A Multi-objective optimized node deployment algorithm for Wireless Sensor Networks Based on the Improved ABC

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Abstract. In the Internet of Things (IoT) for smart fire applications, sensors are deployed at different places and collect multiple types of data during their work time. Since the coverage of a sensor is limited, how to deploy sensors is important to reduce the number of sensors and improve the quality of wireless sensor networks (WSNs) service. The service quality and network lifetime of wireless sensor networks also are dramatically varied across different coverage and node deployment strategies. There are two crucial problems in WSNs, i.e. node deployment with lowest cost, and coverage optimization with maximum coverage rate, need to be solved. In this research, we focus on the problem of coverage optimization and node deployment. Based on the binary coverage probability model, we develop the joint binary coverage probability model and Improved Artificial Bee Colony (IABC) algorithm. The result of simulation shows that our proposed deployment algorithm have a greater coverage ratio in the case of fewer iterations when the volume of deployed sensors is the same compared with the standard ABC algorithm.

1. Introduction

WSNs are a vital part of the Internet of Things (IoT). In recent years, wireless sensor networks (WSNs) have been widely used in medical health, environmental monitoring and industrial fields[14]. The problem of deployment and coverage optimization has therefore become research hotspots in wireless sensor networks. In some special scenarios, the deployment of large amount of sensor nodes is still a challenge for practical requirements[1]. In the application field of WSNs, key techniques must be changed in its environment and user’s requirements so as to increase its fitness with actual applications[2].

WSNs are crucial for many applications, for instance in military sensing, physical security, air traffic control, traffic surveillance, video surveillance, industrial and manufacturing automation, environment monitoring, and building structural monitoring[3]. The nodes deployment of WSNs is a top concern for WSN configuration. It aims to build a powerful network system based on the sensor nodes with the perception capability, the data storage capability, the information treatment and transmission capability. An appropriate network node deployment method can not only reduce redundant nodes and the network cost of deployment, but also efficiently extend the network lifetime[3]. So as to implement the nodes deployment and coverage optimization of WSNs, the location of sensor nodes should be chosen in the first place according to the specific criteria to optimize several targeted objectives like coverage ratio, network lifetime, connectivity, deployment cost or energy consumption and so on. For this reason, node deployment strategies have great impact on the network performance and its operation. And its essential purpose is to propose a network topology with well-defined number and positions of nodes[11].
The coverage in WSNs needs to ensure that the area is monitored with the required degree of reliability. According to previous papers[5], the locations of sensor nodes are the basic input for the coverage optimization algorithms of the network. Coverage problems can be broadly classified as area coverage problem and target coverage problem. Area coverage mainly focuses on monitoring the entire region of interest, whereas target coverage concerns monitoring only certain specific points in a given region. Furthermore, there are two type of sensor node deployments: random deployment and deterministic deployment. There are several ways to compute deployment locations, and Bio-inspired algorithms are proved to be effective for solving the coverage optimization problem[4]. In this paper, we introduce an Improved Artificial Bee Colony(IABC) algorithm to optimize the node deployment cost and the coverage ratio of WSNs.

The remainder of this paper is composed of the following sections. Section 2 reviews the related work. Section 3 formulated the problem of node deployment and coverage. The improved node deployment algorithm different from traditional ABC is proposed in Section 4. The results of the simulation are summarized in Section 5. Conclusion and the future work are given in Section 6.

2. Related Work
As 5G and the Internet of Things (IoT) have developed by leaps and bounds and the wide application of swarm intelligence optimization algorithm in optimization problems, the research involving the performance of wireless sensor network is becoming increasingly important for Internet of Things(IoT). Recently, most of researches realize dynamic deployment of wireless sensor nodes by basing on intelligent optimization algorithm. Coverage optimization and node deployment are the key issues in WSNs. In two-dimensional deployment areas, a large number of deployment strategies and coverage optimization algorithm models have been proposed in order to achieve the goals of improving wireless sensor network coverage, extending network life, repairing and reducing coverage holes, and minimizing node deployment costs. The deployment type of sensor nodes range from static sensors to dynamic sensors, and furthermore realize the research about the optimization of nodes deployment and coverage in hybrid wireless sensor networks. According to sensor nodes’ deployment strategy, the research on the network coverage of mobile sensor nodes is generally divided into three types from an algorithm perspective [1]:

