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# Multi-layer Multi-objective Evolutionary Algorithm for Adjustable Range Set Covers Problem in Wireless Sensor Networks

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**Abstract**

Establishing complete and reliable coverage for a long time-span is a crucial issue in densely surveillance wireless sensor networks (WSNs). Many scheduling algorithms have been proposed to model the problem as a maximum disjoint set covers (DSC) problem. The goal of DSC based algorithms is to schedule sensors into several disjoint subsets. One subset is assigned to be active, whereas, all remaining subsets are set to sleep. An extension to the maximum disjoint set covers problem has also been addressed in literature to allow for more advance sensors to adjust their sensing range. The problem, then, is extended to finding maximum number of overlapped set covers. Unlike all related works which concern with the disc sensing model, the contribution of this paper is to reformulate the maximum overlapped set covers problem to handle the probabilistic sensing model. The problem is addressed as a multi-objective optimization (MOO) problem and the well-known decomposition based multi-objective evolutionary algorithm (MOEA/D) is adopted to solve the stated problem. A Multi-layer MOEA/D is suggested, wherein each layer yields a distinct set cover. Performance evaluations in terms of total number of set covers, total residual energy, and coverage reliability are reported through extensive simulations. The main aspect of the results reveals that the network's lifetime (i.e. total number of set covers) can be extended by increasing number of sensors. On the other hand, the coverage reliability can be increased by increasing sensing ranges but at the expense of decreasing the network's lifetime.

**Keywords:** adjustable sensing range, multi-objective optimization, set covers, heterogeneous wireless sensor networks.

# خوارزمية تطورية متعددة الطبقات و الأهداف لمشكلة تعديل نطاق مجموعة أغلفة في شبكات الأستشعار اللاسلكي

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**الخلاصة**

في الأدبيات تم اقتراح العديد من خوارزميات جدولة أجهزة الأستشعار باعتبارها مشكلة أمتداد لما يسمى مشكلة (DSC) والغاية منها هو ترتيب أكبر عدد ممكن من المجموعات الفرعية المنفصلة لأجهزة الاستشعار. بعد ذلك يتم تعيين مجموعة فرعية واحدة فقط من أجهزة الاستشعار لتكون نشطة لأداء عملية التغطية، في حين يتم تسكين بقية المجموعات الفرعية. أحد أهم امتدادات هذه المشكلة هو تحديد العدد الأقصى من المجاميع الفرعية وبنفس الوقت تضبيط قابلية التغطية لكل مستشعر وعلى هذا الأساس ممكن أن تتحول المجاميع من مجاميع منفصلة الى مجاميع مركبة مؤدية في النهاية الى زيادة تعقيد المشكلة. هدف هذا البحث هو إعادة صياغة مشكلة العدد الأقصى من المجاميع المتراكبة آخذا بنظر الأعتبار القابلية الواقعية لتحسس

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المستشعرات. تم أعتماد الخوارزمية التطورية متعددة الأهداف المعروفة (MOEA / D) في حل المشكلة المذكورة .تم اقتراح تخطيط متعدد الطبقات لتصميم الخوارزمية ، حيث تنتج كل طبقة مجموعة متميزة من أجهزة الاستشعار النشطة. تم تقييم أداء النموذج المقترح من ثلاثة جوانب: من حيث العدد الإجمالي للمجاميع المتراكبة، ومجموع الطاقة المتبقية، وموثوقية التغطية من خلال محاكاة واسعة النطاق. النتائج المتوفرة تبين تأثير العوامل المختلفة بما في ذلك عدد أجهزة الاستشعار ونطاق التغطية للمستشعر. الجانب الرئيسي من النتائج تكشف عن أن عمر الشبكة (أي العدد الإجمالي للمجاميع المتراكبة) يتزايد مع تزايد عدد المستشعرات المتوفرة. من ناحية أخرى، يمكن زيادة موثوقية التغطية عن طريق زيادة نطاقات الاستشعار ولكن على حساب تناقص عمر الشبكة.

## 1. Introduction

Nowadays, many applications have technological platforms based on wireless sensor networks (WSNs). Amongst the main features of WSNs is the dense ad-hoc deployment of sensors from an aircraft into the target area to properly establish the required level of coverage for a long period of time. Unfortunately, recharging sensors' batteries or replacing expired ones may limit their potential intent. This opens the door for many researches in literature to support energy-aware WSN topologies. Considering the two main participants of any WSN (i.e., sensor nodes and sensing data), energy effiecient methods can be broadly classified into two main levels [1 – 5]:

1. Data-wise techniques, where different framework methodologies identify their foundations from understanding how to gather, aggregate, and route sensing data.
2. Sensor-wise techniques, which in turn being classified into sensor scheduling techniques and sensing range adjusting techniques.

Sensor-based energy efficient techniques lay the foundation of their frameworks from the impact of sensor energy utilization on the network life span. Generally, these techniques can either schedule sensor modes to alternate between active and sleep modes, or to adjust their sensing ranges, or to combine both scheduling and adjusting techniques. The main goal of sensor scheduling techniques is to divide sensor nodes into a maximum number of set covers (SC), each set cover being assigned with a subset of sensors being cooperatively capable of covering the whole area of interest. Assume that the lifetime of the WSN is divided into intervals and at each interval only the sensors belong to one SC are set to active, while the remaining sensors are set to sleep. Then scheduling a large number of such set covers will eventually prolong network's life time, wherein each interval, only one SC is activated. For homogeneous WSNs where sensors are equipped with equal sensing range, the maximum set covers problem is turned into finding the maximum number of *disjoint* set covers (DSC) problem. For heterogeneous WSNs, however, sensor nodes have the ability to adjust their sensing ranges into different levels extending the scheduling problem into a constrained maximum non-disjoint or *overlapped* set covers problem, commonly known as *adjustable range* set covers (ARSC) problem. Both DSC and its extended ARSC are proved to be Non-deterministic Polynomial-time complete (NP-complete) problem [6], [7] that recently enjoyed a considerable interest.

Unlike existing techniques, the contribution of this paper is to address the issue of designing an energy efficient algorithm for solving the maximum ARSC problem in WSNs while considering probabilistic sensing ability of the sensor nodes. To the best of our knowledge, this is the first attempt to address such issue. To this end, this paper attempts to answer the following questions. *What is the impact of complicating the sensing model from the commonly used Boolean model to the probabilistic one into the maximum ARSC problem? What is the impact of adopting probabilistic sensing model on the coverage reliability and network's life time? How can maximum ARSC problem be then stated, formulated, and solved?*

To answer the above questions, the following research steps are developed to provide quantitative and qualitative arguments:

1. To open the maximum ARSC problem into a more general statement including the characterization of the probabilistic sensing model of the sensor nodes. The introduced problem statement is divided mainly into three sub-problems: *how to schedule sensors into active and sleep set covers*? *How to adjust sensing range to each sensor in the active set cover*? *How to maximize coverage reliability and number of set covers*?

