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Wireless sensor network target coverage algorithm based on energy saving

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Abstract. Energy efficiency optimization of wireless sensor network is studied based on improved multi-objective particle swarm optimization. The network coverage rate, energy consumption and the number of working node are taken into account comprehensively. The improved multi-objective particle swarm optimization algorithm is based on the dominance method. By means of the dominance relationship, it determines non-dominated solution set, and then it is stored in the external archive set. The particles beyond the scale is deleted by means of arrange crowded distance in descending order, and the disturbance factor is joined to maintain the diversity of swarm. On parameter settings of the iteration formula of particle swarm optimization algorithm, the method of dynamically adjusting inertia weight and learning factors are put forward. The simulation results show that the proposed energy saving algorithm based on improved multi-objective particle swarm optimization enhances the network coverage, saves the energy consumption and prolongs the network life cycle to a certain extent.

Key words. Wireless sensor network, multi-objective article swarm optimization, coverage rate, energy consumption.

1. Introduction

Coverage control is a basic problem in Wireless Sensor Network (WSN). The main content of coverage control is to ensure the network does have certain quality of service. Then, it can be optimized by some technology or protocol, so that it can meet the maximization of coverage area [1]. People may get reliable monitoring data and target tracking service. Effective strategies of the coverage control and algorithms can be used to optimize the allocation of resources of WSN, increase the efficiency of the energy usage of network nodes, and improve the perceived quality of service and the overall survival time [2]. How to combine different environmental demands and design a practical strategy for coverage is a significant research field.

Researchers have put forward the strategies for reducing energy consumption and

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prolong the network life cycle from all aspects of the wireless sensor network [3–6]. These strategies can be divided into four basic categories, sleep scheduling scheme, adjusting the sensing radius of the nodes, choosing the best route, and highly effective data fusion system. A scheduling algorithm for connected target coverage under probabilistic coverage model was proposed by Kim [7]. Energy-efficient probabilistic area coverage in wireless sensor networks was put forward by Qianqian [8]. Sensor scheduling for p-percent coverage in wireless sensor networks was proposed by Li [1]. Sleep scheduling for partial coverage in heterogeneous wireless sensor networks was proposed by Mostafei [9]. Energy-efficient protocol for deterministic and probabilistic coverage in sensor networks was presented by Hefeeda [10]. A coverage monitoring algorithm based on learning automata for wireless sensor networks was put forward by Mostafaei [11]. Centralized and clustered k-coverage protocols for wireless sensor networks was proposed by Ammari [12]. Genetic algorithm for sensor scheduling with adjustable sensing range was put forward by Arivudainambi [13]. Arivudainambi put forward a method to improve energy efficient target coverage in wireless sensor networks [8]. A kind of energy efficient sensor scheduling for target coverage in wireless sensor network was proposed by Arivudainambi [14]. These methods are based on single objective optimization. Optimization problems, especially multi-objective optimization problem using intelligent algorithm is one of the focus areas of evolutionary computation. Particle swarm optimization algorithm as a relatively new optimization technique, the concept is simple, less control parameters, the optimization result has nothing to do with the initial value, with a certain parallelism, and it has gained more attention and has good prospects for development. However, the traditional particle swarm algorithm still has some deficiencies in global search and convergence, the algorithm has attracted the interest of many researchers and scholars and almost all of them are devoted to the study of the performance improvement algorithm. It is confirmed that the particle swarm algorithm has a very good application for single objective optimization problems, but the multi-objective particle swarm optimization algorithm and its application remains to be further studied. Based on the standard particle swarm algorithm and multi-objective optimization theory, the multi-objective particle swarm optimization algorithm is studied intensively in this paper, the concrete content and innovative points can be summarized as follows. In the next section, a kind of improved multi-objective particle swarm optimization algorithm is put forward. In section 3, a novel energy saving model based on improved multi-objective particle swarm optimization algorithm is proposed. In section 4, in order to test the performance of proposed energy saving model, experiments are done. In the end, some conclusions are given.

