Optimizing Coverage in Wireless Sensor Networks Using the Cheetah Meta-Heuristic Algorithm

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Abstract— **A wireless sensor network (WSN) consists of many sensor nodes that self-organize to form a distributed network system. These networks are mostly installed randomly in cities. To ensure data transmission, reception, and processing in smart city development, many sensor nodes need to be installed throughout the city due to factors causing inadequate coverage of monitoring areas. However, heterogeneous distribution may lead to large losses of resources. To solve this problem, in this research, an optimization model for WSN coverage is proposed based on the Cheetah Optimizer (CO) algorithm. CO is a nature-inspired algorithm inspired by cheetah hunting tactics. Three main strategies used by cheetahs for hunting, searching, sitting and waiting, and attacking are included in the algorithm. In addition, a fourth strategy, leaving prey and returning home, is also added to increase population diversity, convergence performance, and robustness. Different test functions demonstrate that CO outperforms other algorithms significantly in the literature. Moreover, for optimizing WSN coverage, CO produces a higher coverage rate compared to other meta-heuristic algorithms and improved algorithms mentioned in the literature for addressing the WSN coverage optimization problem.**

Keywords: cheetah optimizer; coverage optimization; meta-heuristic algorithm; wireless sensor network

I. INTRODUCTION

The emergence of internet technology and artificial intelligence has made the Internet of Things (IoT) a popular research area. Wireless sensor networks (WSNs) are an essential component of IoTs and help achieve target monitoring and information transmission through wireless communication between multiple interconnected homogeneous sensor nodes [1]. The positive aspects of being cost-effective. [2], Adaptability and simple deployment [3] have made WSNs very popular in various industries such as aviation [4], environmental [5], medical [6], and industrial [7]. In recent years, WSNs have been widely implemented in smart transportation [8], smart homes [9], and smart cities [10] with huge applications. However, traditional random deployment methods lead to coverage gaps, high-density overlapping coverage, and wasted resources, which have a direct impact on the overall quality of detection in the targeted region. [11]. Hence, it is very important to explore flexible methods for deploying sensor nodes in WSNs, ensure uniform distribution, higher node coverage, reduce construction costs, and increase network service quality [12].

A number of meta-heuristic algorithms have been proposed by researchers that are influenced by the conduct of natural biological collectives and the laws of physics. [13]. These algorithms are popular for solving the node deployment optimization problem in WSNs due to their basic concepts, small number of parameters, and simple implementation [14]. Some common meta-heuristic algorithms to improve the coverage rate of wireless networks for this purpose are Genetic Algorithm (GA) [15], Particle Swarm Optimization (PSO) [16], Artificial Bee Colony (ABC) [17], Crow Search Algorithm (CSA) [18], Ant Lion Optimization (ALO) [19], Whale Optimization Algorithm (WOA) [20], Gray Wolf Optimization (GWO) [21], Black Hole Algorithm (BHA) [22], Butterfly Optimization Algorithm (BOA) [23], Sine Cosine Algorithm (SCA) [24], Mayfly Algorithm (MA) [25], Tunicate Swarm Algorithm (TSA) [26], Equilibrium Optimization (EO) [27], Marine Predator Algorithm (MPA) [28], Emperor Penguin Colony (EPC) [29], Harris Hawk Optimization (HHO) [30]. While these studies show the possibility of using meta-heuristic algorithms to improve the deployment of WSN nodes, further enhancement of node coverage is required.

Recently, a nature-inspired algorithm called the Cheetah Optimizer (CO) [31] has been introduced, which is inspired by the hunting tactics of cheetahs. Three main strategies used by cheetahs to hunt in CO, search, sit and wait, and attack are included in the algorithm. To increase population diversity, convergence performance, and robustness, a fourth strategy, leaving the prey and returning home, is also added. This study focuses on the efficiency of CO in addressing the coverage optimization challenge in WSNs. Considering the performance of CO in comparison with other meta-heuristic methods, the proposed method to address the matter of optimizing WSN coverage, a specific approach is implemented to provide a solution.

