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# Application of intelligent algorithm in wireless sensor network node deployment optimization

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***Keywords:*** Intelligent algorithm; Wireless sensor; Network node deployment

***Abstract:*** Wireless sensor network is a self-organizing network composed of a large number of nodes with sensing, computing and communication capabilities. It collaboratively senses, collects and processes the information of the sensing objects in the coverage area of the network, and sends the information through self-organizing to replace some manual sensing and processing work, and finally realizes the monitoring of the sensing area. Node deployment is an important research topic in wireless sensor networks. This paper first analyzes the characteristics and difficulties of the node deployment optimization problem, and then elaborates the application of intelligent algorithm in the node deployment optimization of wireless sensor networks.

## 1. Introduction

Wireless sensor network (WSN) is a new kind of network, which realizes the information collection and processing of the monitoring area through a large number of cheap sensor nodes deployed in the network, so as to monitor the monitoring area. Compared with traditional sensor networks, WSN has the advantages of self-organization, low power consumption and easy expansion, and can be widely used in military, environmental protection, security monitoring and other fields. Compared with traditional networks, WSN's application environment is relatively complex, and information transmission is generally carried out by sending data packets periodically, so sensor nodes often need a lot of energy to maintain operation. The problem of node deployment in WSN is to extend the network life through reasonable deployment of sensor nodes, and then improve the service quality of the whole network.

## 2. Features and difficulties of node deployment optimization

### 2.1. Multi-purpose of node deployment optimization problem

The node deployment optimization problem can be transformed into a multi-objective programming problem. In the traditional wireless sensor network node deployment optimization problem, the optimization goal is usually a single objective, that is, only one objective function needs to be considered. However, in practical applications, it is often necessary to consider multiple objective functions, that is, to consider the influence of multiple objective functions at the same time.

For example, in a wireless sensor network, there may be such a scene: there is a node area in a certain corner of the city, there are many objects around, there are some sensor nodes need to sense these objects, but some sensor nodes do not know what objects in the surrounding area, can not sense these objects. If we consider multiple objective functions at the same time, see Table 1 for details[1-3].

Table 1: Multiple objective functions

| Function pointer | Feature |
|---|---|
| Cover | Express sphere of influence |
| Energy consumption | Expressed actual consumption |
| Link quality | Representation stability |

Each objective function in Table 1 and other multi-objective function indicators is independent, so we can regard these independent objective functions as a multi-objective programming problem. When we combine these independent objective functions, we get a multi-objective programming problem. In the node deployment optimization problem, there are multiple objective functions that conflict with each other. For example, in the node deployment optimization problem, there may be a conflict between the two objective functions of coverage and energy consumption. To solve this problem, we can achieve the goal by weighting multiple different objective functions.

### 2.2. Complexity of the node deployment optimization algorithm

The complexity of node deployment optimization problem is mainly reflected in two aspects: (1) the complexity of optimization algorithm. When designing the node deployment optimization algorithm, it is necessary to consider not only the node density and sensing range in the network, but also the distance between nodes and energy consumption. In addition, the objective of node deployment optimization problem is the synthesis of multiple objective functions, so many solving techniques need to be used. (2) Complexity of algorithm design. In the optimization of node deployment, factors such as network coverage, coverage quality, communication range and network life should be considered. In different cases, different algorithms are also needed to solve these problems[4-5].

So far, many algorithms have been proposed for node deployment optimization problems. The representative ones are shown in Table 2.

Table 2: Representative algorithms for node deployment optimization

| Name | Peculiarity |
|---|---|
| Genetic algorithm | A heuristic algorithm is proposed based on the idea of evolution |
| Particle swarm optimization | With global optimization capability |
| Simulated annealing algorithm | It has local optimization ability |

## 3. Optimized deployment scheme combining genetic algorithm and simulated annealing algorithm

### 3.1. Algorithm Introduction

Both genetic algorithm and simulated annealing algorithm are developed based on the idea of biological evolution, and their respective advantages are very obvious. However, the genetic algorithm has the shortcomings of premature convergence and insufficient local search ability, and the simulated annealing algorithm can overcome these shortcomings, but the simulated annealing algorithm is greatly affected by the initial temperature, cooling rate and other factors, so it is not suitable for solving the problem of complex wireless sensor network node deployment. Therefore, this paper presents an optimization scheme of wireless sensor network node deployment which combines genetic algorithm and simulated annealing algorithm. In this scheme, genetic algorithm is introduced to optimize the optimization problem, which can overcome the shortcoming of global searching ability of simulated annealing algorithm. At the same time, the advantages of fast convergence speed and strong local search ability of simulated annealing algorithm are introduced, so as to realize the intelligent optimization scheme[6-8].