Deployment strategy based on Voronoi diagram. Referring to the previous literature, the Voronoi diagram is a basic data structure about space division, which uses Euclidean distance as a metric to differentiate the two-dimensional monitoring area or the three-dimensional space area;

Deployment strategy using virtual force. The virtual force algorithm can effectively guide the spreading process of mobile nodes, and centroid gravity can achieve better global coverage optimization effect. By reasonably setting the distance threshold parameter and priority of the virtual force, the constraints of fixed nodes on mobile nodes are adjusted. There are two types of virtual forces between nodes: attraction and repulsion;

Grid-based deployment strategy. The grid-based strategy divides the WSN into multiple square grids and the sensors are placed in a suitable position on the grid to ensure optimal network coverage.

In addition, the installation cost should be considered when the sensor nodes are deployed. If a large number of sensor nodes are applied for the WSNs application, it will bring high cost of the installation and density of the sensor nodes. However, the installation cost is limited in actual deployment. Therefore, the amount of sensor nodes by deployed should be suitable for the limited installation cost. The fitting number of deployed sensor nodes will as well produce the fitting density of sensor nodes[8,9]. Mini et al.[14]use Artificial Bee Colony (ABC) algorithm to decide the locations of nodes deployment, and the results suggest that ABC algorithm is robust than PSO algorithm for the problem of sensor nodes deployment. Based on the previous researches and the above analysis, in this paper, we improve the standard ABC algorithm and apply it to the node deployment and coverage optimization of wireless sensor networks.
3. System Model and Problem Formulations

3.1. Binary Coverage Model
Based on previous research, we also use classic binary coverage model in our study. This model assumes that each sensor is located in the centre of an induction disk whose radius is equal to the sensing range $r_0$ respectively. Nodes can only detect those points located in their respective induction plates. A binary coverage model can be described as formula (1) from a mathematical point of view. $C_{xy}(s_i)$ represents whether the point $\rho$ is covered by $s_i$:

$$C_{xy}(s_i) = \begin{cases} 1, & \text{if } d(s_i, \rho) \leq r_0 \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

Furthermore, the joint perception probability means that all sensor nodes cover point $C_p$, which can be described by:

$$C_p(s_{all}, \rho) = 1 - \prod_{i=1}^{n} \left(1 - C_{xy}(s_i)\right) \quad (2)$$

Where $s_{all}$ is the number of all sensor nodes located in deployment area. We assume that the detected area is $L1 \cdot W1 \ m^2$. In order to make the calculation more convenient, the deployment area can be divided into $L1 \cdot W1$ grids of equal area, and the monitoring node $m$ is in the centre of the grid. By calculating the joint perception probability, the coverage rate can be expressed as:

$$C_r = \frac{\sum_{x=1}^{L1} \sum_{y=1}^{W1} C_p(s_{all}^m(x-1):(W1+y)))}{L1 \cdot W1} \quad (3)$$

3.2. Problem Description
Given the specific deployment area, we can extract the requirements for coverage quality from the environment model. We firstly set the node deployment area as a two-dimensional plane $T$, and then randomly deploy $N$ nodes with the same sensing radius $R_s$ and communication radius $R_c$ so that represents the mathematical description of the system. The node set is $S = \{S_1, S_2, S_3, ..., S_N\}$, and we assume that a point $\rho$ lies in coordinates $(x, y)$, and node $s_i$ is located at coordinates $(x_i, y_i)$. The Euclidean distance between sensor $s_i$ and point $\rho$ can be calculated as:

$$d(s_i, \rho) = \sqrt{(x_i - x)^2 + (y_i - y)^2} \quad (4)$$

3.3. Mathematical Model
The multiple objective combinatorial optimization problem can generally be regarded as the mapping of a set of parameters (decision variables) to a set of goals. In the problem about the optimal nodes’ deployment for WSNs, it is necessary to consider minimizing deployment costs while increasing node coverage. Therefore, a multi-objective optimization strategy is introduced, and two mathematical models for optimal deployment of target nodes considering deployment cost and node coverage are designed. Because the final deployment strategy is required to ensure that the actual perception probability $p$ of the nodes is bigger than or equal to the coverage ratio threshold $R_0$, in addition, the deployed network also needs to meet the application's demand for connectivity quality. The node deployment optimization problem is modelled as a multiple objective node optimization deployment scheme with node coverage and node deployment cost as the objective function under the two constraints of coverage threshold and connection quality. Consequently, the node deployment problem studied can be transformed into the following multi-objective optimization problem form.

