An optimized deployment strategy of smart smoke sensors in a large space

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Abstract

With the development of the NB-IoT (Narrow band Internet of Things) and smart cities, coupled with the emergence of smart smoke sensors, new requirements and issues have been introduced to study on the deployment of sensors in large spaces. Previous research mainly focuses on the optimization of wireless sensors in some monitoring environments, including three-dimensional terrain or underwater space. There are relatively few studies on the optimization deployment problem of smart smoke sensors, and leaving large spaces with obstacles such as libraries out of consideration. This paper mainly studies the deployment issue of smart smoke sensors in large spaces by considering the fire probability of fire areas and the obstacles in a monitoring area. To cope with the problems of coverage blind areas and coverage redundancy when sensors are deployed randomly in large spaces, we proposed an optimized deployment strategy of smart smoke sensors based on the PSO (Particle Swarm Optimization) algorithm. The deployment problem is transformed into a multi-objective optimization problem with many constraints of fire probability and barriers, while minimizing the deployment cost and maximizing the coverage accuracy. In this regard, we describe the structure model in large space and a coverage model firstly, then a mathematical model containing two objective functions is established. Finally, a deployment strategy based on PSO algorithm is designed, and the performance of the deployment strategy is verified by a number of simulation experiments. The obtained experimental and numerical results demonstrates that our proposed strategy can obtain better performance than uniform deployment strategies in terms of all the objectives concerned, further demonstrates the effectiveness of our strategy. Additionally, the strategy we proposed also provides theoretical guidance and a practical basis for fire emergency management and other departments to better deploy smart smoke sensors in a large space.

Keywords: NB-IoT, optimized deployment strategy, smart smoke sensors, large space, intelligent optimization algorithm, coverage accuracy, deployment cost

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1. Introduction

With the continuous emergence and development of smart cities, complex 3D (Three-Dimensional) urban environments have brought new issues and challenges in the study of WSNs (wireless sensor networks) deployment [1]. WSNs are an essential parts of smart cities construction, and deploying sensors in some monitoring areas is a challenging work[2]. The progress of sensors deployment was primarily motivated by applications in military such as battlefield surveillance. Nevertheless, they have been being applied to many industrial and civilian application areas currently, which includes the monitoring of industrial process, underwater environmental monitoring and residential fire monitoring. As a fundamental problem in WSNs, deploying sensors in a certain mpnitoring area has caught many reseachers' great attention in the past years [3]. In general, the number of sensor nodes and their final deployment positions in the monitoring areas will affect the topological structure of a WSN, which will also determine factors involving the coverage ratio, deployment cost and network life. In a monitoring scene, the efficiency of a WSN depends mainly on the deployment strategy of sensors. Most of researchers at home and abroad have gained a number of achievements research on the deployment strategy of sensors[4]. The deployment problem is formulated as a MOPT problem two or more conflicting objectives in many researches, the aim of the optimization process is to obtain reasonable trade-offs between the two objectives[5]. However, while sensors are used in greater numbers for residential and supermarket environments, the optimal deployment strategies become increasingly significiant[6]. While the coverage quality and network connectivity have been optimized in many literature, the most scenes of deployment only considerre the terrestrial two-dimensional networks. Unfortunately, most of studies cannot be directly applied to 3D networks[7]. How to reduce the network energy consumption and increase the network lifetime to obtain a good coverage quality is a significiant problem in the process of deploying sensors, and we can model it as the MOPs (Multi-objective Optimization Problems). The purpose of solving MOPs with multiple conflicting optimization objectives is to get an approximation of the Pareto front[8]. MOPs should be provided with two or more nondominated solutions involving different objective functions. The deployment of sensors in a large space satisfying two or more objective functions is a challenging problem[8]. As a result, multi-objective method is always the best way in cases dealing with two or more conflicting objectives[7].

The deployment problem of smart smoke sensors is a special type of problem in fire emergency management. The nodes are distributed on the upper surface of this three-dimensional monitoring environment to achieve the purpose of detecting the space. The deployment problem of smart smoke sensors in large spaces is close to practical application scenarios and has a certain degree of complexity, Therefore, there are few researches on this fields. Based on the above analysis, this paper develops an optimized deployment strategy based on an intelligent algorithm, and the deployment problem of smart smoke sensors is modeled as the MOPs problem with two objective functions, namely, the deployment cost and the coverage accuracy. The goal of the deployment process is to develop a reasonable trade-offs between the two objectives we designed. An extensive number of siumlation experiments was conducted systematically to demonstrate the performance of our proposed deployment strategy.

The main contributions of this study are summarized as the following three parts:

1) We first design a structure model in a large space and propose a coverage model; Then we establish a mathematical model including two optimal objectives: the coverage accuracy and the deployment cost. By maximizing the coverage accuracy and minimizing the

deployment cost, the overall coverage quality of smart smoke sensors is improved;

2) This paper develops an optimized deployment strategy of smart smoke sensors that are suitable for large spaces, which considers the probability of fire areas and in the presence of some random obstacles in the monitoring area;

3) The proposed strategy is optimized by the PSO algorithm, and compared with the traditional uniform deployment strategy under different parameter settings. Simulation results show the better performance of our developed optimized deployment strategy.

The organization structure of this paper is desingned as follows. The related work including our research is described in Section 2. Then, we design the structure model in Section 3, as well as the mathematical model, including two objective functions. The PSO algorithm to optimize our developed optimizing deployment strategies is described in Section 4. And in Section 5, we show the simulation experiments and detail analysis. Finally, the conclusions and future work are discussed in Section 6.

2. Related Work

In this paper, we describe the related work involving the deployment strategies of sensors in some monitoring area. According to the placement of deployed sensors, deployment strategies can be classified into random and deterministic deployment[2]. At present, many useful deployment strategies for monitorng the specific spaces have been proposed in literatures[9]. Many researches has mainly focused on sensors deployment schemes in a two-dimensional monitoring environment, Most of which aim at obtaining high coverage ratio and network connectivity, minimizing the deployment cost and energy consumption[10]. Therefore, optimal sensor nodes arrangement is a necessary problem for some essential objectives in the process of deployment, such as cost, coverage ratio, lifetime and connectivity[11]. Moreover, scholars also have performed a comparative study on the different node deployment schemes in more actual environment monitoring systems[12]. This section describes the previous work related to sensors deployment strategies. The work varies in terms of the sensors' actual application scenario, deployment objectives and strategies, and the study on the deployment strategy of sensors is generally divided into three types from the perspective of monitoring areas.