**2.** To cast the contradictory goals of the probabilistic sensing model being realized by the coverage reliability and network's life time on a multi-objective optimization (MOO) model.
**3.** To devise a multi-objective evolutionary algorithm (MOEA) and to project all its characteristic components towards solving the proposed MOO model.

In the remainder of this paper, preliminary concepts to the formulation of the problem are first introduced. The problem is modeled as multi-objective optimization problem in both informal and formal ways. The paper then continues to describe how to project the characteristic components of the adopted multi-objective evolutionary algorithm into the formulated maximum ARSC problem. Simulation results and discussions are also provided. Finally, concludes the whole work of this paper is summarized and further candidate research directions are recommended.

## 2. Preliminaries

Hereinafter, the model being used to represent the WSN system is a two-dimensional rectangle area $\mathcal{A}$ of size $(X_{max}, Y_{max})$, i.e. $\mathcal{A} = \{(x,y)|1 \le x \le X_{max},\ 1 \le y \le Y_{max}\}$. The sensing area $\mathcal{A}$ is equipped with a set $\mathcal{T} = \{t_1, t_2, \dots, t_n\}$ of $n$ targets where $t_{i,\ \forall 1\le i\le n} = (x,y) \in \mathcal{A}$. Additionally, a set $\mathcal{S} = \{s_1, s_2, \dots, s_m\}$ of $m$ sensors are assumed to be deployed randomly in $\mathcal{A}$, i.e. $s_{i,\ \forall 1\le i\le m} = (x,y) \in \mathcal{A}$. Moreover, considering sensing capability, two characteristics can feature the sensor nodes: sensor model and sensing range.

In general, WSN model is either *homogeneously* modeled (where all sensor nodes have a fixed sensing range $R_s$), or *heterogeneously* modeled (where each sensor node $s_i$ is assigned with a sensing range $R_{s_i}$). In the simple uniform circular 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. Formally expressed as a binary detection model in Eq. 1, which says that if a target occurs within the sensing radius of a sensor node, the probability of covering this target is assumed to be always 1, otherwise, it is assumed to be zero.

$$\boldsymbol{Cover(s_i, t_j)} = \begin{cases} \mathbf{1} & \boldsymbol{if} \sqrt{(\boldsymbol{x_i} - \boldsymbol{x_j})^2 + (\boldsymbol{y_i} - \boldsymbol{y_j})^2} \le \boldsymbol{R_{s_i}} \\ \mathbf{0} & \boldsymbol{otherwise} \end{cases} \quad \mathbf{(1)}$$

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 [8]. Adding detection uncertainty factor $R_u$ to the sensor results in three-levels of sensing strength (as expressed in Eq. 2). The coverage probability decays exponentially as the distance between the target and the sensor increases, as expressed in Eq. 2.

$$\boldsymbol{Cover(s_i, t_j)} = \begin{cases} \mathbf{1} & \boldsymbol{if} \sqrt{(\boldsymbol{x_i} - \boldsymbol{x_j})^2 + (\boldsymbol{y_i} - \boldsymbol{y_j})^2} \le \boldsymbol{R_{s_i}} - \boldsymbol{R_u} \\ \boldsymbol{e^{-\lambda a^{\beta}}} & \boldsymbol{if}\ \boldsymbol{R_{s_i}} - \boldsymbol{R_u} < \sqrt{(\boldsymbol{x_i} - \boldsymbol{x_j})^2 + (\boldsymbol{y_i} - \boldsymbol{y_j})^2} < \boldsymbol{R_{s_i}} + \boldsymbol{R_u} \\ \mathbf{0} & \boldsymbol{if} \sqrt{(\boldsymbol{x_i} - \boldsymbol{x_j})^2 + (\boldsymbol{y_i} - \boldsymbol{y_j})^2} \ge \boldsymbol{R_{s_i}} + \boldsymbol{R_u} \end{cases} \quad \mathbf{(2)}$$

Where:

$$\boldsymbol{a} = \sqrt{(\boldsymbol{x_i} - \boldsymbol{x_j})^2 + (\boldsymbol{y_i} - \boldsymbol{y_j})^2} - (\boldsymbol{R_{s_i}} - \boldsymbol{R_u}) \quad \mathbf{(3)}$$

Both $\lambda$ and $\beta$ are probabilistic sensing parameters to measure the strength of detection when a target point lies within the interval $\{R_{s_i} - R_u, R_{s_i} + R_u\}$. On the other hand, complete coverage and no coverage are the cases for points positioned within $R_{s_i} - R_u$ and out of $R_{s_i} + R_u$ distance from the sensor, respectively.

Likewise, sensing range, being specified by the maximum sensing radius and sensing capability of the sensor, can be either *fixed* or *adjustable* [4, 5]. When the sensor is fixed with only one sensing range, it can only sense data over a distance that is less than or equal to its sensing range. However, enabling the sensor node to adjust its sensing ability after an initial set up with different sensing ranges, the sensor can be schedule its sensing ability to large or small range according to the required coverage and the overall energy consumption.

The general definition of ARSC problem is stated as:

***Definition* 1:** *(Maximum Adjustable Range Set Covers Problem – ARSC). Consider a WSN consisting of a set* $\mathcal{T}$ *of* $n$ *targets and a set* $\mathcal{S}$ *of* $m$ *sensors. Each sensor* $s_i \in \mathcal{S}$ *is augmented with the 3-tuple:*

*$\{E, (r_1, r_2, \dots, r_p), (e_1, e_2, \dots, e_p)\}$, where $E$ is the initial energy, $(r_1, r_2, \dots, r_p)$ is an increased option of sensing ranges, and $(e_1, e_2, \dots, e_p)$ is the associated energy consumption for each sensing range. ARSC problem attempts to find a family of set covers $\mathcal{F} = \{\mathcal{S}_1, \mathcal{S}_2, \dots, \mathcal{S}_N\}$ and to adjust sensing range of each sensor $s_i$ in a set cover $\mathcal{S}_j$ (i.e. to adjust $e_{i,j}$ if $s_i \in \mathcal{S}_j$) such that:*

