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Differential Evolution Based Regional Coverage-Enhancing Algorithm for Directional 3D Wireless Sensor Networks

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ABSTRACT Wireless sensor networks (WSNs) are adopted in a variety of fields where coverage enhancing is a critical challenge because of the requirements of service quality, cost, and energy consumption. Coverage-enhancing approaches have currently attracted a lot of interest owing to their superior abilities in the deployment of the WSNs, e.g., maximum coverage, minimum sensors, and minimum energy. In this paper, a differential evolution-based regional coverage-enhancing algorithm is proposed for directional 3D WSNs, which is able to maximizing coverage while minimize the number of sensors. First, a directional cone perception model is designed to better display the actual sensing performance of sensor nodes. Subsequently, the coverage region is established to describe the perceptual range of nodes. Thereafter, a three-stage coverage-enhancing method is derived, which includes the pitch angle optimization, the deflection angle optimization and the redundant node sleeping. These strategies are designed to maximize the perception range of a single sensor node, maximize the coverage rate, and minimize the number of nodes, respectively. Finally, simulation results show that our method is able to ensure better performance compared to the state-of-the-art frameworks.

INDEX TERMS Wireless sensor networks, region coverage, directional sensor, differential evolution.

I. INTRODUCTION

With advancement of the urbanization process in the world, wireless sensor networks (WSNs) are widely adopted in military [1], [2], wireless communications [3]–[5], smart transportation, smart home [6] and many other fields [7], [8]. Indeed, WSNs have become an indispensable prop for various applications [9], [10]. Generally speaking, monitoring an area using WSNs requires a large number of sensors with low energy, and usually it involve three critical issues, i.e., coverage performance, cost and energy consumption. As a result, strategies for the optimal coverage, cost and energy in WSNs are essential requirements.

Coverage-enhancing problem is a fundamental problem in the WSNs. When constructing a WSNs in the region of interest, a large number of sensors are deployed. Each active sensor can monitor targets within its perceived area, so the coverage-enhancing is mainly to determine whether the targets located at diverse places can be covered by the WSNs. We generally refer to coverage performance as the percentage of target areas to be covered successfully by active sensors among entire monitoring area. Better coverage performance often means higher service quality provided by WSNs. The challenges are mainly related to optimizing a huge number of parameters of large-scale sensing model. However, existing approaches are only suitable for small-scale WSNs. A coverage-enhancing algorithm based on overlap-sense ratio was proposed to optimize the coverage in [11]. By adjusting the sensing direction of the sensors, the covered area increased accordingly. In addition, a modified strategy was presented to shut off the redundant sensors so that network lifetime can be prolonged. A genetic simulated annealing-based coverage-enhancing algorithm (GSACEA) was proposed for multimedia directional sensor networks in [12]. GSACEA combined genetic algorithm and simulated annealing algorithm, and was applied for the purpose

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of coverage-enhancing. A two-phase coverage-enhancing algorithm was proposed in [13] to improve the coverage performance. Firstly, differential evolution was used to compute positions of sensors for improving coverage. Secondly, optimization scheme is suggested to reduce moving distance of mobile sensors. In [14] a coverage enhancing of 3D underwater sensor networks based on improved fruit fly optimization algorithm was proposed. This method realized the global optimal coverage based on foraging behavior of fruit flies, and it had the features of higher speed of convergence, few parameters to set up and strong global searching ability. As mentioned, most methods are designed to improve coverage without considering more goals such as cost or energy consumption and so on. So they are not suitable for multi-objectives optimization viewpoint.

Lifetime-related issue is another important problem in WSNs. The deployment of sensors in inappropriate locations or manners, and difficulties in replacing batteries may further aggravate lifetime-related problems. Therefore, strategies for the optimal energy consumption are critical, especially considering that after a small number of sensors have run out of energy, WSNs can not work properly. Challenges mainly involve determining whether some parts of the region of interest covered by a sensor are also covered by other sensors, and determining the sequence of sensor activation or deactivation [15]. A novel sleep scheduling approach (PCLA) was proposed in [16]. It aimed at minimizing the number of sensors to activate for covering a region of interest as well as preserving the connectivity among sensors. A self-adaptive sleep/wake-up scheduling approach was proposed in [17], this approach enabled each sensor to decide its own mode of operation in a distributed way based on the enhancement learning technique.

At present, the research on regional coverage-enhancing for the WSNs mainly includes perception model and coverage-enhancing method [18], [19]. Most perception models focuse on 2D situations. A sector model with main sensing direction and perception radius was proposed in [20]. Two kinds of sensing models based triangles and polygons pattern were suggested in [21]. Fuyou *et al.* designed a seven-tuple directional wireless sensing model based on 2D grid strategy [22]. Zhang *et al.* proposed a rotation direction model with node position and perceptual radius in [23]. Yet above 2D perception model does not conform to physical environment, some studies have developed 3D models. Ma proposed a perception model based on main direction, vertical and horizontal perception range in [24], and Xiao decomposed the main sensing direction into pitch angle and deviation angle for reducing complexity in [25]. Jia put forward the concept of spatial coverage and established a new sensing model in [26], which combined height information of sensors. Rebai presented a comprehensive coverage and connectivity coverage model in [27]. Kumar proposed square and circular node perception model in [28]. By combining exponential decay probabilistic sensing model and omnidirectional probabilistic sensing model, Si proposed a hybrid probabilistic sensing model in [29]. Although the above model has the ability of spatial description, its spatial coverage area has nothing to do with the height information of the target, and its two-dimensional projection plane has no boundary restriction, so it cannot accurately describe the perception performance of nodes.

Coverage-enhancing methods mainly include virtual force [30], [31] and intelligent optimization algorithm [32]. The former converts the coverage enchancing problem into a problem of solving the uniform distribution of the sensors centroids. It is necessary to calculate the centroid position of all sensors, which has high computational complexity. The latter takes the maximization of coverage as an optimization goal and solves it with an intelligent optimization algorithm. Numerous studies have shown that intelligent optimization algorithms display excellent performance [33], [34]. Latif *et al.* proposed a redundant coverage strategy and a coverage blind modification strategy for the energy consumption of underwater wireless sensor networks in [35]. Wu *et al.* proposed an optimal routing protocol based on ant foraging behavior in [36]. Magaia *et al.* used a multi-objective evolutionary algorithm SPEA to simultaneously optimize network delay and expected transmission number [37]. Sun *et al.* proposed an optimal coverage method based on probability model [38]. Jameii *et al.* proposed an adaptive multi-objective optimization framework for coverage and topology control of heterogeneous wireless sensor networks [39]. Song *et al.* proposed a perception probability model based on directed sensors [40]. Qasim *et al.* proposed a deployment method based on improved ant colony algorithm by improving standard ant colony algorithm in [41], which improved the convergence speed effectively. Xu *et al.* proposed a hybrid multi-objective decomposition optimization algorithm in [42], which combined a discrete binary particle swarm optimization strategy to improve coverage and lifetime.

