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An immune-swarm intelligence based algorithm for deterministic coverage problems of wireless sensor networks

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Abstract: A novel immune-swarm intelligence (ISI) based algorithm for solving the deterministic coverage problems of wireless sensor networks was presented. It makes full use of information sharing and retains diversity from the principle of particle swarm optimization (PSO) and artificial immune system (AIS). The algorithm was analyzed in detail and proper swarm size, evolving generations, gene-exchange individual order, and gene-exchange proportion in molecule were obtained for better algorithm performances. According to the test results, the appropriate parameters are about 50 swarm individuals, over 3 000 evolving generations, 20%−25% gene-exchange proportion in molecule with gene-exchange taking place between better fitness affinity individuals. The algorithm is practical and effective in maximizing the coverage probability with given number of sensors and minimizing sensor numbers with required coverage probability in sensor placement. It can reach a better result quickly, especially with the proper calculation parameters.

Key words: wireless sensor network; deterministic area coverage; immune-swarm algorithm; particle swarm optimization; artificial immune system

1 Introduction

Wireless sensor networks (WSNs) have been becoming one of the hot research areas because of their wide potential applications [1−2]. WSNs provide a new class of computer systems and expand people's ability to remotely interact with the physical world and will transform the way we manage our homes, factories, and environment [1]. How well the sensors observe the physical space and how we deploy the sensors are becoming important topics of research. Traditionally, there are two kinds of coverage problems: random coverage and deterministic coverage. If the sensors can be placed exactly according to the need, the corresponding deployment is deterministic. It is very important for interested area monitoring such as a lake, and a forest. Geometric analysis is often used in deterministic coverage problems [3−5].

WANG et al [3] studied efficient coverage area and efficient coverage area node ratio by analyzing coverage problems of WSNs. Minimum number of radio nodes required to cover a sensor field fully and seamlessly was given. However, influences of environment and sensor devices were not taken into account, and the result was based on the theoretically mathematical and geometrical analysis. WANG et al [5] considered variable sensor radii (influence of sensor device) and proposed a Delaunay-Triangulation-based I-coverage technique to obtain energy-efficient k-coverage. Although they went a step further, geometric solutions are difficult to satisfy the complicated coverage requirements. For example, if some node poisons must be changed because of environmental factors, it will influence the deployment of other nodes. The geometric solution is not flexible and it also has the disadvantages of huge calculation for multiple coverage demands. Fortunately, the development of evolution computation offers great advantages [6−7]. Particle swarm optimization (PSO) [8−9], genetic algorithm (GA) and artificial immune system (AIS) algorithm [10−12] were already used in wireless sensor networks and showed their superior performances. However, GA and AIS algorithms had a lower convergence speed and PSO was easy to fall into local optima, respectively. In addition, the detection probability was changed with sensing and communication radius [13−14] because of the behavior of range sensing devices and the influence of environment factors.

In this work, a novel immune-swarm intelligence based algorithm is proposed to improve the convergence speed and obtain better optimization result by combining

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the advantages of swarm intelligence and immune system, and considering the influences of environment factors and behavior of sensing devices to solve the deterministic sensor placement area coverage problems. That is to say, the advantages of swarm intelligence and immune system are taken full use, such as information communication between particles and diversity maintenance in antibodies, and the influence of communication radii, sensing radii, and the coverage probability of sensor nodes in WSNs are considered.

2 Deterministic area coverage problems and model

2.1 Deterministic area coverage problems

Deterministic coverage monitoring is mostly used in WSNs applications. To monitor the area, it is firstly to ensure connectivity amongst sensor nodes. However, connectivity is related to communication radius (R_c) and sensing radius (R_s) of nodes. ZHANG et al [13] figured out that the necessary condition to ensure connection in a given coverage area is $R_c \geq 2R_s$. Therefore, choosing R_c as twice of R_s is a good design choice for sensor nodes. Although maximizing the network lifetime is the fundamental goal for WSNs design, there are still some other important objectives which should be pursued and optimized in deterministic coverage problems considering the cost and the quality of service, such as the excellent coverage probability with given sensors or the minimum number of sensors with given coverage probability. In this work, the interested monitoring areas are divided into grids and the coverage probability is maximized by the proposed immune-swarm intelligence based algorithm. Later, the minimum sensors required for the given coverage conditions are optimized.