(1) *$N$ is maximized,*

(2) *Each set cover $\mathcal{S}_i$ covers the whole $\mathcal{T}$, and*

(3) *Each sensor appearing in the whole $\mathcal{F}$ consumes at most $E$.*

Shortly speaking, the maximum adjustable set covers problem can be formally expressed as:

$$\underset{N}{\boldsymbol{argmax}} \quad \boldsymbol{AR-SC(\mathcal{S},\mathcal{T}) = \mathcal{F}} :: \left\{\{\boldsymbol{\mathcal{S}_i}\}_{\boldsymbol{i=1}}^{\boldsymbol{N}} \,\middle|\, \forall \boldsymbol{\mathcal{S}_i} \in \boldsymbol{\mathcal{F}}: \boldsymbol{SetCover(\mathcal{S}_i) = 1 \; and} \; \forall \boldsymbol{s_j} \in \boldsymbol{\mathcal{S}}: \textstyle\sum_{\boldsymbol{i=1, s_j \in \mathcal{S}_i}}^{\boldsymbol{N}} \boldsymbol{e_{j,i} \le E}\right\} \quad \textbf{(4)}$$

## 3. Multi-objective evolutionary algorithm with decomposition

Consider a vector of $n$ parameters $\mathbb{X} = [x_1, x_2, \dots, x_n]^T$, a MOP can be formulated as a vector of $m$ objective functions $\mathbb{F}(\mathbb{X}) = [\mathbb{f}_1(\mathbb{X}), \mathbb{f}_2(\mathbb{X}), \dots, \mathbb{f}_m(\mathbb{X})]^T$. $\mathbb{F}(\mathbb{X})$ is optimized (in terms of *domination*) towards finding Pareto-optimal set of solutions (or at least towards a near Pareto-optimal set of solutions), each of which is said to be a non-dominated or a non-inferior solution, noted as $\mathbb{X}^* = [x_1^*, x_2^*, \dots, x_n^*]^T \mid \mathbb{X}^* \in \mathbb{X}$. To define domination, consider two vectors $\mathbb{U}$ and $\mathbb{V}$ from the solution space $\Omega(\mathbb{X})$, i.e. $\mathbb{U} \in \mathbb{X}$ and $\mathbb{V} \in \mathbb{X}$. Then, solution $\mathbb{U}$ is said to dominate $\mathbb{V}$ if and only if the following two conditions hold [9], [10]:

1. Solution $\mathbb{U}$ is no worse than $\mathbb{V}$ in all objectives, or formally, $\forall 1 \le i \le m: \mathbb{f}_i(\mathbb{U}) \ntriangleright \mathbb{f}_i(\mathbb{V})$. For example in maximization, the word "no worse" means $\mathbb{f}_i(\mathbb{U}) \nless \mathbb{f}_i(\mathbb{V})$.
2. The solution $\mathbb{U}$ is *strictly* better than $\mathbb{V}$ in at least one objective, or formally, $\mathbb{f}_i(\mathbb{U}) \triangleleft \mathbb{f}_i(\mathbb{V})$ in at least one objective $\mathbb{f}_i$, $i \in \{1,2,\dots,m\}$. For maximization, the word "strictly better" means $\mathbb{f}_i(\mathbb{U}) > \mathbb{f}_i(\mathbb{V})$.

The notation $(\mathbb{U} \triangleleft \mathbb{V})$ is used to denote that solution $\mathbb{U}$ is better than solution $\mathbb{V}$ regardless of the type of the optimization problem (maximization or minimization). Also, the notation $(\mathbb{U} \triangleright \mathbb{V})$ is used in the same way to express that solution $\mathbb{V}$ is better than solution $\mathbb{U}$. Hence, a non-dominated set can be defined as: among a set of solutions $\Omega(\mathbb{X})$, the non-dominated solutions set $\overline{\Omega}(\mathbb{X}) \subset \Omega(\mathbb{X})$ are subset of solutions which are not dominated by any other solution in $\Omega(\mathbb{X})$.

Among the famous multi-objective evolutionary algorithms being successfully applied to many real-world problems is the multi-objective evolutionary algorithm with decomposition (MOEA/D) being proposed by Zhang and Li [9]. Consider a formulated MOP with $m$ objective functions:

$$\boldsymbol{Maximize}\ \mathbb{F}(\mathbb{X}) = [\boldsymbol{f_1}(\mathbb{X}), \boldsymbol{f_2}(\mathbb{X}), \dots, \boldsymbol{f_m}(\mathbb{X})]^{\boldsymbol{T}} \quad \textbf{(5)}$$

Also, consider a reference point $z^* = (z_1^*, \dots, z_m^*)$ to hold the best value obtained so far by MOEA/D for each of the $m$ objective functions, formally speaking:

$\forall i \in \{1, \dots, m\}$

$$\boldsymbol{z_i^* = f_i}(\mathbb{X}^*): \Leftrightarrow \nexists\, \mathbb{X} \in \boldsymbol{\Omega}(\mathbb{X}) \mid \boldsymbol{f_i}(\mathbb{X}) > \boldsymbol{f_i}(\mathbb{X}^*) \quad \textbf{(6)}$$

In MOEA/D, each of the $N$ individual solutions can stand for one scalar optimization problem, thus, MOP is decomposed by MOEA/D into $N$ scalar optimization sub-problems. Each individual $\mathbb{p}_k, 1 \le k \le N$ is associated with one weight vector $\lambda^k$ of length $m$ out of a set of $N$ even spread weight vectors $\{\lambda^1, \lambda^2, \dots, \lambda^N\}$. Recall that there are $m$ objective functions for the MOP, then each $\mathbb{p}_k$ has weight vector $\lambda^k = (\lambda_1^k, \lambda_2^k, \dots, \lambda_m^k), s.t. \sum_{i=1}^{m} \lambda_i^k = 1$ . Moreover, in MOEA/D, each individual is evolved using information gathered from only its $T$ neighbor solutions. Neighbor solutions to $\mathbb{p}_k$, denoted by $B(k)$, are those with the closest distance (using Euclidean distance) weight vectors to $\lambda^k$. Thus, $B(k) = \{k_1, k_2, \dots, k_T\}$ with $B_\lambda(k) = \{\lambda^{k_1}, \lambda^{k_2}, \dots, \lambda^{k_T}\}$.