3.3.1 The Cost of Node Deployment. First of all, the first objective function is to minimize the total deployment cost of all the sensors. Based on [6], which can be expressed as:
\[
f_1 = \text{Minimize } \sum_{s \in S} \sum_{n \in N_b} P_{n,d_{s}} C_{s}^n \tag{5}
\]

### 3.3.2 The Coverage Ratio.

The second objective function's purpose is to maximize the coverage ratio of nodes, and the coverage ratio of nodes mainly depends on the targets that will cover. Each position in the area \( T \) should be monitored by at least \( n_{\min} \) nodes so as to ensure a full coverage. Thus, we use the function (8) to describe the coverage ratio, which can be calculated as:

\[
f_2 = \text{Maximization } \sum_{t \in T} \left( \sum_{s \in S_b} C_{r} - n_{\min} \right) \tag{6}
\]

Among them, \( C_{s}^n \) is the actual deployment cost of a node having a type \( n \in N_b \) and installed a site \( s \in S_b \). \( P_{n,d_{s}} \) will be set to 1 if a node has a type \( n \in N_b \) is deployed in a site \( s \in S_b \); otherwise, it will be 0.

Different functions have different benefits for the deployment of wireless sensors. The first objective function is to minimize the total deployment cost, which can bring optimized cost to the actual deployment of wireless sensors. However, when we optimize the cost, the detection performance of the deployment strategy must also be considered. Therefore, the second objective function is to maximize the coverage of the entire detection area by the wireless sensor.

### 4. Our Proposed Algorithm

In this section, we introduced the standard version of the previous ABC algorithm and furthermore proposed the improved the ABC algorithm about our study.

#### 4.1. ABC algorithm

The Artificial bee colony algorithm is a biological intelligent optimization algorithm that simulates the intelligent search behaviour of bee colony. The minimal model of swarm-intelligent forage selection in a honey bee colony which the ABC algorithm simulates consists of three kinds of bees: employed bees, onlooker bees and scout bees. According to previous literature[11], half of the colony is composed of the employed bees, and the remaining half is the onlooker bees. Every part of the standard ABC algorithm can be described as the following parts:

1. Scout bee searching for new food sources.
   \[
x_{ij}^l = x_{ij}^l + \text{rand}(0,1)(x_{ij}^{\text{max}} - x_{ij}^{\text{min}}) \tag{7}
\]

2. Generate a candidate location from the location of the original food source.

3. The observation bee selects the food source according to the probability value related to the nectar source.
   \[
v_{ij} = x_{ij} + \varphi_{ij} (x_{ij} - x_{kj}) \tag{8}
\]

   \[
f_{it} = \begin{cases} 
   1/(1 + f_i), & \text{if } f_i \geq 0 \\
   (1 + \text{abs}(f_i)), & \text{if } f_i < 0
   \end{cases} \tag{9}
\]

4. The observation bee selects the food source according to the probability value related to the nectar source.
   \[
p_{i} = \frac{f_{it_i}}{\sum_{i=1}^{n} f_{it_i}} \tag{10}
\]

5. The onlookers select food source site on the basis of the information provided by the employed bees.
4.2. The Flow of Algorithm

Furthermore, the coming steps are the main procedure of our proposed IABC:

- **Step1**: Randomly generate CSN (bee colony size) initial solutions, match half of them with bees, and compute the fitness value of each solution, record the best of all solutions.
- **Step2**: cycle = 1.
- **Step3**: The honeybee performs a neighborhood search according to function (8) to generate a new solution $v_{ij}$, calculates its fitness value, then conduct Greedy choice of $x_{ij}$ and $v_{ij}$.
- **Step4**: Calculate the selection probability $p_i$ related to $x_i$ according to function (10).
- **Step5**: The observation bee selects the food source with probability $p_i$ according to the roulette selection method, and performs a domain search according to function (8) to produce a new solution, and calculates the fitness value, then conduct Greedy choice of $x_{ij}$ and $v_{ij}$.
- **Step6**: Judge whether there is a solution to be abandoned. If it exists, use the formula (7) to perform a random search to generate a new solution to replace the old one solution.
- **Step7**: Record the best of all solutions so far.
- **Step8**: cycle = cycle + 1, if cycle < MCN, then go to step3, or output the best result.