2.2 Model

Coverage and connectivity are two of the most fundamental issues in WSNs [15]. The coverage concept is a measure of the quality of service (QoS) for sensing. The goal is to have each location in the physical space of interest within the sensing range of at least one sensor. In this work, the given monitoring area is taken as two dimensions and N sensor nodes with the same parameters are used. The position of each sensor node c_i is (x_i, y_i), (i=1, 2, ⋯, N); the sensing radius is r; the communication radii is R (R=2r).

The set of sensor nodes is $C=\{c_1, c_2, \cdots c_N\}$, where $c_i=\{x_i, y_i, r, R\}$, i=1, 2, ⋯, N.

Suppose that the monitoring area A is divided into $m\times n$ grids and the coordinates of the grid g_j are (x_j, y_j), $j=1,2,\cdots,m\times n$. The area A can be denoted as $A\{g_1, g_2, \cdots g_{m\times n}\}$.

The distance between the node c_i and the grid g_j is

$$d(c_i, g_j)=\sqrt{(x_i-x_j)^2+(y_i-y_j)^2} \tag{1}$$

Definition 1: Grid coverage probability $P(r_{i,j})$

Event $r_{i,j}$: The grid g_j is covered by sensor node c_i.

$P(r_{i,j})$: The probability that event $r_{i,j}$ will take place, that is, the probability that the grid g_j is covered by the sensor node c_i:

$$P(r_{i,j})=P(c_i, g_j)=\begin{cases}1, \text{ if } d(c_i, g_j)<r \\ 0, \text{ otherwise}\end{cases} \tag{1}$$

Due to the nature of sensing devices, obstacles and environment noise, the detection of sensor nodes shows a certain probability distribution with varying coverage radius. In practical applications, the following model [16] is often used:

$$P(c_i, g_j)=\begin{cases}1, \text{if } d(c_i, g_j)\leq r-r_\mathrm{e} \\ \mathrm{e}^{(-\alpha_1\lambda_1^{\beta_1}/\lambda_2^{\beta_2}+\alpha_2)}, \text{if } r-r_\mathrm{e}<d(c_i, g_j)<r+r_\mathrm{e} \\ 0, \text{if } d(c_i, g_j)\geq r+r_\mathrm{e}\end{cases} \tag{3}$$

where $r_\mathrm{e}(r_\mathrm{e}<r)$ is the measure of uncertainty in detection; $\lambda_1=r_\mathrm{e}-r+d(c_i, p)$ and $\lambda_2=r_\mathrm{e}+r-d(c_i, p)$; α_1, α_2, β_1 and β_2 are the detection probability parameters. It must be noted that the model reflects the behavior of range sensing devices. The values of α_1, α_2, β_1 and β_2 depend upon the characteristics of various physical sensors.

In order to improve the probability of detection, the grid is usually covered by several sensor nodes. The joint probability of the grid g_j at sensor node set C is given by

$$P_{\mathrm{cov}}(C, g_j)=1-\prod_{c_i\in c}(1-P(c_i, g_j)) \tag{4}$$

Definition 2: Area coverage probability $P(A, C)$ is the probability for monitoring area A of sensor node set C [16]:

$$P(A, C)=\frac{\sum P_{\mathrm{cov}}(C, g_j)}{A}=\frac{\sum P_{\mathrm{cov}}(C, g_j)}{m\times n\times U_\mathrm{A}} \tag{5}$$

where U_A is the area per grid, $\sum P_{\mathrm{cov}}(C, g_j)$ is the sum of the joint probability of each grid. The analysis and algorithms are based on the above model.

