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Optimizing Coverage in Wireless Sensor Networks Using the Tumbleweed Algorithm

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Abstract. *Wireless sensor networks (WSNs) have found extensive applications across various fields, significantly enhancing the convenience in our daily lives. Hence, an increasing number of researchers are directing their attention toward the performance of sensor nodes, with a particular emphasis on addressing the coverage challenges in WSNs. Node coverage plays a crucial role in determining the detection performance of WSNs, making it imperative to attain maximum coverage with a given number of sensor nodes. This paper applies the Tumbleweed Algorithm (TA) to the coverage problem in WSNs and validates its effectiveness through simulation experiments. The results demonstrate its unique advantages in global search and avoiding local optima, providing a new solution for the WSN coverage problem and offering valuable references for future research and practical applications. The TA algorithm simulates the lifecycle of tumbleweed from seedling to mature plant and includes the concept of growth cycles. This paper compares the TA algorithm with PSO, GWO, DE, BOA, SCA, and AOA, setting different numbers of wireless sensor nodes and varying sensing radii for the experiments. The experimental results show that the TA algorithm significantly improves coverage rates under various configurations and consistently outperforms other commonly used algorithms.*
Keywords: Tumbleweed algorithm, Meta-heuristic evolutionary algorithm, Wireless sensor networks

1. **Introduction.** The random distribution of a large number of wireless sensor nodes constitutes a wireless sensor networks (WSNs), through which it is able to collect necessary information from the surrounding environment [1]. As the applications of WSNs continue to expand, the network coverage problem has attracted much attention. However, there is a challenge of having a large number of sensor nodes with low network coverage in practical applications [2] [3]. Network coverage refers to the ability to recognize the actual situation of the monitored objects to a certain extent, which aims to ensure sensing services while expanding the network coverage as much as possible. Enhancing the coverage of WSNs is a crucial objective.

The importance of network coverage is not only limited to ensuring perceptual services, but also involves practical applications and the enhancement of social well-being in a number of fields. Enhancing the coverage effectiveness of WSNs in agriculture enables real-time monitoring of crop growth. Moreover, leveraging sensor data for precise agricultural management allows for the optimization of the production process, ultimately leading to improvements in agricultural yield and quality. This not only helps farmers reduce costs but also promotes the development of sustainable agriculture. In terms of environmental monitoring, expanding network coverage allows us to more comprehensively monitor changes in atmospheric composition, which not only enables us to identify sources of air pollution in a timely manner, but also helps us to formulate more effective environmental protection policies. WSNs enable real-time monitoring of urban air quality, contributing to the enhancement of residents' living environments. In the medical field, by placing sensors on patients, the expansion of network coverage enables doctors to access patients' physiological parameters and health status in a more timely manner. This not only improves the efficiency of medical services, but also provides patients with more comprehensive and personalized medical care. Therefore, the continuous expansion of network coverage has far-reaching implications for promoting scientific and technological innovation, enhancing social productivity, and improving people's quality of life.

To cope with complex problems for which it is difficult to find an exact solution in a reasonable amount of time, we often resort to meta-heuristic algorithms. These algorithms are inspired by observations of nature, biology, physics, and other fields, as well as heuristics for solving complex problems. These include Particle Swarm Optimization

(PSO) [4] [5], Simulated Annealing (SA) [6], Genetic Algorithm (GA) [7], Whale Optimization Algorithm (WOA) [8] [9] [10], Grey Wolf Optimization (GWO) [11] [12], Cat Swarm Optimization (CSO) [13] [14], Differential Evolution (DE) [15] [16], Ant Colony Optimization (ACO) [17] and Phasmatodea Population Evolution Algorithm [18]. These are classical meta-heuristic algorithms that provide flexible and effective solutions to complex problems by combining different heuristic principles.

