Efficient Cover Set Selection in Wireless Sensor Networks

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Abstract The effectiveness of a cluster-based distributed sensor network, to a large extent, depends on the coverage provided by the sensor nodes. To activate only the necessary number of sensor nodes at any particular moment is an efficient way to save the overall energy. However, this is an NP-complete problem because of the high-density deployment of wireless sensor networks. In this paper, a novel searching algorithm based on improved NSGA-II (elitist nondominated sorting genetic algorithm) is proposed to select an optimal cover set. In contrast to the binary detection model used in the previous work, a probabilistic detection model is adopted in combination with the detection error range and coverage threshold. With the full network coverage being guaranteed, a number of nodes are made into dormancy mode to save energy. The circulated combination and delete operators are proposed to enhance the search capability. Extensive simulation results are presented to demonstrate the effectiveness of our approach.

Key words Wireless sensor networks (WSN), cover set, detection model, improved NSGA-II

Wireless sensor network (WSN) normally consists of a large number of distributed nodes that organize themselves into a multi-hop wireless network[1]. Due to their deployment in potentially harsh scenarios, nodes in sensor networks are usually powered by batteries with finite capacity. It is always desirable to extend the lifetime of sensor network nodes without sacrificing their functionality[2]. Thus, the study of power management is particularly important.

In WSNs, all nodes share common sensing tasks. This implies that not all sensors are required to perform the sensing task during the whole system lifetime. The energy consumption of radio frequency module is the highest in the transmission mode. In the sleeping mode, it consumes the least energy. If all the sensor nodes operate in the active mode simultaneously, an excessive amount of energy will be wasted and the data collected will be redundant. Turning off some nodes does not affect the overall system function as long as there are enough working nodes to assure it. Therefore, if the sensors can be scheduled to work alternatively, the network lifetime can be prolonged correspondingly. Thus, it is of considerate significance to cover the whole monitored area with the least working nodes such that no blind point exists and the network connectivity is kept. This becomes a serious problem in large-scale sensor networks, where hundreds and thousands of nodes are randomly deployed.

The key idea of this paper is to maintain the full coverage in large sensor networks by a small number of sensor nodes. The scheduling algorithm should allow as many nodes as possible to be turned off in most of the time, and at the same time, it should preserve the expected coverage rate and guarantee the network connectivity. Increasing the coverage rate may cause more sensors in working mode, while reducing the number of working sensors may cause lower coverage rate. These two aspects need to be considered simultaneously. Hence, our method is driven by the requirements of these two interrelated aspects. Firstly, both the binary and probabilistic sensor detection models are exploited to handle the problem of cover set selection in WSNs. Secondly, the problem is transformed into a multi-objective optimization problem (MOP) as it involves two simultaneous optimization objectives. Then, a novel searching algorithm, named as efficient cover set selection (ECSS), is proposed, as inspired by the multi-objective genetic algorithms (MOGAs). Finally, a cluster-based architecture is applied to implement ECSS. As a result, the status of all the sensors is determined by one-time computation, and thus the energy consumed by computation and communication is saved effectively.

1 Related work

In general, network coverage, which has direct effect on the network performance, can be considered as the measure of quality of service (QoS) in WSN[3]. The problem of finding the maximum number of disjoint covers in a sensor network was addressed in [4], where a cover was defined as a set of nodes that could completely cover the monitored area. In addition, the problem was proved to be NP-complete. The work reported in [5] attempted to solve the complete coverage problem with centralized solution. However, a large number of nodes were required to operate in the active mode. A distributed localized algorithm, called optimal geographical density control (OGDC), was proposed in [6] to maintain coverage and connectivity. It was proved that if the communication range is at least twice the sensing range, then complete coverage implies connectivity. In particular, coverage and connectivity were studied jointly in [7] with sleep-awake scheduling for energy conservation and surveillance quality provisioning.

