



Evolutionary Based Set Covers Algorithm with Local Refinement for Power Aware Wireless Sensor Networks Design

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Abstract

Establishing coverage of the target sensing field and extending the network's lifetime, together known as Coverage-lifetime is the key issue in wireless sensor networks (WSNs). Recent studies realize the important role of nature-inspired algorithms in handling coverage-lifetime problem with different optimization aspects. One of the main formulations is to define coverage-lifetime problem as a disjoint set covers problem. In this paper, we propose an evolutionary algorithm for solving coverage-lifetime problem as a disjoint set covers function. The main interest in this paper is to reflect both models of sensing: Boolean and probabilistic. Moreover, a heuristic operator is proposed as a local refinement operator to improve the quality of the solutions provided by the evolutionary algorithm. Simulation results show the necessity to inject a heuristic operator within the mechanism of evolutionary algorithm to improve its performance. Additionally, the results show performance difference while adopting the two types of sensing models.

Keywords: Evolutionary Algorithm; Sensing Model; Set Covers Problem; Target Coverage; Wsns.

خوارزمية تطورية مبنية على اساس مجموعة الاغطية مع تحسين محلي لغرض تصميم شبكات الاستشعار اللاسلكي

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الخلاصة

تعتبر عمر التغطية واحدة من المشاكل الرئيسية في شبكات الاستشعار اللاسلكي (WSNs). حيث ان الدراسات الحديثة تشير الى الدور المهم للخوارزميات المستوحاة من الطبيعة في التعامل مع مشكلة عمر التغطية مع جوانب التحسين المختلفة. واحدة من الصيغ الرئيسية هي لتحديد مشكلة عمر التغطية على اساس مشكلة مجاميع التغطية المنفصلة (DSC). في هذا البحث، نقترح خوارزمية تطورية لحل مشكلة عمر التغطية على اساس مشكلة مجاميع التغطية المنفصلة. الأهتمام الرئيسي في هذا البحث، هو عكس كل من نماذج الاستشعار: نموذج الاستشعار الثنائي، و نموذج الاستشعار الاحتمالي. وبالإضافة الى ذلك، اقترحنا عامل الارشادي لغرض التحسين من اداء الخوارزمية. حيث أن نتائج المحاكاة توضح ضرورة عمل العامل الارشادي ضمن الية الخوارزمية، كما وان النتائج توضح اختلاف في الأداء الخوارزمية عند استخدام نوعين من نماذج الاستشعار.

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1. Introduction

Nowadays, we are witnessing the wide and rapid development in the field of wireless sensors networks (WSNs) ranging various applications. One of the key features of a wireless sensor network is how to deploy many sensors in a dense area while determining a sufficient level of coverage for a long period of time. In addition, normally, sensor nodes are characterized by their low cost, low power, have the ability to accomplish several functions at one time, and to communicate with each other wirelessly, but, in short distances. For a successful operation, the sensors must be capable of covering the required area efficiently and for a long period of time.

Network's lifetime and target coverage have been extensively addressed in many contexts, from deployment of sensors towards clustering, routing and mobility techniques, e.g. [1 - 5]. The disjoint set cover problem (DSC) has been introduced as an essential alternative to effective energy management for WSNs. In the DSC problem, one subset of the sensor is set to be active in one set cover to cover the sensing area, while, all remaining subsets are set to sleep. Slijepcevic and Potkonjak [6] were considered the first to introduce the main idea of the DSC problem to regulate network efficiency of WSNs. Several variants are then followed. The problem mainly assumes that the lifespan of WSN is divided into a set of periods and in each period only one set cover is an active state, while the remaining set covers will be in sleep state. The sensors from the active set must be able to monitor all the targets. When the energy of the active set has been consumed, another set will be switched to active state to continue provide the required functionality. All targets must be monitored by all of the set covers and as a result the main objective of this approach is to determine the maximum number of DSC.

In this study, we explore the possibility of incorporating two major issues of WSNs while defining a more realistic single-objective set cover problem. Our candidate argument upon which we formulate the single-objective optimization problem is target coverage under both Boolean and probabilistic sensing models. Moreover, two mutation operators are proposed to serve as local search operators, influencing the algorithms to stress convergence towards target coverage probability, respectively. The remaining sections of this paper describe the details of the new problem statement and the proposed algorithm. The next section presents the main studies interested with designing power efficient WSNs using set cover problem. Section 3 gives preliminarily concepts and background related to the formulated problem and adopted algorithm. Section 4 discusses the details of the defined problem and the designed algorithms. Section 5 provides simulation results on a set of problem and algorithm settings.