2.1 Sensors Deployment Strategy Research for 3D Terrain Coverage

The sensors deployment problem involving the scene of 3D surface have been studied in many literatures. The development of the concept of smart cities and the emergence of 3D urban terrain data have brought new requirements and challenges to the research on deployment of wireless sensor networks. The authors in [1] study the deployment problem of heterogeneous and directional wireless sensor networks in 3D smart cities. The deployment problem is transformed into a multi-objective optimization problem (MOP) based upon three-dimensional urban terrain datas, and then a distributed parallel multi-objective evolutionary algorithms (MOEAs) are designed to solve this problem. The authors both in [14-15] study the node deployement peoblem on 3D terrian, and the aim is to achieve the optimal monitoring of 3D terrian. Boufares[14] proposed a distributed deployment algorithm on the basis of an improved virtual force strategy, which is effective in improving the coverage ratio of different complex terrain surface function models while ensuring the connectivity of sensors network and lowering the deployment cost. While the paper[15] developed an uncertain comprehensive coverage model and a 3D probabilistic sensing model, and an uncertain non-probabilistic fusion operator is adopted to merge the occluded coverage regions in this model. The proposed deployment scheme is more suitable for practical security monitoring spaces and it has more practical importance. Finally, multi-objective optimization algorithm based on deployment approaches are utilized to solve the 3D Terrain deployment problem. In paper[16], the authors proposed a special deployment approach to achieve better sensor deployment effect in terms of coverage rate and the network connectivity in three-dimensional (3D) terrain scenario. The developed deployment methos is combined the distributed particle swarm optimization (DPSO) algorithm with virtual force (VF) algorithm. However, the authors in [17] considered the border monitoring areas as an important concerns to conduct a task of sensors deployment, and the authors proposed a hybrid deployment schemes consisting of multimedia wireless sensor networks and marine wireless networks to detect a border area in the deployment spaces.

2.2 Sensor Nodes Deployment Optimization in UWSNs

The application of wireless sensor networks (WSNs) has been employed gradually in underwater application environments as a significiant field in the study of wireless sensor networks in the past year. Underwater wireless sensor network (UWSN) also has been being a novel research field[18]. Currently, the UWSNs have been applied to many fields including environment exploration, military surveillance and the collection of sensing data. The optimizing deployment of sensors in UWSNs is a significiant aspect in the real world; however, it is a difficult problem because of the uncertaion and complex underwater environment[19]. The authors in [19-20] study the deployment stratrgies and recent developmetn in UWSNs, which solving the exist of coverage holes on the basis of achieving the target of maximizing the coverage rate and energy balance.The paper [10] analyzes the impacts of deployment strategies on localization performances in a three-dimensional underwater sapce; the experimental results suggest that the regular tetrahedron deployment strategy performs better than the deployment strategy randomly, and the cube deployment strategy in improving the localization error and localization rate while obtaining satisfactory coverage qulity network connectivity.

2.3 Sensor Nodes Deployment Optimization in Three-dimensional Full Space

The three-dimensional full space mainly includes tall and complex indoor spaces such as unmanned supermarkets, unmanned warehouses, gymnasiums, etc. The authors in [12-13] partically studies the deployment problem of WSNs in an indoor environment, and design a node deployment algorithm of wireless sensor networks that applied to indoor space, which optimizes the deployment stratgy with better coverage quality through the method of experiment and comparison. The author of [21-22] realized the optimization of coverage, deployment cost and other goals by deploying sensor nodes on a two-dimensional plane and using intelligent optimization algorithms to find the optimal location of nodes. The comparison of experimental results suggests that the use of multiple objectives evolutionary algorithms is significantly better than genetic algorithms traditionally. Therefore, we can know that the previous studies used a multi-objective optimal approach to solve the node deployment problem from the above analysis. Although the above algorithm strategies can achieve a better coverage quality in terms of sensors deployment problem, more practical and significant issues have yet to be addressed[22]. The current research in this area is relatively ideal, and in the real environment, there will be more or less obstacles and fire areas with different fire probabilities, so there are still some shortcomings in the research of three-dimensional whole space. The existing studies on the deployment of WSNs in confined indoor spaces have not comprehensively considered various deployment application requirements and the interference of obstacles to wireless sensor signals, which leads to waste of sensor perception and communication capabilities. It is evident that environmental obstacles and type can affect the computation of the network coverage rate[24]. Smart smoke sensors have been universally studied and developed in recent years[18]. Thus, compared with previous studies, this paper considers the sensor node deployment problem in a complex and tall dynamic space environment including a certain number of obstacles, also considers the situation that there are fire areas with different fire probabilities in the monitoring, and mainly deploys smart smoke sensor nodes not the wireless sensor nodes. For this purpose, this artical proposes an optimized deployment strategy to minimize the deployment cost while obtaining the optimal coverage accuracy. Maintaining a high coverage ratio and minimizing the network deployment cost are two conflicting essential problems concerned by service providers in the real world. The proposed strategy is well established in most cases[25].

3. Smart smoke sensor node deployment Model in large space

In this section, we describe the coverage model, as well as introduce the objective functions need to be optimized, which includes the coverage accuracy and the deployment cost. And furthermore, we conclude the relevant constraints in the process of nodes deployment. **Table 1** presents the list of symbols used in this paper.

Table 1. List of symbols used in the paper

Symbol	Description
L, W	Length, width of the monitoring area
A_r	Monitoring area
S	The set of deploying smart smoke sensors
P	The set of fire area
O	The set of obstacles
n	The number of smart smoke sensors
m	Number of fire areas
k	The number of obstacles
(x_i, y_i)	Position coordinate of smart smoke sensors
$d(s_i, p_j)$	Distance between smart smoke sensors and fire area
(x_j, y_j)	The location coordinates of fire area
$V(S, P)$	Coverage perception probability of fire area
δ_{ij}	The state of coverage
τ_{ij}	The sensitivity of smart smoke node
$n_{obstracle}(s_i, p_j)$	The number of obstacles between S and P
$f_{Coverage}$	The Coverage rate
f_{CA}	The Coverage Accuracy
$f_{DeploymentCost}$	The Depoyment Cost
Pd_s^i	The installation cost of a smart smoke sensor
$\mathcal{M}_s^i$	The maintenance cost of a smart smoke sensor
C_s^n	The economic cost of a smart smoke sensor

3.1 The Structure Model in large space

Assumed that the smart smoke sensors are scattered to the space upper surface, then initially form a connected network on this two-dimensional plane. Considering that there are obstacles and fire-prone areas in high space, we mesh the deployment area from the perspective of a two-dimensional plane. The fire areas and obstacles are randomly set according to the probability of fire and the actual situation. The fire area and obstacles are set according to the actual characteristics of the large space. The considered scenario in our paper is shown in **Fig. 1**. Where the red points are the deployed sensor nodes, the yellow dots represent the areas of fire, and the darker the color is, the greater the probability of fire. The rectangular blocks are obstacles that will have a certain impact on the coverage accuracy. When there is an obstacle between the fire area and the deployment node, it will affect the speed and concentration of smoke diffusion in the fire area, thus affecting the coverage accuracy of intelligent smoke sensors deployed near the fire area. Moreover, the greater the degree of obstruction to the fire area, the greater the impact on the performance of intelligent smoke detection.