3 Principle of immune-swarm intelligence algorithm

3.1 Particle swarm optimization algorithm

Particle swarm optimization (PSO) is an active branch of swarm intelligence (SI). It was firstly introduced in the late of 20th century and inspired by the emergent motion of swarms and flock behavior. Instead of producing new individuals through information recombination as in evolutionary algorithms, particles in PSO iteratively explore optima in a multi-dimensional search space by utilizing personal memories and information sharing between individuals. The swarm is typically modeled by particles with a position and a velocity, where each particle stands for a candidate solution to the optimization problem. During the optimization procedure, particle individuals communicate with each other and adjust positions according to their history and the experience of their neighbors. Due to the nature of individual memories and information sharing, particles can reach the best solution quickly. However, PSO iteration is a heuristic method and it is not able to guarantee convergence to a global optimum, but to a good solution or a local optimum. PSO is a stochastic algorithm. The general principle is as follows:

$$v_{id}(n+1)=v_{id}(n)+c_1r_1(p_{id}(n)-x_{id}(n))+ c_2r_2(p_{gd}(n)-x_{id}(n)) \tag{6}$$

$$x_{id}(n+1)=x_{id}(n)+v_{id}(n+1) \tag{7}$$

where v is the velocity of particle; x is the position of particle; the subscripts i and d denote particle index and particle dimension index, respectively; n is the index of recursive computation, c_1 and c_2 are the system control parameters; r_1 and r_2 are the random numbers in (0, 1); P_{id} is the present best position of particle i, and P_{gd} is the present global best position of all the swarm particles. The particle position $x_{id}(n)$ is updated using its current value and the newly computed velocity $v_{id}(n+1)$. The optimum of the optimization function is obtained after N recursive computations. Since PSO is a random heuristic method, usually the average of several N iterations is required to analyze the convergence performance. The algorithm routine [17] is described:

1) Problem analysis. Define the particle and the optimization function.

2) Decide the number of particles (M) and randomly assign an initial value to each particle;

3) Calculate the value of the optimization function and locate the best particle, P_{gd};

4) Ascertain the best particle of the i-th particle in all produced generations, i.e., P_{id};

5) Take the best globe particle P_{gd} and the best particle of the i-th particle generations to produce a new swarm according to Eqs. (6) and (7);

6) Repeat Steps 4)−6) for N iterations.

3.2 Artificial immune system algorithm

Artificial immune system (AIS) is also an active branch of evolutionary computation. It encompasses unique and distinguished characteristics of pattern recognition, self-identity, data analysis, machine learning, and diversity keeping that attempt to algorithmically mimic the behavior of natural immune systems [18].

The human immune system has two types of immune responses: innate immune response and acquired immune response. Once pathogens enter the body, they trigger the two immune responses. The acquired immune response recognizes pathogens (antigens) with the help of the produced specific antibodies, which are particular for the antigens and can capture a broad group of them. In order to bind antigens and antibodies, their molecule shapes must match. The forces that determine the matches of them are called affinity. A closer match between antibody and antigen results in a stronger molecular binding and a higher stimulation of the B cells, and thus attains superior recognition. The stimulated B cells can produce antibodies with high affinity, which are selected to proliferate. Therefore, they divide themselves and produce lots of similar antibodies.

The antibody molecules are made up of light and heavy protein chains. Each of them has a variable region and a constant region. The variable region can be divided into several distinct protein segments which are encoded by a group of genes. A gene for each protein segment is randomly chosen and is folded into place by B cell rearrangement. The mechanism results in millions of possibilities and thus allows the immune system to possess a wide range of antibody types. Together with new naturally produced antibody molecules, this is the diversity maintenance mechanism of immune system. The process is called "gene mutation and gene exchange".