2. Improved multi-objective particle swarm optimization algorithm

For solving multi-objective optimization problem, it is not as direct and simple as to solve the single objective optimization problem. It only needs to compare the size of the fitness value, and the key is to find a series of multi-objective better trade-off solution set that is called the non-dominated solution set, namely the Pareto optimal set (Pareto optimal set). The key of using particle swarm optimization algorithm to solve multi-objective optimization problem is to determine the individual optimal value and global optimal value, so as to guide the population search to Pareto optimal set of the optimization problem. Due to the velocity updating formula of particle swarm algorithm mainly relies on a certain individual optimal location and the global optimal position, but the multi-objective optimization problem does not has the only optimal solution, so particle swarm optimization needs to be modified in combination with other methods, so as to choose the individual optimal solution and the global optimal solution of each particle. In solving multi-objective optimization problems, compared with other optimization algorithm, particle swarm optimization algorithm is simple, search efficiency is high, and the general performance is good. Combining with other algorithm is easy. So, research and improvement of multi-objective particle swarm optimization algorithm has important significance for solving multi-objective optimization problem.

Basic particle swarm optimization algorithm can only return a solution, but the main goal of multi-objective optimization algorithm is to find a set of solutions, and the optimal solution set makes best trade-off of different target for multi-objective problems, so the basic particle swarm algorithm cannot be directly used for solving multi-objective optimization problem. To make it widely used in the multi-objective optimization problem, the key task of multi-objective particle swarm optimization algorithm is to generate multiple solutions, thus to determine a set of solutions, namely the Pareto optimal set.

Multi-objective algorithm not only should complete the task, but also should cover the true Pareto optimal boundary approximately. At the same time it should achieve three goals. The distance between the solution and Pareto boundary should be minimized. The diversity of the non-dominant solution should be maximized to represent Pareto boundary as fully as possible. The found non-dominated solution should be maintained. In order to achieve the first goal, we should determine an appropriate fitness function to measure the quality of a solution on the multi-objective level. Fitness function has three kinds. The first kind is based on aggregation and fitness function is a weighted sum of the objective function. The second is based on the criterion and fitness function varies between different targets under different condition in the process of optimization. The third is based on the Pareto dominance, fitness function is directly proportional to control sequence of solution scheme. Most of the control sequence scheme uses a series of non-dominant methods.

In order to achieve the second goal, we will introduce a variety of methods to keep the diversity of non-dominated solutions. These methods increase the probability of decision vector tending to Pareto boundary. Finally, in order to realize the third goal, the use of previously found solution archives can be used to implement which is a kind of elite strategy, and in this strategy, the best solution is stored in a repository. To sum up, several basic particle swarm optimization algorithm based on modified methods mainly include the method based on aggregation, the method based on rules and the method based on dominant. These methods are able to fix the basic particle swarm algorithm to generate multiple solutions.

Archive of the multi-objective optimization algorithm is used to track all non-dominated solution so far. The use of the archive is similar to elite strategy in the evolutionary algorithm. In addition, in order to maintain the found solution, archive is used to select the global optimal position and individual optimal position. In archive method, global optimal and individual optimal non-dominant solution is called global wizard and individual wizard, respectively. The wizard's goal is to attract particles to fly to Pareto front. A lot of methods are used to select the guide, these methods usually cause each particle produce different global guide. Generally speaking, it is because of these different guides selection, the Pareto optimal set diversity can be maintained. For archive design, the most important is to prevent the explosive expansion of archive size. Allowing uncertainty increasing of archive has the following advantages.

The number of the non-dominant solutions is not restricted. Multi-objective optimization algorithm without using archive can position number of non-dominated solution at maximum. For one archive, more than solutions can be found. The obvious advantage is that archive algorithm can use small group than the non-archive method.

Using unlimited archive is helpful to maintain better diversity of population. Unlimited archive, however, also has its own disadvantages. When the archive size and target quantity increase, the computational complexity will increase significantly. Computational complexity increasing is mainly due to the non-dominated sorting and the choice of the guide. In order to solve the problem of archive algorithm computational complexity, a series of methods have been developed. We can use different data structure to express non-dominant solution. Non-dominant solution is clustered, and clustering center is used to replace each focus class. The archive is truncated, for example, the size of the archive is restricted to a predetermined value. We investigate a kind of multi-objective optimization algorithm based on truncated archive. An upper limit is set on the size of the archive. Once the archive reaches its limit capacity, the non-dominated solution beyond the size are deleted. So at this time, we should pay attention to keep the diversity of population. If we do not pay attention, the deletion of non-dominant can make the Pareto optimal set diversity loss.