In order to handle coverage-enhancing problem as well as taken energy consumption and cost into consideration, a novel differential evolution based regional coverage-enhancing algorithm is proposed in this paper, i. The main contributions of this paper are listed as follows:

- we contribute a 3D cone directional perception model with introducing the height information of target and the perceptual radius of sensor to accurately depict node perception performance.
- we propose a three-stage coverage-enhancing paradigm that involves pitch angle optimization, deflection angle optimization and redundant node sleeping. These strategies are designed to maximize the sensing range of a single sensor, maximize the coverage rate of entire WSNs, and minimize the number of sensors respectively. As a result, coverage and cost and energy consumption of a WSNs get a good promotion.
- Our algorithm is different from the existing coverage-enhancing approaches, as we focus on simultaneous optimization of multiple objectives rather than a single objective of the WSNs, which enables the WSNs to

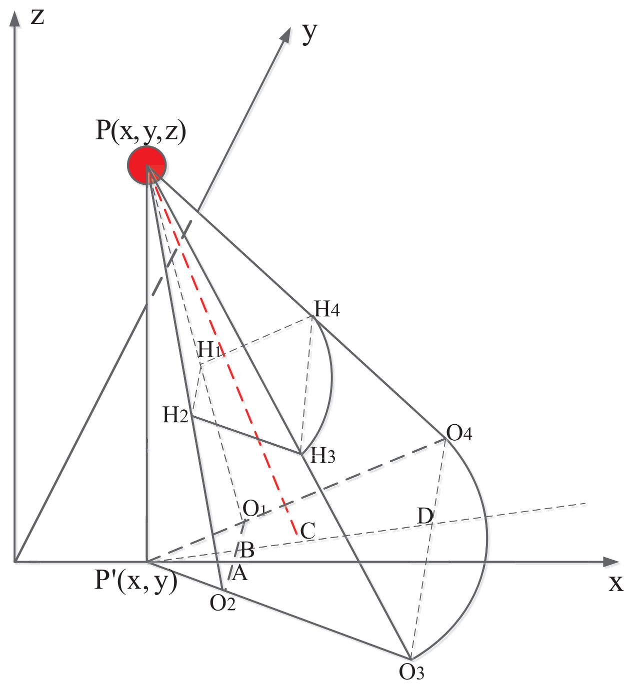

FIGURE 1. 3D cone directional sensing model.

provide higher quality of service. Furthermore, the computational complexity of our algorithm is reduced.

- Numerical simulations are designed to exam the performance of the proposed algorithm.

The reminder of this paper is organized as follows. Section II presents 3D cone directional perception model and its related concepts. Section III introduces differential evolution algorithm for optimizing parameters of the WSNs. Section IV suggests a three-stage coverage enhancing algorithm to solve the regional coverage-enhancing problem. Section V discusses the simulation setup and experimental results. Finally Section VI reports the conclusion remarks.

II. 3D CONE DIRECTIONAL PERCEPTION MODEL

The application effect of coverage enchancing method is directly determined by perception model, which is the basis of the coverage problem in the WSN. But the current perception models mainly have the following defects, such as mismatch with 3D physical environment and no boundary limitation in 2D projection region. To this end, the height information of target and the perceptual radius of sensor are introduced in the proposed 3D cone directional sensing model, as shown in Fig. 1.

The above model rotates with center P, perception radius R, and angle β. It is represented by a five-element array (P, C, α, β, R). P' is the projection of P on the X-Y plane. $C(\lambda,\phi)$ is the main perception direction of P, the angle between C and Z axis is pitch angle λ, and the angle between the projection of C on the X-Y plane and X axis is deviation angle ϕ. 2α and 2β are horizontal sensing angle and vertical sensing angle respectively.

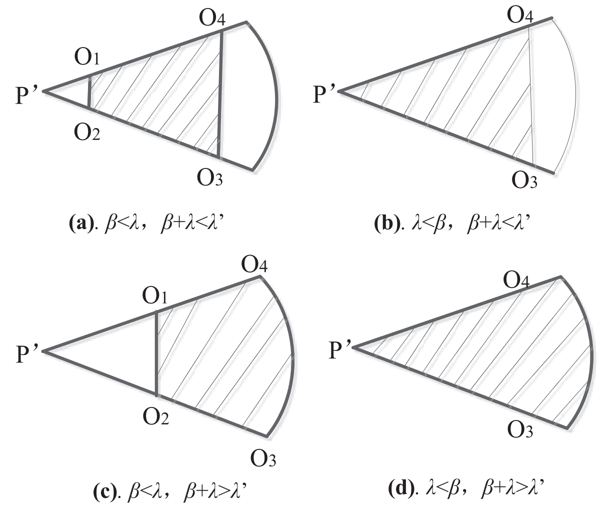

FIGURE 2. perception region of a single sensor in the X-Y projection plane ($\lambda' = \arccos(z/R)$, z is the height of the sensor, R is the perceptual radius of the sensor).

Due to the limitation of vertical sensing angle, different pitch angle causes the following four cases of the projected shape on the X-Y plane, as shown in Fig.2.