AIS is a simulating process for natural immune systems, which is mostly used for a diverse range of applications. In the work, our attention is focused on the diversity keeping mechanism of AIS and the combination with information sharing of PSO. The algorithm routine [19] is described below.

1) Problem analysis. Define antigen, antibody and the fitness function.

2) Randomly initialize a group of antibodies as the first generation swarm (M).

3) Figure out affinity of each antibody to antigen (the value of the fitness function), choose the highest affinity antibody and generate its copy to the next generation (clone selection).

4) Choose m_1 of the highest elements in M, exchange some regions of the molecules randomly and generate new m_1 antibodies to the next generation. The higher the affinity is, the less the exchange is.

5) Randomly generate new antibodies m_2, and form the new generation antibodies together with the new antibody/antibodies produced in Steps 3) and 4) ($1+m_1+m_2=M$).

6) Repeat Steps 3)−5) until a criterion is met, such as N generation.

3.3 Immune-swarm intelligence algorithm

The strategy of PSO algorithm is to maximize the use of individual memories (the best particle of individual in all generations) and information sharing (the globe best particle with particle individuals). It can quickly reach the optimum, and is more likely to produce premature convergence and fall into a local optimal equilibrium state. AIS algorithm is similar to genetic algorithm in some ways. It produces the next generation by gene mutation and molecular partial exchange. It can keep the diversity of individuals and reach the globe optimum. In the long run, however, its speed is slow. ISI (immune swarm intelligence) algorithm combines the advantages of information sharing in PSO and the mechanism of diversity keeping in AIS. Each individual in ISI can be related to a particle in PSO, and at the same time, as an antibody in AIS. It produces the next generation partially as that in PSO and AIS. The detailed procedure of the algorithm is as follows.

1) Problem analysis. Identify the meaning of individuals and the fitness function.

2) Randomly produce the first generation of swarm individuals (M).

3) Calculate the value of the fitness (optimization) function, find the globe best individual, and then sequence individuals according to the fitness (optimization) function.

4) Evaluate the best individual for one in all generations.

5) Clone the globe best individual to next generation.

6) Choose the sub-best individuals (m_1) and produce the same number of individuals in the next generation according to Eqs. (6) and (7).

7) Choose the sub-best individuals (m_2) and produce the same number of individuals in the next generation according to gene mutation and partial molecular exchange.

8) Randomly produce some new individuals (m_3). Together with the individuals produced in Steps 5)−8) these form new next swarm generation (m_1+m_2+m_3+1=M).

4 Coverage optimization and sensor node deployment

4.1 Optimization and deployment with ISI algorithm

Suppose the interested monitoring area is 1 km× 1 km, and divide it into 100 grids (10×10). The area of each grid is 0.01 km^2, that is, U_A=0.01 km^2=1 Unit Area. The central coordinates of each grid are (x_j, y_j). We will place 10 sensors into the area and find the deployment positions that can maximize area coverage probability. Each antibody individual in the algorithm stands for the positions of 10 sensors for a certain deployment. So, the dimension of each antibody individual is 20 (10×2).

Sensor node parameters:

Sensing radius, R_s=2.5; Communication radius, R_c=2R_s=5; α_1=1; α_2=0; r_e=0.5R_s=1.25; β_1=1; β_2=0.5.

Algorithm parameters:

M=30; m_1=9; m_2=10; m_3=10; N=300; proportion of gene-exchange in molecule, 20%.

Gene-exchange individuals are chosen from the sub-best individuals in m_1 and the globe best antibody individual. So, the total number of gene-exchange individuals is 10.

Five trials are conducted and the average convergence curve of optimization function is shown in Fig. 1. The average, the best and the worst coverage probabilities of five trials, and the sensor nodes placement coordinates (x_i, y_i) (i=1, 2, ⋯, 10) in accordance with the best coverage probability are given in Table 1. It can be seen that the area coverage probability can reach more than 90% and the best differs not too much to the worst when the swarm individuals evolve to 300 generations. The algorithm can practically solve deterministic deployment problems of sensor nodes with better area coverage probability.

