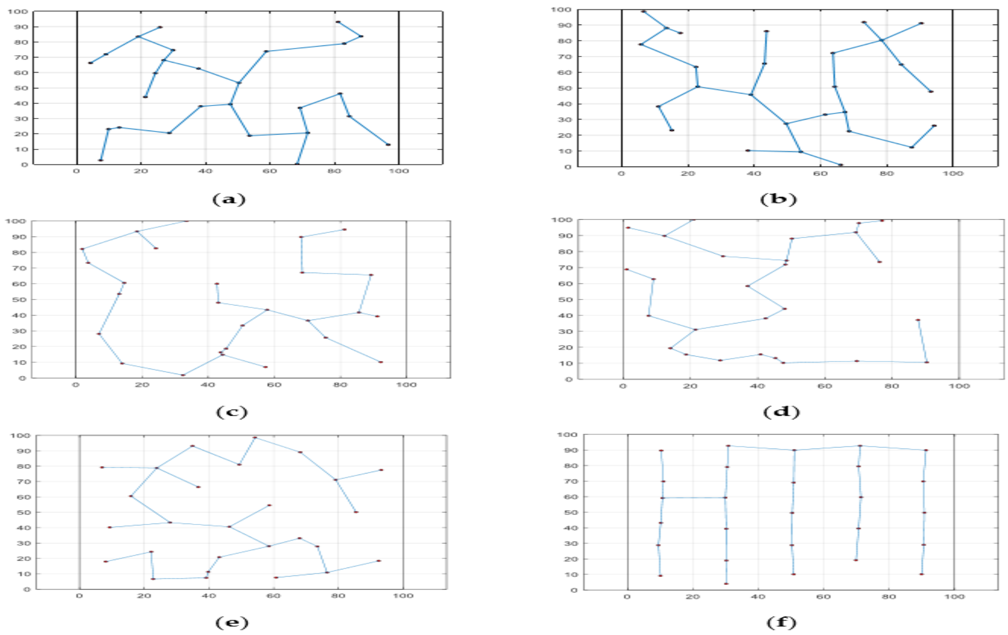


Figure 4: The composition of sensor nodes (a) BOA, (b) DOA, (c) AOA, (d) SOA, (e) BES, (f) WaOA

In terms of outcomes and uniformity of communication distance, the WaOA algorithm outperforms the other five comparison algorithms. Furthermore, by putting more sink nodes near the edge, the WaOA algorithm's optimized communication network reduces the amount of energy used during data transmission and helps minimize node distances. Throughout the node deployment process, all six options can optimize node placement to maximize network coverage. In the trials indicated above, we varied the number of deployed sensor nodes (N). Specifically, we address how the step size drops to 5 and how N increases from 10 to 30 in terms of network coverage. Table 4 displays the outcomes of the experiment. The network coverage optimized by the WaOA algorithm has a more even node distribution and shows the highest level of performance. In addition to saving energy during data transmission and extending network working duration, this serves to increase the network's overall dependability.

Table 4: Outcome of the experiment

Methods	N=10		N=15		N=20		N=25		N=30	
	avg	std	avg	std	avg	std	avg	std	avg	std
BOA	34.63%	0.00877	47.70%	0.01028	57.51%	0.01102	66.70%	0.01215	73.96%	8
DOA	37.73%	0.00657	53.55%	0.01176	64.77%	0.01743	73.12%	0.02305	79.83%	0.01749
AOA	34.59%	0.00685	47.58%	0.01183	57.85%	0.0186	65.42%	0.01425	72.50%	0.01506
SOA	34.52%	0.00919	46.03%	0.01634	55.40%	0.02252	62.08%	0.02008	67.43%	0.02664
BES	37.87%	0.00264	54.04%	0.01373	67.29%	0.01785	75.84%	0.02531	82.70%	0.02263
WaOA	38.29%	0.00042	56.72%	0.00381	72.16%	0.00747	88.75%	0.00105	93.71%	0.00272

The graph demonstrates how the number of sensor nodes changes in relation to the network coverage trend. In particular, there is not much of a coverage difference between the various approaches when the number of nodes is smaller than 20. After clearing this threshold, however, the picture progressively becomes clearer. The figure makes it clear that WaOA outperforms other algorithms with an equal number of nodes in terms of network coverage. Furthermore, the curve indicates that WaOA's coverage grows at the highest rate in relation to the number of nodes, demonstrating its excellent competitiveness against other algorithms.

WaOA for WSN Coverage Practical Application

$$\begin{cases} 0.325x < y < 0.077x + 950, & 0 < x \leq 260 \\ 0.325x < y < -0.281x + 1043.125, & 261 < x \leq 400 \\ 4.167x - 1536 < y < -0.281x + 1043.125, & 401 < x \leq 580 \end{cases} \quad (17)$$

The rise in popularity of fifth-generation mobile communication technology (5G) is being attributed to the unparalleled development of big data. Global operators are already steadily deploying 5G networks, and there are a lot of promising developments and applications for 5G technology. In addition to supporting additional device connections, it can help build smart cities and advance the Internet of Things. In this section, we handle a real-world scenario using the wireless sensor coverage optimization problem. Using Jilin Shanzhou University as an example, Figure 5a illustrates how its outline may be abstracted into an uneven pentagon. The figure is rotated 90 degrees counterclockwise for ease of calculation, as shown in Figure 5b. Equation (25) places constraints on the new boundary range. Within the pentagonal region described above, 13 target locations with coverage radii of 100 meters each were evaluated in this experiment. We carried out 30 tests, each of which was repeated 200 times, to make sure that our experimental results were more believable. Table 5 displays the experimental parameter settings.