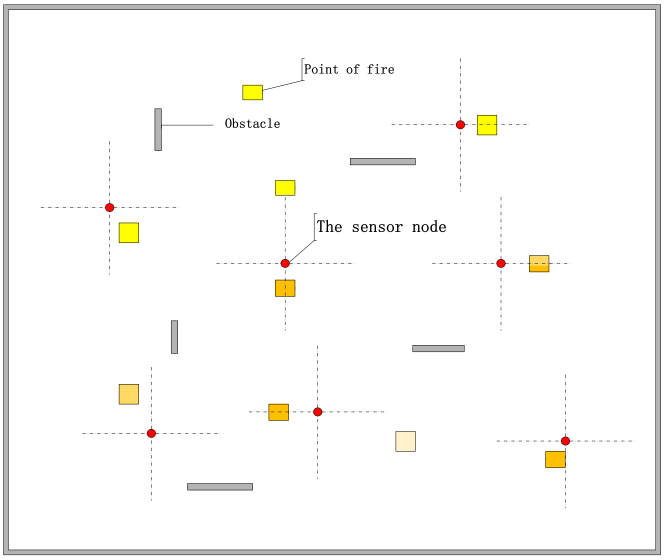


Fig. 1. The plane structure model of node deployment

3.2 The coverage model

3.2.1 Assumptions

In the process of deployment, smart smoke sensors are placed to the optimal in the monitoring area so that fewer sensors can provide optimal coverage accuracy with lower network maintenance and management cost[26]. In our model, we put forward the following assumptions:

• The monitoring area varied from a square shape to a rectangular shape of different sizes;

• Each smart smoke sensor node has the same detection range of r. In the initial phase, the sensor nodes are deployed randomly in the monitoring area, the size of which is denoted as $L \times W$, and the number of smart smoke sensors is denoted as n;

• There are some areas of fire P with different fire probabilities in the deployment area. There are some obstacles O in the monitoring area.

3.2.2 Line of Sight (LOS)

Assume that a sensor S, to cover a fire point P on the large space, there should exist a line of sight (LOS) between S and P, which means that the straight-line distance between them is not occluded by some obstacles; the visibility of this target point P is equal to 1 in this case.

Otherwise, no line of sight (NLOS) [15] indicates that there are some obstacles between them; the visibility of this fire point p is equal to 0. The calculation expression is as follows:

$$V(S,P) = \begin{cases} 1, & if\ LOS \\ 0, & if\ NLOS \end{cases} \quad (1)$$

3.2.3 Problem Description

Let $A_r = L \times W$ be a cross section in a complex high space including a certain number of fire areas and obstacles, given randomly n smart smoke sensors in the target area A_r. The deployed sensor nodes are defined by $S = \{s_1, s_2, \ldots, s_n\}$, and each node has the same detection range r. While the points of fire are $P = (p_1, p_2, \cdots, p_m)$. Assume that there are some obstacles in the monitoring area, which can be described by $O = (o_1, o_2, \ldots, o_k)$. Furthermore, for any target point of fire p_j in the monitoring, the Euclidean distance between sensor node $s_i = (x_i, y_i)$ and point of fire $p_j = (x_j, y_j)$ can be expressed by:

$$d(s_i, p_j) = \sqrt{(x_i - x_j) + (y_i - y_j)} \quad (2)$$

For most parts, any points of fire p_j in the deployment area need to meet the following conditions to be considered to be covered by the sensor node s_i:

$$\delta_{ij} = \begin{cases} 1, & if\ d(s_i, p_j) \leq r \\ 0, & otherwise \end{cases} \quad (3)$$

δ_{ij} denotes that whether the fire area is covered by deployed nodes. $\tau_{ij}$is defined as the sensitivity of smart smoke node s_i to target node p_j. If there is no obstacle between the two, the sensitivity is 1. If there is an obstacle, the visibility of the monitored node will be reduced, the distance at which the smoke spreads will be longer so that the detection sensitivity will be reduced, and the calculation expression is:

$$\tau_{ij} = \begin{cases} 1, & if\ obstacles\ not\ exist \\ \frac{V(S,P)}{1+n_{obstacle}(s_i,p_j)}, & if\ obstacles\ exist \end{cases} \quad (4)$$

where $n_{obstracle}(s_i, p_j)$ is the number of obstacles between the sensor and the fire area, which depends on the concept of adaptive *LOS* theory[15].

Furthermore, the multi-objective optimization problem can be transfromed into a linear function f consisting of many objectives to be maximized for the problem considering constraints[27]. The objective function can be express by:

$$maxf(x) = \alpha f_1(x) + \beta f_2(x) + \cdots + \gamma f_i(x) \quad (5)$$

where $f_i(x)$ is the objective function to be optimized for the problem by considering $\alpha + \beta + \cdots + \gamma = 1$.

3.3 Optimization objectives

There are two optimization objectives considered in the process of node deployment. The first is coverage accuracy maximization, and the second is total deployment cost minimization.

3.3.1 The coverage Accuracy

The detection accuracy should be maintained to an optimal level in the problem of deployment. In this paper, we mainly consider the following main factors: the coverage rate, the sensitivity of the sensor and the presence of obstacles. First, the coverage rate of the smart smoke node s_i can be defined as:

$$f_{Coverage} = \frac{sum(Count_{p>\varphi})}{L \times W} \tag{6}$$

where the calculation form is the ratio of the number of covered grids to the total number of grids, and φ is the coverage threshold value.

where the coverage accuracy is the coverage ratio under the condition that the certain coverage ratio P_{th} is achieved. Then the coverage accuracy f_{CA} of the monitoring area is calculated as:

$$\begin{cases} f_{Coverage} \geq P_{th} \\ f_{CA} = \delta_{ij} \times \tau_{ij} \times f_{coverage} \end{cases} \tag{7}$$

3.3.2 The Deployment Cost

In the phase of sensor node deployment, we first should take into consideration the available budget. One of the deployment goals, from an economic point of view, is to reduce the cost while reaching a satisfactory detection performance according to the specification of the application [28]. In this paper, we mainly consider the number of sensor nodes we deployed in the monitoring area. We use $f_{DeploymentCost}$ to represent the deployment cost function. Therefore, the deployment cost function value in our model can be defined as:

$$f_{DeploymentCost} = \sum_{i=1}^{n} (Pd_s^i + \mathcal{M}_s^i + C_s^n) \tag{8}$$

Where Pd_s^i represents the installation cost of the i smart smoke sensor, C_s^n represents the economic cost of a smart smoke sensor, $\mathcal{M}_s^i$ represents the maintenance cost of the i smart smoke sensor after deployment.

3.3.3 Constrains

Based on the above description of relevant models and objective functions, the optimization problem solved can be described as:

$$\begin{cases} max\, f_{CA} \\ Min f_{DeployementCost} \\ s.t. O, S, P \in A \\ (x_i, y_i), (x_j, y_j) \in A_r \\ 1 \leq i \leq n, n \in [2,50] \\ 1 \leq j \leq m, m \in [10,20] \end{cases} \tag{9}$$

4. Proposed Methodology of Optimizing Deployment Problem

In this section, we introduce the idea of the optimized deployment strategy of smart smoke sensors, and describe the PSO algorithm to deploy smart smoke sensors in a large space.