Although it is not a new approach to achieve energy conservation in WSN by scheduling some nodes to sleep, none of the existing algorithms satisfy the complete set of requirements. Several algorithms were proposed aiming at the close-to-optimal solution. Reference [8] used information coverage based on parameter estimation to find the relationship between the sensor density and the average field vacancy in a randomly deployed WSN. The work reported in [9] adopted linear programming techniques to minimize the cost of sensors for complete coverage of the sensor field. A distributed probing-based density control mechanism for robust sensing coverage named probing environment and adaptive sleeping (PEAS) was developed in [10], where a set of nodes were made active to maintain coverage while others were put into sleep to conserve energy. By adjusting the probing range of sensor nodes, different coverage redundancies could be achieved. Although PEAS guaranteed that the distance between any pair of the working nodes was at most the probing range, it did not completely preserve the original sensing coverage after turning off some nodes.

The remainder of this paper is organized as follows. In Section 2, preliminary assumptions and the coverage models for WSN are discussed. In Section 3, an efficient cover set selection algorithm is proposed, namely ECSS, based on an improved NSGA-II. In Section 4, simulation results are presented in various situations to validate our analysis. Finally, conclusions are given in Section 5.

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2 The coverage model for WSN

2.1 The preliminary assumptions

Clustering mechanism is especially effective in increasing network scalability and reducing data latency, which is investigated in this paper to distribute the management responsibility from the base station (BS) to the cluster heads. The election of cluster heads is similar to hybrid energy-efficient distributed (HEED) clustering[11] that periodically selects cluster heads according to a hybrid of the node residual energy and a secondary parameter, such as node proximity to its neighbors or node degree. The following assumptions are made regarding WSN:

1) Each sensor has its own location determination capabilities (e.g. GPS) and schedules itself for the active/sleep intervals.

2) After the initial deployment, all sensor nodes are able to communicate with the cluster head and send their location information to the BS or the cluster head.

3) The cluster head is responsible for executing the ECSS algorithm and broadcasting the status when each node is activated.

As the node selection mechanism is our major concern, the problem with data gathering protocol and node synchronization are not addressed in this paper. To transmit data from sensors to the BS efficiently, a mechanism like low energy adaptive clustering hierarchy (LEACH)[12] or power efficient gathering in sensor information systems (PEGASIS)[13] can be used. For node synchronization, one method is to make the BS send short beacons periodically.

2.2 The sensor network coverage model

Consider that N sensors are randomly deployed to cover the target area T, which is digitized into $m \times n$ grid points. The cover set in the deployment region is defined as $sov = \{s_1, s_2, \cdots, s_N\}$, where each sensor has a sensing range r_s and a communication range r_c. In order to ensure coverage connectivity, we set $r_c \geq 2r_s$. Assume that sensor s_i is deployed at point (x_i, y_i). For any grid point $P(x, y)$, the Euclidean distance between s_i and $P(x, y)$ is denoted as $d(s_i, P)$.

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

Equation (2) shows the binary detection model[9] expressing the detection probability $c_{xy}(s_i)$ of a grid point $P(x, y)$ by sensor s_i.

$$C_{xy}(s_i) = \begin{cases} 1, & \text{if } d(s_i, P) < r_s \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

While the binary detection model assumes that sensor readings have no associated uncertainty, if $d(s_i, P)$ is not larger than r_s, $P(x, y)$ is said to be covered by sensor s_i. In reality, it has limitations due to the imprecise detection probability, which plays a significant role in sensor detection. Hence, a detection error range r_e $(r_e < r_s)$ is introduced to measure the uncertainty of sensor detection. A probabilistic detection model[14] is expressed as

$$\begin{aligned} &C_{xy}(s_i) = \begin{cases} 0, & \text{if } r_s + r_e \leq d(s_i, P) \\ \mathrm{e}^{-\lambda a^{\beta}}, & \text{if } r_s - r_e < d(s_i, P) < r_s + r_e \\ 1, & \text{if } r_s - r_e \geq d(s_i, P) \end{cases} \\ &\alpha = d(s_i, P) - (r_s - r_e) \end{aligned} \tag{3}$$

where α and β are parameters measuring the detection probability when $r_s - r_e < d(s_i, P) < r_s + r_e$. This model reflects the behavior of the sensing devices, such as infrared and ultrasonic sensors.