2. Related literature

Although the field of disjoint set cover problem (DSC) has enjoyed a good volume of literature for maintaining WSNs with efficient power organization, the researchers were traditionally focused on the family of mathematical programming and heuristic based optimization. They considered several variants of DSC problem. These methods were, however, unable to beat the family of evolutionary algorithm meta-heuristics. The objective of this section is to take a brief account of the main efforts made in adopting DSC problem for the design of power aware WSNs.

The first effort proposed to consider DSC problem for WSNs is the work of Slijepcevic and Potkonjak in 2001 [6]. They introduced a heuristic approach to select mutual exclusive sets of sensor nodes, where the sensors of each set should together cover all the monitored area. This work is then followed by the work of Cardei et al. in 2002 [7]. They proposed a heuristic method to select a subset of sensors to cover all the target areas. Subsequent heuristic and theoretical analysis based approaches are then developed to solve several variants of DSC for WSNs. Cardei and Du in 2005 transformed the DSC problem into maximum-flow problem (MFP) and proposed a Mixed Integer Programming (MIP) to solve it [8]. They showed that their approach provides more set covers than the heuristic work in [6]. In [9], Yang et al. formulated two extensions to the minimum sensor set to satisfy both k -coverage and connectivity conditions. Both k -coverage set (kCS) and k -connected coverage set (kCCS) are proved to be NP-complete problems and two LP-based approximation algorithms are proposed to solve them. In [9], the problem remained in its simple form and they didn't generalize it to the maximum number of such minimum sensor sets.

All of the above efforts remained in their majority for solving set covers problem using mathematical heuristic and greedy methods. Genetic Algorithm for Maximum Disjoint Set Covers (GAMDSC) [10] is considered the first attempt to use evolutionary algorithm in the context of DSC

for WSNs. The two main characteristics of GAMDSC are the integer based chromosome representation and the scattering operator. They determined an upper bound of the number of set covers which is decided by the number of sensors covering the most sparsely covered target. Their simulation results showed improved quality over those provided by the heuristic algorithms of [6] and [7]. However, with an alternative and carefully designed genetic algorithm, Hu et al. [11] and Abdulhalim and Attea [12] successfully reached more improved solutions than [10]. Both meta-heuristic algorithms proposed in [11] and [12] consider the set cover problem in the formulation of the objective function, however, they did not consider the impact of coverage reliability in their formulation. The evolutionary algorithm proposed in this paper, on the other hand, considers both number of set covers and coverage reliability in the formulation of the objective function. Further, we proposed a local refinement operator to work as a heuristic to improve the quality of the generated solutions provided by the algorithm.

3. Preliminaries

3.1 System model and assumptions

The model being used is a two-dimensional sensing area \mathcal{A} with predetermined size (X_{max}, Y_{max}) , i.e., $\mathcal{A} = \{(x, y) | 1 \leq x \leq X_{max}, 1 \leq y \leq Y_{max}\}$. The sensing area \mathcal{A} is equipped with a set $\mathcal{T} = \{t_1, t_2, \dots, t_n\}$ of n targets, also, with predetermined locations: $t_i, \forall 1 \leq i \leq n = (x, y) \in \mathcal{A}$. Furthermore, a set of sensors $\mathcal{S} = \{s_1, s_2, \dots, s_m\}$ comprises m sensors are supposed to be deployed randomly in \mathcal{A} , i.e., $s_i, \forall 1 \leq i \leq m = (x, y) \in \mathcal{A}$. Moreover, taking sensing capability in consideration, the sensor nodes can be featured through two characteristics: sensing range and sensing model. Generally, the WSN model is performed either homogeneously (where a fixed sensing range r_s assigned to all sensor nodes), or heterogeneously (where each sensor node s_i is assigned with a sensing range r_{s_i}). In the simple uniform disc sensing model, a target t_i is said to be covered by a sensor s_i if and only if target t_i is located within sensor sensing range. This model can be formally expressed in Eq. 1, which states that the probability of covering a target is assumed to be always 1 if it occurs inside the sensing radius of a sensor node; otherwise, it is supposed to be zero. In the simple uniform disc sensing model, a sensor s is said to cover a target t if and only if target t lies within s circle sensing range. A more realistic sensing model, however, should consider the impact of both environmental and physical arguments which in turn affects the sensing capability of the sensor nodes.

