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Particle Swarm Optimization Algorithm based on Dynamic Acceleration Factor in Wireless Sensor Network

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Abstract. The coverage problem is one basic problem in the wireless sensor networks (WSN). In one limited region, how to reasonably arrange the sensor nodes to achieve the best coverage is the key to improve the performance of the whole networks. So this paper proposes an improved particle swarm optimization algorithm based on dynamic acceleration factor (PSO_DAC). It adopts decreasing inertia weight coefficients and introduces dynamic acceleration coefficients. The experimental results show that the algorithm has improved the coverage ratio by 34.6% than that of the standard particle swarm algorithm (SPSO), which is 29.3% higher than the particle swarm algorithm based on the decreasing inertia weight coefficient (LDWPSO). It is proved that the PSO-DAC algorithm can effectively improve the convergence speed and improve the coverage rate of nodes, so as to improve the coverage effect of the whole network and prolong the network lifetime.
Keywords: Wireless sensor networks, PSO-DAC, Probability model, Network coverage, Inertia weight coefficient.

1. **Introduction.** Wireless sensor networks (WSN) are composed of lots of sensor nodes deployed in the monitoring region [1, 2]. The sensor nodes have the capabilities of sensing, processing, and communicating [3]. Therefore, they can be widely used in a variety of contexts: geophysical monitoring, environmental monitoring, target tracking, battlefield monitoring, smart home and etc. But sensor nodes layout generally uses the method of random tossed in the air, then causing random deployment of nodes. Thus it is difficult to monitor the whole area. So coverage becomes a major problem in the whole network [4].

Under the premise of ensuring the performance of network services, It mainly addresses how to use the least nodes to cover the maximum area so that the wireless sensor networks can provide accurate data collection information and target tracking services. The traditional way is to deploy static nodes on a large scale, but the static nodes will lead to communication conflicts. Therefore, mobile nodes can be used to improve that situation. However, how to optimize the coverage of mobile nodes has become one of the hot topics in current research [5, 6, 7]. When optimizing the location of mobile nodes, the efficient algorithm can allocate the resources of the whole wireless sensor network reasonably, arranging the mobile nodes effectively, improving the service quality and prolonging the network monitoring time. In [8], proposing the method of the maximum coverage of the mobile node, which establishes two models and uses the distance between nodes to adjust the node position, has the disadvantage of relatively large computation; In [9], Zhang Qingguo uses the cellular structure to calculate the mobile node candidate target location, repair loopholes, improve network coverage; In [10], the artificial fish swarm algorithm is mainly optimization using animal autonomyt toImprove the optimization efficiency of the algorithm; In [11], Huang Yuyue takes the nodes' utilization and the efficiency of network coverage as the optimization goal and uses the artificial fish swarm algorithm to optimize network coverage. But the drawback is the latter search blindness; In [12, 13], Mao Keji uses the improved ant colony algorithm to optimize the network coverage problem, but it is easy to lead to stagnation phenomenon and slower rate of convergence; In [14], Wu Yile applies the particle swarm algorithm based on improved inertia weight coefficient to the wireless sensor network coverage optimization, but its convergence rate and its overall search performance is poor.

Therefore, in this paper we propose particle swarm optimization algorithm based on dynamic acceleration coefficients to adjust for wireless sensor networks area covering problem. The particle swarm algorithm introduces decreasing inertia weight coefficients and dynamic acceleration coefficients, then taking network coverage rate as the optimization goal; Thus it can improve the speed of convergence, avoid the phenomenon of premature and arrange nodes effectively, so as to improve the coverage efficiency of the whole network.

2. **Coverage model.**

2.1. **Network Model.**

Supposing the monitoring region is a two-dimensional space and N sensor nodes are randomly dispersed in this region. Node density is large enough in network with redundancy. We assume that:

(1) These sensor nodes are isomorphic. The sensing radius of each mobile node is r and communication radius is R. In order to ensure the entire network connectivity and prevent wireless interference set $R = 2r$.

(2) The coordinates of each node are known.

