Node deployment method of Intelligent smoke sensors across high space using many-objective optimization algorithm

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Abstract. NB-IoT promotes innovation in the field of wireless sensor networks[7], the problem of deployment and coverage optimization of intelligent smoke sensors based on NB-IoT technology in high space has become a new research trend subsequently. In this article, we study the problem of the node deployment and coverage optimization of intelligent smoke sensors in a tall indoor space environment. Firstly, an intelligent smoke sensor nodes deployment method suitable for tall spaces is designed through the analysis of the tall environment and the particularity of the intelligent smoke sensors. Then we establish a three-dimensional directed coverage perception model. The node coverage range and deployment cost are the objective functions, which need to be optimized. Furthermore, a node deployment approach across specific high space is developed on the basis of multi-objective optimization algorithm to optimize the two objective functions. Compared with existing deployment schemes, the results of simulations demonstrate that our proposed deployment strategies can achieve better Quality of Coverage (QoC) and detection performance while enlarges the monitoring scope.

1. Introduction
With the progress perpetually and maturity gradually of NB-IoT technology, it provides a foundation for the large-scale deployment of intelligent smoke sensors based on NB-IoT technology. At present, a variety of deployment strategies and coverage perception models regarding the deployment and coverage optimization of sensors in the designated monitoring areas and specific three-dimensional spaces have been proposed, which are optimized using intelligent optimization algorithms. The deployment of a sensor network in a real environment presents several challenging issues that are often oversimplified in the existing solutions, and different approaches have been proposed in the works of literatures to solve this problem[1]. Existing research shows that two scenarios with the equal coverage ratio may not have the same Quality of Coverage (QoC)[6]. Moreover, the traditional deployment and coverage research on wireless sensor networks (WSNs) has mainly focused on a 2D plane and underwater space, and also including 3D terrain scene, the sensors considered are almost always General wireless sensor. However, this type of research cannot fulfill the diverse requirements required for practical situations[4]. In this paper, we summarize the current research status in the field of wireless sensors and the actual deployment problem of intelligent smoke sensors across specific three-dimensional spaces. The research studies the optimal deployment of NB-IoT intelligent smoke sensors in large space environments (such as shopping malls, stadiums, etc.) to optimize node detection performance and deployment costs. Through the above research, NB-IoT can realize the networked management of smart smoke sensors while provide strong support for urban fire safety.
management simultaneously, so as to improve the management efficiency of fire protection enterprises and fire-related departments. Ultimately, these studies promoted the development of smart fire protection and the construction of smart cities.

The remainder of the paper is arranged as follows. The related work involving our study is discussed in Section 2. Then in Section 3, we design a node deployment method and large space coverage perception model (LSCP Model), also including two objective functions. A node deployment and coverage optimization algorithm based on MSSA algorithm is proposed to optimize the node deployment strategies we proposed in Section 4. Section 5 shows the simulation results and performance evaluation. Finally, the conclusions and future work are described in Section 6.

2. Related Work

Most research that has been done on the problem of nodes deployment and coverage use two-dimensional scene as its model. It is a lot easier to develop algorithms for a two-dimensional area than a three-dimensional area but this is not sufficient for many real-world environments[14].

Currently, the research on 3D monitoring space mainly involves the research on 3D terrain and underwater detection environment. The deployment optimization issues of directional WSNs are studied in the 3D terrain in [4], which also presented a modified differential evolution algorithm by adopting crossover rate sort and polynomial-based mutation based on the cooperative coevolutionary framework. The paper [3] summarizes the application research of underwater sensor deployment including the network structure and classification of sensor nodes deployed in the underwater monitoring scenario. A new hybrid optimization algorithm in a three-dimensional indoor space environment is proposed in [5], the algorithm combines the user preference (PI-EMO-VF) strategy with the genetic algorithm (NSGA-III) combined with the multi-objective recent variants, the effectiveness of the algorithm is greatly improved, and the deployment strategy and coverage effect are more optimized. The sensing range of a traditional sensor node is a circular region with the sensor node as the centre and the perceived distance as the radius. In a real environment, because of the restrictions of the topography of the deployment region, the sensing model usually has an irregular shape. Thus, the traditionally considered sensing model is too idealized and simplistic. It is still a challenge to deploy sensor nodes reasonably in accordance with actual applications[4].