If $r_e \approx 0$, the binary sensor detection model given by (2) is used. We attempt to make the detection regions of two sensors not overlapped, thereby minimizing the wasted overlap area and covering more grid points with a small number of sensors.

If $r_e > 0$, r_e is not negligible and the probabilistic sensor detection model given by (3) is used. Due to the uncertainty of the sensor detection responses, the grid points are not covered uniformly with the same probability. Some grid points will have a low detection probability if they are covered only by one sensor and far from other sensors. In this case, it is necessary to make the detection area overlapped to compensate for the low detection probability of the grid points that are far from any sensor. Consider a grid point $P(x, y)$ lying in the overlap region of s_i and s_j. Let $c_{xy}(s_i, s_j)$ be the interference probability of a target at $P(x, y)$ detected by these two sensors. The sensors within a cluster are assumed to operate independently in their sensing activities. Then, the interference probability is given by

$$c_{xy}(s_i, s_j) = 1 - (1 - c_{xy}(s_i))(1 - c_{xy}(s_j)) \tag{4}$$

Let c_{th} be the desired coverage threshold for all the grid points. It is implied that

$$\min_{x,y}\{c_{xy}(s_i, s_j)\} \geq c_{th} \tag{5}$$

When a detection area is overlapped by multiple sensors, the closer are the sensors to each other, the higher is the detection probability of the grid points. Note that (4) can be extended to a region, which is overlapped by a set of k sensors, denoted as $sov_k = \{s_1, s_2, \cdots, s_k\}$, $sov_k \subset sov$. In this case, the detection probability for the cover set is given by

$$c_{xy}(sov_k) = 1 - \prod_{s_i \in sov_k} (1 - c_{xy}(s_i)) \tag{6}$$

Furthermore, the coverage rate $P_{cov}(sov_k)$ for the cover set can be calculated as the fraction of grid points exceeding the threshold c_{th}.

$$P_{cov}(sov_k) = \sum_{x=1}^{m}\sum_{y=1}^{n} \frac{c_{xy}(sov_k)}{m \times n} \tag{7}$$

2.3 Mathematical description of the problem

Problem formulation (Cover set selection problem). Given a set of N sensors, $sov = \{s_1, s_2, \cdots, s_N\}$, find a subset $sov' \subset sov$, such that the coverage rate is maximized with the number of sensors minimized. The subset sov' is considered as the optimal cover set of the target area.

It can be described as the following multi-objective optimization problem (MOP)

$$\begin{aligned} &\begin{cases} y_1 = f_1(sov') = \displaystyle\sum_{x=1}^{m}\sum_{y=1}^{n} \frac{c_{xy}(sov')}{m \times n} \\ y_2 = f_2(sov') = \dfrac{|sov'|}{|sov|} \end{cases} \\ &sov' = \arg\max / \min(\boldsymbol{H}) = \\ &\qquad \arg\max/\min\{f_1(sov'), f_2(sov')\} \\ &\boldsymbol{H} = \{y_1, y_2\} \in Y \end{aligned} \tag{8}$$

where $sov' = \{(x_1, y_1), (x_2, y_2), \cdots, (x_k, y_k)\}$, sov' is called the decision space and Y is called the objective space. Let us consider the cover set selection problem. The coverage rate $f_1(sov')$ needs to be maximized while the sensors usage rate $f_2(sov')$ needs to be minimized. It can be proved that the cover set selection problem is NP-complete. For the sake of brevity, the proof is omitted.