2.2. **Node Measure and Coverage Area Model.**

Setting the location of the mobile node s_i in the network is (x_i, y_i) for $i = 1, \dots, N$. The set of all sensors is denoted with $S = \{s_1, s_2, \dots, s_N\}$. By changing the location of the mobile node achieves the maximum coverage of the network area. Monitoring area S is digital discreted into a pixel of $m \times n$ and p represent pixel point. The location of pixel point p is (x, y). The euclidean distance between target pixel p and each sensor node is as follows:

$$d(s_i, p) = \sqrt{(x_i - x)^2 + (y_i - y)^2} \tag{1}$$

Now, there are many network monitoring models, such as binary model, power model, probability model, etc. The binary model is a simplified version of the probabilistic model. r_i represents events that can be covered by sensor nodes. The $p\{r_i\}$ is the probability that the point $p(x, y)$ is covered by all the sensor points s_i in the region. The binary model [15, 16] is as follows:

$$P(r_i) = \begin{cases} 1 & \text{if } d(s_i, p) < r \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

But in fact, the sensor node monitoring model should use the probability model because of the surrounding environment and the noise of the monitored area.

$$P(s_i, p) = \begin{cases} 1 & d(s_i, p) \leq r - r_e \\ e^{(\frac{-\lambda_1 \alpha_1^{\beta_1}}{\alpha_2^{\beta_2} + \lambda_2})} & r - r_e < d(s_i, p) < r + r_e \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

Where r is the sensing radius, $r_e (r_e < r)$ represents the measure of uncertainty in detection, and λ_1, λ_2, β_1, β_2 are parameters which depend on physical characteristics of sensors and $d(s_i, p)$ is euclidean diatance. α_1 and α_2 represent input parameter. The formula is as follows:

$$\begin{aligned} \alpha_1 &= r_e - r + d(s_i - p) \\ \alpha_2 &= r_e + r - d(s_i - p) \end{aligned} \quad (4)$$

In the monitoring area, when all nodes monitor the pixel p, the joint coverage rate is as follows:

$$P(S, p) = 1 - \prod_{i=1}^{n} [1 - P(s_i, p)] \quad (5)$$

Finally, Definition of coverage: The ratio of the size of effective coverage area by the N mobile nodes and the total size of the limited area. The formula is as follows:

$$P_{area} = \frac{\sum P(S, p)}{m \times n} \quad (6)$$

Where $m \times n$ represents the area of monitoring region D.

Supposing the WSN monitoring area is $20 \times 20\,\mathrm{m}^2$. The distribution of mobile nodes is shown in Fig. 1. Where "o" represents the location of the mobile nodes.

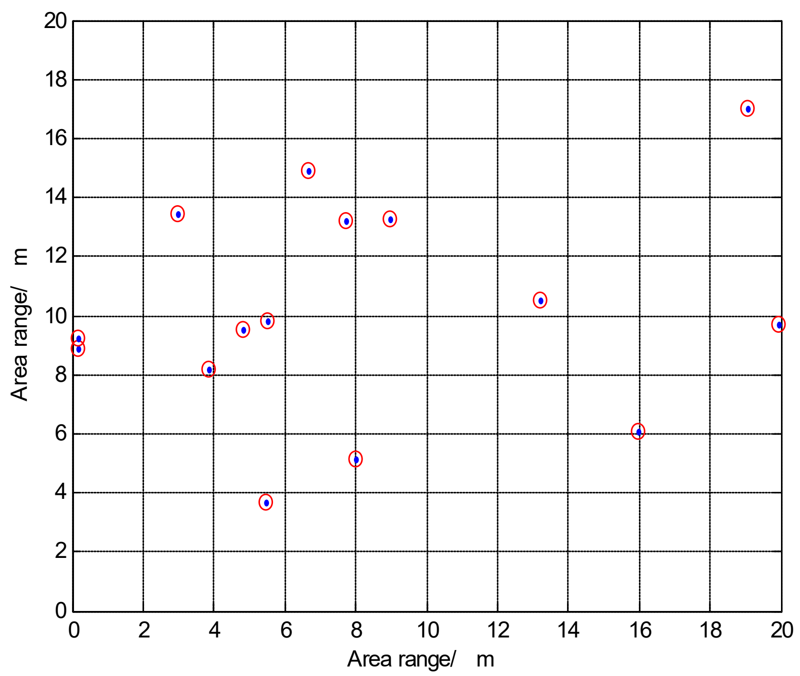

FIGURE 1. Monitoring area distribution nodes

The coverage optimization problem is outlined as follows.