The proposed multi-objective particle swarm optimization algorithm is mainly based on the control method. The non-dominated solutions are determined according to the Pareto dominance relation, which is the optimal solution of optimization problem. A competitive mechanism is used to quickly compare the dominance relationship between swarm individual. External archive set is used to store the non-dominant solutions, and the truncation archive method is used to limit the size of the archive. If the non-dominated solution set is beyond archive size, the descending order is carried out according to the crowded distance between each particle, thus eliminating the particles beyond the archive size. At the same time, in the process of searching dominant solutions, disturbance factor is joined to maintain the diversity of population following a certain probability. We also put forward the improvement strategy for speed update formula of particle swarm algorithm, and the main research object is inertia weight and learning factors. We propose a kind of competition mechanism, which can quickly search the non-dominant solution and build the external archive set. In swarm S, a particle x is chosen randomly and $S = S - \{x\}$. The other particles are compared with particle x in turn according to Pareto dominant relation of target function value. If $x \prec y$, the particle y is deleted from the particle swarm. If $y \prec x$, $x = y.N = N \cup \{x\}$, it stops until $S = \emptyset$ and N is the non-dominant solution set. For non-dominated solution set being inserted into the external file set, we also adopt the same method. When more particles are eliminated, the algorithm runs faster, and also it reduces the complexity of the algorithm.

Particle swarm algorithm needs to generate a set of Pareto solutions in each iteration for solving multi-objective optimization problem. Therefore, the external archive is used to store each generation of non-dominated solution, and these solutions construct Pareto frontier. Along with the iteration, each generation of Pareto solution is used to update the external archive. However, with the increasing of the number of iterations, the external archive size also gradually increases, then algorithm computational complexity will be increased extremely. If we don't control the external archive size, it will greatly increase the computational complexity. Therefore, we use the crowding distance descending order to limit the size of the external archive set. In the whole iterative process of particle swarm optimization, it will continue to produce the non-dominated solution to be stored in one external archive set, global optimal location of each particle is randomly selected from the archive, the selection strategy can make non-dominant solutions in dense area get more opportunities, thus it loses the diversity of population and is easy to cause the algorithm into premature convergence and local optimum.

So, in order to keep the diversity of particles, improve population's ability to jump out of local optimal solution, based on a certain probability p, the Pareto solutions in external archive are disturbed to produce new solutions and guide population flight. The perturbation expression is

$$x_i^d = x_i^d \cdot (0.5 + \sigma)\,, \tag{1}$$

where σ represents disturbance factor between $0 < \sigma < 1$ with mean value 0 and variance 1, x_i^d represents the dth dimension of variable of particle i. The large inertia weight is advantageous to the particle's ability to explore new areas, namely the swarm global search for population. And small inertia weight is beneficial to the particle's local search ability, which is conducive to local search of the population. At first, the population tends to global search, and later it will gradually tends to local search. According to this characteristic, dynamic adjustment calculation formula is

$$w(r) = [w_{\max} - w_{\min}]\frac{r_{\max} - r}{r_{\max}} + w_{\min}\,, \tag{2}$$

where r represents iteration times, $r_{\max}$ represents the maximum iteration times, $w_{\min} = 0.4$ and $w_{\max} = 0.9$. The dynamic adjustments of learning factor are

$$c_1 = 1 + \frac{r_{\max} - r}{r_{\max}} \tag{3}$$

$$c_2 = 1 + \frac{r}{r_{\max}} \tag{4}$$

The process of improved multi-objective particle swarm optimization is shown in Fig. 1 and explanation of particular steps follows.