3 Optimal cover set selection based on improved NSGA-II

3.1 An improved NSGA-II algorithm

As discussed above, the goal of ECSS is to find the solutions giving the best trade-off between the two conflict objectives, known as Pareto optimal. MOGAs[15−16] are recognized to be well qualified to tackle multi-objective optimization problems. NSGA-II[15] is one of the most popular MOGAs. Some concepts of multi-objective optimization problem are defined as follows.

Definition 1 (Multi-objective optimization problem). Given an n-dimensional decision vector $\boldsymbol{x} = \{x_1, x_2, \cdots, x_n\}$ in the solution space X, find a vector $\boldsymbol{x}^*$ that maximizes a given set of k objective functions $f(\boldsymbol{x}^*) = \{f_1(\boldsymbol{x}^*), f_2(\boldsymbol{x}^*), \cdots, f_k(\boldsymbol{x}^*)\}$. The solution space X is generally restricted by a series of constraints, such as $g_j(\boldsymbol{x}^*) = b_j$ for $j = 1, 2, \cdots, m$.

Definition 2 (Dominance/Inferiority). A vector $\boldsymbol{u} = \{u_1, u_2, \cdots, u_n\}$ is said to dominate a vector $\boldsymbol{v} = \{v_1, v_2, \cdots, v_n\}$ if and only if $\boldsymbol{u}$ is partially less than $\boldsymbol{v}$, i.e., $\forall\, i = 1, 2, \cdots, n,\ u_i \le v_i \wedge \exists\, i = 1, 2, \cdots, n,\ u_i < v_i$.

Definition 3 (Pareto optimal solution). A solution $\boldsymbol{x}_u \in X$ is said to be Pareto optimal if and only if there is no $\boldsymbol{x}_v \in X$ for which $\boldsymbol{v} = f(\boldsymbol{x}_v) = (v_1, v_2, \cdots, v_n)$ dominates $\boldsymbol{u} = f(\boldsymbol{x}_u) = (u_1, u_2, \cdots, u_n)$.

Definition 4 (Pareto optimal set and front). Let $A \subseteq X$. The nondominated set regarding A, represented by X_p, is defined as $X_p = \{\boldsymbol{z} \in A\,|\,\boldsymbol{z}$ is nondominated regarding X $\}$. The corresponding objective function values in the objective space are defined as $Y_p = F(X_p) = \{f(\boldsymbol{z})\,|\,\boldsymbol{z} \in X_p\}$, where X_p is called the Pareto optimal set and Y_p is called the cohere Pareto optimal front.

However, the solutions found by original NSGA-II are likely to be inferior or only comparable to that by classical heuristic search algorithms because of premature convergence. To find perfect solutions, a delete operator for NSGA-II is proposed to enhance the search capability. When selecting the elitist, if neither of the two individuals in a population wins out and their genes are the same, then delete one of them. Furthermore, a circulation selection is presented to preserve excellent genes of the parent population. Suppose there are K individuals in a population $(ind_1, ind_2, \cdots, ind_K)$ when the crossover operations are carried out. The first time the operation is carried out with (ind_1, ind_2) as parents, the second time (ind_2, ind_3) are taken as parents, and so on. Similarly, the last child is done by (ind_K, ind_1). By this way, K offspring individuals are generated. The genes of each parent are inherited by two offspring individuals, thus avoiding the loss of excellent solutions.

3.2 An efficient cover set selection algorithm

Now, we can construct the cover set using the optimal Pareto solutions generated by the improved NSGA-II algorithm. The chromosomes of a genetic algorithm contain all the building blocks to a solution for the genetic operators and the fitness function. In our implementation, each individual node is represented by a one-bit binary number called gene. This one-bit gene defines the status of the sensors as follows

$$a_i = \begin{cases} 1, & \text{if } s_i \text{ is selected} \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

For example, in a 20-nodes system, the number of bits required to represent the complete system will be 20 bits. For the scenario shown in Fig. 1, the resulting chromosome structure is 10101010101010101010. With this coding representation, the initial population of the improved NSGA-II algorithm is generated.