Step 1: Use the formula (3) to calculate the coverage probability of each mobile node to a pixel;

Step 2: Use the formula (5) to calculate the joint coverage of each pixel point.

Step 3: Repeat step1 and step 2 to calculate the joint coverage of all pixels in the region;

Step 4: Use the formula (6) to calculate the coverage ratio of the monitored area, and set the formula (6) as the fitness function of the whole network coverage optimization.

3. Coverage Optimization Strategy of Improved Particle Swarm Optimization.

3.1. Particle swarm optimization algorithm. Particle swarm optimization (PSO) [17, 18, 19] is designed by simulating bird predation behavior. It mainly uses the best position of individual and the best position of group to change the position and speed of individual, so as to find the best location of food source. Firstly, the initial value of the particle is initialized, and the original position and speed of the particle are changed by the experience of the individual and the experience of the group. Secondly, the objective function equation is used to calculate the fitness value of the particle. Finally, we judge the quality of the current particle position according to the fitness value, so as to find the best position of the particles and the best location of the population.

Supposing the space is D dimension, the position of the i -th particle can be expressed as: $X_i = (x_{i1}, x_{i2}, \cdots, x_{iD})$, velocity can be expressed as: $V_i = (v_{i1}, v_{i2}, \cdots, v_{iD})$, the best location of the particle individual: $P_i = (p_{i1}, p_{i2}, \cdots, p_{iD})$, the best location of the particle population: $P_g = (p_{i1}, p_{i2}, \cdots, p_{iD})$, i represents the number of particles: $i = \{1, 2, \cdots, m\}$, The update equations for the speed and position are expressed as:

$$v_{id} = wv_{id} + c_1 r_1 (p_{id} - x_{id}) + c_2 r_2 (p_{gd} - x_{gd}) \tag{7}$$

$$x_{i(d+1)} = x_{id} + v_{id} \tag{8}$$

In (7), c_1, c_2 are the acceleration factor, usually set $c_1 = c_2 = 2$; r_1, r_2 are random number. Generally these value are in the range [0, 1]; w is the inertia weight coefficient, the experimental results show [20, 21, 22] that when the coefficient of inertia weight w is larger, it can enhance the overall searching ability of particles, and the local search ability of particles can be enhanced when the inertial coefficient w is small.

3.2. PSO-DAC algorithm. Particle swarm optimization based on dynamic acceleration coefficients (PSO-DAC) is improved over the basic particle swarm algorithm. First, we use a linearly decreasing inertia weight coefficient so that it can enhance the ability to weigh the local search and the overall search. Secondly, we increase the convergence rate of the particle swarm algorithm by using the dynamic acceleration factor, that is, c_1 gradually decreasing and c_2 gradually increasing. The inertia weight coefficient and the acceleration factor are calculated as follows:

$$w(k) = w_{ini}(w_{ini} - w_{fin})(T_{\max} - k)/T_{\max} \tag{9}$$

$$c_1(k) = c_{1ini} - (c_{1ini} - c_{1fin}) \times (k/T_{\max}) \tag{10}$$

$$c_2(k) = c_{2ini} + (c_{2fin} - c_{2ini}) \times (k/T_{\max}) \tag{11}$$

Where w_{ini} refers to the inertia weight coefficient at the beginning; w_{fin} refers to the weight coefficient when the number of iterations reaches the maximum; T_{max} is the maximum number of iterations; k is the current number of iterations. Experiments show that PSO-DAC algorithm has the best performance when $w_{ini} = 0.9$ and $w_{fin} = 0.4$. In (10) and (11), c_{1ini}, c_{1fin} represent the start and final values of the accelerator c_1; c_{2ini}, c_{2fin} represent the start and final values of the accelerator c_2.

A new rate update equation can be obtained:

$$v_{id} = w\,(k)\,v_{id} + c_1(k) r_1 (p_{id} - x_{id}) + c_2(k) r_2 (p_{gd} - x_{id}) \tag{12}$$

In (12), the first part represents particle previous velocity; The second part represents the effect of the particle itself on the current rate; The third part represents the effect of the other remaining particles on the current rate.