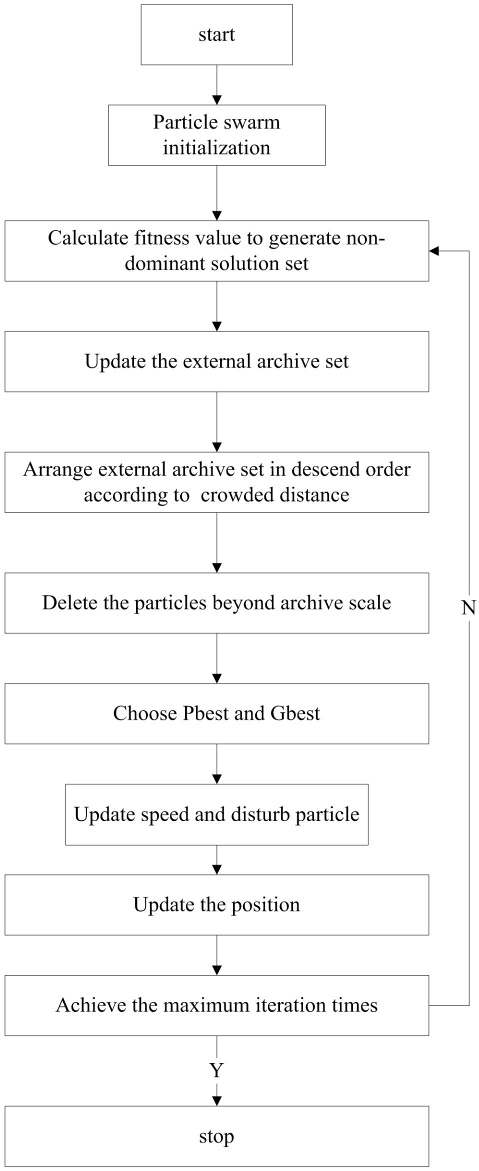

Fig. 1. Process of improved multi-objective particle swarm optimization

1. Initialize speed and position of all the particles and the swarm size is n.
2. Calculate the fitness function value of each particle. Based on dominance relation, it forms non dominated solution set.
3. Update external archive set.
4. The crowded distance between each particle of the external archive set is sorted in descending order. Check whether it is beyond the distance according to the set scale. If it is beyond the distance, the non-dominant solutions beyond the scale are deleted.
5. Update individual optimal P_{best}. If it is the first generation, the initial position of each particle is directly set to be P_{best}. If it is not the first generation, it chooses whether to replace update based on the Pareto dominance relation.
6. The global optimal position G_{best} is selected from the external archive set in the top $10\,\%$ of the non-dominant solution.
7. Update speed of the particle. If the speed $v_i > v_{\max}$,then $v_i = v_{\max}$. If the speed $v_i < v_{\min}$, then $v_i = v_{\min}$.
8. Update the position of the new generation of particle and the particle is disturbed according to probability $p = 1 - r/r_{\max}$ to prevent the algorithm from being trapped into local optimum.
9. Determine whether it achieves the maximum iteration times. If it meets the termination condition, the algorithm stops. Otherwise, it turns to step 2 to go on.

3. Energy saving model based on improved multi-objective PSO

Wireless sensor network usually has a dense area of sensor nodes within the target area in monitoring. If these sensors nodes work at the same time, causing collision conflict of a large number of sensor nodes in the network, at the same time, a lot of data redundancy also causes the network energy waste. Therefore, on the premise of guarantee the quality of network service, scheduling activities of sensor nodes make part of the sensor nodes into the active state, and the redundant nodes into idle state, to save the network energy consumption and prolong network lifetime, which is an important content in the research of wireless sensor network.

Suppose N number of sensor nodes randomly deployed in the target monitoring area, which is responsible for collecting all target information in the monitoring area. All sensor nodes perception radius and information computing ability are the same. Sensor perception model is the disc perception model. When perception radius of the sensor is R, it can cover all the target points taking itself as the circle center with radius R. A large number of sensor nodes is randomly deployed in the target area, the sensor node is divided into several subsets, and each covered subset can completely cover the target area. The proposed scheme can periodically schedule these covers subset, maximize the sum of the working time of each subset, and extend the life cycle of the whole network.

Let k be the number of covered set $(N_1, N_2, \ldots, N_k)$. Each subset is endowed with random number between 0 and 1. When the random number is greater than idle probability, the particle set is set to be 1 and the corresponding particle goes into work state. Otherwise, the particle set is set to be 0 and the particle goes into idle state. The idle probability is calculated as

$$p = a\left(1 - \frac{E_{\mathrm{c}i}}{E_{\mathrm{m}i}}\right) + b\,\frac{I_n - 1}{I_n}\,, \tag{5}$$

where a and b are constants such that $a + b = 1$. Symbol $E_{\mathrm{c}i}$ represents the left energy of node i and symbol $E_{\mathrm{m}i}$ represents initial energy of node i. Symbol I_n represents the number of neighbor nodes within perception range of node i, N is the number of sensors that are deployed in the whole target area randomly ($N = \{n_1, n_2, \cdots, n_N\}$). Each sensor has initial energy E, the sensor radius is R, the corresponding energy is $\{e_1, e_2, \ldots, e_n\}$. Subset $N' \in N$ is defined which satisfies the following objective: the first object is to make network coverage rate maximum.