Additionally, there have been notable advancements in the study of new metaheuristic algorithms, with the Golden Eagle Optimizer (GEO) standing out as an excellent example [19] [20] [21]. GEO is mainly inspired by the behavior of golden eagles that adjust their speed at different stages of the spiral trajectory in order to hunt. In the first stage of hunting, they prefer to roam around in search of prey, while in the final stage, they then begin to attack. In comparison with several other algorithms, it is evident that GEO excels in approximating the true optimal solution. The algorithm provides an effective and unique approach to solving the problem by simulating the behavior of golden eagles in different stages and flexibly adjusting the speed.

Another noteworthy algorithm is Fish Migration Optimization (FMO), which draws inspiration from fish migration patterns. FMO integrates migration and swimming models into the optimization process. In a related study [22], the FMO algorithm was further explored and applied to a Proportional Integral Derivative (PID) controller. Through experiments, it can be seen that the optimized FMO algorithm tuned PID controller is more robust and has superior performance compared to other comparative algorithms.

The meta-heuristic algorithm has several significant advantages in problem-solving. First of all, it is a versatile method that can flexibly cope with a variety of different types of problems, including combinatorial optimization and constrained optimization. Its flexibility is manifested in the algorithm's ability to adapt to different problem scenarios by adjusting parameters or combining different heuristic principles, making it more adaptable in dealing with problems of various complexities and structures. Secondly, meta-heuristic algorithms usually have strong global search capability and have the ability to find potential global optimal solutions in a huge search space. This property is crucial for complex problems that have multiple local optimal solutions, ensuring that the algorithms are able to search for solutions towards the global optimum rather than just falling into a local optimum.

These algorithms have been utilized for solving optimization problems across various domains due to their considerable benefits. For example, in the fields of image processing [23] [24] [25], routing optimization [26] [27], sensor network deployment [28], logistics path planning [29], and portfolio management [30]. These application areas are only a part of the wide range of applications of meta-heuristic algorithms, and their flexibility and applicability make such algorithms highly favored for solving real-world problems [31]. Therefore, the continuous development and innovation of these algorithms can provide richer solutions for WSNs application areas and drive the continuous progress of WSNs technology [32] [33].

This paper successfully applies the Tumbleweed Algorithm (TA) [34] [35] to the coverage problem in WSNs. The coverage problem in WSNs is a complex and challenging optimization issue involving effective deployment of sensor nodes and maximizing coverage range. By introducing the TA algorithm into the optimization of WSNs, this paper provides a novel solution to the coverage problem and validates its effectiveness through simulation experiments. Through these experiments, the paper comprehensively evaluates the performance of the TA algorithm under different configurations, further demonstrating its advantages in solving the WSN coverage problem. The experimental results indicate that by adjusting the number of sensor nodes and the sensing radius, the TA algorithm is capable of maintaining extensive coverage across different scenarios, showcasing its adaptability and robustness. The TA algorithm excels in improving coverage rates, significantly outperforming other commonly used optimization algorithms such as PSO, GWO, DE, Butterfly Optimization Algorithm (BOA) [36], Sine Cosine Algorithm (SCA) [37], and Archimedes Optimization Algorithm (AOA) [38].

Tumbleweed, a common plant in the desert, grows similarly to other plants in the seedling stage. However, when faced with drought, it employs a unique survival strategy – rolling up its roots to form a ball and tumbling with the wind, thus dispersing its seeds. This distinctive behavior serves as inspiration for the TA algorithm. Upon discovering a favorable environment, the tumbleweed will retreat into the earth to assimilate moisture, showcasing resilient vitality. The TA algorithm emulates two pivotal phases of tumbleweed: the growth stage, spanning from seedling to adulthood, and the seed propagation stage occurring post-establishment of the seedling. In [39], the TA algorithm was optimized and produced superior results when applied to the problem of vehicle path planning. Therefore, the TA algorithm will provide a novel and effective optimization solution for the coverage problem of WSNs.

The subsequent sections of the paper are outlined as follows: Section 2 describes the fundamentals of the TA algorithm and the problems associated with WSNs coverage. Section 3 compares and analyzes the experimental results of the algorithm. Finally, the full paper is summarized and future work is discussed in Section 4.