In order to determine whether the target point T is within perceptual area of the sensor node P, taking Fig. 2(a) as an example, coordinates of vertex O_1, O_2, O_3, O_4 are derived, as shown in formulas (1)-(6). Further, when T falls in the sensing area of P, two conditions should be met, as shown in formula (7) and formula (8).

$$O_1 = \left(x + |P'O_1| \cos(\alpha+\phi), \quad y+|P'O_1| \sin(\alpha+\phi)\right) \tag{1}$$

$$O_2 = \left(x+|P'O_2| \cos(\alpha-\phi), \quad y-|P'O_2| \sin(\alpha-\phi)\right) \tag{2}$$

$$O_3 = \left(x+|P'O_3| \cos(\alpha-\phi), \quad y-|P'O_3| \sin(\alpha-\phi)\right) \tag{3}$$

$$O_4 = \left(x+|P'O_4| \cos(\alpha+\phi), \quad y-|P'O_4| \sin(\alpha+\phi)\right) \tag{4}$$

$$|P'O_1| = |P'O_2| = z\tan(\lambda-\beta)/|\cos(\alpha)| \tag{5}$$

$$|P'O_3| = |P'O_4| = z\tan(\lambda+\beta)/|\cos(\alpha)| \tag{6}$$

$$|P'B| \leq |P'T| \leq |P'O_4| \tag{7}$$

$$\overrightarrow{P'T} \cdot \overrightarrow{P'C}/|\overrightarrow{P'C}| \geq |\overrightarrow{P'T}| \cos(\alpha) \tag{8}$$

The above proposed model can be extended to 3D space coverage problem by setting the height of targets. The 3D space perception area of the sensor can be mathematically represented as $O_1O_2O_3O_4H_1H_2H_3H_4$.

In order to assess the coverage rate of the whole WSNs, an evaluation method is designed subsequently, and specific steps are as follows: 1) The monitored area is discretized into square grids, and the accuracy of discretization depends on actual needs; 2) The total number of discrete grid points in monitored area is obtained, denoted as Q, and the number of grid points covered by all sensors in the X-Y plane can be calculated, denoted as Q_t. 3) The total coverage rate of the WSNs is $C_t = Q_t/Q$.

III. DIFFERENTIAL EVOLUTION ALGORITHM

Differential evolution (DE) algorithm has become one of the most representative evolutionary algorithms because of its simple operation, strong global ability and high robustness. Some studies have shown that the performance of DE is better than other evolutionary algorithms in solving complex optimization problems. In this paper, DE is employed to enhance coverage. The mutation, crossover and selection of DE are respectively shown as formulas (9)-(11).

$$\mathbf{V}_i(t+1) = \mathbf{X}_{r1}(t) + F \times (\mathbf{X}_{r2}(t) - \mathbf{X}_{r3}(t)) \tag{9}$$

where F is a scaling factor, $\mathbf{X}_{r1}$, $\mathbf{X}_{r2}$, $\mathbf{X}_{r3}$ are diverse vectors selected in evolution population, and $r1$, $r2$, $r3$ are distinct integers chosen from the set $\{1, 2, , N\}$. $\mathbf{V}_i = \left[\mathbf{V}_{i,1}, \mathbf{V}_{i,2}, \cdots, \mathbf{V}_{i,n}\right]$ is a mutation vector.

$$\mathbf{U}_{i,j} = \begin{cases} \mathbf{V}_{i,j}, & rand(j) \le CR \\ \mathbf{X}_{i,j}, & otherwise \end{cases} \tag{10}$$

where CR is a parameter within interval (0, 1), which controls the fraction of vector components inherited from the mutation vector. $\mathbf{U}_i = \left[\mathbf{U}_{i,1}, \mathbf{U}_{i,2}, \cdots, \mathbf{U}_{i,n}\right]$ is a crossover vector. $\mathbf{U}_{i,j}$ is the j-th dimension of $\mathbf{U}_i$, and $\mathbf{X}_{i,j}$ is the j-th dimension of $\mathbf{X}_i$.

$$\mathbf{X}_i(t+1) = \begin{cases} \mathbf{U}_i(t+1), & f(\mathbf{U}_i(t+1)) < f(\mathbf{X}_i(t)) \\ \mathbf{X}_i(t), & otherwise \end{cases} \tag{11}$$

where t is the number of evolutionary iterations, $f(\cdot)$ is the fitness function.

IV. COVERAGE ENHANCING PROCESS

The pitch angle of sensor controls the projection shape and area in 2D plane, while the deviation angle determines projection overlap region between different sensors, so the coverage rate of WSNs is essentially only related to the pitch angle and deviation angle of sensors. However, it's too complex to optimize them at the same time, thus pitch angle optimization and deviation angle optimization, is designed in this paper to improve coverage rate of the WSNs. Moreover, when the number of randomly deployed nodes increases, there may be considerable redundant nodes in the WSNs, which will lead to waste of energy consumption. So a redundant node sleeping strategy is proposed to reduce the number of working sensors and extend the life cycle while guarantee coverage.

A. PITCH ANGLE OPTIMIZATION

The projection area of a single sensor on X-Y plane is only related to the pitch angle, so the pitch angle can be adjusted to maximize the coverage area. Taking Fig.2(a) as an example, we have the coordinates of vertex O_1, O_2, O_3, and O_4.

TABLE 1. Algorithm 1: Pitch angle optimization.

Input
- G_{max}: the evolutionary iterations
- N: the population size
- F: the scaling factor
- CR: the crossover probability

Output
- S_t: the optimal solution found by DE

1: P ←Initialize population, each individual $X_i = \lambda_i, i = 1, \cdots, N$
2: $t = 0$
3: **While** $t \le G_{max}$
4: O_t ←Create offspring by mutation and crossover
5: P_t ←Form offspring population by selection
6: Output the best solution in P
7: **End**

Then, the projection area of the sensor node P on the X-Y plane can be derived as follows.

$$\begin{aligned} &S_{O_1O_2O_3O_4} \\ &\quad = S_{\Delta O_3P'O_4} - S_{\Delta O_1P'O_2} \\ &\quad = \left|\frac{|P'O_3||P'O_4|\sin(2\alpha)}{2}\right| - \left|\frac{|P'O_1||P'O_2|\sin(2\alpha)}{2}\right| \\ &\quad = \left|\frac{\tan^2(\lambda+\beta)\sin(2\alpha)}{2\cos^2(\alpha)}\right| - \left|\frac{\tan^2(\lambda-\beta)\sin(2\alpha)}{2\cos^2(\alpha)}\right| \\ &\quad = \tan(\alpha)\left(\tan^2(\lambda+\beta) - \tan^2(\lambda-\beta)\right) \end{aligned} \tag{12}$$

There are parameters α, β, λ in formula (12), in which α and β are the fixed parameter of the sensor, and only pitch angle λ needs to be optimized. Obviously, the form of S is complex non-linear function. It is very suitable for solving maximum value of S by DE. The process of the pitch angle optimization based on DE is illustrated in Table 1, and the specific steps are as follows.

step.1 Parameters initialization, including the maximum generation (G_{max}), the size of population (N), the scaling factor (F), the crossover probability (CR);

step.2 Generate the initial population P_0 that includes N individuals, each individual X_i is produced by $X_i = l + rand() \times u$, $i = 1, 2, \ldots, N$, rand() is a random number in [0,1], $l = 0$, $u = \pi/2$;

step.3 Execute mutation and crossover operation, and generate the offspring population (O_t);

step.4 Execute selection operation, and form the next generation population (P_{t+1});

step.5 Judge whether the G_{max} is satisfied? If so, output the optimal solution; if not, go to step 3.