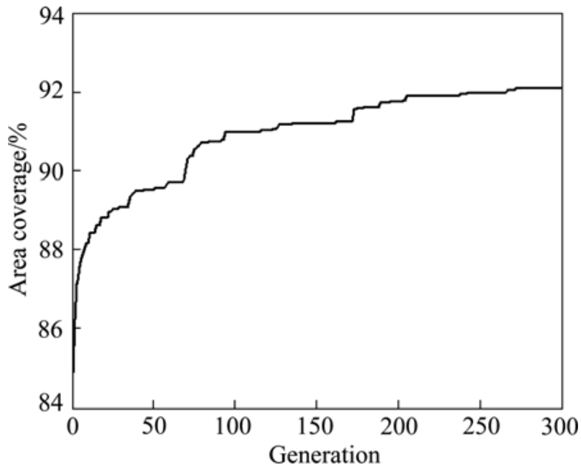

Fig. 1 Area coverage optimization with ISI algorithm (Average of 5 times)

4.2 Analysis of different algorithms

In order to evaluate the performance of the ISI algorithm, we compare the results obtained using PSO and AIS algorithms. The sensor node parameters and the ISI algorithm parameters used are the same as those in Section 4.1. The optimization curves with ISI, AIS and PSO algorithms are shown in Fig. 2.

Table 1 Sensor nodes placement coordinates with ISI algorithm of 300 generations

No.	X_i	Y_i
1	4.515 6	1.929 9
2	5.310 8	8.459 6
3	8.468 0	1.892 6
4	1.597 1	7.781 6
5	7.641 3	8.651 4
6	2.871 2	8.598 9
7	2.249 2	5.065 3
8	8.196 7	5.598 8
9	5.579 5	4.750 7
10	1.558 7	1.473 7
Average/%	92.098 1	
Best/%	93.466 4	
Worst/%	91.311 9	

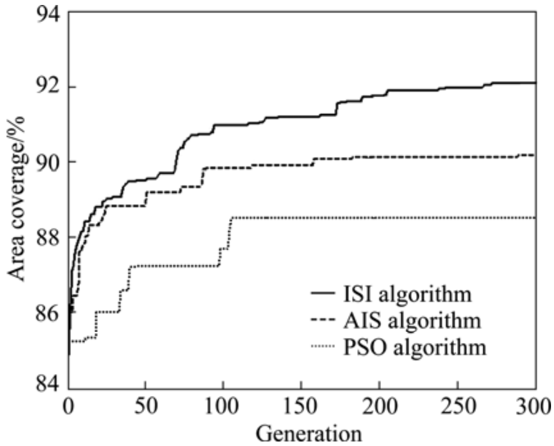

Fig. 2 Coverage optimization with different algorithms

The algorithm parameters of AIS are M=30, m_1=9 and N=300. The gene-exchange proportion in a molecule and the gene-exchange individuals are the same as those in AIS. The algorithm parameters of PSO are M=30 and N=300. It can be seen that the PSO algorithm is easy and quickly reaches a local optimum. The AIS algorithm performs better than PSO, but it is slower than ISI. ISI combines the advantage of information sharing and diversity keeping mechanism. The best sensor deployments amongst the five trails are shown in Fig. 3. The results of the ISI algorithm are more well-proportioned and reasonable than the other two. The ISI algorithm is practical and effective.

4.3 Influence of algorithm parameters

In order to analyze the effect of different parameters, we will change the order of gene-exchange in ISI, the proportion of gene-exchanged part in molecule, the number of evolving generations and the number of individuals in a swarm.