Table 5: Parameter of WSN coverage optimization problem

Parameters	Values
Region size	400 m×400 m
Sensing Range	100m
Sensor Node Number N	13
Individual Number	50
Iteration	200
Test time	30

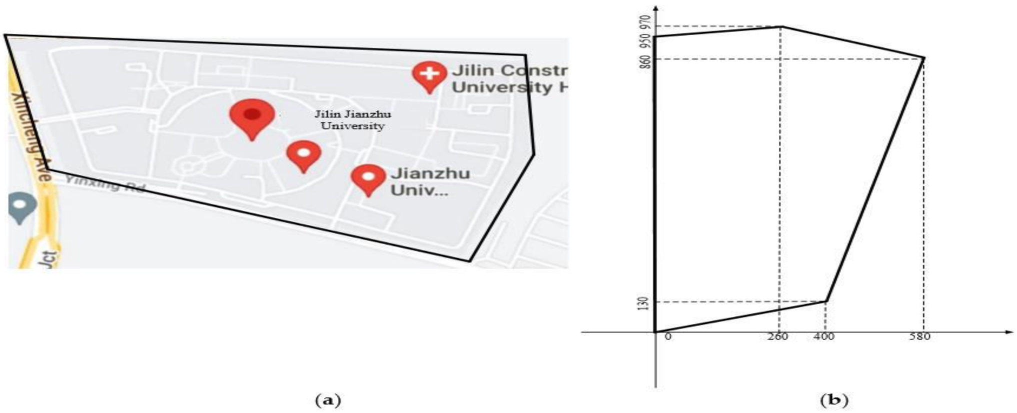


Figure 5: Jilin Jianzhu University. (a) Map of Jilin Jianzhu University, (b) Abstract of the Outline of Jilin Jianzhu University.

Comparison of WaOA with Other Basic Algorithms

We evaluate WaOA's efficiency in relation to BOA, DOA, AOA, SOA, and BES in this subsection. The comparison algorithms' parameter configurations are all derived from this body of research. The algorithm suggested in this article was tested against the five collective intelligence algorithms mentioned above. Table 6 displays the results of the program computation.

Table 6: Coverage ratio comparison of WOA-LFGA with other basic algorithms

Method	Avg	Std	C
BOA	11.4011%	0.0159	0.1229
DOA	53.0607%	0.0530	0.5722

AOA	52.3511%	0.0306	0.5645
SOA	52.2734%	0.0579	0.5637
BES	37.2967%	0.0935	0.4022
WaOA	83.7718%	0.0035	0.9033

As seen in Table 6, WaOA considerably enhances the coverage optimization of WSN when compared to BOA, DOA, AOA, SOA, and BES. By comparison, higher optimization performance is demonstrated by the coverage rates of DOA, AOA, and SOA, all of which reach more than 50%. In this experiment, BOA and BES also offered workable options for wireless sensor coverage. The usefulness of these algorithms has been demonstrated in real-world scenarios. More specifically, with a coverage of around 52%, AOA and SOA yield comparable optimization outcomes. DOA yields optimization outcomes that are marginally better—above 53%. With an average coverage of 83.77%, the enhanced BES algorithm in this research outperformed the second-place method's 30.71% optimization outcomes. WaOA's diverse boundary processing techniques and superior global search capabilities are mostly to blame for this. WaOA has the best stability and the lowest dispersion value (0.0035) when looking at dispersion. WaOA outperforms all other algorithms in terms of node coverage efficiency, which suggests reduced redundancy among nodes and a more uniform distribution of nodes within the region. The enhanced BES algorithm performs noticeably better than the other five algorithms when these three-assessment metrics are taken into account.

Table 7 shows that the WaOA proposed in this work provides the largest coverage and the fastest convergence speed. As you repeat, keep getting bigger. Growth is fast, especially in the first thirty percent of iterations, but subsequently it slows down. The ways in which DOA and AOA optimize are comparable. This is as a result of the iterative process's minimization of notable increases. Despite the comparatively quick development that BWO displayed, the outcomes did not differ substantially from DOA. Although BOA and BES are likewise excellent algorithms, the experiment's findings were unimpressive. This research suggests an improved BES that performs better than current approaches in terms of convergence speed and accuracy. It also demonstrates high practicability and efficiency in real-world applications.

Table 7: Iteration vs Coverage Ratio

Iteration	BOA	DOA	AOA	SOA	BES	WaOA
25	0.23	0.35	0.43	0.5	0.52	0.58
50	0.27	0.38	0.47	0.5	0.52	0.61
75	0.3	0.42	0.5	0.5	0.52	0.63
100	0.34	0.44	0.52	0.5	0.52	0.66
125	0.36	0.46	0.54	0.5	0.52	0.69
150	0.38	0.49	0.56	0.5	0.52	0.71

CONCLUSION

A method for building the coverage of a wireless sensor network using the WaOA (Walrus Optimization Algorithm) was created. In wireless sensor networks, this is a crucial field for study. The network coverage and coverage issue calculations are done using the probabilistic detaection approach. The optimal node coverage objective function may be mathematically modeled by measuring the distances between nodes and examining the detection range and communication capabilities of each sensor node in the deployed wireless sensor network. This article is primarily focused on static wireless sensor networks, even though the WaOA algorithm described here somewhat enhances WSN's network coverage performance. Subsequently, my primary focus will be on the optimization of coverage in mobile and heterogeneous wireless sensor networks. Application processes also over aggregate nodes in certain regions at the same time. Furthermore, WaOA considerably improves coverage, convergence, and algorithm stability when applied to WSN coverage optimization issues, yielding superior optimization outcomes over other intelligent optimization algorithms. WaOA has high competitiveness in the field of intelligent optimization, as demonstrated by the experimental findings reported in this paper. Future study will focus on decreasing the node set area and increasing uniformity of WSN coverage.

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