4.1 Proposed deployment strategy of Smart Smoke Sensor

4.1.1 The design of node deployment strategy

An optimial deployment strategy can improve the coverage quality of sensor networks and reduce deployment cost. As show in **Fig. 2**, the sensor node deployment phase includes the four following steps.

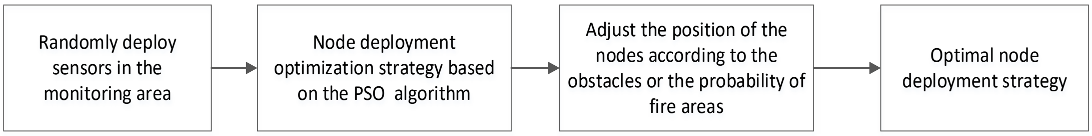


Fig. 2. The flow of optimizing deployment strategy

4.2 Node deployment method based on an intelligent optimization algorithm

4.2.1 PSO algorithm

In actual deployment scenarios, finding the optimal positions of sensor nodes so that the coverage accuracy is maximized and deployment cost is minimized are so challenging. The multi-objective optimization algorithm is a relatively suitable solution to achieve the minimum number of sensors and maximize the coverage accuracy.

To date, various approaches including heuristics and approximation algorithms, have been used to solve the optimization deployment problem of sensor nodes in some actual environments[29]. In this paper, we choose the particle swarm optimization (PSO) algorithm that was mentioned in paper [29] to solve the deployment problem of smart smoke sensors in large spaces the we mentioned above the sections, and some parameters are improve to better optimize our objectives. It can be known that PSO algorithm faces the multimodal problem in most application-oriented sensors deployment scenarios. Therefore, the optimized deployment algorithm must track and observe the value of each peak in the actual application, as each peak may be the optimal peak that we need[6]. In general, the particle swarm optimization (PSO) algorithm initializes the solution set of the multi-objective problem that needs to be optimized as a group of random particles. Afterwards, according to the corresponding formula the current position and speed are updated. In the trational PSO algorithm, the deployment problem of the sensors in monitoring areas is simulated as swarm particles, which move at the surrounding search space and are improved by both their own and swarm's best position through constant generations to find the optimal solutions that we need[27].

We have summarized the steps of the optimization PSO algorithm suitable for the deployment optimization problem we proposed in this article. **Table 1** shows the node deployment strategy steps for the PSO-based algorithm to maximize the coverage accuracy and minimize the deployment cost.

Table 2. The Pseudocode of optimized PSO algorithm

Node deployment strategy in high space based on PSO algorithm
Input: the number of nodes n, deployment space $L \times W$ and maximum iteration $maxgen$
Initializes each particle with a swarm of n
While ($maxgen$ is not reached)
For each swarm **do**
For each particle in the current swarm **do**
Update the context vector
Calculate the fitness values and put in in $\boldsymbol{Fitness_{current}}$
If $\boldsymbol{Fitness_{current}} > \boldsymbol{pbest}$ **then**
Set the current values as the new $pbest$ for this particle
End if
End for
End for
Choose the particles with the best fitness values among all the particles as $gbest$ so that they can satisfy the requiring conditions of the deployment problem our proposed
Fill the context vector with $gbest$
For each particle **do**
Update speed and location of particle
End for
End while
Output: Global optimal $gbest$

5. Simulation Experiments and Analysis

In the previous section, the developed problem is described as MOPs with two objectives including the coverage accuracy and the deployment cost that may conflict with each other[30]. Then, we design a deployment strategy on the basis of the PSO algorithm to solve this problem and compare with the uniform deployment strategy. Therefore, in this part, we introduce our detail experimental parameters and analyze the performance of the different deployment strategies of smart smoke sensors. We use MATLAB R2020a for simulation experiments, randomly distribute sensor nodes in the monitoring area and randomly set up a certain number of fire areas with different fire probabilities and rectangular obstacles in the monitoring area.

To verify the superiority of our proposed optimized deployment strategy of smart smoke sensors in dealing with the deployment problem in a large space, we will conduct many simulation experiments using PSO algorithms to evaluate the perfromance of the expe rimental results. First, two types of deployment strategies are compared, including our proposed optimized deployment strategy of smart smoke sensors and traditional uniform deployment. Second, the size and shape of the monitoring area, the number and fire probability of the fire areas, and the number of obstacles is varied; and we conducted a large number of simulation experiments to verify the coverage performance of two deployment strategies under the conditions of different parameters. Then, the number of sensors required for different deployment strategies to achieve the deployment scheme is compared. Finally, we analyze the coverage accuracy of two deployment strategies under different parameter settings.

5.1 Deployment Simulation with Different Levels of Fire Probability

5.1.1 Parameter Setting

According to the GB50116-98 standard design specification for automatic fire alarm systems, we assume that the sensing radius of the smart smoke sensor is approximately *5m*. The main parameter settings of the simulation experiment are shown in **Table 3**. The detailed parameter settings for different monitoring scenarios are shown in **Table 4**. And **Table 5** shows the setting of fire probability parameters in the fire area.

Table 3. Simulation Parameter

Parameter Description	**Parameter setting**
Node Perceived Radius R	5
Monitoring Area Type	Square monitoring area
	Rectangular monitoring area
Number of smart smoke sensor nodes	[2,50]
The number of obstacles	[2,10]
The number of fire areas	[2,20]
Classification of fire area	High risk areas
	Medium risk area
	Low risk area

Table 4. Specific parameter values for different deployment scenarios

Monitoring area shape	Monitoring area size	Number of obstacles	Number of fire areas	Number of deployment nodes
Square monitoring area	25×25	5	10	[2,12]
	32×32	5	10	[2,18]
	45×45	10	20	[2,25]
	55×55	10	20	[2,50]
Rectangular monitoring area	30×40	5	15	[2,20]
	32×55	10	20	[2,25]

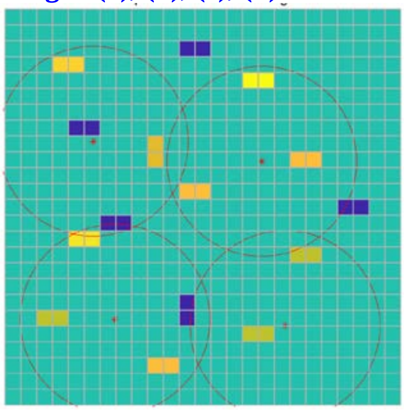
Table 5. Fire probability parameter

Risk Area Level	High risk areas	Medium risk area	Low risk area
Fire probability range	[0.1,0.3]	[0.4,0.6]	[0.7,0.9]

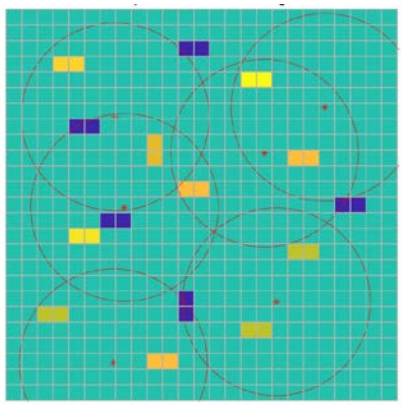
5.1.2 Deployment Simulation under the different square monitoring areas

To prove the effectiveness of the optimized deployment strategy of smart smoke sensors based on the PSO algorithm that we proposed, we conducted a large number of simulation experiments under the above parameters. The final deployment position results of our proposed optimized deployment strategy and uniform deployment strategy under the different parameter settings are shown in **Fig. 3** to **Fig. 6**. Where in the Figures, the blue blocks represent obstacles in the monitoring area, the yellow blocks with different colors represent futures areas with different fire probabilities, the red asterisks represent deployed sensor nodes, and circles represent the coverage of nodes.