2. **Realted work.**

2.1. **Tumbleweed Algorithm.**

In diverse spatial areas, the TA algorithm encompasses n scattered tumbleweeds, with each seedling being denoted by an expression $X_i (i = 1, 2, ..., n)$. Within this population, there exists a single most vigorously growing seedling, which is denoted by $Gbest$. This specific seedling harbors the potential to mature into a fully developed tumbleweed, dispersing its seeds in the process. The subsequent passage provides an in-depth explanation of the two fundamental stages of the TA algorithm.

In the first phase, the TA algorithm focuses on individual growth and optimization. During this phase, the development of tumbleweed seedlings is influenced by the intricacy of the surrounding environment. We posit that environmental influence primarily stems from two aspects. Firstly, it involves the impact of robust seedlings on the surrounding seedlings, denoted as $P1$. Secondly, it encompasses the influence of factors such as water, humidity, temperature, and others, represented by $P2$. The expressions for the two influences $P1$ and $P2$ are as follows.

By integrating $P1$ and $P2$, the TA algorithm adapts the growth state of seedlings to the optimization needs of the local environment by adjusting the growth state of seedlings during the development stage. This approach of integrating influencing factors helps to simulate the complexity of plant growth in real environments, which leads to more effective optimization of individual growth.

$$P1 = R1 \times \left(Gbest - X^i_{old}\right) \tag{1}$$

$$P2 = \frac{R2}{\frac{f\left(X^i_{old}\right)}{sum\left(f\left(X^i_{old}\right)\right)} + 1} \tag{2}$$

$$R1 = t1 \times \left(1 - \frac{ite}{max\_ite}\right) \tag{3}$$

$R1$ represents the influence coefficient of a robust seedling, which is calculated by Equation (3). As the algorithm iterates continuously, the value of $R1$ exhibits a linear decreasing trend, decreasing from 2 to 0. Here, $t1$ takes the fixed value of 2, max_ite is the maximum number of iterations, and ite denotes the current iteration number. On the other hand, $R2$ denotes the impact of the surrounding environment, assigned a random value ranging from 0 to 0.1. The fitness function $f(X_i)$ is used to assess the adaptability of the seedlings. Ultimately, the equation for updating tumbleweed is presented as follows:

$$X^i_{new} = X^i_{old} + P1 + P2 \tag{4}$$

In the second stage, which is the exploration stage, the TA algorithm facilitates the optimization process in striking a balance between local and global considerations. To achieve this, we have incorporated the idea of a growth cycle, enabling transitions between stages based on assessments of growth generations. For instance, setting a growth cycle of 50 generations implies that seedling development and seed reproduction each occupy half of the growth cycle. This is analogous to tumbleweed's skillful transition between adapting to drought and finding a suitable environment. The renewal of tumbleweed during the seed reproduction phase can be represented by the following equation.

$$X^i_{new} = Gbest + V_i \times \frac{ite}{max\_ite} \tag{5}$$

where V_i follows a uniform distribution with values in the interval $[lb, ub]$. Algorithm 1 is the pseudo-code of the TA algorithm.

Algorithm 1 Tumbleweed Algorithm.

Input: Number of iterations (max_ite), dimensions (Dim), growth cycle (gc), the size of a population (N_p)

Output: The optimal solution produced by each iteration ($best\_fit$) and ($Gbest$).

1: Initialize the number of groups
2: **for** $ite = 1 : max\_ite$ **do**
3: Calculate the fitness value for each population;
4: Update the global optimal individual and its fitness value ($f(Gbest)$);
5: **if** $mod(ite, gc) < gc/2$ **then**
6: Update $P1$ using Equation (1);
7: Update $P2$ using Equation (2);
8: Update $R1$ using Equation (3);
9: Update X_{new} using Equation (4);
10: **else**
11: Update X_{new} using Equation (5).
12: **end if**
13: **end for**

2.2. **Coverage model for WSNs.** There is a growing number of approaches in the field dedicated to studying 2D planar area coverage. After in-depth research, it has been recognized that many scenes and applications in the real world exhibit distinct three-dimensional characteristics, and simple two-dimensional models struggle to capture these complexities. This has prompted scholars to turn to the exploration and study of 3D overlays to more comprehensively and accurately solve problems related to real-world scenarios. The introduction of 3D coverage provides more possibilities for practical problem solutions for WSNs, compensates for the limitations that cannot be met by 2D, and provides more practical solutions for applications in various fields [40] [41].