$$\mathrm{Max}\ f_1(x) = \frac{A_{\mathrm{area}}(N')}{A_s}\,, \tag{6}$$

$$\mathrm{s.t.}\ \ U = \frac{1}{N}\sum_{i=1}^{N} U_i = \sqrt{\frac{1}{k_i}\left(d(n_i, n_j) - D_j\right)^2}\,, \tag{7}$$

where U represents the uniformity, k_i represents the number of neighbors of node n_i, $d(n_i, n_j)$ represents the distance between two nodes, D_i denotes the mean distance value of all nodes intersected with perception radius of node n_i. The second objective is that the number of sensors should be minimized.

$$\mathrm{Max}\ f_2(x) = 1 - \frac{\left|N'\right|}{N}\,. \tag{8}$$

The third objective is to make unit energy consumption minimum.

$$\mathrm{Max}\ f_3(x) = -u\sum_{i=1}^{n} r_i^2 / A_{\mathrm{area}}\,, \tag{9}$$

where A_{area} represents the monitoring area of N' and n represents the total number of work nodes.

The process of energy saving model based on improved multi-objective PSO is as follows.

Step l: Initialize the N number of particles, namely produce position and speed of each individual randomly in the problem domain.

Step 2: Initialize the external sets and individual extreme, calculate the fitness of

each particle value.
Step 3: The swarm is divided into several sub-swarm, and give each child population a random number between 0 and 1.
Step 4: Calculate idle probability of each particle.
Step 5: Update the particle's position and speed.
Step 6: Calculate the new fitness value. The fitness value of each particle is compared with its own best locationP_{best}, if it is better, P_{best} is reset.
Step 7: Coverage of each particle is compared with coverage of group best position G_{best}, if it is better,G_{best} is reset.
Step 8: Update the external set. If the stop condition is met, the algorithm stops. Otherwise, it returns to step 4.

4. Verification

In order to test the performance of proposed energy saving model, improved multi-objective optimization algorithm are compared with traditional multi-objective optimization algorithm. Coverage rate is shown in Fig. 2 and energy consumption curve is shown in Fig. 3. In 20 m×20 m monitoring area, 30 sensor nodes are deployed. The perception radius of the node is 5 and swarm scale is 30. It can be seen that the network coverage rate and energy consumption of improved multi-objective particle swarm optimization is better than traditional multi-objective particle swarm optimization. Another experiment is also done to test the influence of perception radius to coverage performance. The number of node is 40 and iteration time is 300.