B. DEVIATION ANGLE OPTIMIZATION

After the pitch angle optimization, the coverage area of each sensor is maximized, but there are many perceptual overlapping areas and perceptual blind areas between

TABLE 2. Algorithm 2: Deviation angle optimization.

Input
G_{max}: the evolutionary iterations
N: the population size
M: the number of sensors
F: the scaling factor
CR: the crossover probability
Output
S_t: the optimal solution found by DE
1: P ←Initialize population, each individual
$X_i = (\phi_{i1}, \cdots, \phi_{ij}, \cdots, \phi_{iM}), i = 1, \cdots, N, j = 1, \cdots, M.$
2: $t = 0$
3: **While** $t \leq G_{max}$
4: O_t ←Create offspring by mutation and crossover
5: P_t ←Form offspring population by selection
6: Output the best solution in P
7: **End**

diverse sensors. Therefore, the deviation angle optimization is proposed to reduce these areas and further improve the coverage rate of the whole WSNs. The detailed depiction of the deviation angle optimization is shown in Table 2, and the specific steps are as follows.

step.1 Parameters initialization, including the maximum generation (G_{max}), the size of population (N), the number of deployed sensor nodes (n), the scaling factor (F), the crossover probability (CR);

step.2 Generate the initial population P_0 that includes N individuals, the jth dimension x_j of each individual $X_i = (x_1, x_2, \ldots, x_n)$ is produced by $X_j = l_j + rand() \times u_j$, $j = 1, 2, \ldots, n$, $i = 1, 2, \ldots, N$, rand() is a random number in [0,1], $l = 0$, $u = 2 \times pi$;

step.3 Execute mutation and crossover operation, and generate the offspring population (O_t);

step.4 Execute selection operation, and form the next generation population (P_{t+1});

step.5 Judge whether the G_{max} is satisfied? If so, output the optimal solution; if not, go to step 3.

C. REDUNDANT NODE SLEEPING

With optimization of pitch angle and deviation angle, the coverage rate of monitored area has been greatly improved. However, due to the random deployment of a substantial number of sensors in WSNs, there will be some redundant nodes, which are not helpful for improving coverage while result in wasting energy. Hence, a redundant node sleeping strategy is proposed to dormancy the sensors that have no effect on coverage enhancement, so as to maximize the coverage rate of WSNs with the smallest number of sensors.To determine whether a sensor is dormant, it is necessary to judge whether this sensor is redundant. For this purpose, two important definitions are defined.

TABLE 3. Algorithm 3: Redundant node sleeping.

Input
All deployed sensors
Output
All working sensor nodes
1: Calculate SDP, CCP of all deployed sensors
2: According to SDP, ensure redundant sensors, and sort the CCPs of the redundant sensors in ascending order.
3: Select redundant sensor with the smallest CCP to sleep
4: Update the WSNs, until the coverage descend
5: Output the working sensors

Definition 1 (Sleep Decision Parameter (SDP)): Assume that the number of discrete grid points in the region covered by sensor P is N_o. If P is closed, and the total number of discrete grid points covered by other sensors is N_t. Let $SDP = N_o/N_t$, when SDP is less than δ (δ is a preset parameter), sensor P enters the sleeping state, then SDP is called the sleep decision parameter.

Definition 2 (Coverage Contribution Rate (CCR)): Suppose that sleep decision parameter of node P is SDP. Let $CCR = 1 - SDP$, then CCR is known as as the coverage contribution rate.

In case all redundant nodes are dormant simultaneously, it will inevitably affect the coverage of the WSNs. To this end, the CCR of all redundant nodes are sorted, the node with the smallest CCR will be dormant until coverage of WSNs decreases to an unacceptable level. The process of redundant node sleeping is as follows, and is shown in Table 3.

step.1 Calculate the SDP and CCR of all sensors in the WSNs;

step.2 Identify the redundant nodes according to SDP, and sort the CCPs of the redundant nodes in ascending order;

step.3 Select the redundant node with the smallest CCP to sleep;

step.4 Update the working sensor nodes in the WSNs, and repeat step 3 until coverage rate of the WSNs drops.

V. SIMULATION SETUP AND EXPERIMENTAL RESULTS

A. EXPERIMENTAL SETTINGS

All the experimental settings in the proposed algorithm are listed as the following. 1) The monitoring area is set at 200m*200 m, the pitch angle is [0, $\pi/2$], the deflection angle is [0,2π], the horizontal perception angle and the vertical perception angle are respectively $2\pi/3$ and $\pi/3$, the perception radius R is 30m, and the sensor height z is 6 m. 2) Number of runs: Each algorithm is run 30 times independently for all nodes. 3) Termination criterion: The termination condition of an algorithm is specified in the form of the maximum number of generations (G_{max}). We use the same G_{max} for 200 in all nodes. 4) Population size: The setting of population size N is 100 in all problems. 5) Parameters for evolution process: $F = 0.5$, $CR = 0.9$. In order to verify the effectiveness

TABLE 4. Contrast experiments before and after the pitch angle optimization.

number of nodes	before optimization	after optimization	improvement rate
20	21.8%	34.1%	12.3%
50	41.2%	59.7%	18.5%
80	54.3%	76.5%	22.2%