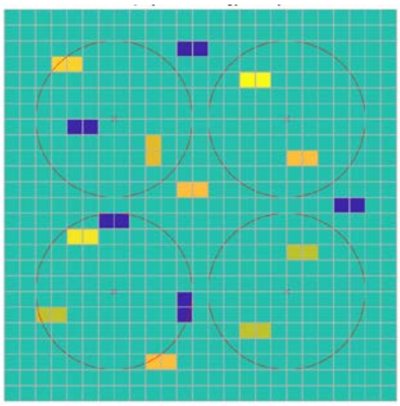
The optimization strategy based on the PSO algorithm that we proposed prioritizes the fire areas and obstacles in the monitoring area in the process of node deployment. The sensor nodes will search whether there is a fire area in the surrounding 5 units through the action of the intelligent optimization algorithm, and if there is a fire area, a sensor node will be deployed around this fire area. While the sensor nodes encounter an obstacle, it will automatically avoid the obstacle. Moreover, when the number of sensor nodes is less than the number of fire areas, the nodes will preferentially move to the area with higher fire probability. When considering square monitoring areas of different sizes, including $25 \times 25m^2$, $32 \times 32m^2$, $45 \times 45m^2$, and $55 \times 55m^2$, the node deployment situations of our proposed strategy and the uniform deployment strategy are shown in **Fig. 3** to **Fig. 6**. Among them, **Fig. 3 (a) and (b)** denotes the final deployment location optimized by PSO algorithm when the number of smart smoke sensors is 4 or 6, while **Fig. 3 (c) and (d)** shows the final deployment location under the uniform deployment stratergy whem the number of sensors is 4 or 9 under the same parameter settings. Then, Change the square monitoring area of size to size $32 \times 32m^2$, and other parameters remain unchanged, the final deployment location under the deployment strategy based on PSO algorithm and the uniform deployment stategy are shown in **Fig. 4 (a), (b), (c), (d)**. Moreover, we varied the size of the monitoring area, the number of obstacles and fire areas and other parameters, and the final deployment results are shown in **Fig. 5 (a), (b), (c), (d) and Fig. 6 (a), (b), (c), (d)**.



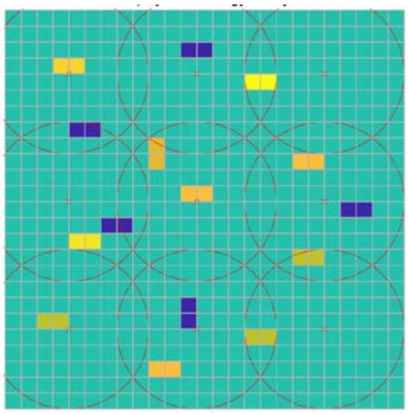
(a) PSO: 4 nodes



(b)PSO: 6 nodes



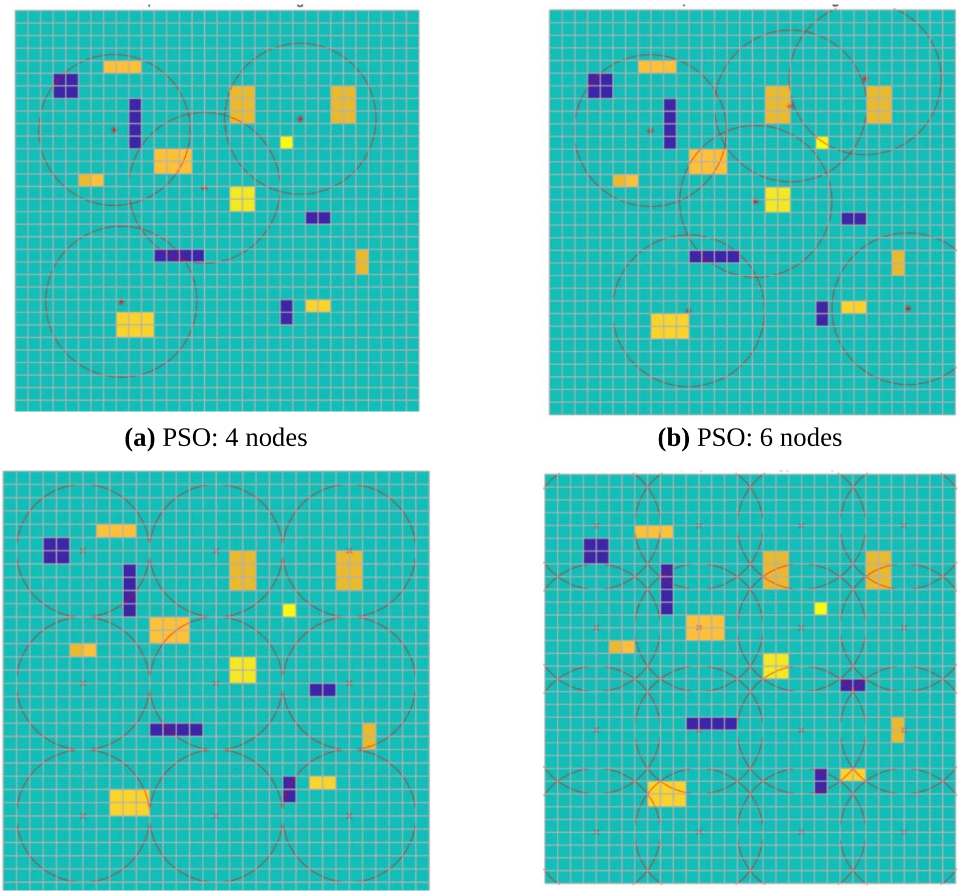
(c) Uniform deployment:4 nodes



(d) Uniform deployment:9 nodes

Fig. 3. The final deployment of the smart smoke sensors with the square monitoring area is $25 \times 25\ m^2$. (**a**) Optimizing deployment based on the PSO algorithm: 4 nodes; (**b**) Optimizing deployment based on the PSO algorithm: 6 nodes; (**c**) Uniform deployment of 4 nodes; (**d**) Uniform

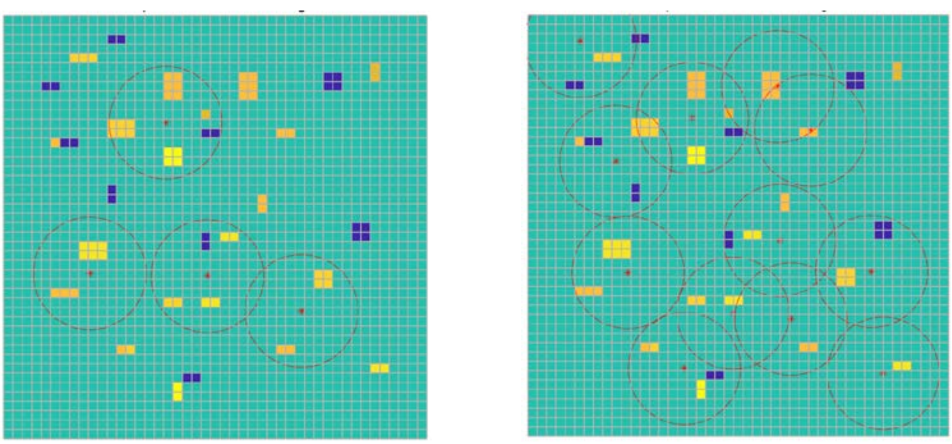
deployment of 9 nodes.