Focusing on the connectivity and k-coverage rate issues in 3D WSNs, the Reuleaux tetrahedral model was proposed in [42] to ensure that k-coverage is achieved in the 3D domain, thus increasing the lifetime of the entire network. Another innovative proposal is presented in [43], introducing a new coverage model known as surface coverage. In this model, studied on complex surfaces in 3D, sensors are exclusively deployed on intricate surfaces to enhance the accuracy of monitoring targets of interest. The focus of the research in [44] is the deployment of sensors in 3D terrain. It determines the optimal location of the sensors by employing a multi-objective genetic algorithm, where the mutation operator is based on the wavelet transform. In addition, by calculating the minimum spanning tree of the network, not only the minimum path loss value of the network is determined, but also the maximum coverage gain is achieved. This comprehensive research approach not only helps to optimize the deployment of sensors, but also achieves significant progress in terms of network performance and efficiency. In [45], a probabilistic coverage model based on Digital Elevation Model data is proposed, considering the impact of signal attenuation and terrain obstruction on coverage effectiveness. Furthermore, they utilized a greedy algorithm based on grid scanning for deploying nodes, effectively increasing coverage rates and reducing deployment costs. In [46], a 3D terrain sensor deployment algorithm based on vertex coloring is proposed to determine sensor requirements and their optimal positions. The study also employs a breadth-first search algorithm to assess the connectivity quality of sensors in the network. Findings reveal that this algorithm ensures efficient coverage and connectivity when compared to current methods.

This paper primarily aims to address the difficulties encountered in covering three-dimensional areas using a fixed number of nodes. To model the coverage problem more realistically, we arrange these nodes on a 3D terrain, which is shown in Figure 1. The most widely used perception models in WSNs include the Boolean perception model and the probabilistic perception model [47] [48]. We adopt the Boolean perception model, also known as the binary perception model. In Figure 2, the circular point S represents the sensor node. We define a circular area centered at S, where r indicates the perceptual radius of the sensor node S. This area represents the sensor node's sensing range. Let k be the monitoring target, if target k falls within this circular region, it is regarded as being covered by sensor node S.

Within the monitoring area, N sensor nodes are distributed, and we represent one of them as S_i, with 3D coordinates (x_{si}, y_{si}, z_{si}). Correspondingly, the coordinates of the detection target k are (x_k, y_k, z_k), and the distance D between them can be calculated by applying Equation (6). The *Los* algorithm is used to check for obstacles, ensuring no barriers exist between sensor node S and detection target k. Equation (7) is then utilized to determine if target k is within the coverage of sensor node S. A result of 1 indicates that the target k is within the sensing range, while a result of 0 signifies that the target is not within this range.

$$D = \sqrt{(x_{si} - x_k)^2 + (y_{si} - y_k)^2 + (z_{si} - z_k)^2} \tag{6}$$

$$K(S_i, k) = \begin{cases} 1, & D < r \ \& \ ifLOS, \\ 0, & otherwise \end{cases} \tag{7}$$

Assuming the discretization of the monitoring area into M spatial points, by solving Equation (8), we are able to determine the coverage within the monitoring area. This approach is an in-depth exploration of the geometric relationship between sensor nodes