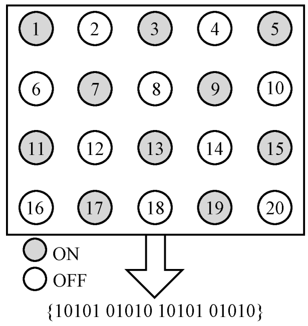


Fig. 1 Code representation

Assign each individual with two fitness functions, the coverage rate and the sensors usage rate. By introducing the nondominated sorting approach, the crowded distance operator and the controlled elitism, our replacement scheme is executed. First, a combined population $R_t = P_t \cup Q_t$ is formed with the parent population P_t and the child population Q_t, where t is the generation number. Then, the population R_t will be of size $2N$. By adding solutions from the first front till the size exceeds N, the new parent population P_{t+1} is formed. Thereafter, the solutions of the last accepted front are sorted according to the crowed comparison and the first N points are picked. In this way, the population P_{t+1} of size N is constructed. Subsequently, it is used for the circulated selection, crossover, and mutation to create a new population Q_{t+1} of size N. The recombination operator used in this paper is two-point crossover. After recombination, the mutation operator is applied to complement some genes in the chromosomes of the child randomly.

Similar to the virtual force algorithm (VFA)[14], the ECSS algorithm is designed to be executed by the cluster head, which is equipped with better resource to manage one-time computing status of the sensors within a cluster. As only the final results obtained are sent back to the sensor nodes, the power consumption can be reduced effectively. The main procedure of the ECSS algorithm is described as follows.

Input. Cover set $sov = \{s_1, s_2, \cdots, s_N\}$, the number of generations $Max\_generation$, population size N, recombination probability P_r, mutation probability P_m, reduction rate of the controlled elitism ρ.

Output. Nondominated solutions in P.

Step 1 (Initialization). Set $t = 0$, $P' = \emptyset$. Generate an initial population P randomly. Calculate the objective functions for each individual.

Step 2 (Nondominated sorting). $P = P \cup P'$. Do fast nondominated sorting approach resulting nondominated fronts $\{F_1, F_2, \cdots, F_r\}$.

Step 3 (Controlled elitism). Set $r = 1$, $P = \emptyset$. While $|P| < K$, do: 1) calculate n_r according to the controlled elitism scheme with ρ; 2) sort F_r in descending order using crowded comparison; 3) put the first n_r members of F_r in P, i.e., $P = P \cup F_r[1 : n_r]$; 4) $r = r + 1$.

Step 4 (Fitness assignment). Assign fitness to each individual according to its position in P.

Step 5 (Reproduction). Generate an offspring P' from P with size of K according to the genetic operators; Calculate $f_1(sov')$ and $f_2(sov')$ for each individual in P'.

Step 6 (Termination). $t = t + 1$. If $t > Max\_generation$ or the required $f_1(sov')$ and $f_2(sov')$ are met, then terminate; else go to Step 2.

When the cluster head is not available, the parallel ECSS algorithm can be executed by the individual sensors only based on its neighborhood information. In this case, the sensors need to undergo status transformation after some generations. Then, computing and comparing the full coverage would not be feasible. The number of generations must be limited to reduce the power consumption in sensor communication.

4 Performance evaluation

To study the performance of ECSS, three experiments have been conducted using the binary and probabilistic detection models in different scenarios. Throughout these experiments, the communication radius r_c is set as twice the sensing radius r_s. This is to ensure that even when the sensing range is very small and two neighboring sensors are barely jointly placed (i.e., the distance between two neighboring sensors is $2r_s$), it is still possible to establish a communication link between the two sensors. For all these simulations, distances are measured in units of m. The simulations were run on a Pentium 2.0 GHz PC using Matlab 7.0.