3.3. **PSO-DAC node coverage optimization strategy.** In PSO-DAC algorithm coverage optimization, it is assumed that there are M particles in the population, each particle contains N nodes, and each particle represents a node placement scheme. The position of the particle is denoted by X: $X_i = (x_{i1}, y_{i1}, x_{i2}, y_{i2}, \cdots, x_{iN}, y_{iN})$, Where (x, y) represents the position coordinate of each sensor, The velocity of the particle is expressed by V: $V_i = (v_{x_{i1}}, v_{y_{i1}}, v_{x_{i2}}, v_{y_{i2}}, \cdots, v_{x_{iN}}, v_{y_{iN}})$, Where (v_x, v_y) is used to represent the velocity component of each sensor in the vertical and horizontal direction. Different particles have different location. The PSO-DAC algorithm is based on the particle swarm algorithm, using the mobile node location information as the input value and the coverage rate of the wireless sensor network as the fitness function. So the coverage rate is as follows:

$$P\_\{area\} = \frac{\sum P(s,p)}{m \times n} \tag{13}$$

The specific steps are as follows:

Step 1: The position and speed information of M particles are generated randomly, and then the fitness value of each particle in the whole population is calculated by using the fitness function (13);

Step 2: Find the best value of each particle P_{best} and the group best value G_{best};

Step 3: Use the formulas (8), (12) to update the position and speed information of the individual particle in the region, and then calculate their fitness values;

Step 4: Compare the best value of the particles before and after the update, and the best value of the whole group, G_{best}, and replace it with a large value instead of a small value.

Step 5: If k reaches the maximum number of iterations, the algorithm will stop; otherwise it returns to step 3.

The workflow diagram of the PSO-DAC algorithm is shown in Fig. 2.

4. Simulation experiment.

4.1. **Simulation settings.** Supposing there are 15 mobile nodes that are placed arbitrarily in the area of $20 \times 20\,\text{m}^2$. The sensing radius of all mobile nodes is the same. The sensing radius is $r = 3\,\text{m}$, the communication radius is $R = 6\,\text{m}$; In probability model, $\lambda_1 = 1, \lambda_2 = 0, \beta_1 = 1, \beta_2 = 1$; The reliability measurement parameters is $r_e = 0.5r = 1.5\,\text{m}$; The maximum number of iterations $T_{\max} = 400$; At the same time, we use Matlab software to simulate a series of experiments.

4.2. **Simulation results and analysis.** In order to compare and analysis the performance of the algorithms, we use a consistent simulation condition. The initial location of the mobile node is randomly generated in the monitored area and as shown in Fig. 3. In this figure, "o" is the position of the mobile node in the region, and the circle is the size of the mobile node's perceived range.

Fig. 4 – Fig. 6 is the mobile node position layout optimized respectively by particle swarm optimization (SPSO), Linear decreasing weight particle swarm optimization (LDWPSO) [23], PSO-DAC optimization.

It can be seen from Fig. 3, Fig. 4 and Fig. 5 that PSO algorithm and LDWPSO algorithm optimized mobile node distribution is not very uniform, Some areas are covered repeatedly. it is mainly reason that the algorithm is easy to fall into a local optimum in the search, and it is difficult to find the global ideal value. In contrast, the distribution of nodes in Fig. 6