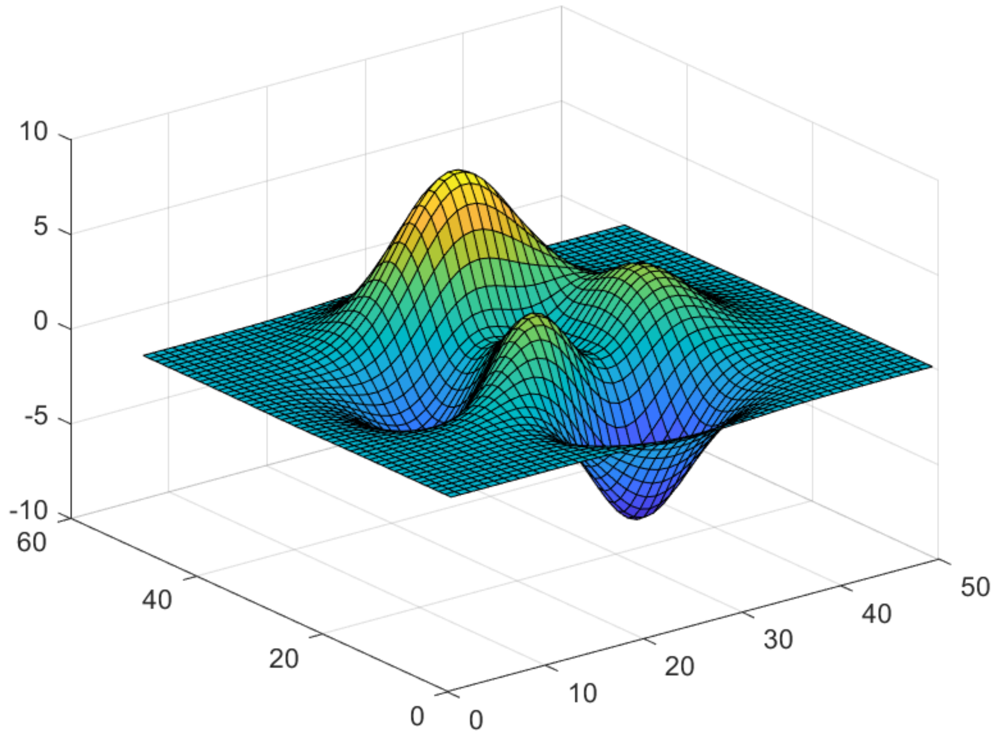

FIGURE 1. 3D model.

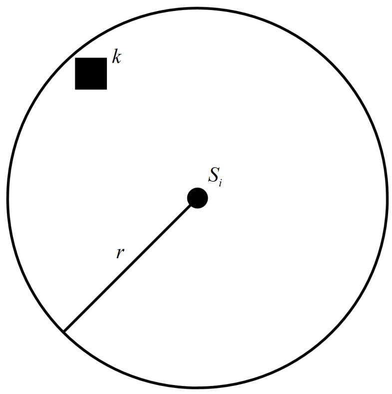

FIGURE 2. Boolean perception model.

and targets and the effect of obstacles on coverage judgments to provide a comprehensive understanding of the coverage within the monitored area.

$$CR = \frac{\sum K\left(S_i, k\right)}{M} \tag{8}$$

3. **Experimental analysis of WSNs coverage.** In order to assess the TA algorithm's effectiveness in wireless sensor network coverage, we compared its application in a three-dimensional scenario with PSO, GWO, DE, BOA, SCA and AOA. Table 1 outlines the parameters for each algorithm. In a mountainous area with a size of 50*50, we carried out random deployment of wireless sensors. To maintain experimental fairness, we standardized the population size for each algorithm to 30. Additionally, we performed 30 independent runs for each algorithm, subsequently computing the average coverage for comprehensive analysis. This design intends to thoroughly evaluate the performance of

the seven algorithms under identical conditions, enabling a more precise comparison of their coverage effects.

Two test cases were carried out: one varied the size of the radius while keeping the number of sensor nodes constant, and the other varied the number of sensor nodes while maintaining a constant radius. During testing, the algorithm's dimension was set to twice the number of nodes. By conducting tests with various parameter settings, we demonstrate the strong performance of the TA algorithm. These tests are designed to offer a thorough understanding of the algorithm's performance across different configurations and highlight the flexibility and effectiveness of the TA algorithm in dealing with different scenarios.