Test 1. 200 potential sensors are randomly distributed in the target area of 100 m × 100 m. The sensing radius for all the nodes is set to 14 m. The genetic algorithm (GA) parameters used in the simulation are listed in Table 1.

Table 1 GA parameters used in Test 1

Parameter	Value
Population size	200
Recombination rate	0.9
Mutation rate	0.005
Reduction rate	0.5

Fig. 2 shows the simulation results of ECSS run of 200 generations for the binary detection model in Test 1. The initial population is randomly generated, as shown in Fig. 2 (a). After running a number of generations, the Pareto optimal solutions are shown from Figs. 2 (b) ∼ (d).

Since the nodes deployment is random, 20 experiments have been made to observe the average results. The obtained Pareto optimal front is shown in Fig. 3. At the beginning, there are only a few nondominated solutions, which constitute a nondominated front (the short curve in Fig. 3). After 10 generations, more nondominated solutions are found, and the Pareto optimal front becomes fully outspread. By observing the history from the beginning to generation 200, it can be clearly seen that the search is directed toward the global Pareto optimal set.

Test 2. 200 potential sensors are randomly distributed in the target area of 100 m × 100 m on the basis of binary detection model. The GA parameters used are the same as for Test 1.

Fig. 4 compares the nondominated solutions achieved by ECSS and the original NSGA-II, where only values of the two objectives are displayed in order to make the comparison clear. Both algorithms were running through 150

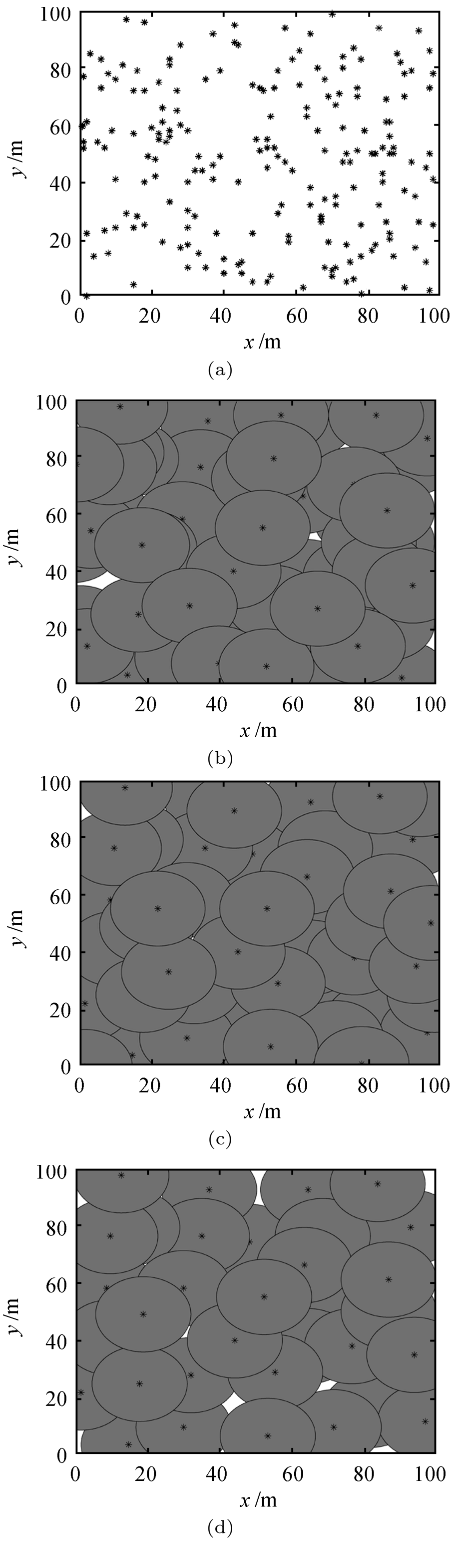


Fig. 2 Illustration of nondominated solutions obtained in the simulation of Test 1 ((a) Initial distribution; (b) The 50-th generation, coverage rate 98.56 %, 50 sensors; (c) The 100-th generation, coverage rate 99.68 %, 44 sensors; (d) The 200-th generation, coverage rate 97.32 %, 33 sensors)