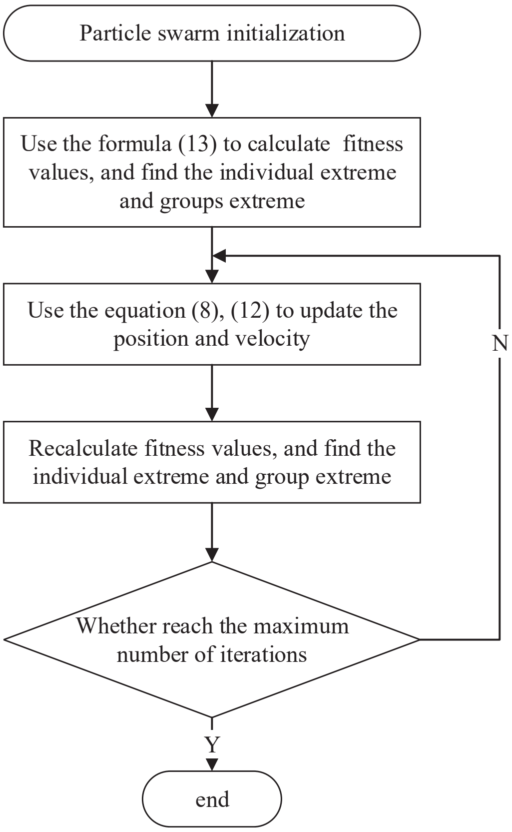

FIGURE 2. PSO-DAC algorithm flow chart

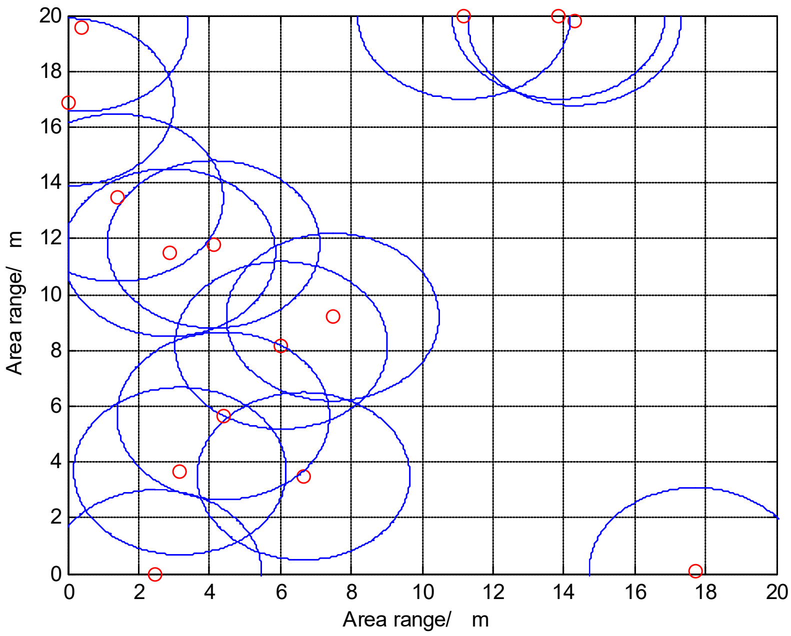

FIGURE 3. Initial nodes distribution

is more uniform and the overlap is less. Therefore, the PSO-DAC algorithm optimized mobile node layout is more decentralized than the PSO algorithm and the LDWPSO algorithm, so as to cover more area.

Table 1 shows that the PSO-DAC algorithm has a higher network coverage rate than SPSO and LDWPSO. The PSO-DAC algorithm is 34.6% higher than the SPSO algorithm