Nevertheless, the above studies mainly consider 2D planar regions, while the real sensor nodes exist in 3D space. Therefore, studying 3D coverage and deployment problems of sensor nodes is more suitable for practical needs. For the current study, there are relatively little researches on the deployment of smart smoke sensors in the environment of tall indoor spaces. How to effectively deploy smart smoke sensors in a specific tall indoor space environment is still facing a lot of problems, also is a valuable research direction in the future.

3. System Model and Problem Formulations

3.1. Intelligent smoke sensor nodes deployment method

In this paper, we propose a hybrid node deployment scheme taking into account the particularity of Intelligent smoke sensors and the complexity of the deployed three-dimensional tall space simultaneously. In the process of deploying the nodes, the three-dimensional monitoring space is divided into sensor nodes deployment area (Sensor Area, $S_A$) and fire area (Fire Area, $F_A$), and sensors are deployed randomly in $S_A$. Some obstacles are randomly set up in $F_A$. Assume that the obstacle points exist between the sensor nodes and the target points to be monitored. Given a sensor node $s$, the point that needs to be covered in the given three-dimensional space is $p$, and we assume that the obstacle between the two is $o$. For example, the $S_2$ will be redeployed at $S_3$ if there exist barriers between the node $S_2$ and the point $p_{1}$, etc. The actual deployment situations of our proposed hybrid node deployment method are illustrated in Figure 1.
3.2. LSCP Model

We adapt the uncertain coverage perception model mentioned in the previous literature. The probability of the target point being monitored is not a constant in the actual application scenarios, but a variable determined by many factors such as the distance between the target and the deployed node, the relevant physical characteristics of the node, and the number of neighbours around the node. Therefore, the uncertain probability coverage model can more accurately describe the coverage capacity of the network, and it is more in line with the needs of practical applications. The probabilistic perception model shows that the probability \( P_{ij} \) of the target to be monitored by the sensor node changes exponentially with the distance between the target and the sensor node. Assuming that the distance is \( d \), the probability of the target being monitored by this node is \( e^{-\alpha d} \), and the monitoring parameter \( \alpha (\alpha > 0) \) is used to indicate the rate at which the probability of the target point being monitored by the deployed sensor node decreases as the distance between the two increases. When the perception probability of a target for a smart smoke sensor is greater than \( \beta \), the target is considered to be covered (or perceived) by the node, and the parameter \( \beta \) is called Monitoring probability threshold. It can be described formally as:

\[
P_{ij} = e^{-\alpha d} \quad (1)
\]

\[
R_s = -\frac{1}{\alpha} \log \beta \quad (2)
\]

Among them, the perception probability \( P_{ij} \) represents the probability that the target at point \( j \) is monitored by the sensor node \( i \). Regardless of the existence of obstacles in the three-dimensional monitoring area, \( P_{ij} = P_{ji} \). \( R_s \) represents the detection and perception radius of intelligent smoke sensors. Therefore, for a sensor node \( s \) and a monitored target \( p \) in the given three-dimensional space, when there is an obstacle \( o \) between the two, we can describe the overall sensing probability as follows:

\[
SP(s, p) = P_{sp} \times P_d(s, p) \times P_o(s, p) \quad (3)
\]

Where \( P_d(s, p) \) is the perception probability when the distance between the sensor node and the target point is \( d \), where \( P_o(s, p) = 1 \) means that there is no obstacle between the sensor node and the target point, while \( P_o(s, p) = 0 \) means there are obstacles between the two.

3.3. problem description

Assuming the sensor nodes set is \( S = \{s_1, s_2, s_3, ..., s_n\} \) (\( n \) is the number of smart smoke sensors deployed). According to paper[4], the value of \( SP_s(p) \) varies from 0 to 1. Thus, to evaluate the network coverage ratio under this model, the following definition is used:

\[
SP_s(p) = \begin{cases} 
1, & S_d(p) \geq \beta \\
0, & \text{otherwise}
\end{cases}
\]

(4)
Furthermore, $CQ$ represents the coverage quality after the deployment operation, which can be expressed as:

$$CQ = \frac{1}{N} \sum_{j=1}^{N} SP_j(p_j)$$  \hspace{1cm} (5)