The innovation of the proposed method is that it uses CO, which requires a few equations, while most hunting strategies try to model the hunting process. These strategies create a trade-off between exploratory and exploitative searches and prevent premature convergence in different optimization problems. strategies or methods can be employed to ensure that the optimization process continues beyond local optima and reaches the global optimal solution. Therefore, the concepts of the proposed strategy can be effectively used to improve the coverage performance in WSNs.

The structure of this paper is as follows. Section 2 presents the mathematical description of the WSN coverage problem. Section 3 explains the proposed algorithm, including its mathematical model and computational process. Section 4 provides an analysis of the results obtained from the conducted CO tests in comparison with other methods for solving the WSN coverage problem. Finally, the conclusion summarizing the findings of this study is presented in Section 5.

II. WSN Coverage Model

Consider a WSN consisting of n identical sensor nodes randomly deployed in a two-dimensional plane sensing field of dimensions S_1 and S_2, respectively. Figure 1 shows sensing radius R_s and communication radius R_c of all the sensor nodes are identical [11]. We denote the set of wireless sensor nodes as $L = \{l_1, l_2, \dots, l_n\}$ and their corresponding positions as (x_i, y_i) where i belongs to the set $\{1,2,\dots,n\}$ is to evaluate the node coverage more accurately, the 2-dimensional plane M is discretized into $m \times n$ grid points, each grid point, denoted by k_j has a geometric center that is considered as the coverage target point (x_j, y_j). If there exists a node within the perceived radius R_s from the network point in the target area, then the WSN completely covers the network point. the Euclidean distance between sensor node li and grid point k_j is shown by Equation (1):

$$d(l_i, k_j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}. \quad (1)$$

The probability that the network node k_j is covered by the sensor node l_i is determined by Equation (2):

$$P_{cov}(l_i, k_j) = \begin{cases} 0 & if\ r_s + r_e \le d(l_i, k_j) \\ e^{-\delta a^{\beta}} & if\ r_s - r_e < d(l_i, k_j) < r_s + r_e \\ 1 & if\ r_s - r_e \le d(l_i, k_j) \end{cases}, \quad (2)$$

where r_e is the radius of perceptual error, δ and β are constant coefficients, and $a = d(l_i, k_j) - (r_s - r_e)$. In this area, any network can be covered by several sensor nodes simultaneously. Equation (3) represents the mathematical model for joint coverage probability.

$$P(L, k_j) = 1 - \prod_{i=1}^{N} \left(1 - P_{cov}(l_i, k_j)\right). \quad (3)$$

The set L contains all the sensor nodes located in the target area. To calculate the overall extent of network coverage in the specified region, you need to divide the number of networks that are covered by the total number of networks present in that area. Therefore, the mathematical representation of the R_{cov} coverage value is as Equation (4):

$$R_{cov} = \frac{\sum_{i=1}^{m*n} P(L, k_j)}{m * n}. \quad (4)$$

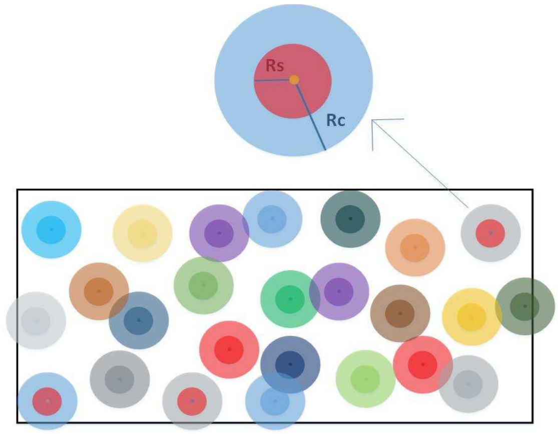


Figure 1. Random deployment of WSN with uniform sensor radius $\boldsymbol{R_s}$ and communication radius $\boldsymbol{R_c}$

The goal of WSN coverage optimization, as shown in Equation (4), is to strategically place an appropriate number of sensor nodes in a sensible region in order to reach the highest possible level of R_{cov}. To achieve this goal, this research uses a CO and applies it to obtain an optimal value for R_{cov}, which in turn improves the overall coverage of the WSN.