$\forall t \in \{1, \dots, T\}$

$$\boldsymbol{k_t \in B(k)}: \Leftrightarrow \nexists\, \boldsymbol{\lambda^j} \in \{\boldsymbol{\lambda^1, \lambda^2, \dots, \lambda^N}\} \mid \textstyle\sum_{\boldsymbol{i=1}}^{\boldsymbol{m}} \left(\boldsymbol{\lambda_i^k - \lambda_i^{k_t}}\right)^{\boldsymbol{2}} > \sum_{\boldsymbol{i=1}}^{\boldsymbol{m}} \left(\boldsymbol{\lambda_i^k - \lambda_i^j}\right)^{\boldsymbol{2}} \quad \textbf{(7)}$$

The problem of approximating the Pareto Front (PF) of the MOP defined in Eq. (5) can be decomposed into $N$ scalar optimization sub-problems, each with its objective function:

$\forall k, 1 \le k \le N \; and \; \forall i, 1 \le i \le m$

$$\boldsymbol{g_k}(\mathbb{p}_k \mid \boldsymbol{\lambda^k, z^*}) = \boldsymbol{max_{1 \le i \le m}}\{\boldsymbol{\lambda_i^k} |\boldsymbol{f_i}(\mathbb{p}_k) - \boldsymbol{z_i^*}|\} \quad \textbf{(8)}$$

In terms of maximization, MOEA/D maximizes all these $g_k$ objective functions simultaneously in a single run. MOEA/D with the Tchebycheff approach evolves a population of $N$ solutions $\{\mathbb{p}_1,$

$\mathbb{p}_2, \ldots, \mathbb{p}_N\} \subset \Omega(\mathbb{X})$ where, $\mathbb{p}_k$ is the current solution to the $k^{th}$ sub-problem with $(\mathbb{p}_k) = [f_1(\mathbb{p}_k), f_2(\mathbb{p}_k), f_m(\mathbb{p}_k)]^T$. Also MOEA/D maintains an external population $EP$, for archiving the non-dominated solutions found during the search. At each generation, MOEA/D performs four main operations while generating $N$ new solutions $\{\mathbb{p}_1', \mathbb{p}_2', \ldots, \mathbb{p}_N'\}$:

- First, for each individual $\mathbb{p}_k, 1 \leq k \leq N$, a new offspring solution $\mathbb{p}_k'$ is generated, using problem-specific genetic operators (e.g., crossover and mutation), from only $B(k)$ neighbors.
- Second, if necessary it updates the reference points $z^* = (z_1^*, \ldots, z_m^*)$. $\forall i, 1 \leq i \leq m$, if $z_i^* < f_i(\mathbb{p}_k')$, then it sets $z_i^* = f_i(\mathbb{p}_k')$.
- Third, it updates the neighbors of $\mathbb{p}_k$: $\forall t, 1 \leq t \leq T$, if $g_k(\mathbb{p}_k'|\lambda^k, z^*) \geq g_t(\mathbb{p}^{k_t}|\lambda^{k_t}, z^*)$, then it sets $\mathbb{p}^{k_t} = \mathbb{p}_k'$ and $\mathbb{F}(\mathbb{p}^{k_t}) = \mathbb{F}(\mathbb{p}_k')$.
- Finally, it updates $EP$ by removing from it all solutions $\mathbb{Y}$ where $\mathbb{F}(\mathbb{p}_k') \lhd \mathbb{F}(\mathbb{Y})$ and insert $\mathbb{p}_k'$ into $EP$ if $\nexists \mathbb{Y} \in EP \rightarrow \mathbb{F}(\mathbb{Y}) \lhd \mathbb{F}(\mathbb{p}_k')$.

The general framework of MOEA/D can then be outlined as in Algorithm 1 [9].

**Algorithm 1 The general outline of MOEA/D**

**Input:**

- Multi-objective maximization problem $f(\mathbb{x}) = (f_1(\mathbb{x}), f_2(\mathbb{x}), \ldots, f_m(\mathbb{x}))$
- Number of sub-problems to be evolved, i.e. population size, $N$
- Uniform spread of $N$ weight vectors: $\{\lambda^1, \lambda^2, \ldots, \lambda^N\}$ such that $\lambda^k = (\lambda_1^k, \lambda_2^k, \ldots, \lambda_m^k)$
- Neighborhood size of each weight vector, $T$
- Maximum number of generations, $max_t$
- Probability of crossover, $p_c$
- Probability of mutation, $p_m$

**Output:** External archive of non-dominated solutions, $EP$.

**Step 0 - Setup:**

- $EP = \emptyset$
- $t = 0$

**Step 1 – Initialization**

- Uniformly, *generate* an initial population, $\mathbb{P}_0 = \{\mathbb{p}_1, \mathbb{p}_2, \ldots, \mathbb{p}_N\}$.
- *Evaluate* fitness vector for each individual, $\forall i = 1,2, \ldots, N$ : $f(\mathbb{p}_i) = \{f_1(\mathbb{p}_i), f_2(\mathbb{p}_i), \ldots, f_m(\mathbb{p}_i)\}$.
- *Initialize* ideal vector $z^* = (z_1^*, z_2^*, \ldots, z_m^*)^T$ by a problem-specific method.
- *Compute* Euclidean distance between weight vectors $\{\lambda^1, \lambda^2, \ldots, \lambda^N\}$ and *assign* the $T$ closest vectors $= \{\lambda^{k_1}, \lambda^{k_2}, \ldots, \lambda^{k_T}\}$ to each $\lambda^k$. $\forall k = 1,2, \ldots, N$.
- Set neighbors for each weight vector, $\forall k = 1,2, \ldots, N$: $B(k) = \{k_1, k_2, \ldots, k_T\}$.

**Step 2 – Evolve cycle: For $i = 1,2, \ldots, N$**

- Randomly *select* two indices $k, l$ from $B(i)$, and *generate* a new solution $\mathbb{Y}$ from $\mathbb{P}_k$ and $\mathbb{P}_l$ using crossover and mutation operators.
- *Update* $z^*$, $\forall j = 1, \ldots, m$, if $z_j^* > f_j$ ($\mathbb{Y}$), then set $z_j^* = f_j$ ($\mathbb{Y}$).
- *Update* neighboring solutions: For each index $j \in B(i)$, if $g^{te}(\mathbb{Y}|\lambda_j, z^*) \leq g^{te}(\mathbb{P}_j|\lambda_j, z^*)$, then *set* $\mathbb{P}_j = \mathbb{Y}$ and $f_j = f(\mathbb{Y})$.
- *Update* EP: *Remove* from EP all vectors dominated by $f(\mathbb{Y})$.

*Insert* $f(\mathbb{Y})$ to EP if no vector in EP dominate $f(\mathbb{Y})$.

**Step 3 – Stopping criteria**

- *If* $t = t_{max}$, then *stop* and *output* EP
  *else* $t = t + 1$ and *go to* Step 2.