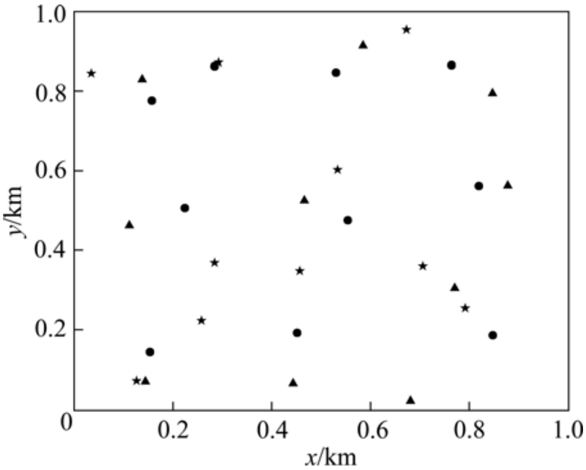

Fig. 3 Sensors deployment in 100 grids (10 sensor nodes) (★−PSO algorithm; ▲−AIS algorithm; ●− ISI algorithm)

4.3.1 Antibody individual gene-exchange orders

Figure 4 shows the ISI algorithm performance with different gene-exchange orders. As we know, individuals in m_1 have better fitness affinity than those in m_2. It is shown that an optimization function with better gene-exchange of affinity individuals will reach the optimum faster. The better fitness affinity the individuals have, the stronger the production of antibodies (individuals) and sooner they reach the optimum.

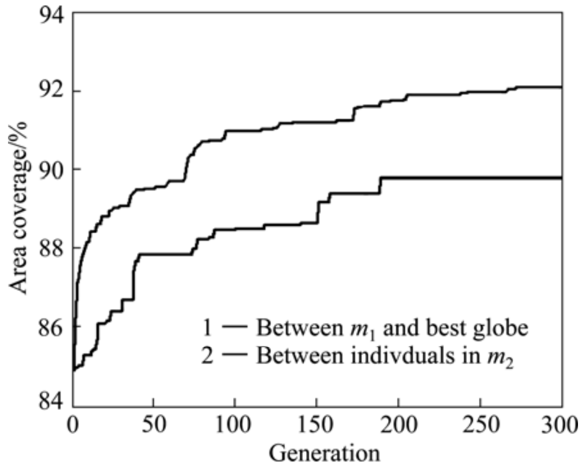

Fig. 4 Coverage optimization with different gene-exchange orders in ISI algorithm (Averaged results of five trials)

4.3.2 Antibody molecule gene-exchange proportion

The proportion of the gene-exchanged part in the molecule is changed to evaluate its influence on the algorithm. The convergence curves are shown in Fig. 5. Exchanging the molecule’s part with 20% and 25% achieves a faster convergent speed within 500−600 generations. However, the later has a good ability to avoid being trapped into local optima. Exchanging with 30% shows a slower convergent speed than exchangings with 20% and 25%, and there are no signs of reaching an optimum even 1 000 generations are evolved. It can be seen that more exchanged molecule parts are helpful to keep the diversity of antibody types and to avoid being trapped into the local optimum. But more exchanged parts will slow down the optimization convergent speed. From Fig. 5, we can see that it is better to retain the exchanging part at about 25%, although the diversity keeping is helpful to reach the global optimum.

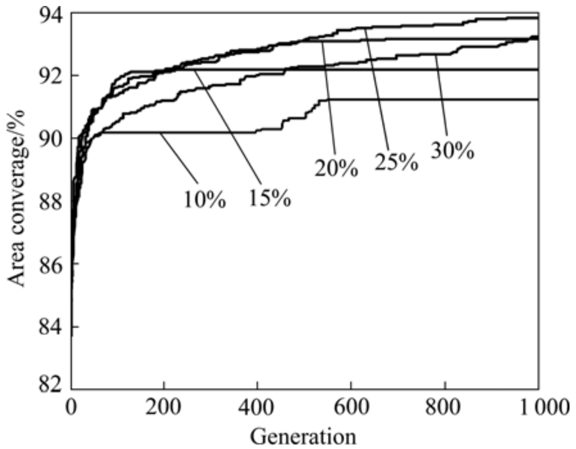

Fig. 5 Coverage optimization Generation with different proportions of gene-exchange in ISI algorithm