III. Proposed Method

CO is one of the fast optimization algorithms that is able to effectively and efficiently find the optimal solution for complex and large-scale problems in a short time. For this reason, this algorithm has been used in the proposed method of coverage optimization. CO is a meta-heuristic optimization algorithm inspired by the hunting behavior of cheetahs. The goal of this algorithm is to find an optimal solution to a problem by mimicking the search behavior of a cheetah while hunting prey. Cheetahs have different approaches to hunting prey. It may detect prey while scanning or patrolling its surroundings, or it may wait for prey to get closer before attacking. The attack consists of two stages: rushing toward the prey at maximum speed and catching it using speed and flexibility. However, if the cheetah is unable to catch prey for reasons such as fatigue or fast prey, it may abandon the prey and return home to rest before starting a new hunt. To determine which approach to use, the cheetah considers factors such as the position, condition, area, and distance of the prey. CO uses these strategies during hunting periods to improve the cheetah's success rate. These strategies include searching for prey, sitting and waiting for better conditions, rushing to attack and capture, and leaving prey and returning home under certain conditions.

To apply CO for coverage optimization, we need to define the problem data and dimensions (D) appropriately. For example, we can consider a set of points to be covered by a fixed number of sensors on a 2D plane. In this case, D represents the number of sensors and the problem data contains the coordinates of the points to be covered.

To initialize the population of cheetahs X_i where $i = \{1,2,\dots,n\}$ we can randomly place sensors in the plane and evaluate the fitness function of each cheetah by computing the coverage obtained from the sensor placement. The fit function measures the coverage quality by calculating the percentage of points covered by the sensors.

After initializing the population, we can proceed with CO. However, we need to modify the algorithm to accommodate the specific requirements of the coverage optimization problem. For example, we can change the phase of the attack to ensure that the sensors do not move outside the region's boundary. Similarly, we can modify the bait-and-return strategy to ensure that the sensors do not stray too far from the points to be covered.

The search strategy of cheetahs includes two modes of scanning and active patrolling, which depends on the density and activity of prey in the area. A mathematical model is proposed to simulate this strategy, where the position of each cheetah is denoted by X_t.

The position, (i, j) is updated using a stochastic search equation using their current coordinates and the magnitude of their individual steps. The position of the leader is updated based on the position of the prey, and the CO can use any randomization parameter and step size to solve optimization problems. The sit-and-wait strategy is also used when prey is close and the cheetah stays still to avoid detection before attacking.

The attack strategy of cheetahs involves using their speed and flexibility to chase and intercept their prey. They adjust their movement based on the position of the prey and use a rotation factor and interaction factor to catch it. In group hunting, each cheetah adjusts its position based on the fleeing prey and the position of the leader or neighborhood cheetah. Mathematically, the rotation coefficient represents the interaction between the cheetah or between the cheetah and the leader in a holding position.

In the following, the steps of the proposed algorithm for optimizing the coverage in WSN are explained:

• First, initialize WSN with a random algorithm.

• Then calculate the distance between coverage points and define it as coverage cost.

• Then, for each sensor, consider a set of neighboring sensors and calculate the coverage cost with new changes.

• Improve the sensor location due to the cost of the new cover. Here is the place that is transferred exactly to the point where the coverage cost is lower.

• Using inspiration from the group behavior of cheetahs, CO improves the location of sensors in a parallel and coordinated manner. By using the mathematical formulas of CO, the location transfers of the sensors are carried out in a coordinated and optimal way.

• Steps 3 to 5 continue until it has no other sensors to improve its location.

• If the coverage cost is minimized or reaches a steady state, the algorithm stops.

• Otherwise, the algorithm continues recursively until all sensors are recovered.

The flowchart of the proposed method is shown in Figure 2. By using CO, WSN is covered more optimally. In general, CO can be a useful tool for solving cover optimization problems, especially when there are multiple local optima or the search space is large.

Covering WSN with CO has many advantages, some of which are mentioned below:

• Improvement of network coverage: CO improves the coverage of WSN. This algorithm is able to automatically and intelligently determine the level of network coverage, and thus there is no need for manual and costly adjustments to manage network parameters.