$$Cover_B(s_i, t_j) = \begin{cases} 1 & \text{if } d(s_i, t_j) \leq r_s \\ 0 & \text{if } d(s_i, t_j) > r_s \end{cases} \quad (1)$$

The impact of environmental and physical arguments should be considered for a more realistic sensing model which in turn affects the sensing capability of the sensor nodes [8]. Moreover, if we add factor of uncertainty detection r_u to the sensor results will have three potentials of sensing strength (as shown in Eq. 2). The probability of coverage will decay exponentially when the distance between target and sensor will be increased.

$$Cover_P(s_i, t_j) = \begin{cases} 0 & \text{if } d(s_i, t_j) \geq r_s + r_u \\ e^{-\lambda \alpha^\beta} & \text{if } r_s - r_u < d(s_i, t_j) < r_s + r_u \\ 1 & \text{if } d(s_i, t_j) \leq r_s - r_u \end{cases} \quad (2)$$

Where r_u is a measure of the precariousness in the detection radius of the sensor. Euclidian distance between the sensor point (s_i) and target point (t_j) is denoted by $d(s_i, t_j)$. Also, in $\alpha = d(s_i, t_j) - (r_s - r_u)$, both λ and β are decay factors used to measure the strength of detection when a target point located within the interval $(r_s - r_u, r_s + r_u)$. It causes the value of coverage to exponentially decrease as the distance increment. When the coverage $Cover_P(s_i, t_j)$ is 1, means t_j lies within a distance of $(r_s - r_u)$ from sensor s_i .

3.2 Single-objective evolutionary algorithm

Evolutionary algorithms (EAs) are stimulated through natural process of evolution. The common language between them includes competition, selection, reproduction, and random perturbation.

Naturally, evolution is the process of optimization; therefore, the difficult engineering optimization problem can be solved by using evolutionary algorithm. The privacy of EAs is to divide the search space of an optimization problem ($F(X)$) into a discrete set Ω of points or solutions (where $|\Omega| \in \mathbb{N}$ is said to be search space size or decision space) and work on a very small arbitrary subset of points (called population of individuals). In notations, the population is described here by \mathbb{I} of $\mu \in \mathbb{N}$ individuals, $\mathbb{I}^\mu = (I_1, I_2, \dots, I_\mu)$. Each individual $I \in \mathbb{I}$ is the genotype representation of the phenotype X (though sometimes both I and X representations are similar. Both notations are used interchangeably in this paper). With a real valued fitness function $F: I \rightarrow \mathbb{R}$, the population is used to evaluate different regions in the search space. Population transformation $T: \mathbb{I}^\mu \rightarrow \mathbb{I}^\mu$ is applied via composition of selection (s), recombination (r), and mutation (mu) operators. The transformation $T = s \circ r \circ mu$ is applied in a generational loop framework to generate succeeding populations until a stopping criterion $u: \mathbb{I}^\mu \rightarrow \{true, false\}$. While selection operator focuses on individuals representing better regions in the search space $s: \mathbb{I}^\mu \rightarrow \mathbb{I}^\mu$, recombination and mutation operators make, respectively, primary and occasional, variations on these selected individuals to find new unexplored search regions. The characteristics of recombination and mutation operators can be defined by operator type $\Theta_r: \mathbb{I}^\mu \rightarrow \mathbb{I}^\mu$ and $\Theta_{mu}: \mathbb{I}^\mu \rightarrow \mathbb{I}^\mu$, and operator pressure p_c and p_m . The canonical framework of an evolutionary algorithm can be expressed as in Algorithm 1.