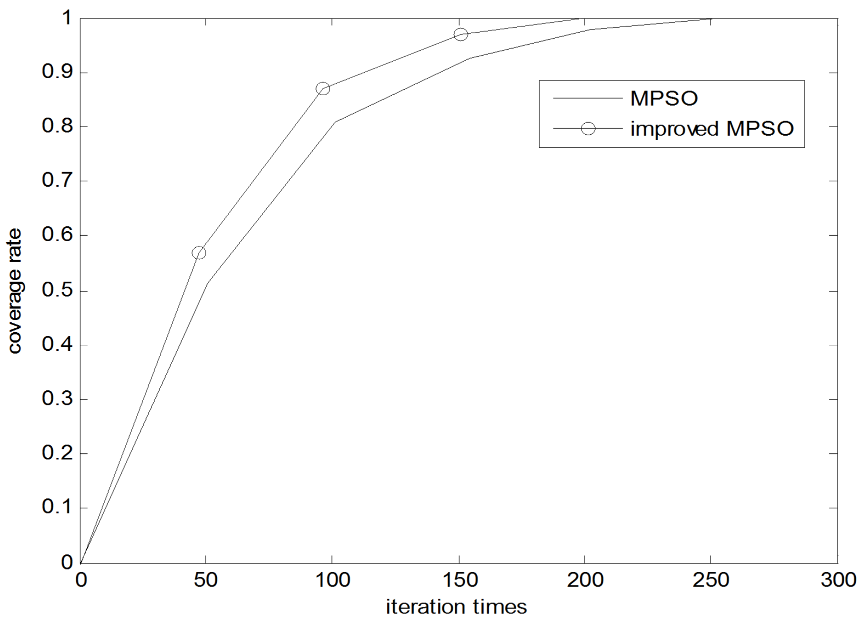

Fig. 2. Coverage rate comparison

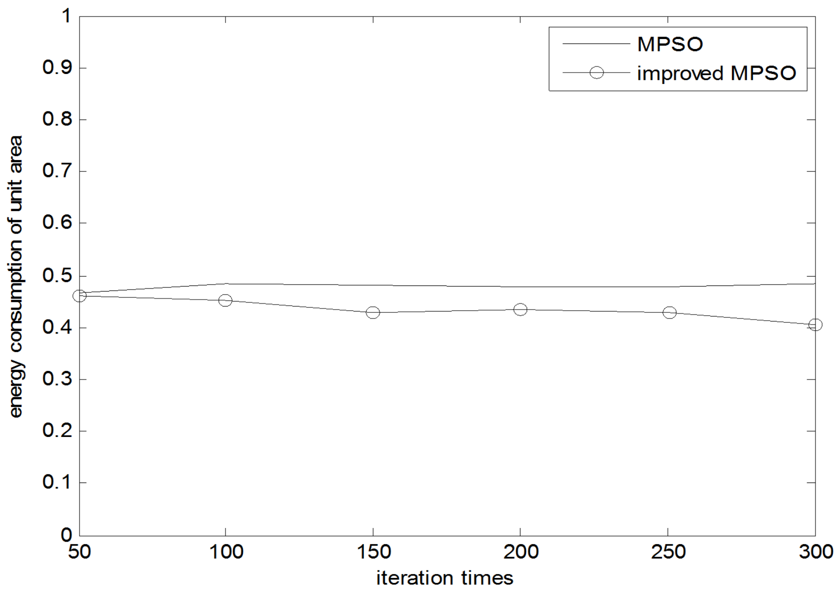

Fig. 3. Energy consumption comparison

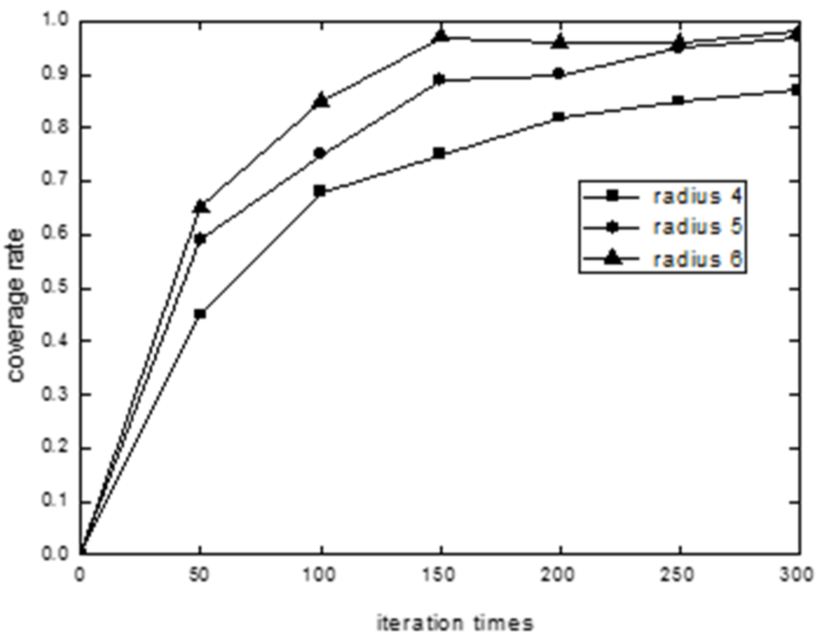

Fig. 4. Coverage rate with different radius

From Fig. 4, we can see that coverage rate has obvious ascension with the increasing of perception radius. At about 200 generation, network coverage rate of perception radius of 5 and 6 is almost the same. When the perception radius is 4, coverage rate is slightly lower. It can be seen that energy consumption of unit area is associated with perception radius (see Fig. 5). The greater the perception radius, the greater the energy consumption of unit area. Considering coverage rate and energy consumption, the network coverage performance is better when the perception radius is 5.