## 4. Multi-objective ARSC problem: Definition and formulations

In this section, a discussion illustrating an informal account of the different characteristics of the proposed multi-objective model for solving ARSC problem in WSNs is first presented. This is followed by casting the proposed MO-ARS model into a more formal expression.

### 4.1 MO-ARSC: Problem statement and formal development

The fundamental idea of the formulated multi-objective adjustable range set covers (MO-ARSC) problem is to maximize two contradictory objective functions in an attempt to provide the WSN with a maximum collection of overlapped set covers, each of which can completely covers the whole target set.

The first objective function concerns with finding the maximum number of generated set covers. Searching for a larger number of set covers can be emphasized by scheduling sensor nodes into complete set covers, each of which consumes as less energy as possible. Recall that each active sensor has the ability to adjust its sensing range from $p$ different settings (i.e. $\{r_1, r_2, \dots, r_p\}$ where $r_1 < r_2 < \cdots < r_p$) corresponding to $p$ different energy consumption $\{e_1, e_2, \dots, e_p\}$ where $e_1 < e_2 < \cdots < e_p$. Then, the formulated objective function prefers those chromosome solutions where competitions between the still alive sensors are allowed in the small-end ranges associated with the low energy consumptions. Consider still alive sensor $s_i$ with residual energy $E_r$ has been encoded by a given chromosome solution to be active at radius $r_k$. Also, consider that target $t_j$ is placed inside the coverage area of $s_i$ (i.e. Euclidean distance $d_{i,j} \le r_k$). For Boolean sensing model, this is interpreted as sensor $s_i$ completely covers target $t_j$ (i.e. $Cover(s_i, t_j) = 1$). In terms of energy consumption, $E_c$, this causes sensor $s_i$ to consume $100\%$ of the energy required to adjust its sensing radius to $r_k$ (i.e. $100\% \times e(r_k)$). In other formal words, this can be expressed as:

$$\boldsymbol{E_c(s_i|\, r_k) = 100\% \times e(r_k)} \quad \textbf{(9)}$$

$$\boldsymbol{E_r(s_i|\, r_k) = E_r(s_i) - E_c(s_i|r_k)|\, \exists t_j \colon Cover(s_i, t_j|\, r_k) = 1} \quad \textbf{(10)}$$

Where $E_c(s_i)$, and $E_r(s_i)$ are the consumed energy and the residual energy of sensor $s_i$ at radius $r_k$.

However, the perspective of the probabilistic sensing model as an alternative and more realistic sensing approach (as presented in Eq. 2) opens up a different energy consumption formula. It suggests that sensor $s_i$ at sensing radius $r_k$ has to consume *at most* an amount of energy equals to $Cover(s_i, t_j|\, r_k) \in [0,1]$ where $t_j$ is the most distant target laying inside the coverage area of sensor $s_i$ being adjusted with radius $r_k$. Thus, the previous two equations will be re-formulated as:

$$\boldsymbol{E_c(s_i|\, r_k) = Cover(s_i, t_j|\, r_k) \times e(r_k)} \quad \textbf{(11)}$$

$$\boldsymbol{E_r(s_i|\, r_k) = E_r(s_i) - E_c(s_i|r_k)|\, \forall 1 \le j \le n \colon max\{Cover(s_i, t_j|r_k)\}} \quad \textbf{(12)}$$

One can clearly see that the residual energy $E_r(s_i|\, r_k)$ of sensor $s_i$ in Eq. 12 can be maximized by minimizing the right-hand side operand (i.e. consumed energy $E_c(s_i|r_k)$) which is totally casted by the adjusted radius $e(r_k)$. The smaller the adjusted radius, the more energy will be reserved. Similarly, the smaller the sensing ranges adjusted to all active sensors set, the more likely that this set can support target area with whole coverage and with less energy consumption. The demand for prolonging network's lifetime through increasing the total number of complete set covers, then, suggests the need for *maximizing* the total residual energy of sensor nodes. To this end, the proposed MO-ARSC model, states the problem of maximizing sensors residual energy as follows.

*Definition 2: (Maximum residual energy $\Phi_1(\mathcal{S}_i)$) Consider a set cover $\mathcal{S}_i = \{s_j\}$ of a group of active sensors from the whole sensor set $\mathcal{S}$ (i.e. $\{s_j\} \subset \mathcal{S}$ ) to cover the whole target set $\mathcal{T}$.The residual energy of $\mathcal{S}_i$ can be maximized by minimizing the sensing range adjusted to $\{s_j\}$ while satisfying full target coverage.*

$$\boldsymbol{Maximize\ \Phi_1(\mathcal{S}_i) = \textstyle\sum_{s_j \in \mathcal{S}_i} E_r(s_i|\, r_k)} \quad \textbf{(13)}$$

Such that

$$\boldsymbol{SetCover(\mathcal{S}_i) = 1} \quad \textbf{(14)}$$

The second objective function handles the reliability of the generated set covers. The objective is formulated by the means of increasing the reliability of gathered coverage from the whole set covers. For each set cover $\mathcal{S}_i$, the formulated objective function qualifies the reliability of each target $t_j \in \mathcal{T}$ by the maximum strength of detection being reported by the different sensing radii adjustments $r_k$ of the active sensors in set $\mathcal{S}_i$. The coverage reliability of each target $t_j \in \mathcal{T}$, under set cover $\mathcal{S}_i$, can be formally expressed as:

$$\boldsymbol{R(t_j|\, \mathcal{S}_i) = argmax\{\, \forall s \in \mathcal{S}_i \colon Cover(s, t_j|\, r_k)\}} \quad \textbf{(14)}$$

Altogether, the reliability of set cover $\mathcal{S}_i$ can be maximized by maximizing coverage reliability of each target can be stated as:

*Definition* 3: *(Maximum coverage reliability $\Phi_2(\mathcal{S}_i)$) Consider a set cover $\mathcal{S}_i = \{s_j\}$ of a group of active sensors from the whole sensor set $\mathcal{S}$ (i.e. $\{s_j\} \subset \mathcal{S}$ ) to cover the whole target set $\mathcal{T}$. The coverage reliability of $\mathcal{S}_i$ can be maximized by maximizing the sensing reliability of each target in $\mathcal{T}$.*

$$\boldsymbol{Maximize}\ \boldsymbol{\Phi_2(\mathcal{S}_i) = \sum_{j=1}^{n} R(t_j | \mathcal{S}_i)} \quad \textbf{(15)}$$