4.3. IABC Algorithm

The search equation in the standard ABC algorithm has great randomness. We need to accelerate the convergence speed of the algorithm so that the population can evolve towards the better individuals. Referring to paper[15], the classic ABC algorithm is modified by means of introducing a control parameter, modification rate (MR) and also improving the solution search equation so as to improve the efficiency of the algorithm. Through these improvements, a uniformly distributed random number for each parameter. We can find a new food source on the basis of function (11), which can be expressed by:

$$v_{ij} = \begin{cases} x_{ij} + \varphi_{ij}(x_{ij} - x_{kj}), & \text{if } R_{ij} < \text{MR} \\ x_{ij}, & \text{otherwise} \end{cases}$$

(11)

The improved search equation is expressed as:

$$v_{ij} = x_{\text{best},i} + \varphi_{ij}(x_{r1,j} - x_{r2,j})$$

(12)

And among them, $i = 1,2,\ldots,SN, j = 1,2,\ldots,D$. $SN$ is the number of total food sources and $D$ is the amount of optimization parameters[11]. Moreover, counters which store the numbers of all trials’ solutions are reset to 0 at this stage. $\varphi_{ij}$ is a distributed real random number equally in the range $[-1,1]$. And $fit_i$ is the fitness value of the solution. $r_1, r_2$ are two random samples different from $i$. $k$ is the nectar source other than $i$. where $f_i$ is the cost of the solution $v_{ij}$. Furthermore, $0 \leq R_{ij} \leq 1$.

5. Simulation and Performance Evaluation

In this part, to evaluate the performance of our proposed Improved Artificial Bee Colony (IABC) algorithm, the previously presented ABC based coverage algorithm are selected to compared coverage ratio under different iteration time. Simulation experiment is conducted in MATLAB R2020a environment.

5.1. Simulation Parameter Setting

Based on the previous literatures, the results are evaluated using simulation with parameters given in table1.

| Simulation Parameters | Values         |
|-----------------------|----------------|
| Node deployment       | Random deployment |
| Parameter                      | Value       |
|-------------------------------|-------------|
| The number of sensors         | 100         |
| Size of sensing area (T)      | 100m*100m   |
| Sensor radius                 | 7m          |
| The number of colony size     | [20, 50]    |
| The Number of iterations “Limit” | [100, 2000] |
|                               | 100         |

Figure 1. ABC algorithm: Coverage rate vs. The number of cycles foraging

Figure 2. IABC algorithm: Coverage rate vs. The number of cycles foraging

In the case of the same number of sensors, the traditional ABC algorithm reaches the maximum coverage rate of 0.9753 when iterates 2000 rounds. Decreasing or increasing the number of iterations will reduce the coverage rate, as shown in Figure 1. The improved ABC algorithm that we proposed reached the maximum probability of 0.993 in 200 iterations, as shown in Figure 2, which increased the calculation speed and maximized the coverage of the sensor. Simulation results verify the effectiveness of our improved ABC algorithm.

6. Conclusion
In this paper, we try to summarize the research status of node deployment and coverage optimization in WSNs, which includes the coverage objects, node deployment strategies and network cost. Motivated by previous coverage optimization algorithms, we proposed the IABC algorithm aiming at the problem of node deployment and coverage optimization in wireless sensor networks (WSNs), and the ABC algorithm is modified by introducing a control parameter, modification rate (MR) and improving search equation. The analysis of experimental results shows that our improved algorithm has a good coverage ratio for the specific 2D zone. In the future work, we will consider wireless sensor networks and coverage optimization issues in complex 3D environments.

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