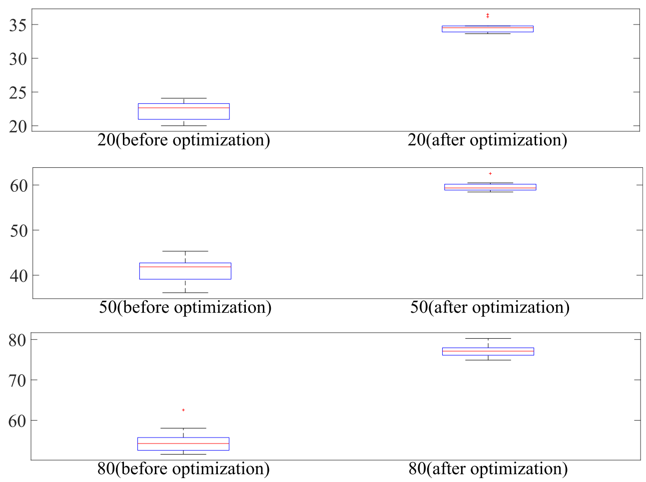

FIGURE 3. Contrast between before and after pitch angle optimization with 20, 50, 80 nodes.

of our method, the comparative experiments are carried out: 1) the effects before and after pitch angle optimization and deflection angle optimization; 2) the effects before and after redundant node sleeping; 3) comparing with other excellent methods. All experiments were carried out on a computer. The PC Configuration is system: Windows XP_SP3; RAM: 2G; CPU: G620; CPU 2.60 GHz; Computer Language: MATLAB 2010.

B. CONTRAST BEFORE AND AFTER PITCH ANGLE OPTIMIZATION

In order to verify the effect of the pitch angle optimization, the comparison experiments were performed, and the results are shown in Table 4 and Fig. 3-9.

It can be seen from Table 4 and Fig. 3, after the pitch angle is optimized, coverage rate of the WSNs is evidently improved, which verifies the effectiveness of the pitch angle optimization. Since the perceptual region of a single sensor is affected by its pitch angle, setting diverse pitch angles will lead to different perception areas of the sensor. So adjusting the pitch angle to the best state can maximize the perception area of the sensor.

As can be seen from Fig. 4-Fig. 9, before the pitch angle is optimized, the pitch angle of each sensor is different, and its projection shape and area in 2D plane are also different. After optimizing the pitch angle, the coverage of each sensor achieves optimal. As a result, the coverage of the entire

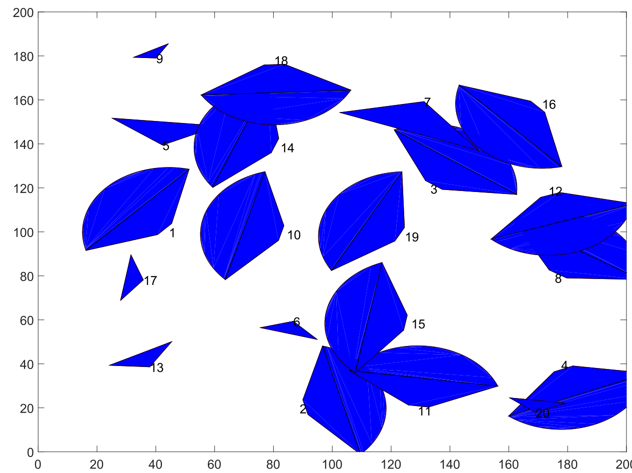

FIGURE 4. Before pitch angle optimization(20 nodes).

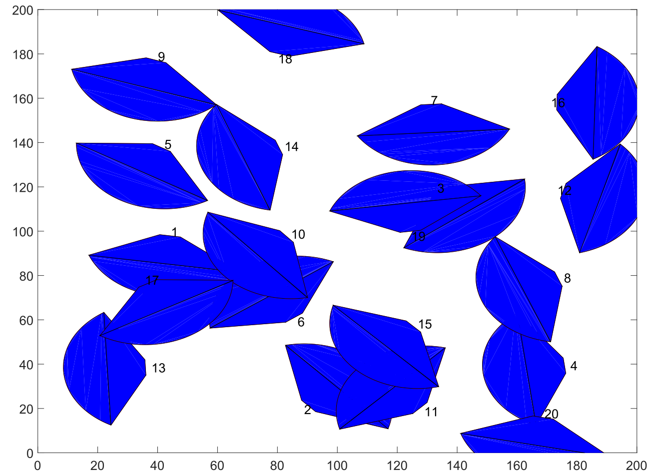

FIGURE 5. After pitch angle optimization(20 nodes).

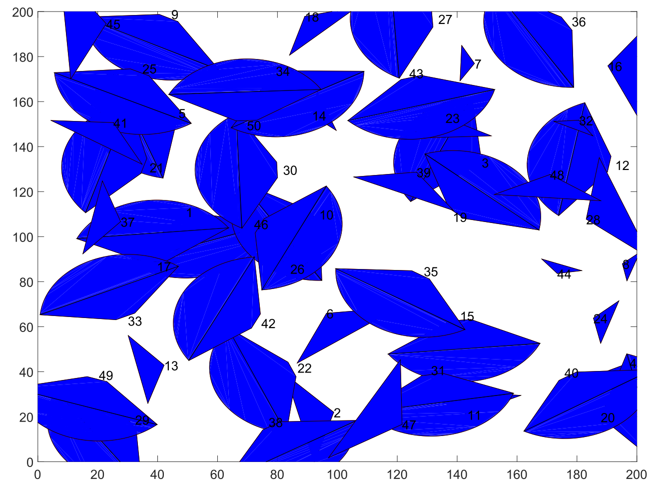

FIGURE 6. Before pitch angle optimization(50 nodes).

WSNs increases. However, there are still a large number of perceptual overlap areas and perceptual blind areas between distinct sensors. Meanwhile, there is still much room for

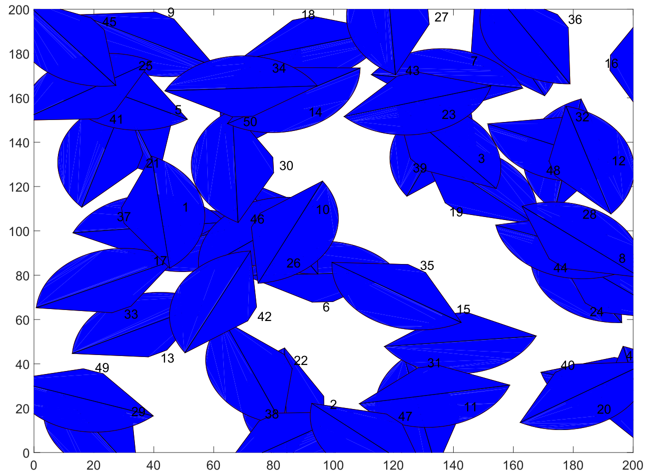

FIGURE 7. After pitch angle optimization(50 nodes).