4.3.3 Swarm size

As shown in Fig. 5, the forced high proportion gene-exchange is helpful for retaining diversity. Then, the swarm size is enlarged to see the result of diversity maintenance by randomly producing more antibody individuals to the next generation. Some researchers proposed that the size of antibody swarm is better with 50 individuals in AIS algorithm [19]. M=50 is chosen and its performance is compared with that of M=30. The ISI algorithm parameters are the same as those in Fig. 1 except for the swarm size and the number of evolving generations. As depicted above, diversity keeping is helpful in reaching the globe optimum and it may slower down the convergence speed. So, a large N is chosen, for example 3 000 and 5 000, respectively, to reduce single calculation influence of the random algorithm. For every combination of algorithm parameter, three tests are conducted, and the optimization results are given in Table 2. We can see that with 50 individuals, it can reach a better optimum than that with 30 individuals. And it can reach its optimal solution with 3 000 generations (similar results are achieved with 5 000 generations). The results with 30 individuals are nearly the same with 1 000 generations (see Fig. 5), irrespective of whether it evolves to 3 000 or 5 000 generations.

Table 2 Optimization results with different swarm size

50 individuals			30 individuals		
G	3 000	5 000	G	3 000	5 000
1	95.062 7	95.223 4	1	93.003 1	93.112 1
2	95.606 0	95.750 0	2	93.677 3	92.975 5
3	95.450 4	95.653 4	3	92.955 8	93.645 7

4.3.4 Evolving generations

In order to study the influence of evolving number of generations, Fig. 5 and Table 2 with different evolving generations are analyzed. The convergence curves of 50 individuals (better diversity maintenance) and 3 000 evolving generations in Table 2 are shown in Fig. 6. From Fig. 5, it can be seen that with higher gene-exchange proportion (better diversity maintenance), the curves continue to show an upward optimization tendency. From Fig. 6, it can be seen that the optimization convergence curves are nearly flat when evolving to 3 000 generations. It is shown that the number of evolving generations is better over 3 000 with 50 individuals swarm size and higher gene-exchange proportion.

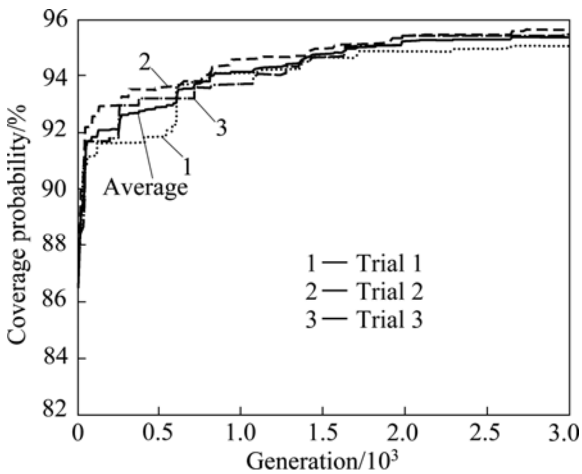

Fig. 6 Coverage optimization curve with 50 individuals and 3 000 evolving generations

5 Analysis of other coverage requirements for deterministic coverage problems

As pointed out in Refs. [1, 15], to find the minimum number of sensors required for an interested area to meet the coverage and connectivity requirements is also a fundamental issue in deterministic wireless monitoring. Suppose that an area is 1 km×1 km and the area coverage probability requirement is 95%. The ISI algorithm can also be used to solve these kinds of problems, though the dimensions of individual are changeable. According to the analysis in the previous sections, the algorithm parameters are chosen as follows: M=50; m_1=9; m_2=10; m_3=10; N=3000; proportion of gene-exchange: 20%.

The area is divided into 100 grids. The algorithm routine is as follows.