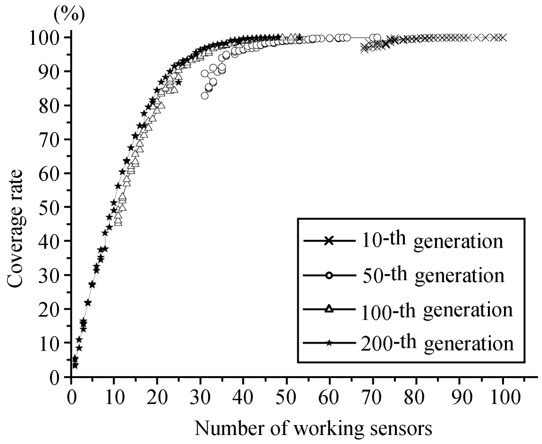


Fig. 3 Simulation results of Test 1 using ECSS

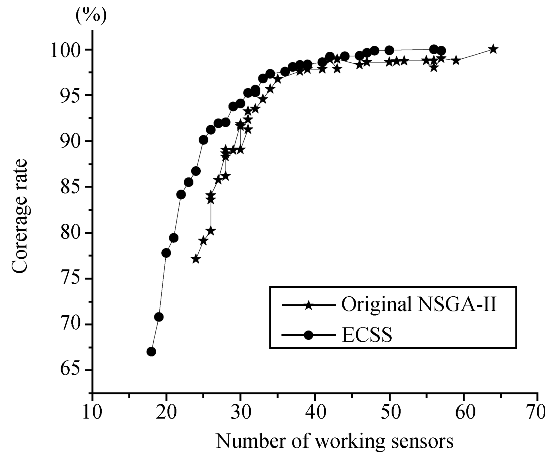
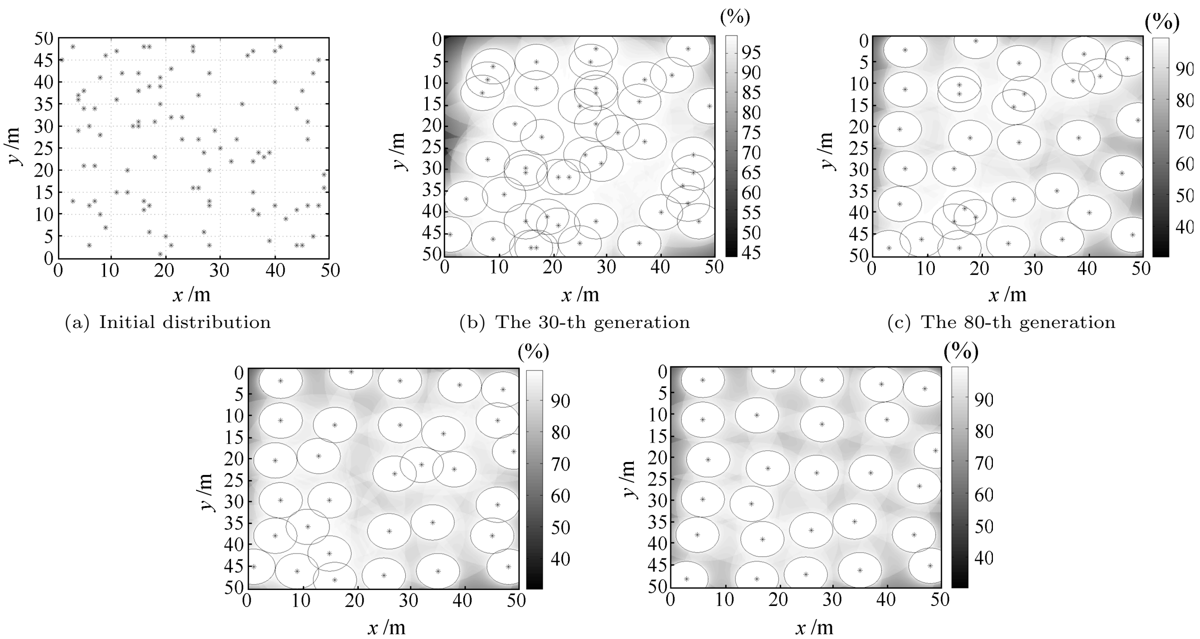