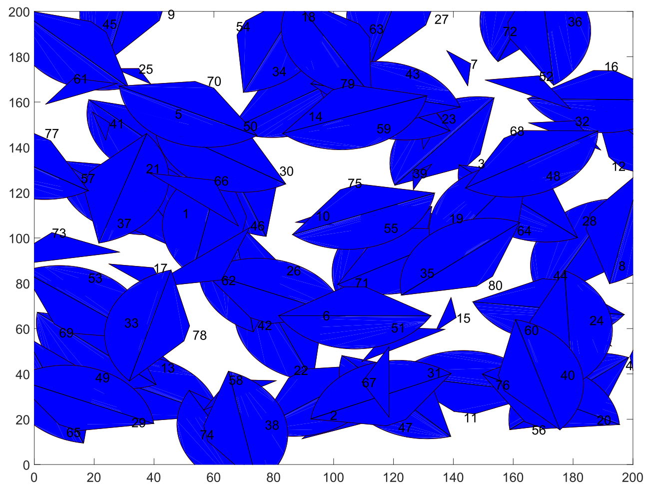

FIGURE 8. Before pitch angle optimization(80 nodes).

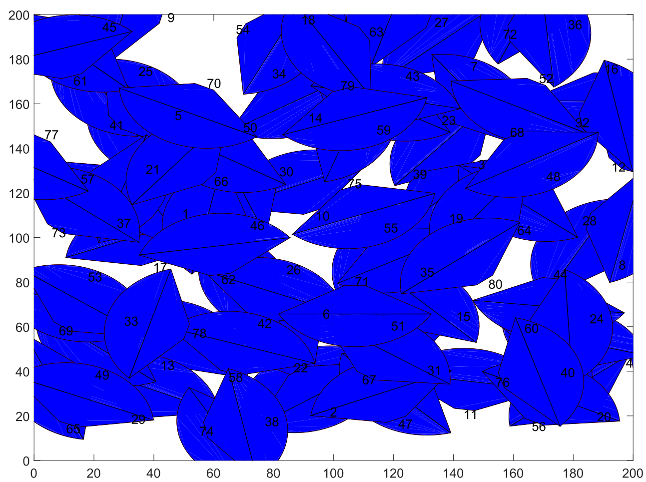

FIGURE 9. After pitch angle optimization(80 nodes).

improvement in coverage. Thus, it is necessary to further optimize the deflection angle for reducing the perceptual overlap area between different sensors and the perceptual blind areas uncovered by the sensors.

TABLE 5. Contrast experiments before and after the deflection angle optimization.

number of nodes	before optimization	after optimization	improvement rate
20	34.1%	45.3%	11.2%
50	59.7%	81.8%	22.1%
80	76.5%	95.3%	18.8%

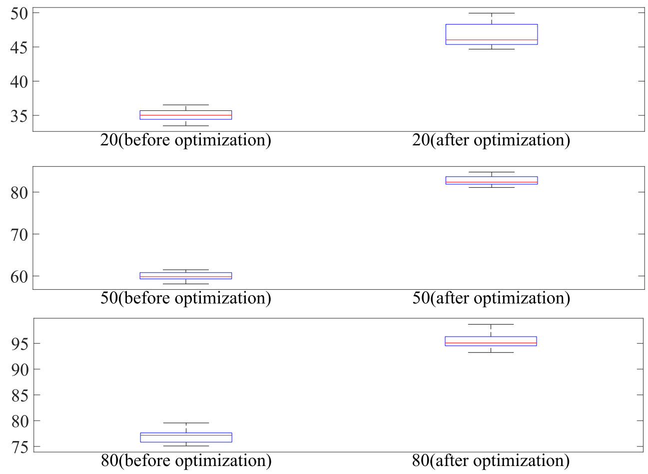

FIGURE 10. Contrast between before and after deflection angle optimization with 20, 50, 80 nodes.

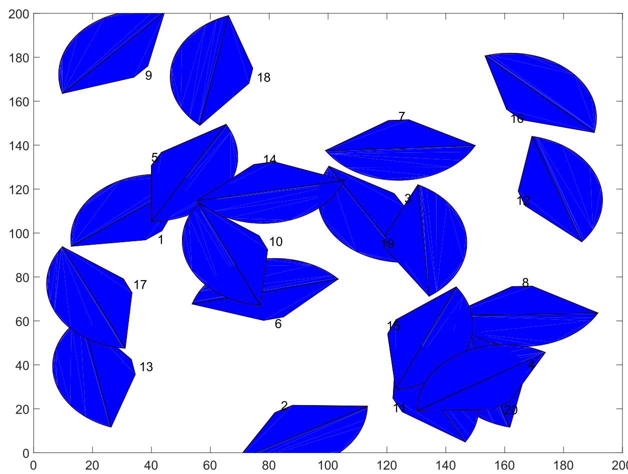

FIGURE 11. Before deflection angle optimization(20 nodes).

C. CONTRAST BEFORE AND AFTER DEFLECTION ANGLE OPTIMIZATION

In order to verify the effect of the deflection angle optimization, the comparison experiments were carried out. The results are shown in Table 5 and Fig. 10-17.

From Table 5 and Fig. 10, it can be seen that the coverage has been greatly improved after deflection angle optimization, which further demonstrates the effectiveness of proposed method.

As can be seen from Fig. 11 and Fig. 12, there is a certain overlapping area when 20 sensors are deployed. After the adjustment of the deflection angle, the overlapping

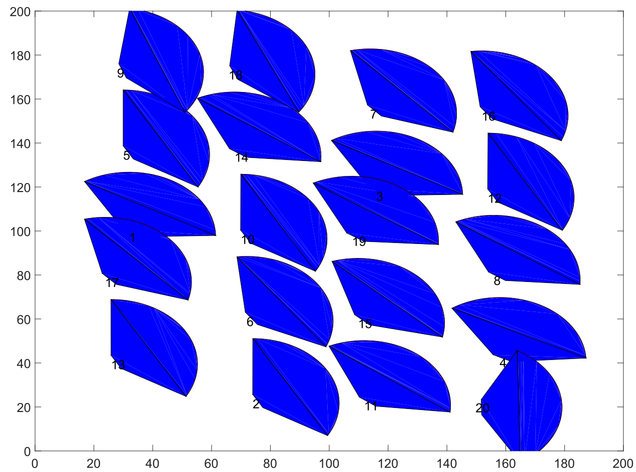

FIGURE 12. After deflection angle optimization(20 nodes).