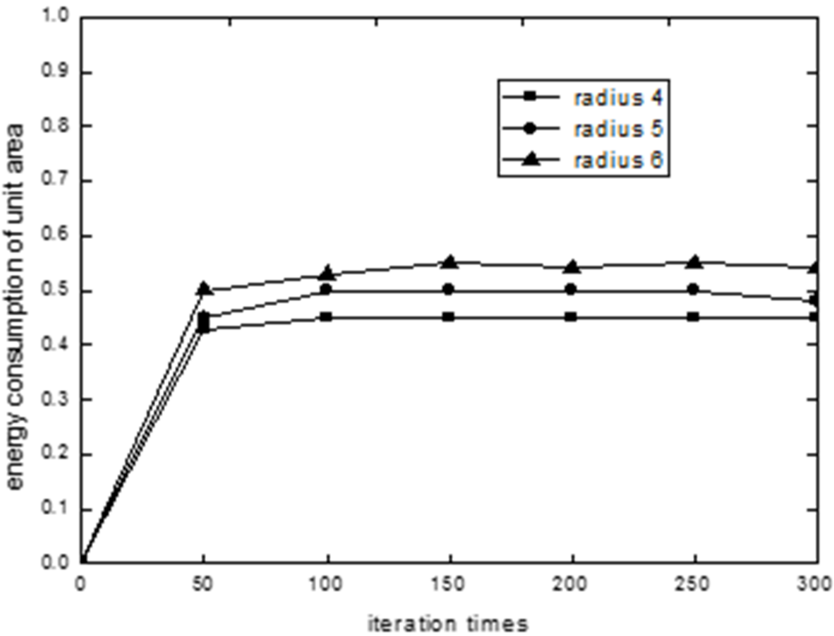

Fig. 5. Energy consumption with different radius

Figure 6 shows energy consumption with different sensor nodes. We can conclude that with the increasing of sensor nodes, energy consumption of unit area of the improved energy saving model does not exhibit much change. On the whole, the proposed model has higher energy efficiency.

5. Conclusion

Wireless sensor network has a wide range of applications in military, environment science, health care and other areas. Because it involves many disciplines and fields, there are some problems need to be solved. Coverage is one of the fundamental issues in research of wireless sensor network. Because random high density of node distribution may result in coverage area overlapped and large energy consumption, we propose a kind of energy consumption covering strategy based on multi-objective

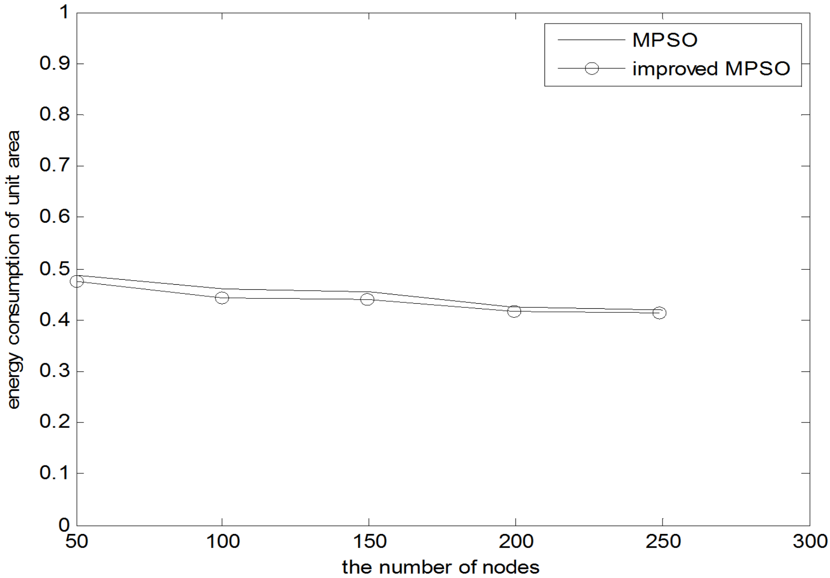

Fig. 6. Energy consumption with different nod

particle swarm. When selecting the optimal coverage node set, we consider the network energy consumption and the coverage rate at the same time. In each cycle, node calculates its sleep probability according to its own energy consumption and their neighbor's information. Network coverage, the number of working nodes and the energy consumption are taken as the optimized goal, and then improved multi-objective particle swarm optimization algorithm is used to get the optimal coverage solution. Simulation results show that the coverage control strategy can achieve high coverage rate and effectively reduce the energy consumption at the same time. So it ensures the network energy balance, keep stable network operation and prolong survival time of the network.

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