4. Problem formulation and algorithm development

4.1 Problem definition: Single-objective statement

The essential ingredients of the formulated single objective set covers (SC) problem combining two objectives in an attempt to provide the WSN with a maximum number of set covers, each of which can satisfy coverage for the whole target set. In particular, we generalize the set covers problem to the general form of single-objective optimization form.

$$\max SC(X) = 0.5 \times f_{SC}(X) + 0.5 \times f_{kcov}(X)$$

(3)

subject to $X \in \Omega$

Let $\Gamma(X) = SetCovers$ be a solution decoding function (to be discussed in the next section), while $X = (x_1, x_2, \dots, x_m)$ represents the scheduling of the set $\mathcal{S} = \{s_1, s_2, \dots, s_m\}$ of m sensors into a set $SetCovers = (sc_1, sc_2, \dots, sc_l)$. Maximizing $|SC|$ towards l is maintained by the first function, $f_{SC}(X)$. The second function, $f_{kcov}(X)$, on the other hand, aims at maximizing the probability of coverage for each target in the area of interest. The following definitions state the proposed SC problem.

Algorithm 1: EA

Input: $\mu, s, \Theta_r, \Theta_{mu}, p_c, p_m, l$

Output: best individual I^*

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1   t ← 0;
2   initialize  $\mathbb{I}^\mu(t) \leftarrow (I_1, I_2, \dots, I_\mu)$ ;
3   while ( $u(\mathbb{I}^\mu(t)) \neq true$ ) do
4       for i ← 1 to  $\mu$  do
5           | evaluate  $F(I_i(t))$ ;
6       od
7        $\mathbb{I}^\mu(t) \leftarrow s(\mathbb{I}^\mu(t))$ ;
8        $\mathbb{I}^\mu(t) \leftarrow \Theta_r(\mathbb{I}^\mu(t), p_c)$ ;
9        $\mathbb{I}^\mu(t) \leftarrow \Theta_{mu}(\mathbb{I}^\mu(t), p_m)$ ;
10      t ← t + 1;
11  od
12  return  $I^*(t)$ ;

```

Definition (SC) Let $WSN = (\mathcal{J}, \mathcal{S})$ be a wireless sensor network with a target set $\mathcal{J} = \{t_1, t_2, \dots, t_n\}$ of n targets and a sensor set $\mathcal{S} = \{s_1, s_2, \dots, s_m\}$ of m sensors, such that each sensor s_i can be represented by a subset $\mathcal{J}_i \subseteq \mathcal{J}$. Let WSN be represented, in terms of the target set \mathcal{J} , as $WSN = (\mathcal{J}, \mathbb{T})$ where $\mathbb{T} = \{\mathcal{J}_1, \mathcal{J}_2, \dots, \mathcal{J}_m\}$. Given an integer $k < m$, SOSOC is then defined as designing WSN as a collection of set covers $SC = (sc_1, sc_2, \dots, sc_l)$ such that:

- 1) Each set cover sc_i is a proper subset of the whole set of sensors: $sc_i \subset \mathcal{S}$,
- 2) In terms of target set, each set cover sc_i should represent the whole target set: $\bigcup_{sc_i} = \mathcal{J}$,
- 3) Any two set covers should be disjoint: $sc_i \cap sc_j = \emptyset$, which means that any sensor should belong to only one set cover,
- 4) Each target is covered by at least k sensors in each set cover sc_i .
- 5) Each set cover sc_i contains as minimum as k sensors: $|sc_i|$ is minimum, but, as less as k ,
- 6) Probability of coverage for each set cover sc_i to each target t_j , $coverage(sc_i, t_j)$, is maximized, and
- 7) The length of collection of set covers, $|SC|$, is maximized.