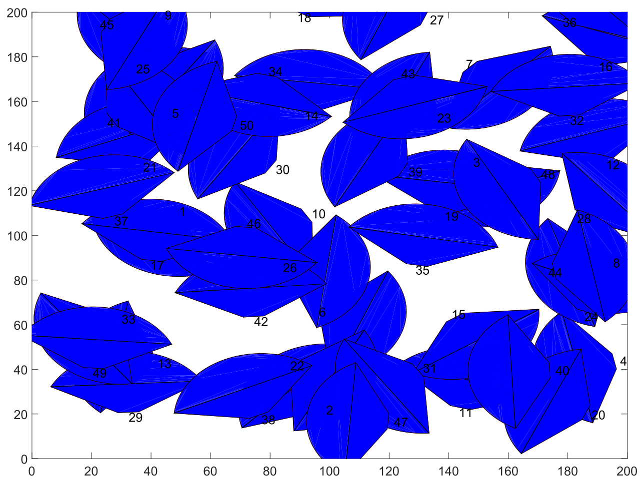

FIGURE 13. Before deflection angle optimization(50 nodes).

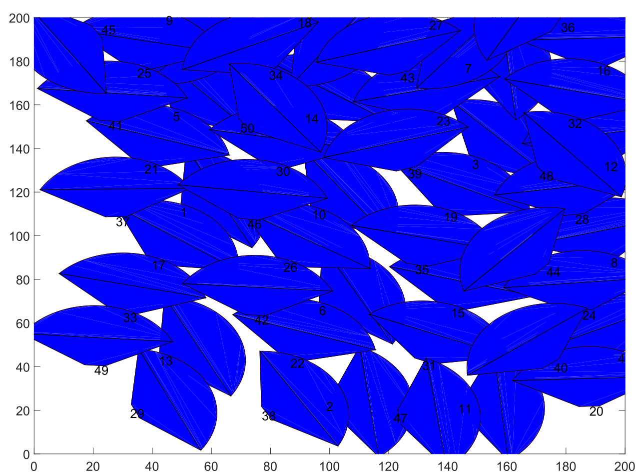

FIGURE 14. After deflection angle optimization(50 nodes).

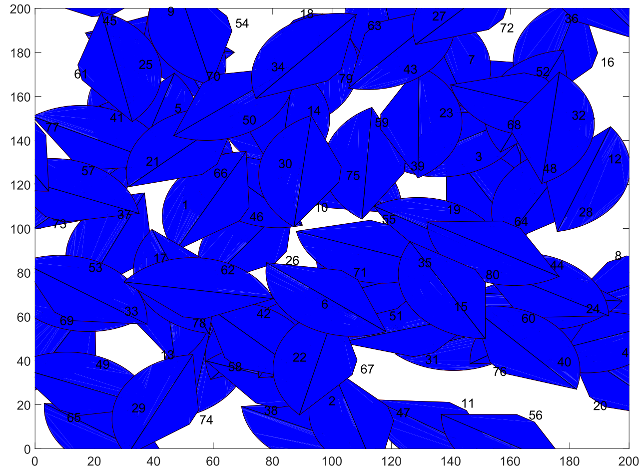

FIGURE 15. Before deflection angle optimization(80 nodes).

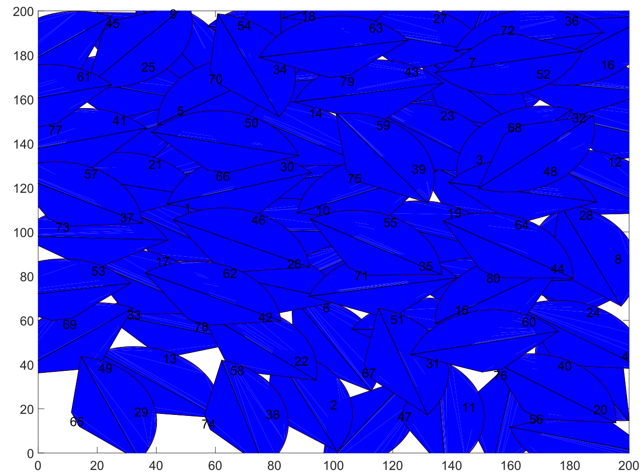

FIGURE 16. After deflection angle optimization(80 nodes).

area almost disappeared, and the coverage is subsequently improved by 11.2%. It can be seen from Fig. 13 and Fig. 14, when 50 sensors are deployed, there are many overlapping areas in monitoring region before the optimization of deflection angle. After the deviation angle of sensors is adjusted to optimum, the overlap phenomenon is better improved, and the coverage increases by 22.1%. As can be seen from Fig. 15 and Fig. 16, when 80 nodes are deployed, the sensors have covered most of the monitoring areas, but there are still some uncovered areas. After the deflection angle optimization, uncovered areas are significantly reduced, and the coverage improves by 18.8%. Simultaneously we can find that as the number of deployed sensors raises, the monitoring area is basically well covered, but the overlapping areas also increase. Therefore, the number of working sensors can be reduced by the proposed redundant node sleeping.

D. CONTRAST BEFORE AND AFTER REDUNDANT NODE SLEEPING

In order to verify the effect of the redundant node sleeping, the comparison experiments were performed, and the results are shown in Fig. 17-20.