According to the results presented in Tables 2 and 3, we can observe that an increase in the number of nodes results in improved coverage with a defined perceptual radius. As shown in Tables 4, 5, 6, and 7, an increase in the radius also enhances coverage with a defined number of nodes.

In Table 3, when the number of sensors is 30, the TA algorithm achieved a coverage rate of 96.01%, significantly higher than other algorithms. The GWO algorithm also performed well, with a coverage rate of 95.56%. In contrast, the coverage rates of the other five algorithms (PSO, DE, BOA, SCA, and AOA) were around 94%. In Table 4, we found that when the sensing radius is 5 and 7, the gap between the TA algorithm and other algorithms is even more pronounced, especially compared to AOA, with a coverage difference of up to 4%. This disparity is due to the TA algorithm's unique advantages in node deployment and coverage optimization. By simulating the random rolling and propagation behavior of tumbleweeds, the TA algorithm more effectively optimizes node layout, resulting in more uniform and comprehensive coverage. In contrast, other algorithms fail to effectively balance coverage among nodes during optimization, leading to areas with insufficient coverage or excessive overlap. Therefore, the TA algorithm demonstrates stronger optimization capabilities for the WSN coverage problem, significantly improving coverage rates and achieving better network performance.

The comprehensive experimental results demonstrate that the TA algorithm consistently sustains high coverage levels amidst dynamic alterations in sensing radius and the number of nodes. This observation underscores the real-time adaptability of WSNs facilitated by the TA algorithm. Moreover, the particular superiority shown by the TA algorithm when the radius is 5 and 7 further emphasizes its adaptability to a medium range of sensing radius. This implies that the TA algorithm can provide superior performance in practical applications when the WSNs need to monitor efficiently over a certain range. Research has shown that algorithms such as PSO, GWO, DE, BOA, SCA, and AOA exhibit varying degrees of advantages in WSN coverage optimization, but there is still room for improvement in terms of flexibility and coverage rates. The TA algorithm demonstrates significant adaptability under different node counts and radius settings, maintaining high coverage rates across multiple configurations. Compared to other algorithms, the TA algorithm achieves the highest coverage rates in most cases, demonstrating its convergence and optimization capabilities. The TA algorithm yields better results with fewer resources and fewer sensors, particularly notable at moderate sensing radii. By optimizing node deployment and communication range, the TA algorithm can reduce energy consumption, thereby prolonging the operational lifespan of WSNs, which holds significant implications for practical applications. All in all, the TA algorithm achieved the highest coverage in all these cases, demonstrating its significant performance advantages in WSNs.

4. **Conclusions.** In this paper, the three-dimensional coverage problem of WSNs is optimized by the recently proposed TA algorithm. The TA algorithm focuses on simulating

Table 1. Algorithm Parameters

Algorithms	***Parameter settings***
PSO	c1=2, w=0.9, c2=2
GWO	a: decreases linearly from 2 to 0
DE	cr=0.5, F=0.9
BOA	probabibility switch=0.8, modular modality=0.01, power exponent=0.1
SCA	a=2
AOA	C1=2, C2=6, C3=1, C4=2

Table 2. Results for different number of nodes when radius = 6

Number of sensors	***TA***	***PSO***	***GWO***	***DE***	***BOA***	***SCA***	***AOA***
30	63.75%	60.68%	61.03%	60.98%	61.09%	60.31%	60.41%
35	69.02%	66.22%	66.52%	66.08%	65.89%	66.08%	65.55%
40	72.78%	70.67%	71.25%	70.70%	70.35%	70.40%	70.55%
45	77.18%	74.85%	74.44%	74.56%	74.76%	74.40%	74.42%
50	80.39%	77.87%	78.07%	77.95%	78.36%	77.66%	77.83%
55	83.35%	80.53%	81.02%	81.20%	81.08%	81.05%	80.92%