### 3.4. Objective Functions

The first objective function is to maximize the coverage ratio. Coverage is an important reference indicator for optimal deployment of sensor nodes. In our paper, we assume that the number of sensors deployed in a tall three-dimensional space is fixed, and ultimately optimize node coverage $f_{coverage}$ through multi-objective optimization algorithms, which is calculated using the following equation:

$$f_2 = \text{Max} f_{coverage} = \text{Max}(1 - CQ)$$  \hspace{1cm} (6)

The second objective function we optimized is the total deployment cost $f_{deployment cost}$. We mainly consider the hardware cost ($H\text{cost}$) of the intelligent smoke sensors and the complexity (Environment complexity, $E\text{complexity}$) of the large space environment. The higher the complexity of the three-dimensional space that needs to be covered, the higher the deployment cost will be. Therefore, the objective function for minimizing the deployment cost is expressed by the following formula:

$$f_1 = \text{Min} f_{\text{DeploymentCost}} = \text{Min} \frac{f_{E\text{complexity}} + f_{H\text{cost}}}{2}$$  \hspace{1cm} (7)

### 4. Node deployment Method based on MSSA algorithm

#### 4.1. The MSSA algorithm

The sparrow search algorithm is a new intelligent optimization algorithm proposed in 2020, which is gradually used in multi-objective optimization fields. In order to solve the problem of node deployment and coverage optimization involving the scenes of high indoor space, we adapt the multi-objective sparrow search algorithm (MSSA) developed by [15].

#### 4.2. The Flow of the MSSA Algorithm

- Step1: Initialize the sparrow population $N$, set the maximum size of the external Archive $N'$, the maximum number of iterations $T$, the initial ratio of discoverers $w$, the number of warning sparrows $SD$, the warning value $R_2$, the initial solution is sorted non-dominantly, and the external Archive is updated;
- Step2: While ($t < T$);
- Step3: Sort the population in a non-dominated manner, and select the best individual and the worst individual in the result;
- Step4: for $i = 1$ to $N * w$;
- Step5: Update the individual position of the sparrow and calculate the probability of mutation;
- Step6: end for;
- Step7: for $i = (N * w + 1)$ to $N$;
- Step8: Produce chaotic population candidate, and judge whether there is a chaotic alternative operation. If it exists, perform the substitution operation, else go to next step;
- Step9: end for;
- Step10: for $j = 1$ to $SD$;
- Step11: Use the corresponding formula to update the position of the individual sparrow;
- Step12: end for;
- Step13: Update the parameters with the corresponding formula;
5. Simulation and Performance Evaluation

5.1. Simulation Parameter Setting
To evaluate the performance of our proposed node deployment method and the MSSA algorithm on this problem, a large number of simulations experiment is conducted in MATLAB R2020a environment. Based on the previous literatures, the results are evaluated using simulation with parameters given in table1.

| Simulation Parameters     | Values       |
|------------------------|-------------|
| 3D simulation area      | 32m*32m*12m |
| The number of sensors   | 30          |
| Node perception radius  | 7m          |
| Obstacle shape          | rectangle   |
| Number of iterations    | 100         |

5.2. Result analysis
For verifying the effectiveness of proposed optimization method, we use MSSA algorithm to conduct a large number of simulation experiments in the case of randomly placing a few regular obstacles. And it can be seen in Figure 3 that the coverage ratio is obtained by MSSA algorithm is approaching to 100% as the number of iterations increases, which proves the reliability of MSSA algorithm to the problem of coverage optimization.

6. Conclusion and Future Work
In this paper, we proposed a node deployment method and a multi-objective optimization algorithm to solve the problem of deploying intelligent smoke sensors in tall spaces. The analysis of experimental results shows that the effectiveness of our proposed methods, and it can provide a good reference value for the deployment of intelligent smoke sensors in tall spaces. However, our proposed method
still has some shortcomings, such as idealized spatial three-dimensional environment and few obstacles, etc. In the future work, we will consider the deployment of intelligent smoke sensors in tall spaces under more restrictive conditions and more real environment.

Acknowledgments
This research was supported by the National Natural Science Foundation (61762029, U1811264), Guilin Science and Technology Development Program (20190211-20).

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