1) The estimated value of minimum number of needed sensors should be given based on prior experience. It is important to note that it is related to the dimension of the swarm individuals and the amount of computation of the algorithm.

2) The ISI algorithm is used to optimize the coverage probability with the above parameters. For each sensor, evaluate the coverage probability three times. If the optimized coverage probability meets our requirement, terminate the calculation. If the best individual meeting our coverage requirement cannot be found in all three trials, the number of sensors will increase by one.

3) For each added sensor, repeat the process in Step 2) until the best individual that meets the coverage requirement is found. The best individual is the placement coordinate of the optimized coverage probability.

For the above problem, 10 sensors are required to meet the coverage requirement of 95% and the optimized coverage probability is 95.030 4%. If the coverage requirement is changed to 98%, thus, to meet the requirements, 13 sensors are needed and the optimized coverage probability is 98.380 1%. The deployments for the two problems are shown in Fig. 7.

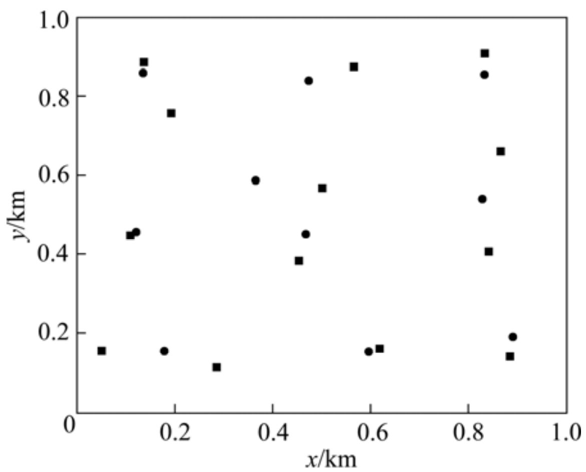

Fig. 7 Minimum sensor nodes deployment in 100 grids (●− 95%, 10 sensors; ■−98%, 13 sensors)

In order to show the practicality of our algorithm, the area is changed to 1.5 km×1.5 km and the area is divided into 225 grids. Then, minimum sensors for 95% and 98% coverage requirement are obtained at 25 and 28 s, and the optimized coverage probabilities are 95.0430% and 98.0211%, respectively. The deployments for 1.5 km×1.5 km area are shown in Fig. 8. The results show that the algorithm practically solves problems associated with deterministic coverage areas.

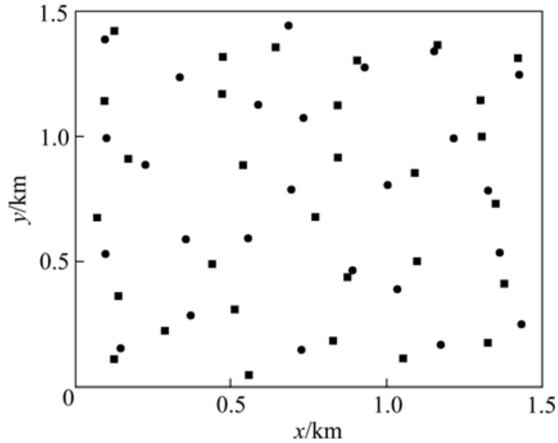

Fig. 8 Minimum sensor nodes deployment in 225 grids (●− 95%, 25 sensors; ■−98%, 28sensors)

6 Conclusions

1) The ISI algorithm is better than PSO algorithm and AIS algorithm in solving WSNs deterministic coverage problems. It has a quick speed and a better result.

2) Swarm size, evolving generations, gene-exchange individual order and gene-exchange proportion in a molecule influence the performance of the algorithm. The proper calculation parameters greatly improve the performance of the algorithm.

3) According to the test samples, the appropriate parameters are about 50 swarm individuals, over 3 000 evolving generations, 20%−25% gene-exchange proportion in molecule with gene-exchange taking place between better fitness affinity individuals.

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