It can be seen from Fig. 17 and Fig. 18, when the redundant sensors are dormant, the coverage decreases slightly by 2.6%,

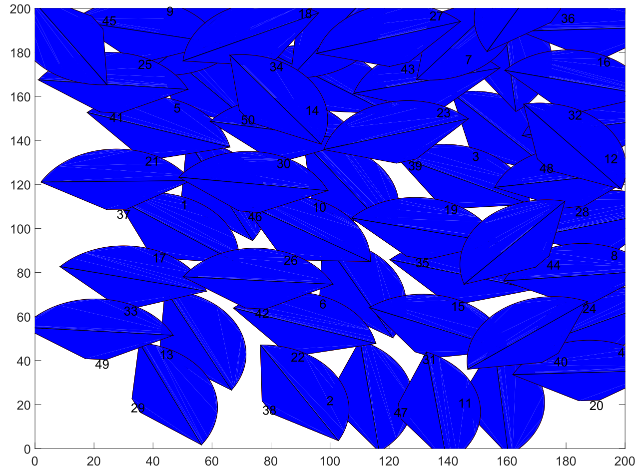

FIGURE 17. Before redundant node sleeping(50 nodes).

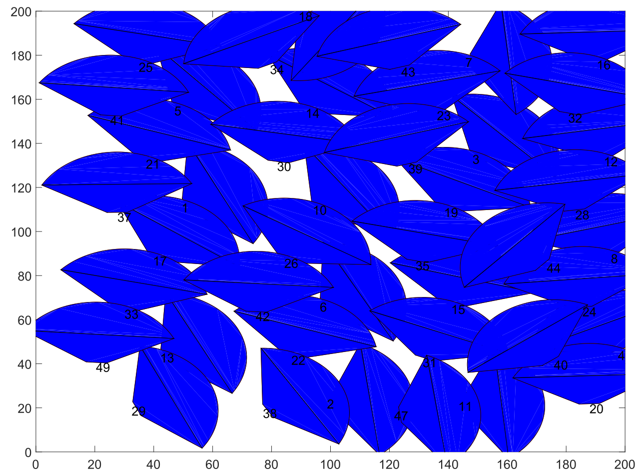

FIGURE 18. After redundant node sleeping(50 nodes).

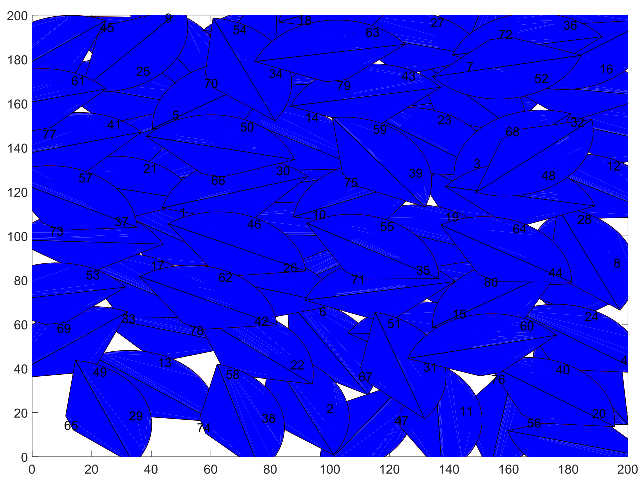

FIGURE 19. before redundant node sleeping(80 nodes).

but the number of sensors reduces from 50 to 43. As can be seen from Fig. 19 and Fig. 20, after the redundant node sleeping, the coverage of the WSNs decreases by 2.5%, while the number of sensors reduces dramatically from 80 to 61.

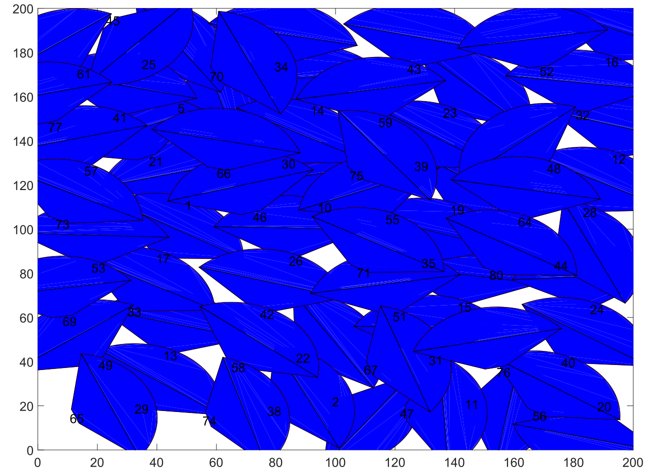

FIGURE 20. After redundant node sleeping(80 nodes).

TABLE 6. Comparison of coverage effects of different methods.

initial nodes	initial coverage	methods	optimal coverage	final nodes
20	22.3%	article [23]	41.5%	20
		PSO	42.9%	20
		TLBO	43.2%	20
		our method	**45.3%**	**20**
50	42.4%	article [23]	77.4%	50
		PSO	78.2%	50
		TLBO	76.9%	50
		our method	**79.2%**	**43**
80	57.8%	article [23]	90.7%	80
		PSO	91.1%	80
		TLBO	91.8%	80
		our method	**92.9%**	**61**

Thus, the redundant node sleeping can decrease a substantial number of working sensors and effectively improve the energy consumption and the cost of the WSNs. At the same time, it can guarantee high coverage.

E. CONTRAST OF DIFFERENT METHODS

In order to verify the advancement of the proposed method, comparative experiments with article [23], TLBO and PSO are carried out. The results are shown in Table 6.

From Table 6, it can be seen that with the increase of the number of sensors, the final coverage obtained by our method is on the rise and it has certain advantages compared with the other methods. In the meantime, we can see that the proposed method in this paper eventually achieves the fewer deployed sensors while ensure the better coverage of the WSNs.

VI. CONCLUSION

In this paper, we stressed the problem of directional 3D WSNs. First of all, a 3D cone directional perception model is first established. Then, a three-stage coverage-enhancing method is proposed, which includes the pitch angle optimization, the deflection angle optimization and the redundant node sleeping. These strategies are respectively designed to maximize the sensing range of a single node, maximize the coverage rate of entire WSNs, and minimize the number of nodes. Moreover, our method is different from the existing research, as we focus on simultaneous optimization of multiple objectives rather than a single objective of the WSNs and reduction of computational complexity, which enables the WSNs to provide higher quality of service. The numerical simulation results show that the proposed algorithm can gain the better coverage rate as well as the fewer sensor nodes. Our future work will focus on spatial coverage issues and the connectivity of network nodes.

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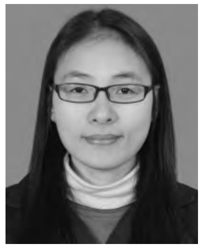

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