• Cost reduction: by optimizing the coverage of WSN with CO, the implementation costs of the network can be reduced. For example, the use of this algorithm causes the consumption of energy and network resources to be significantly reduced, and thus the costs of network management can be reduced.

• Increased efficiency: by optimizing the coverage of WSN, the efficiency of the network increases dramatically. Efficiency in WSN is very important for data collection, and CO improves network efficiency significantly.

• Increasing battery life: by optimizing the WSN coverage with a meta-heuristic algorithm, the battery life of network devices can be significantly increased. By optimizing the network coverage, sending data and replaying them is reduced, which makes the device's battery last longer.

• Error reduction: using CO, the error in data collection in WSN is significantly reduced. This algorithm intelligently and automatically tries to data.

IV. Evaluation

To test the effectiveness and feasibility of the proposed method for optimizing node coverage in WSN, the performance of CO was compared with SCA [24], TSA [26], MA [25], EO [27], and MPA [28]. The parameters used in the experiments were set as in Table 1. This experiment was conducted with the aim of validating the effectiveness of CO in optimizing WSN node coverage.

According to the findings presented in Table 2, it is evident that the CO algorithm outperforms other algorithms in terms of both mean and standard deviation (SD) of the optimal solution. Moreover, the CO algorithm achieves these better results within a reasonable time frame.

TABLE I. SPECIFIC SETTINGS AND VARIABLES USED IN EACH ALGORITHM

Algorithm	Parameter
SCA [24]	$f_{max} = 2.5, f_{min} = 0$
TSA [26]	$c_1, c_2, c_3 \in (0,1), P_{min} = 1, P_{max} = 4$
MA [25]	$g = 0.8, gdamp = 1, a_1 = 1, a_2 = 1.5, a_3 = 1.5, dance = 5$
EO [27]	$a_1 = 1, a_2 = 1.5, GCP = 0.5$
MPA [28]	FADs = 0.2, P = 0.5
CO [31]	r_2, r_3, r_4 $are\ random$

TABLE II. TIME COMPARISON OF THE PERFORMANCE OF SEVERAL POPULAR METAHEURISTIC ALGORITHMS

Algorithm	Proposed CO	SCA [24]	TSA [26]	MA [25]	EO [27]	MPA [28]
Mean	4.12	60.37	42.00	33.97	77.02	28.37
SD	20.01	121.30	165.60	151.59	66.53	40.54
Average run time for 50 runs (s)	1.45	3.16	4.60	2.27	3.75	1.77

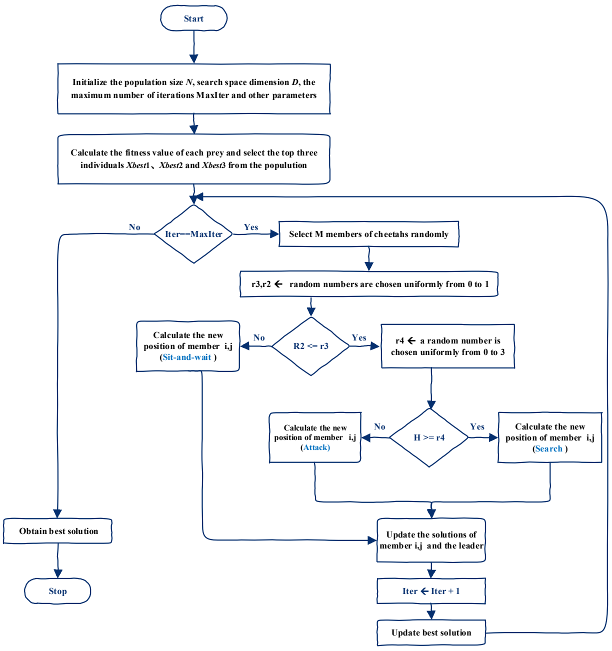


Figure 2. Flowchart of the proposed method

Suppose there are 40 sensor nodes in a sensor field with dimensions $M = 50m * 50m$. The sensing radius of each sensor node is set to $R_s = 5m$, while the communication radius is set to $R_c = 10m$. The maximum number of iterations is $T_{max} = 500$. Table 3 shows the specific values of these parameters.