It has been shown in [13] the extreme limit or upper bound, L , of the maximum number of disjoint and complete set covers depends on both targets set and sensors set. It mainly depends on the location of the targets, the total number of sensors and their locations, and sensing range (r_s). In general, L can be computed as the minimum number of sensors within their sensing ranges the most sparsely covered target lies. The set of sensors that cover the most sparsely covered target is said to be the *critical sensor set*, $\mathcal{S}_L = \{s_1, s_2, \dots, s_L\}$. The SC function stated in Eq. 3 decouples the problem into a weighted sum of two maximization functions. Eq. 4 expresses the first term: $f_{SC}(X)$, which aims to schedule the set of sensors $\mathcal{S} = \{s_1, s_2, \dots, s_m\}$ to find the maximum number of set covers l that approaches L . The second terms, on the other hand, $f_{kcov}(X)$ seeks to maximize the probability of coverage for each target (Eq. 5). The value of f_{kcov} considers the average over all targets in all set covers resulted from X , thus $f_{kcov} \in [0,1]$.

$$f_{SC}(X) = \max \Gamma(X) = |SC| \tag{4}$$

$$f_{kcov}(X) = \frac{\sum_{\forall sc \in \Gamma(X)} \sum_{i=1}^n coverage(sc, t_i)}{n * \max \Gamma(X)} \tag{5}$$

4.2 Solution variation

In EA, a new solution $I = (I_1, I_2, \dots, I_m)$ is generated by varying the genotype representation of its parent solutions $I_1 = (I_{1,1}, I_{1,2}, \dots, I_{1,m})$ and $I_2 = (I_{2,1}, I_{2,2}, \dots, I_{2,m})$. Uniform recombination is used and achieved with a chromosome-wise recombination probability set to its most commonly used setting: $p_c = 0.6$. Here, the set cover assignments of the two parents are mixed uniformly. Figure 1 pictorially depicts the process of uniform crossover in an example. In the figure, one can see that the value of the child's gene is inherited from the first parent if the random value is less than or equal to the recombination probability, otherwise, the value is received from the second parent.

$$\Theta_r: (I_1, I_2, p_c) \rightarrow I$$

$$\forall i, 1 \leq i \leq m:$$

$$I_i = \begin{cases} I_{1,i} & \text{if } r \leq 0.6 \\ I_{2,i} & \text{otherwise} \end{cases} \tag{6}$$

Where $r \sim [0,1]$ is a uniform random number.

A heuristic mutation operator Θ_{mu} is proposed to improve the solution quality of the child individual in terms of coverage reliability. Each set cover sc is checked for the possibility of increasing its coverage reliability. Initially, the proposed heuristic operator observes the set of useful

sensors S^+ to find and select the nearest k sensors to each target. The proposed heuristic operator is continued to examine and modify all set covers in SC .

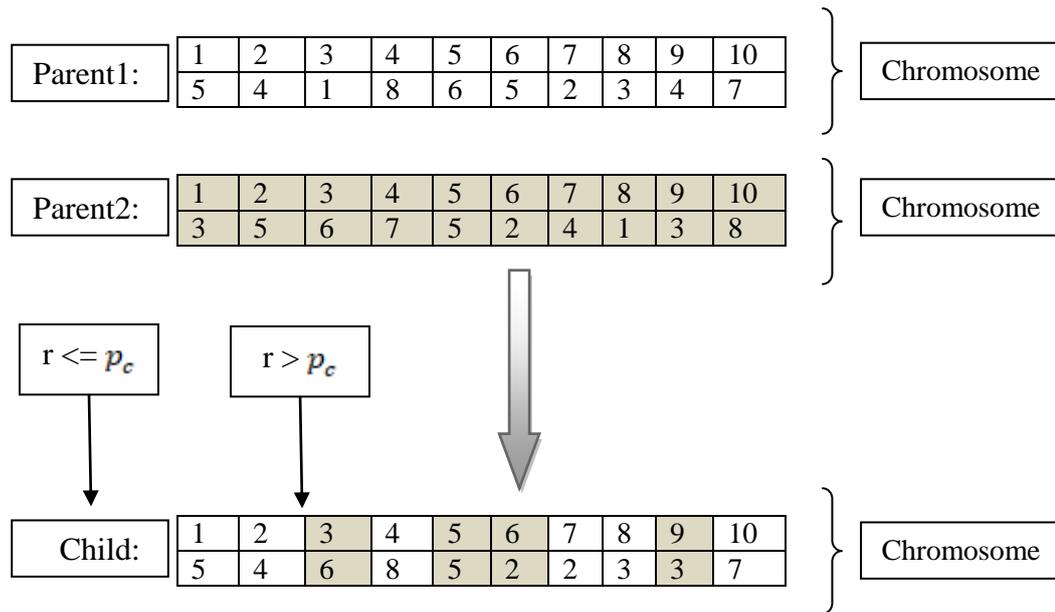


Figure 1-Illustration of uniform crossover

5. Experimental results

This section inspects the performance of EA algorithm for solving the formulated SC problem. The different parameter settings that impact on the performance of the algorithm are summarized in Table-1.

Table 1-Different settings characterizing the sensing field and the tested algorithm.

Parameter name	Acronym	Possible settings
Dimensions of \mathcal{A}	$X_{max} = Y_{max}$	500
Number of targets	n	{10, 20, 30}
Number of sensors	m	{100, 200, 300}
Sensing radius	r_s	200
Communication radius	r_c	400
Population size	μ	100
Number of generations	t_{max}	100
Probability of crossover	p_c	0.6
Probability of mutation	p_m	0.1
Number of runs	-	30