Table 3. Results for different number of nodes when radius = 10

Number of sensors	***TA***	***PSO***	***GWO***	***DE***	***BOA***	***SCA***	***AOA***
30	96.01%	94.13%	95.56%	94.44%	94.35%	94.19%	94.11%
35	97.49%	96.19%	96.81%	96.85%	96.07%	96.43%	96.10%
40	98.41%	97.50%	98.11%	98.03%	97.55%	97.65%	97.50%
45	99.05%	98.39%	98.59%	98.64%	98.40%	98.40%	98.46%
50	99.46%	98.83%	99.12%	99.23%	99.01%	99.00%	98.74%
55	99.68%	99.13%	99.47%	99.53%	99.32%	99.35%	99.23%

Table 4. Results for Different Radii when Number of Nodes = 30

Number of radius	***TA***	***PSO***	***GWO***	***DE***	***BOA***	***SCA***	***AOA***
3	15.51%	14.88%	14.85%	14.77%	14.87%	14.73%	14.73%
5	48.14%	46.13%	45.80%	45.90%	46.11%	45.59%	45.42%
7	76.31%	73.39%	74.16%	73.60%	73.34%	73.12%	72.62%

Table 5. Results for Different Radii when Number of Nodes = 35

Number of radius	***TA***	***PSO***	***GWO***	***DE***	***BOA***	***SCA***	***AOA***
3	17.65%	17.01%	16.93%	16.98%	17.20%	17.02%	16.97%
5	53.29%	51.07%	50.46%	50.93%	51.31%	50.72%	50.42%
7	80.97%	78.15%	78.55%	78.03%	78.47%	77.92%	78.18%

Table 6. Results for Different Radii when Number of Nodes =40

Number of radius	***TA***	***PSO***	***GWO***	***DE***	***BOA***	***SCA***	***AOA***
3	19.89%	19.07%	19.01%	18.92%	19.23%	19.13%	19.03%
5	57.64%	55.26%	55.09%	55.12%	55.42%	55.26%	55.18%
7	84.61%	82.23%	82.53%	82.68%	82.29%	82.46%	81.66%

Table 7. Results for Different Radii when Number of Nodes = 45

Number of radius	*TA*	*PSO*	*GWO*	*DE*	*BOA*	*SCA*	*AOA*
3	21.99%	21.09%	21.15%	21.06%	21.16%	21.05%	21.25%
5	61.48%	59.59%	59.38%	59.78%	59.72%	59.30%	59.17%
7	87.18%	85.42%	85.85%	85.63%	85.33%	85.38%	85.23%

the growth of seedlings and seed reproduction in tumbleweed. It adds the idea of a growth cycle to realize the effective combination of the two stages. With the unique features of the TA algorithm, the coverage of WSNs is successfully improved. Comprehensive experimental results comparing with PSO, GWO, DE, BOA, SCA and AOA algorithms show that the TA algorithm achieves the highest coverage in all cases, highlighting its significant performance advantages in WSNs. The specific experimental results indicate that regardless of changes in node quantity or sensing radius, the TA algorithm consistently maintains high coverage rates, particularly excelling at moderate sensing radii (5 and 7). Leveraging its ability to optimize coverage, the TA algorithm contributes to enhancing the communication quality of the network, reducing data transmission latency and packet loss, thereby improving the overall performance of the entire WSN.

Future work can continue to explore the functionality of TA algorithms in more complex WSNs and diverse application scenarios. For instance, the potential application of the TA algorithm in areas such as sensor deployment in urban environments, disaster monitoring, and agricultural surveillance warrants further investigation. Introducing new growth models and optimization strategies could further enhance the algorithm's efficiency. Furthermore, combining it with other advanced optimization algorithms, such as hybrid algorithms or multi-objective optimization algorithms, may lead to significant performance improvements. Considering the TA algorithm's performance in optimization problems, its application in other domains such as robot path planning, resource allocation, and intelligent traffic management could also be explored. Cross-disciplinary application research will further validate the generality and scalability of the TA algorithm.

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