### 4.2 Individual representation

In the proposed MOEA/D, each candidate solution $\mathbb{p}$ is represented as a vector of length equals to the total number of sensors in the area, i.e. $m$. Then, a population $\mathbb{P}$ of $K$ individuals can be formally expressed as $\mathbb{P} = \{\mathbb{p}_k | \mathbb{p}_k = (\mathbb{p}_{k,1}, \mathbb{p}_{k,2}, \dots, \mathbb{p}_{k,m})\}_{k=1}^{K}$. Each $gene_i\ |i \in \{1,2,\dots,m\}$ controls both the *active/sleep scheduling* and *sensing range assignment* of the corresponding $i^{th}$ sensor. Assuming that each sensor is augmented with $p$ sensing ranges $(r_1, r_2, \dots, r_p)$, each $gene_i$ will then take an integer value from the range $\{-1,0,1,\dots,p\}$ where $-1$ means that the corresponding sensor *expires its energy*, and 0 corresponding to setting the sensor to the *sleep mode*. The remaining values $j = \{1,\dots,p\}$ corresponding to setting the sensor to the *active mode* with sensing range $j$. Formally speaking, for a population of $K$ individuals, each of $m$ genes,

$\forall k \in \{1,\dots,K\}\ and\ \forall i \in \{1,\dots,m\}$:

$\mathbb{p}_k = (\mathbb{p}_{k,1}, \mathbb{p}_{k,2}, \dots, \mathbb{p}_{k,m})\ where:$

$$\mathbb{p}_{k,i} = \begin{cases} \boldsymbol{-1\ \ if\ s_i\ is\ dead} \\ \boldsymbol{0\ \ if\ s_i\ is\ sleep} \\ \boldsymbol{j\ \ if\ s_i\ is\ active\ at\ sensing\ range\ j} \end{cases} \quad \textbf{(16)}$$

### 4.3 Repair operator

Although population initialization creates a set of candidate solutions, some candidates could be infeasible or lethal to the MO-ARSC problem. Infeasible solution $\mathbb{p} = (\mathbb{p}_1, \mathbb{p}_2, \dots, \mathbb{p}_m)$ is stated in terms of existence of coverage-holes where one or more targets are out of coverage of any active sensor.

$$\boldsymbol{CoverageHole}(\mathbb{p}) = \begin{cases} \boldsymbol{1\ \ \exists\ t \in \mathcal{T} |\ \forall i,\ 1 \le i \le m\ and\ \mathbb{p}_i > 0\ \Rightarrow\ Cover(\mathbb{p}_i, t) = 0} \\ \boldsymbol{0\ \ otherwise} \end{cases} \quad \textbf{(17)}$$

On the other hand, a feasible solution $\mathbb{p} = (\mathbb{p}_1, \mathbb{p}_2, \dots, \mathbb{p}_m)$ may be over satisfied in terms of target coverage that leads to over energy consumption (see Eq. 3.5).

$$\boldsymbol{OverCoverage}(\mathbb{p}) = \begin{cases} \boldsymbol{1\ \ \forall\ t \in \mathcal{T} |\ \exists \mathbb{p}_i > 0\ \Rightarrow\ Cover(\mathbb{p}_i, t) > 0} \\ \boldsymbol{0\ \ otherwise} \end{cases} \quad \textbf{(18)}$$

A repair operator, Γ, is formulated to make a guarantee that the constructed solutions have both hole-free as well as enough-coverage conditions. The fundamental idea of repair operator can be simply stated as follows. For a coverage-hole solution, it *activates as less as possible* of sleep sensors and *randomly adjusting* their sensing ranges. On the other hand, for an over coverage solution, it *deactivates as much as possible* of active sensors.

The process of the proposed repair operator $\Gamma: \mathbb{p} \to \mathbb{p}'$ is presented in Algorithm 2. It takes as input an individual $\mathbb{p}$ and checks whether the active sensors set $S$ being signified by $\mathbb{p}$ (i.e., $\{\mathbb{p}_i | \mathbb{p}_i > 0\}_{i=1}^{m}$) forms coverage-hole or over-coverage. In case of coverage-hole, Γ will repeatedly select one random sleep sensor, activate it, adjust its sensing range, and group it with the active sensors of $\mathbb{p}$ until the new set form hole-free set cover. On the other hand, if the active sensors of $\mathbb{p}$ forms over coverage, Γ will repeatedly deactivate one random active sensor until it can form complete coverage with less number of sensors or less ranges of sensing.

**Algorithm 2: Repair Operator ($\mathbb{p}_k$; $\mathbb{p}_k{}'$)**

**Input:** $\mathbb{p}_k |\ k \in \{1,2,\dots,K\}$

**Output:** $\mathbb{p}_i{}'$

**1:** // group all active sensors of $\mathbb{p}_k$ into $S_{active}$
$\forall j \in \{1,2,\dots,m\}: S_{active} \leftarrow \{\mathbb{p}_{k,j} | \mathbb{p}_{k,j} > 0\}$

**2:** // group all sleep sensors of $\mathbb{p}_k$ into $S_{sleep}$
$\forall j \in \{1,2,\dots,m\}: S_{sleep} \leftarrow \{\mathbb{p}_{k,j} | \mathbb{p}_{k,j} = 0\}$

**3:** **if** $OverCoverage(\mathbb{p}_{i,1}, \mathbb{p}_{i,2}, \dots, \mathbb{p}_{i,m})$ // hole-free set cover
// repair over-coverage

**4:** **while** $OverCoverage(\mathbb{p}_{i,1}, \mathbb{p}_{i,2}, \dots, \mathbb{p}_{i,m})$

```
        select random sensor s_j ∈ S_active
        set p_{k,j} ← p_{k,j} − 1 // adjust its sensing range to the preceded value
    end
    // exit while loop with coverage-hole status
    set p_{k,j} ← p_{k,j} + 1 // return back to the last adjustment
else // coverage-hole set cover
    while CoverageHole(p_1, p_2, ..., p_m)
        select a random sensor s_j ∈ S_sleep
        set p_{k,j} ← rand(1, p) // adjust its sensing to a random value from 1 to p
    end
end
```

**4.4 Selection and perturbation operators**

Any EA lays its main operation on three commonly used evolutionary operators: parent selection, parent recombination, and child mutation. In the proposed MOEA/D, these three evolution operators will be formally expressed as an iterative function $\Psi: \{\mathbb{P}, \mathbb{EP}\} \rightarrow \{\mathbb{P}', \mathbb{EP}'\}$ where $\Psi(\mathbb{P}_i) = \mathbb{P}_i{}' = \mathbb{P}_{i+1}$, $i$ is the generation number and $\mathbb{P}_i$ is the population at generation $i$. $\mathbb{EP}$ is an external population of the generated non-dominated solutions. The population starts with an initial random population $\mathbb{P}_0$ and continues evolution by $\Psi$ for a maximum number of $i_{max}$ generations.