TABLE III. SETTINGS OF COVERAGE PARAMETERS IN WSN

Parameter	Value
Area	50m*50m
Number of sensor node	40
perceptual radius	5m
Communication radius	10m
Maximum number of iterations	500

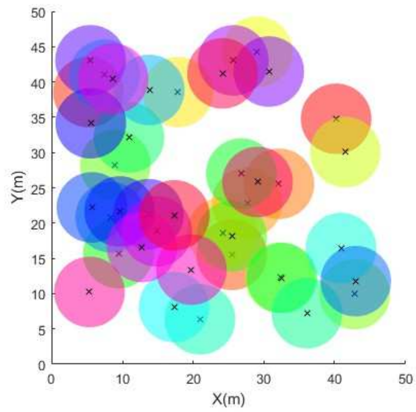
TABLE IV. COMPARISON OF AVERAGE COVERAGE RATE OF OPTIMIZATION ALGORITHMS

Algorithm	Percentage of average coverage rate (%)
Random deployment [11]	74.62
EO [27]	89.44
SCA [24]	76.88
MPA [28]	88.81
Proposed CO	93.72

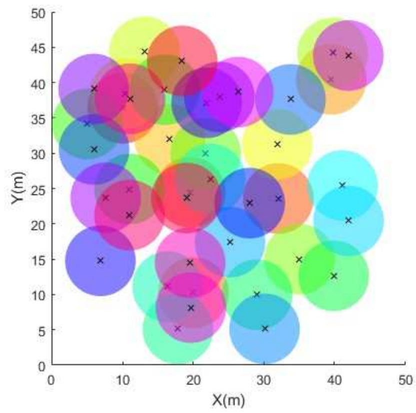
Through these simulations, the effectiveness of CO in addressing WSN coverage was evaluated. Table 4 compares the proposed method with other approaches and it shows that CO achieves a coverage rate of 93.72%, which is 19.10%, 4.28%, 16.84%, and 4.91% better than random deployment [11], EO [27], SCA [24], and MPA [28], respectively.

Figure 3 shows the node coverage graphs for each algorithm. Figures 3 (a) and 3 (c) demonstrate a wide range of coverage voids in the middle area that were optimized through a combination of random deployment and the SCA algorithm. In contrast, Figures 3 (b) and 3 (d) show that the upper left region optimized by the EO and MPA algorithms suffers from serious overlap issues. In comparison, Figure 3 (e) shows that the node coverage obtained by CO is more uniform and full coverage of the target area is achieved.

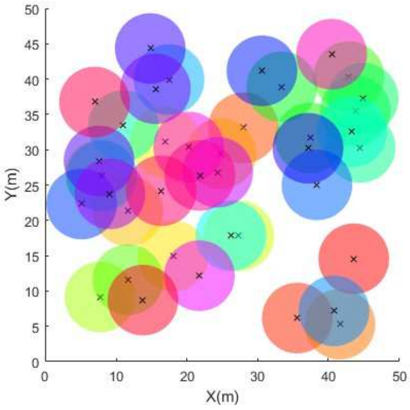
To investigate the effect of the number of sensor nodes on the optimized coverage by WSN, Simulation tests were carried out on the target area using various quantities of identical sensor nodes (ranging from 35 to 55) for the random deployment algorithm, MPA, and CO. The other parameters used in the experiment corresponded to those specified in Table 3. Figure 4 displays the fluctuating pattern of the coverage ratio for each algorithm with respect to the varying number of nodes.



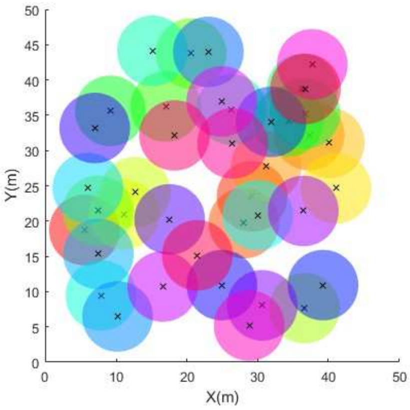
(a) Random Deployment [11]