### 3.2. Scheme Analysis

#### 3.2.1. Fitness function design

In WSN, the deployment of sensor nodes has a strong randomness, and the choice of node deployment scheme is not fixed, but changes in different environments. Therefore, how to determine an optimal sensor node deployment scheme has become a challenging and global problem. Both Genetic algorithm (GA) and simulated annealing algorithm (SA) have strong global optimization ability, but GA has better local search ability. Therefore, GA is chosen as the fitness function and SA as the global optimization algorithm. In this paper, in order to reflect the complementary advantages of different algorithms, genetic algorithm and SA are combined. Using the strong global optimization ability of genetic algorithm, the optimal solution is quickly found. However, SA has some advantages in global optimization capability, it can better local search and convergence. In order to realize the complementary advantages of the two algorithms, this paper combines the two algorithms as fitness functions:

$$S = \frac{p_m}{c_{nm}} - d_{nm} / A \tag{1}$$

Where: S is the number of sensor nodes in WSN; p means that the sensor node detects m target events at the p time; c is the coverage radius of m target events monitored by the NTH sensor node. d is the time interval for the NTH sensor node to detect m target events; A is the fitness function of the individual.

#### 3.2.2. Design of coding mode

In this paper, the improved genetic algorithm is used to solve the node deployment problem. The algorithm adds the fitness calculation on the basis of the individual fitness function, and retains the optimal solution as far as possible while ensuring the individual can better adapt to the environment. The fitness function is defined in Table 3.

Table 3: Definition of fitness function

| Step sequence | Definition |
|---|---|
| 1 | Is the fitness of the individual in the population, and is the fitness value corresponding to the gene individual |
| 2 | Is the average fitness of gene individuals in the population |
| 3 | Is the average fitness of the best individual and the worst individual in the population |
| 4 | Is the number of genes corresponding to the optimal individual |

In the specific coding mode, this paper adopts binary coding, and then adds the two variables in the fitness function and performs normalization processing. In the process of evolution, the algorithm only considers the relationship between the best solution and the worst solution for each individual, and ignores the possible information exchange between the intermediate individuals. So we use two binary codes, one is the binary code of the relationship between the best and the worst solution for each individual in the population, and the other is the binary code of the information exchange between each individual in the population[9-10].

### 3.2.3. Genetic operator design

In GA, the design of genetic operators directly affects the performance of the algorithm, and the selection of genetic operators directly affects the efficiency of the algorithm. Poor design of genetic operators will lead to instability of the algorithm and even fail to converge to the optimal solution. Selection and crossover of genetic operations are the most basic and important operations in GA, which determine the fitness of individuals in a population. Cross operations can combine multiple individuals to improve group diversity. Variation manipulation can improve individual fitness of population. The design of genetic operators in GA directly affects the performance of the algorithm. Aiming at the optimization of node deployment in wireless sensor networks, this paper uses mutation operator as genetic operator in GA.

In this paper, the improved adaptive crossover method and the improved adaptive variation method are adopted. The adaptive crossover method is mainly used to modify the crossover probability and mutation probability in GA. In this paper, the adaptive crossover method is used to optimize the individual. The mutation operator mainly deals with the interaction between individuals in the population. The main function of the mutation operator is to eliminate the influence between the two individuals, so that the individuals can get the optimal solution. In this paper, the improved self-learning adaptive crossover operator and the improved adaptive mutation operator are used to optimize the individual, so as to improve the performance and efficiency of the algorithm.

### 3.2.4. Algorithm flow design

Table 4: Detailed steps of the algorithm flow

| Step sequence | Procedure |
|---|---|
| 1 | Code each individual |
| 2 | a subpopulation is randomly generated in each chromosome, that is, each individual in subpopulation a,b is made up of all individuals in a,b |
| 3 | Each subpopulation is taken as the fitness function of GA and SA algorithms, and the crossover and mutation operations are carried out |
| 4 | After each iteration, the fitness functions of GA and SA algorithms are adjusted by selecting parameters such as probability, crossover probability and mutation probability |
| 5 | Subpopulations are regrouped after each iteration, and the subpopulations that meet the conditions are moved out of the iteration space |
| 6 | Genetic manipulation was performed on the i - th newly generated subpopulation a,b |
| 7 | If a and b meet the conditions, the optimal subpopulation of the newly generated subpopulation is selected as the fitness function of GA and SA algorithms |
| 8 | If Condition b is met, GA and SA algorithms end |

In order to improve the convergence speed and stability of the algorithm, genetic operations are introduced into GA and SA algorithms. In the selection operation of GA, the binary encoding method is adopted in this paper, that is, the individual has only one chromosome. When selecting, GA selects individuals with higher fitness, while SA selects individuals with higher fitness. See Table 4 for detailed steps.

## 4. Conclusion

In summary, genetic algorithm and simulated annealing algorithm can converge to the global optimal solution in a very short time, and can effectively prevent falling into the local optimal solution, and have the characteristics of fast convergence speed and strong global search ability. Particle swarm optimization algorithm is easy to fall into local optimal solution in the optimization process, while genetic algorithm and simulated annealing algorithm have the disadvantage of poor local search ability, so it is necessary to properly adjust the proportion of the two in the optimization process to improve the optimization efficiency. Although the particle swarm optimization algorithm is effective in solving multi-constrained optimization problems, it is easy to fall into local optimal solutions, so it is necessary to combine simulated annealing algorithm and genetic algorithm to improve the particle swarm optimization efficiency.

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