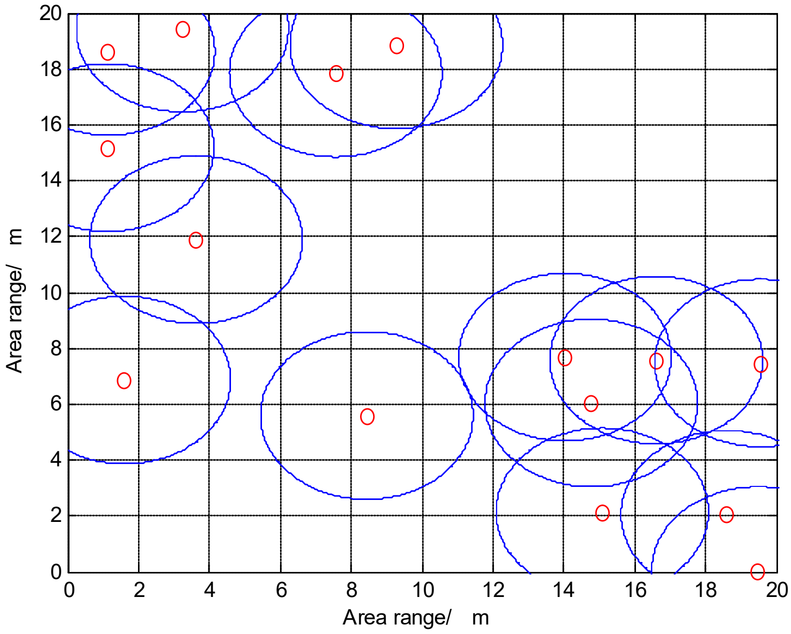

FIGURE 4. PSO algorithm optimized node distribution

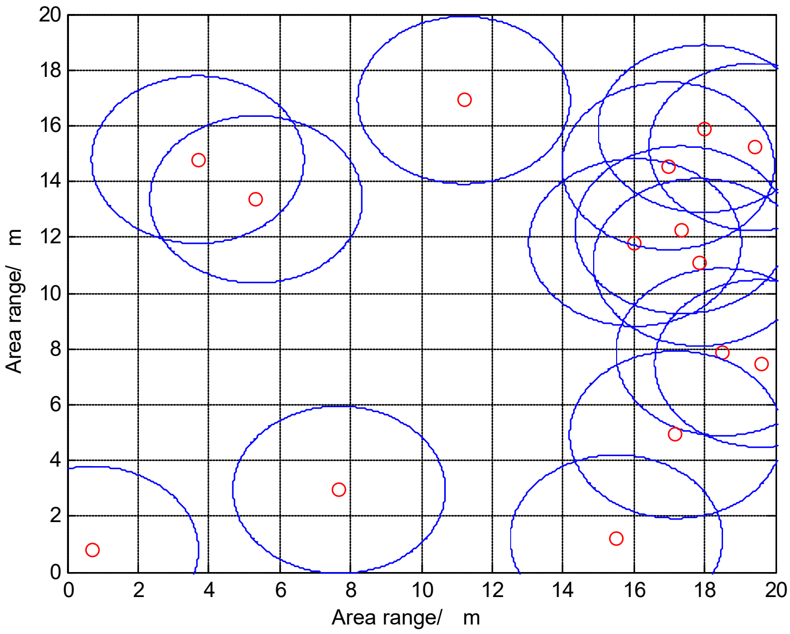

FIGURE 5. LDWPSO algorithm optimized node distribution

TABLE 1. Statistical coverage of different algorithms

Algorithm name	PSO-DAC	LDWPSO	SPSO
Coverage rate	81.8%	63.3%	60.8%

and 29.3% higher than the LDWPSO algorithm. Therefore, PSO-DAC algorithm network coverage optimization efficiency is higher. In Table 2, it can be concluded that the PSO-DAC requires a relatively short operating cycle over the other two methods.

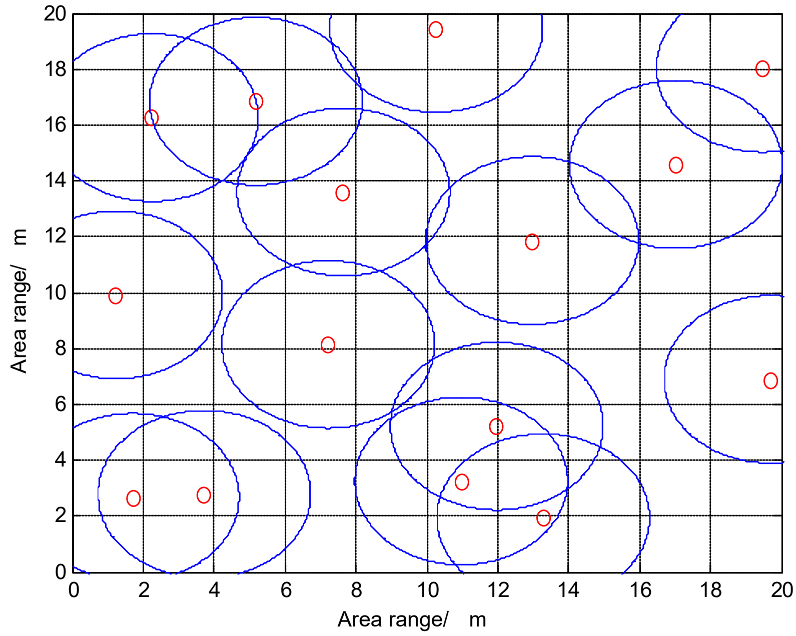

Figure 6. PSO-DAC algorithm optimized node distribution

Table 2. Different algorithm run time statistics

Algorithm name	PSO-DAC	LDWPSO	SPSO
Running time(second)	2.689 122	2.831 005	2.826 707

At the same time, this paper optimizes for different size of the coverage area to compare the optimization performance of the three algorithms. The simulation data is shown in Table 3.