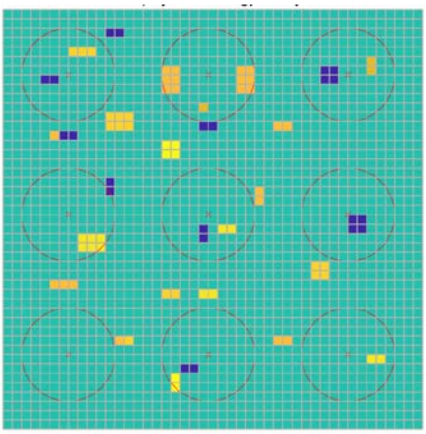
(a) PSO: 4 nodes **(b)** PSO: 6 nodes

(c) Uniform deployment:9 nodes **(d)** Uniform deployment:16 nodes

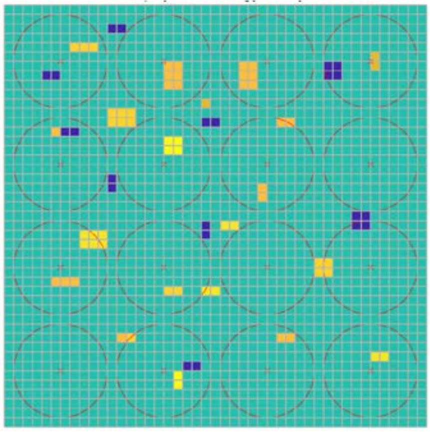
Fig. 4. The final deployment of the smart smoke sensors with the square monitoring area is $32 \times 32\ m^2$. (**a**) Optimizing deployment based on the PSO algorithm: 4 nodes; (**b**) Optimizing deployment based on the PSO algorithm: 6 nodes; (**c**) Uniform deployment of 9 nodes; (**d**) Uniform deployment of 16 nodes.



(a) PSO: 4 nodes **(b)** PSO: 12 nodes

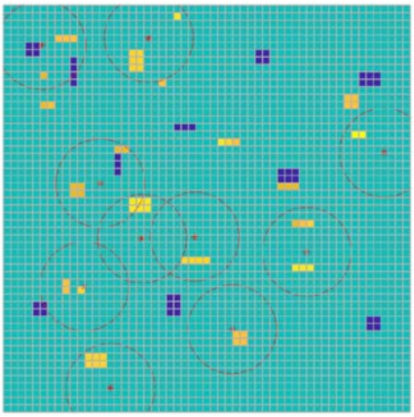


(c) Uniform deployment:9 nodes

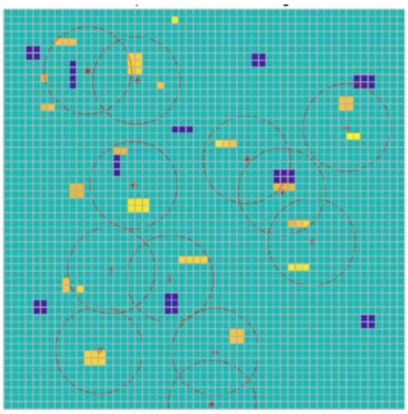


(d) Uniform deployment:16 nodes

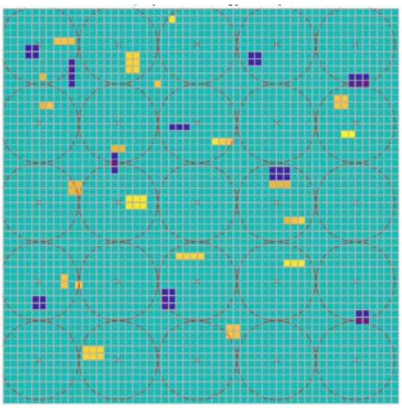
Fig. 5. The final deployment of the smart smoke sensors with the square monitoring area is $45 \times 45\ m^2$. (**a**) Optimizing deployment based on the PSO algorithm: 4 nodes; (**b**) Optimizing deployment based on the PSO algorithm: 12 nodes; (**c**) Uniform deployment of 9 nodes; (**d**) Uniform deployment of 16 nodes.



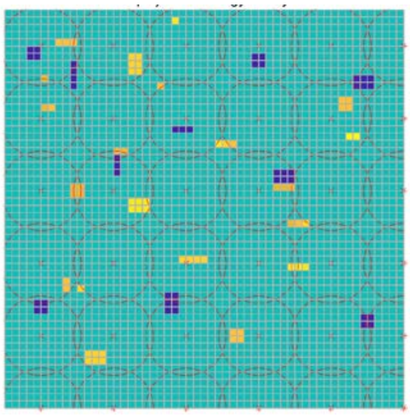
(a) PSO: 10 nodes



(b) PSO: 12 nodes



(c) Uniform deployment:25 nodes



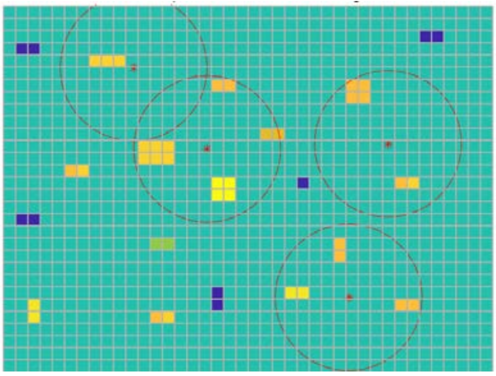
(d) Uniform deployment:36 nodes

Fig. 6. The final deployment of the smart smoke sensors with the square monitoring area is $55 \times 55\ m^2$. (**a**) Optimizing deployment based on the PSO algorithm: 10 nodes; (**b**) Optimizing deployment based on the PSO algorithm: 12 nodes; (**c**) Uniform deployment of 25 nodes; (**d**) Uniform deployment of 36 nodes.