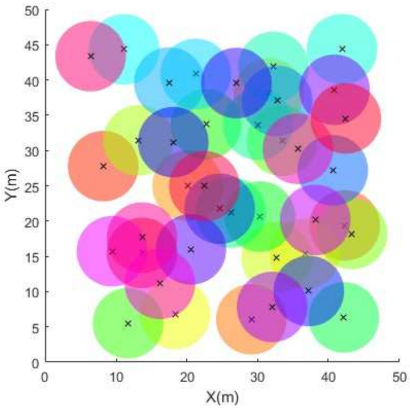
(b) EO optimization [27]



(c) SCA optimization [24]



(d) MPA optimization [28]



(e) Proposed CO optimization

Figure 3. Node coverage graphs for each algorithm (a) Random deployment node coverage graph, (b) Node coverage graph optimized by EO, (c) Node coverage graph optimized by SCA, (d) Node coverage graph optimized by MPA, and (e) node coverage diagram optimized by CO.

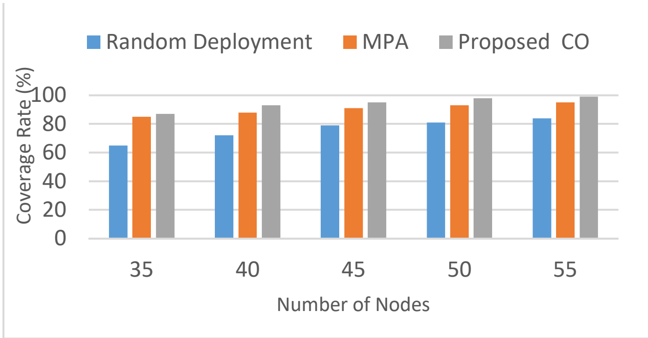


Figure 4. Comparison of coverage rate with different numbers of nodes in random deployment [11], MPA [28] and Proposed CO

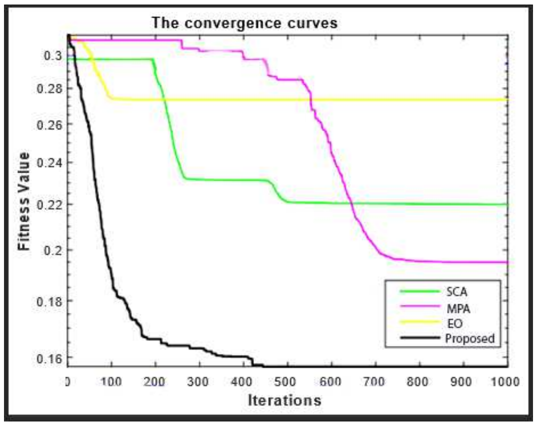


Figure 5. Convergence characteristics of EO, MPA, SCA and proposed algorithm on shifted-rotated CEC2005 benchmark functions [32]

As shown in Figure 4, the proposed algorithm outperforms random deployment and MPA in terms of node coverage rate for WSNs with different numbers of nodes. The CO strategy yields an almost perfect coverage rate of 99% when there are 55 nodes. These results show that the strategies used by CO are effective in increasing the probability of avoiding local optima and balancing global exploration, which leads to the improvement of the effective coverage rate for WSN nodes.

To analyze the convergence of different algorithms plots the convergence curves for benchmark functions. Figure 5 show Convergence characteristics of EO, MPA, SCA and Proposed algorithm on shifted-rotated CEC2005 benchmark functions.

V. Conclusion

This research proposes the CO meta-heuristic algorithm as a tool to increase the coverage rate of node deployment in WSNs to enhance the coverage efficiency of WSNs in monitoring regions and reduce resource wastage. The performance of CO was tested against existing meta-heuristics and improved algorithms. The results show that CO outcomes are better than other algorithms in terms of stability and optimization performance. Finally, CO was applied to a WSN coverage optimization problem, which showed higher coverage compared to random deployment, EO, SCA, and MPA. Future research will focus on other objectives in addition to the issue of optimizing coverage in WSN, such as estimating energy consumption and adjusting the size of sensor node perceptual radii to increase the network life cycle by reducing sensor redundancy.

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