To generate a new individual $\mathbb{p}'_{1\le k\le K}$, *select* two neighbors $\mathbb{p}_1$ and $\mathbb{p}_2$ from the neighbor set $B(k)$ of $\mathbb{p}_k$, to be the parents to generate (by recombination and mutation) a new solution $\mathbb{p}_k{}' = \mathbb{y}$ from $\mathbb{p}_1$ and $\mathbb{p}_2$. A proportion $p_c = 0.6$ of $\mathbb{p}_1$ and $\mathbb{p}_2$ genes are recombined using 2-point crossover operator $\Psi_x$. Two cut points are randomly selected from the total length of the chromosome (i.e. $r_1, r_2 \sim \{1, \dots, m\}, where\ r_1 \le r_2$), and the pair $\mathbb{p}_1$ and $\mathbb{p}_2$ are then swapped at $\mathbb{p}_{1,j}\ and\ \mathbb{p}_{2,j} | r_1 < \mathbb{p}_{1,j}, \mathbb{p}_{2,j} < r_2$.

$\forall k \in \{1, \dots, K\}\ and\ rand \le p_c$

$\Psi_x: \{\mathbb{p}_1 \sim B(k), \mathbb{p}_2 \sim B(k)\} \rightarrow \mathbb{y}_k$

$$\mathbb{y}_k = \left(\mathbb{p}_{1,1}, \cdots, \mathbb{p}_{1,r1}, \mathbb{p}_{2,r1+1}, \cdots, \mathbb{p}_{2,r2-1}, \mathbb{p}_{1,r2}, \cdots, \mathbb{p}_{1,m}\right) \quad \textbf{(19)}$$

Each gene in the new child solution $\mathbb{y}_{1\le k\le K}$ is then controlled by mutation operator $\Psi_m$ with a small probability $p_m = 0.1$. For a mutated genes corresponding to only still alive sensors, mutation operator can change their activities and/or sensing range adjustments.

$\forall k \in \{1, \dots, K\}$

$\Psi_m: \mathbb{y}_k \rightarrow \mathbb{y}_k{}'$

$$\forall \mathbb{p}_{k,j:1\le j\le m} \ne -1\ \ and\ rand \le p_m \Rightarrow \mathbb{p}_{k,j} \sim \{0, 1, \dots, r_{max}\} \quad \textbf{(20)}$$

Where $r_{max} \le r_p$ is the maximum sensing range that sensor $\mathbb{p}_{k,j}$ can operate with.

**4.5 Handling external population $EP$**

Working with MOEA/D can generate a number of non-dominated solutions among which the desired solution exists. The generation of these non-dominated solutions can appear at any generation of MOEA/D. Thus, an external repository, $EP$, for archiving the population of non-dominated solutions is required. Two main operations should be provided to update the content of $EP$, these are insertion and deletion.

Consider an $EP = \{\mathbb{p}^i_{NonDom}\}_{i=1}^{M}$ of a set of non-dominated solutions, with cardinality $M$, i.e. $|EP| = M$. A chromosome solution $\mathbb{p} = (\mathbb{p}_1, \mathbb{p}_2, \dots, \mathbb{p}_m)$ with the proposed objective function vector $\mathbb{F} = \{\Phi_1(\mathbb{p}), \Phi_2(\mathbb{p})\}$ can enter $EP$ if and only if it is not dominated by any of $EP$ solutions. Formally speaking,

$$insert(\mathbb{p}, EP) = \begin{cases} EP \cup \mathbb{p}\ \ if\ \ \nexists \mathbb{p}^i_{NonDom} \in EP |\ \mathbb{F}(\mathbb{p}^i_{NonDom}) \lhd \mathbb{F}(\mathbb{p}) \\ EP\ otherwise \end{cases} \quad \textbf{(21)}$$

Intuitively, if $EP$ is empty then $insert(\mathbb{p}, \{\}) = \{\mathbb{p}\}$. Moreover, given a new generated chromosome solution $\mathbb{p}$, the status of a non-dominated solution belongs to $EP$ could be changed to a dominated solution by $\mathbb{p}$, and thus, should be removed from $EP$. Formally speaking,

$\forall\ 1 \le i \le M$

$$delete(EP, \mathbb{p}^i_{NonDom} | \mathbb{p}) = \begin{cases} EP \backslash \mathbb{p}^i_{NonDom}\ \ if\ \mathbb{F}(\mathbb{p}) \lhd \mathbb{F}(\mathbb{p}^i_{NonDom}) \\ EP\ \ otherwise \end{cases} \quad \textbf{(22)}$$

**4.6 MOEA/D layers**

The proposed MOEA/D operates in a layer wise, where each layer $i$ can establish a candidate $i^{th}$ set cover. Thus, the proposed multi-layer MOEA/D can be formally expressed as:

$$\mathbb{MOEA}/\mathbb{D} = \boldsymbol{MOEA/D^1} \circ \boldsymbol{MOEA/D^2} \circ \ldots \circ \boldsymbol{MOEA/D^l} \quad \textbf{(23)}$$

where $l$ is the maximum number of layers that $\mathbb{MOEA}/\mathbb{D}$ can generate with them a collection of complete set covers without extinguishing sensors total energy. At each layer $i$, if the minimum requirement for targets coverage can be satisfied, then $MOEA/D^i$ excludes all dead sensors and plays only with still alive sensors to search for best set cover. Consider sensor $s_k$ belongs to set cover $j$ consumes in $j$ an energy $e_{k,j}$, then this sensor is dead at layer $i$ and later on if it appears in all or some of the previous $i-1$ layers and consumes all its energy (i.e., $\sum_{j=1, s_k \in \mathcal{S}_j}^{i-1} e_{k,j} \geq 0$). On the other hand, if the sensor satisfies $\sum_{j=1, s_k \in \mathcal{S}_j}^{i-1} e_{k,j} < E$ then it can be assigned in $i$ and later layers. Formally speaking, if:

$$\boldsymbol{SetCover}(\mathcal{S}_{alive}) = \begin{cases} \mathbf{1}\ \boldsymbol{if}\ \ \forall \boldsymbol{j}, \mathbf{1} \leq \boldsymbol{j} \leq \boldsymbol{n} \Rightarrow\ \exists \boldsymbol{s_i} \in \mathcal{S}_{alive} | \boldsymbol{cover}(\boldsymbol{s_i}, \boldsymbol{t_j}) > \mathbf{0} \\ \mathbf{0}\ \boldsymbol{otherwise} \end{cases} \quad \textbf{(24)}$$

**where** $\mathcal{S}_{alive} = \{\boldsymbol{s_i} | \boldsymbol{E_r}(\boldsymbol{s_i}) > \mathbf{0}\}$ **(25)**

## 5. Simulation Results

This section reports the performance of the proposed multi-layer MOEA/D for solving MO-ARSC problem. The evaluation is presented in terms of total number of set covers obtained, total residual energy, and total coverage reliability.