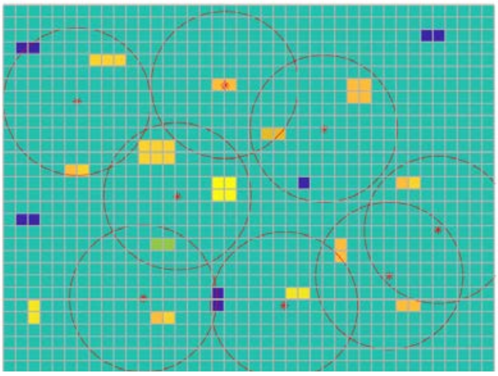
5.1.3 Deployment Simulation under the different rectangular monitoring areas

To further prove the superiority of our proposed strategy, while keeping the other simulation parameters unchanged, when considering rectangular monitoring areas of different sizes, including $30 \times 40m^2$ and $32 \times 55m^2$, the sensor node distributions of our proposed optimized deployment strategy and uniform deployment are shown in **Fig. 7** to **Fig. 8**. Where blue blocks represent obstacles in the monitoring area, yellow blocks with different colors represent futures areas with different fire probabilities, red asterisks represent deployed sensor nodes, and circles represent the coverage of nodes.

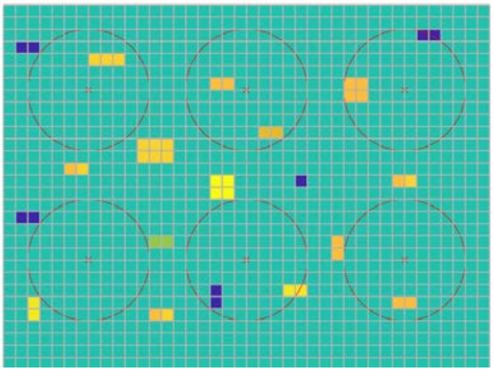
Among them, **Fig.7 (a) and (b)** denotes the final deployment location optimized by PSO algorithm when the number of smart smoke sensors is 4 or 8, while **Fig. 7 (c) and (d)** shows the final deployment location under the uniform deployment stratergy whem the number of sensors is 6 or 12 under the same parameter settings. Then, Change the rectangular monitoring area of size to size $32 \times 55m^2$, and other parameters remain unchanged, the final deployment location under the deployment strategy based on PSO algorithm and the uniform deployment stategy are shown in **Fig. 8 (a), (b), (c), (d)**.



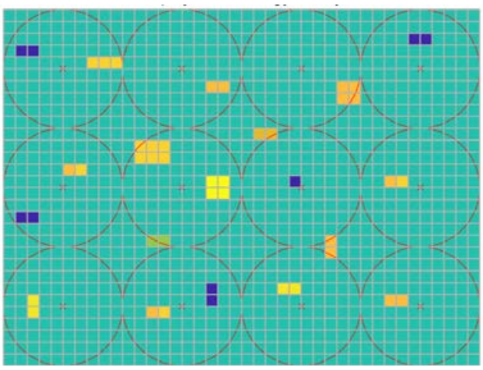
(a) PSO: 4 nodes



(b) PSO: 8 nodes

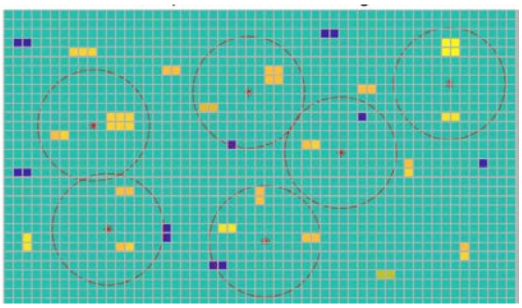


(c) Uniform deployment:6 nodes

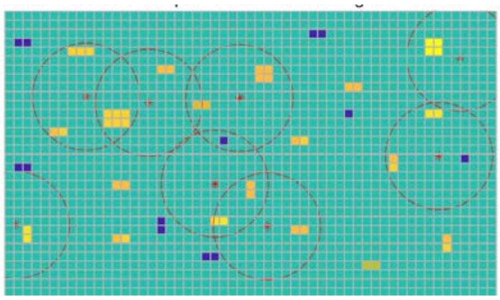


(d) Uniform deployment:12 nodes

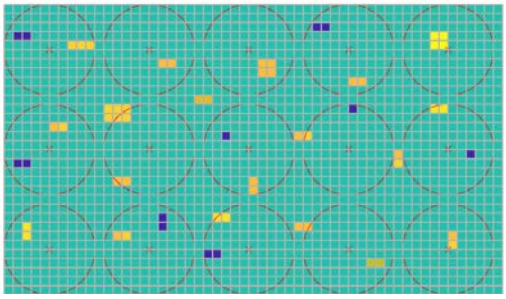
Fig. 7. The final deployment of the smart smoke sensors with the rectangular monitoring area is $30 \times 40\ m^2$. (**a**) Optimizing deployment based on the PSO algorithm: 4 nodes; (**b**) Optimizing deployment based on the PSO algorithm: 8 nodes; (**c**) Uniform deployment of 6 nodes; (**d**) Uniform deployment of 12 nodes.



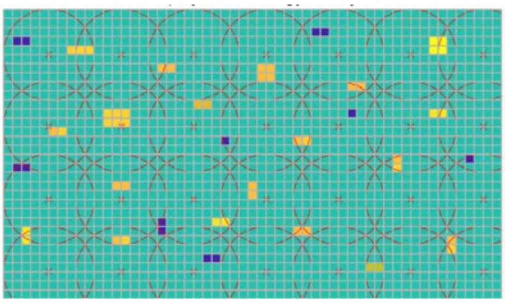
(a) PSO: 6 nodes



(b) PSO: 8 nodes



(c) Uniform deployment:15 nodes

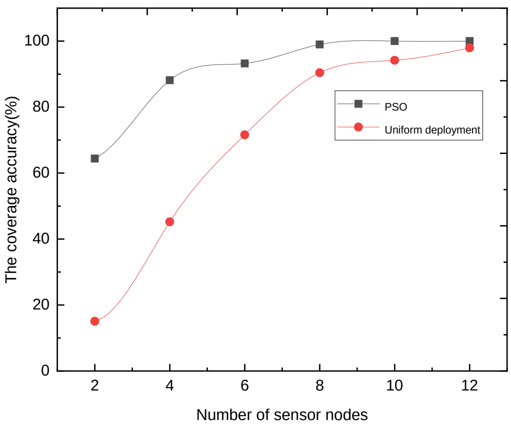


(d) Uniform deployment:28 nodes

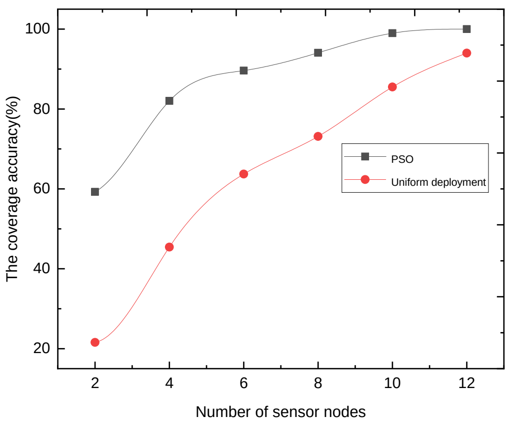
Fig. 8. The final deployment of the smart smoke sensors with the rectangular monitoring area is $32 \times 55\ m^2$. (**a**) Optimizing deployment based on the PSO algorithm: 6 nodes; (**b**) Optimizing deployment based on the PSO algorithm: 8 nodes; (**c**) Uniform deployment of 15 nodes; (**d**) Uniform deployment of 28 nodes.