Fig. 4 Comparison between ECSS and NSGA-II



(a) Initial distribution (b) The 30-th generation (c) The 80-th generation

(d) The 120-th generation (e) The 150-th generation

Fig. 5 Illustration of nondominated solutions obtained in the simulation of Test 3
((a) 100 sensors; (b) 45 sensors, coverage rate 93.92 %; (c) 33 sensors, coverage rate 99.89 %;
(d) 31 sensors, coverage rate 99.89 %; (e) 27 sensors, coverage rate 99.12 %)

generations. From the simulation results, we can see that the ECSS algorithm improves the network coverage rate considerably compared with the original NSGA-II, and it does not require more working nodes. By using the circulation crossover and delete operators, ECSS achieves a longer nondominated line with the nondominated solutions distributed uniformly over the Pareto optimal front. Based on the trade-off information obtained by ECSS, the decision maker can find a compromise solution between the conflicting objectives.

Test 3. 100 potential sensors are distributed randomly in the target area of 50 m × 50 m on the basis of probabilistic detection model. Each sensor has a sensing range of 9 m ($r_s = 9$) and a detection error range of 5 m ($r_e = 5$). The parameters in the probabilistic detection model are set as $\lambda = 0.5$, $\beta = 0.5$, and $c_{th} = 0.7$.

Fig. 5 presents simulation results for the probabilistic detection model in Test 3. The initial distribution is shown in Fig. 5 (a). Nondominated solutions obtained in different generations are illustrated from Figs. 5 (b) ∼ (e). With the gray bar shown on the right hand sides of the figures, we can see each grid point of the target area is detected or not intuitionally. The grid points with the detection probability 1 are represented by a circle of which the center is sensor location and the radius is $(r_s - r_e)$. The sub-optimal solutions are obtained after 150 generations, as shown in Fig. 5 (e), which use only 27 sensors to achieve the coverage rate of 99.12 %. When running more than 1 000 generations, no better solutions can be found to dominate the sub-optimal solution discussed above. Although all the surrounding neighbor nodes should be considered for the influence of each other with respect to the coverage and interference, ECSS can converge to the optimal solution more rapidly for our studies.

5 Conclusions

In this paper, the relationship between the network coverage rate and the sensors usage rate is investigated. For a practical approach, a probabilistic sensor detection model is adopted in combination with the detection error range and coverage threshold. As a new contribution, ECSS, an efficient cover set selection algorithm based on improved NSGA-II is proposed. The basic goal of ECSS is to activate only a minimum number of sensor nodes in a densely deployed environment. It is subjected to two constraints: one is the desired coverage rate of the network and the other is the number of the working nodes chosen from the whole network. By searching through the whole state-space, it can avoid partial optimized solutions. ECSS offers a number of important advantages, including negligible computation time and one-time resetting the status of all the sensor nodes. Moreover, the desired sensor field coverage and model parameters can be provided as inputs to the ECSS algorithm, thereby ensuring flexibility.

In the future, the optimal distributions with different coverage thresholds will be developed for the probabilistic detection model, including the calculation of the minimum sensors and the optimal topology control. We will also focus on the fully distributed density control algorithm in heterogeneous sensor networks, where sensors may differ from each other in the detection modalities and parameters.

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