Table 3. Three algorithms for different regions of the coverage optimization performance

Coverage area	Number of mobile nodes	PSO-DAC algorithm		LDWPSO algorithm		SPSO algorithm	
		Coverage rate	Number of convergent iterative	Coverage rate	Number of convergent iterative	Coverage rate	Number of convergent iterative
20×20	15	81.8%	87	63.3%	21	60.8%	90
30×30	20	84.1%	148	77.4%	120	70.8%	136
40×40	30	80.9%	164	72.9%	135	68.1%	88

It can be seen from Table 3 that compared with the SPSO algorithm and LDWPSO algorithm, the PSO-DAC algorithm can achieve the global optimal solution regardless of the coverage area is $20 \times 20\,\mathrm{m}^2$, $30 \times 30\,\mathrm{m}^2$ or $40 \times 40\,\mathrm{m}^2$. The PSO-DAC algorithm can cover the entire monitoring area with the best layout of the nodes.

In Fig. 7, the abscissa indicates the number of iterations and the ordinate indicates coverage rate. The simulation results show that although the number of iterations of PSO-DAC is larger than that of SPSO and LDWPSO, SPSO and LDWPSO are easy to fall into the local optimal solution, and early convergence lead to low coverage and regional

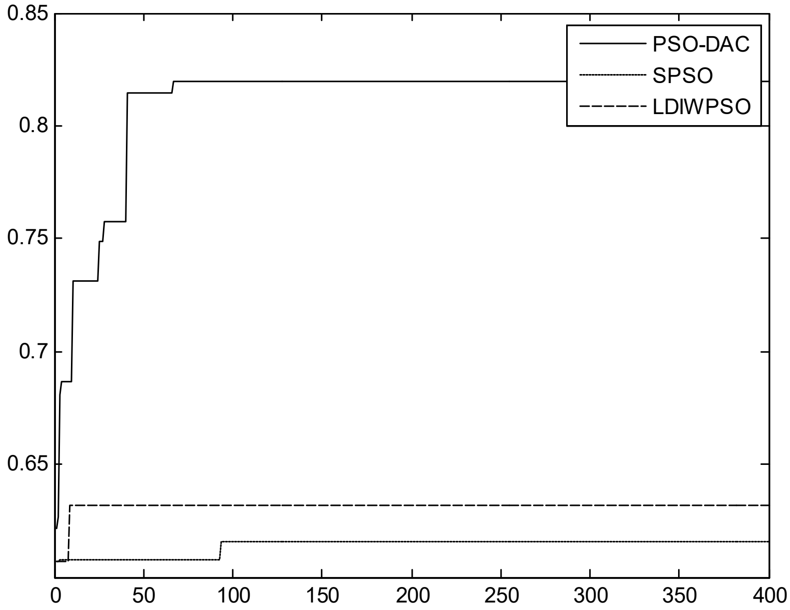

FIGURE 7. PSO-DAC, SPSO, LDWPSO algorithm coverage optimization curve

coverage redundancy. Therefore, the PSO-DAC algorithm avoid premature phenomenon. The coverage is relatively large and less overlapping area, so that it can more effectively adjust the mobile node layout and enhance the network coverage of the monitoring area. Simultaneously, the wireless sensor networks can provide accurate data collection information and target tracking services.

5. **Conclusion.** The particle swarm optimization algorithm based on dynamic acceleration coefficient and inertia weight coefficient is applied to the problem of node coverage optimization in the monitored area. It mainly uses the dynamic inertia weight coefficient and the dynamic acceleration coefficient to improve the standard particle swarm algorithm, then using the probability perception model and taking regional coverage rate as objective function to change the location of the node, so as to achieve the maximum coverage. Experimental results show that comparing with SPSO, the area coverage ratio of PSO-DAC is increased by 34.6% and comparing with LDWPSO, PSO-DAC is increased by29.3%. Therefore, the algorithm can adjust the layout of mobile nodes more efficiently, reduce the redundancy of nodes and increase the coverage rate, so as to extend the network lifetime. In the next stage, we will consider the introduction of chaos algorithm to further improve the overall performance of the network.

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