5.2 Comparison of the results with different deployment strategies

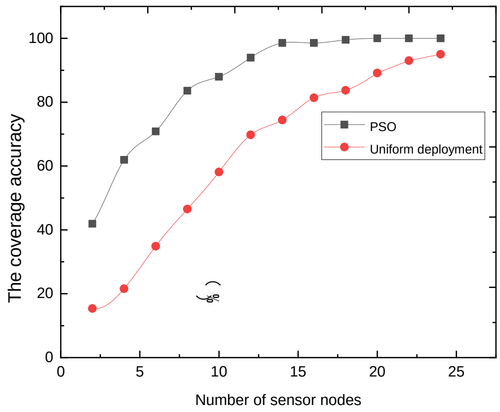
Through a lot of simulation experiments, the effectiveness of our proposed optimized deployment strategy of smart smoke sensors is fully verified. In this section, we compare the coverage accuracy of our proposed deployment strategy with the uniform deployment strategy under different numbers of sensors. As we can see from **Fig. 9**, in general, we can find that our proposed optimized deployment strategy requires fewer sensors to be deployed while achieving the same coverage accuracy, which not only saves deployment costs, but also obtains better coverage accuracy.



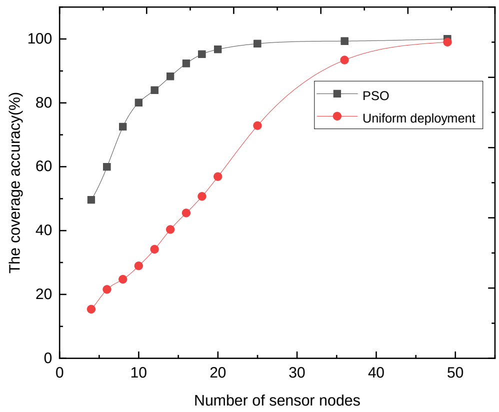
(a) Monitoring area: 25×25



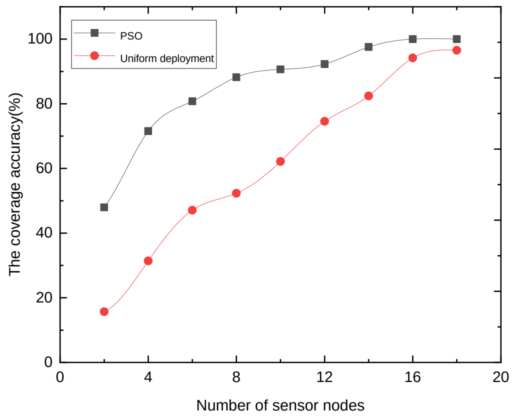
(b) Monitoring area: 32×32



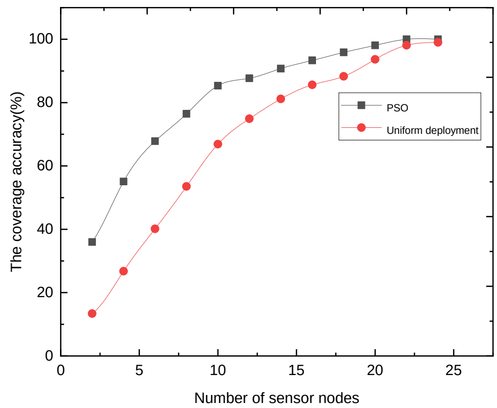
(c) Monitoring area: 32×32



(d) Monitoring area: 55×55



(e) Monitoring area: 30×40



(f) Monitoring area: 32×55

Fig. 9. Comparison of the coverage accuracy under different deployment strategies. (**a**) The monitoring area is 25×25; (**b**) The monitoring area is 32×32; (**c**) The monitoring area is 45×45; (**d**) The monitoring area is 55×55; (**e**) The monitoring area is 30×40; (**f**) The monitoring area is 32×55.

It can be seen from **Fig. 9(a)** that compared with the uniform deployment strategy, our proposed optimized deployment strategy requires fewer nodes to be deployed while achieving the same coverage performance, and uses the coverage capacity of each node to the maximum efficiency so that the deployed smart smoke sensing nodes give priority to areas with fire risk. While ensuring the coverage effect, the deployment cost is reduced. As shown in **Fig. 9(b), (c) and (d)**, we obtain the same simulation results when we increase the size of the square monitoring area. To further prove the applicability of our proposed optimized deployment strategy in monitoring areas of different shapes and sizes, we conduct the simulation experiment again under the condition of changing the size and shape of the monitoring area and setting up fire areas with different fire probabilities and a certain number of obstacles. Then, we compared the experimental results with the uniform deployment strategy. It can be seen from **Fig. 9(e) and (f)** that after changing the shape and size of the monitoring area, our proposed optimized deployment strategy requires fewer nodes to be deployed while achieving the same coverage accuracy compared with the uniform deployment strategy, and utilizes the coverage capacity of each sensor to the maximum efficiency so that the deployed smart smoke sensor nodes are prioritized considering areas at risk of fire. The above analysis of the results fully proved the effectiveness and superiority of our proposed optimized deployment strategy in a large space.

6. Conclusions and Future Research Issues

To solve the smart smoke sensor deployment optimization problem in a large space, this paper develops an optimized deployment strategy based on the PSO algorithm considering different fire probabilities of fire areas and obstacles, which effectively improves the coverage accuracy of smart smoke sensors and dramatically reduces the deployment cost. First of all, a deployment model of smart smoke sensor nodes that is more consistent with the actual application scenario is constructed considering the characteristics of smart smoke sensor and large spaces. The model takes into account the influence of obstacles and fire areas in the monitoring area, divides the monitoring area into fire risk areas while sets different levels of fire probability. Secondly, we established a coverage model and a mathematical model containing two optimization objectives, namely minimizing the cost of node deployment and maximizing coverage accuracy, and certain constraints are set. Then, a deployment strategy based on PSO algorithm is designed on the basis of the established related model. Finally, the performance of our proposed deployemnt strategy is verified with the method of simulation experiments through comparison with the uniform deployment. Experimental results show that our proposed deployment strategy based on the PSO algorithm is better than uniform deployment in terms of the coverage accuracy and deployment cost, and has been improved to a certain extent. The deployment strategy we put forward is more focused on the probability of fire in areas prone to fire, and the maximum effect of the deployed nodes is played. When there are obstacles in the monitoring area, our developed strategy can avoid obstacles for deployment and better improve the coverage accuracy and reduce coverage holes, since it increases the utilization of smart smoke sensor nodes. However, in practical applications, the situation of the fire areas and obstacles in the monitoring area may be more complicated. Therefore, we will consider the situation of more complex constraints in the next steps of this study.

Acknowledgments

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