Table-2 reports the results (in terms of percentage of generated set covers $|SetCovers|\%$ with respect to L . See Eq. 7) where coverage of 100%, 90%, 80%, and 70% from the whole sensing area are expected. For example, in 90% coverage, a set cover sc is said to be feasible if it satisfies at least 90% of area coverage, otherwise it said to be lethal. The reported results clearly clarify the increment of average number of feasible set covers as the constraint for percentage of area coverage is delighted. This is expected as the number of sensors required to construct a set cover with less percentage of area coverage is generally less than those required to construct a set cover of heavier coverage.

$$|SetCovers|\% = 100\% - \frac{|SetCovers|}{L - |SetCovers|} \tag{7}$$

Table 2-Average number of set covers over 30 different runs

TEST#	<i>n</i>	<i>m</i>	L	100% Targets coverage	90% Targets coverage	80% Targets coverage	70% Targets coverage
1	10	100	19	0.8947	0.8947	0.9263	0.9579
2		200	35	0.9000	0.8943	0.9143	0.9429
3		300	58	0.9138	0.9172	0.9241	0.9310
4	20	100	19	0.8789	0.8789	0.8947	0.8895
5		200	35	0.8743	0.8943	0.9086	0.8943
6		300	58	0.8621	0.8845	0.8983	0.8914
7	30	100	19	0.8158	0.8263	0.8368	0.8474
8		200	35	0.8257	0.8571	0.8714	0.8657
9		300	58	0.8138	0.8466	0.8517	0.8500

Table 3-Performance comparison of EA (with no heuristic) against EA (with heuristic). Probabilistic sensing model is used. Each test includes average of 30 different runs.

TEST#	<i>n</i>	<i>m</i>	EA (with no heuristic)	EA (with heuristic)
1	10	100	0.3847	0.8378
2		200	0.3761	0.8502
3		300	0.3541	0.8502
4	20	100	0.2326	0.9109
5		200	0.2830	0.9060
6		300	0.2681	0.9029
7	30	100	0.3510	0.9637
8		200	0.3279	0.9329
9		300	0.3454	0.9453

Table 4-Performance comparison of EA (with no heuristic) against EA (with heuristic). Boolean sensing model is used. Each test includes average of 30 different runs.

TEST#	<i>n</i>	<i>m</i>	EA (with no heuristic)	EA (with heuristic)
1	10	100	0.7339	0.9867
2		200	0.6246	0.9738
3		300	0.6053	0.9819
4	20	100	0.8367	0.9854
5		200	0.6591	0.9938
6		300	0.9920	0.9967
7	30	100	0.5129	0.9804
8		200	0.6220	0.9936
9		300	0.9898	0.9910

The results provided in Tables -(3, 4) report the performance of the proposed EA based set covers algorithm when the sensing model is operated in either probabilistic or disc model. The results present the impact of adopting the heuristic operator on improving the performance of the proposed EA. As reported, the results clearly prove the positive impact of injecting the heuristic operator within the mechanism of the EA. Further, one can see that in both Boolean and probabilistic models, increasing number of targets and/or decreasing number of sensors shorten the lifetime of the network while reducing number of generated set covers. Shortly speaking, maximizing number of set covers requires increasing number of sensor nodes in the sensing field and needs the algorithm to be more heuristic towards finding more suitable solutions.

6. Conclusions

In this study, we extend the definition of set covers problem in WSN design to handle a constrained version for a combination of two contradictory objectives (i.e. network's lifetime and coverage probability). The framework of EA is developed by adjusting their characteristic components to solve the formulated problems. Our extensive simulation results clearly show a successful combination of the different components proposed for the algorithm.

Alternative ramifications of this work could reflect the heterogeneous ability of sensors, where each sensor is augmented with a set of adjustable sensing ranges. For this case, the considered formulations should be towards finding the maximum number of overlapped set covers.

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