### 5.1 Parameter settings

The results are obtained after setting WSNs and algorithm parameters into the following. The simulation area is square-shaped with $X_{max} = 1000m$, number of targets $n = \{10, 15, 20, 25\}$, and number of sensors $m = \{25, 50, 75, 100, 125, 150\}$, where each sensor is augmented with four sensing radii. Each radius has one and half times the sensing radius of the preceding one. In each group of results, we will vary the smallest sensing range $r_1$ to two different values $r_1 = \{150, 250\}$, Uncertainty level $R_u$ is set to $R_s * 0.5$ units, both $\lambda$ and $\beta$ are set to 0.5, and $c_{th}$ is set to $0.001$. Population size is set to $100$ and will be allowed to evolve $100$ times. A combination of all varying parameters carries out 24 different test instances, wherein the results of each test are average of 10 random WSNs. Altogether, 240 different WSNs are examined in this simulation.

### 5.2 Results

Tables-1 and -2 report the performance of the proposed model in terms of total number of set covers and total coverage reliability. The results reported in the tables reveal the following points. Fixing all parameters to one setting and just increasing number of sensors $m$ from 25 to 75 will eventually lead to an increased number of set covers (i.e. prolonging network's lifetime), an increase in total residual energy, and an increase in total coverage reliability. For example, fixing $n$ to 10 and $r_1$ to 150 resulting in an increase from 7.2 up to 19.8, from 0.78 up to 0.9893, and from 0.2138 up to 0.3285 in average number of set covers, total residual energy, and total coverage reliability, respectively. Again, for similar parameter settings, increasing number of sensors $m$ from 25 (Table-1) to 150 (Table- 2) has, also, a positive impact on the total number of generated set covers, residual energy, and coverage reliability, in average, from 7.2 up to 32.8, from 0.78 up to 14.4, and from 0.2138 up to 0.7390, respectively.

Secondly, varying only initial sensing radius $r_1$ from 150 to 250 while fixing all other parameters (including the initial energy $E$) will *generally* leads to decreasing the total number of set covers and total residual energy but an increase in coverage reliability. This is due that larger radii need more energy consumption than smaller radii and that larger radii have more chance to cover more targets with more reliability. For example, consider the case mentioned above where $n$ is fixed to 10, $m$ is fixed to 75 and varying $r_1$ from 150 to 250. The results in Table 1, reports a general decrease from 19.8 down to 14.1, from 0.9893 down to 0.9849, and from 0.3285 up to 0.4706 in average number of set covers, total residua energy, and total coverage reliability. Also, for the results in Table 2, one can see a decrease from 21.6 down to 18.6, from 11.9 down to 0.9889, and from 0.3595 up to 0.4433 in average number of set covers, total residual energy, and total coverage reliability.

Figures -1 - 4 quantitatively report the impact of varying number of sensors and sensing radii on the final number of set covers. As shown in the figures, increasing number of sensors will eventually leads to increasing average number of set covers. Another interesting remark is that increasing total number of targets while fixing total number of sensors to a fixed value, results in decreasing the average number of set covers. This can be turned back to the fact that more targets needed to be covered, means more energy required to be consumed. This in turns means less residual energy and less number of set covers. Finally, increasing initial sensing range from 150 to 250 can cause a general decrease in the average number of set covers.

**Table 1**-Performance of $MO - ARSC$in terms of $average$ number of complete set covers, average residual energy, and average reliability for 10 WSNs in each test case where $number\ of\ sensors: m = \{25,50,75\}$, $number\ of\ targets: n = \{10,15,20,25\}$, $initial\ energy\ for\ each\ sensor: E = 1000$, and $r_1 = \{150, 250\}$.

| $MO - ARSC$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| $Test\#$ | $n$ | $m$ | Number of set covers | | Residual energy | | Reliability | |
| | | | $r_1 = 150$ | $r_1 = 250$ | $r_1 = 150$ | $r_1 = 250$ | $r_1 = 150$ | $r_1 = 250$ |
| 1 | 10 | 25 | 7.2000 | 4.8000 | 0.7800 | 0.8748 | 0.2138 | 0.3069 |
| 2 | | 50 | 16.0000 | 11.3000 | 0.9862 | 0.9781 | 0.3253 | 0.4518 |
| 3 | | 75 | 19.8000 | 14.1000 | 0.9893 | 0.9849 | 0.3285 | 0.4706 |
| 4 | 15 | 25 | 5.9000 | 4.7000 | 0.8645 | 0.9331 | 0.3320 | 0.5391 |
| 5 | | 50 | 9.4000 | 8.9000 | 0.9658 | 0.9648 | 0.4852 | 0.5550 |
| 6 | | 75 | 15.9000 | 12.0000 | 0.9771 | 0.9762 | 0.4770 | 0.6145 |
| 7 | 20 | 25 | 4.1000 | 4.1000 | 0.5582 | 0.7317 | 0.3170 | 0.9598 |
| 8 | | 50 | 10.8000 | 9 .3000 | 0.9639 | 0.9556 | 0.9160 | 0.9990 |
| 9 | | 75 | 15.4000 | 11.0000 | 0.9650 | 0.9692 | 0.9654 | 1.0000 |
| 10 | 25 | 25 | 2.4000 | 4.9000 | 0.3669 | 0.9000 | 0.2395 | 0.1949 |
| 11 | | 50 | 9.2000 | 6.5000 | 0.9489 | 0.9306 | 0.7334 | 0.9928 |
| 12 | | 75 | 13.3000 | 8.1000 | 0.9650 | 0.9692 | 0.9416 | 0.9992 |

**Table 2**-Performance of $MO - ARSC$ in terms of $average$ number of complete set covers, average residual energy, and average reliability for 10 WSNs in each test case where $number\ of\ sensors: m = \{100,125,150\}$, $number\ of\ targets: n = \{10,15,20,25\}$, $initial\ energy\ for\ each\ sensor: E = 1000$, and $r_1 = \{150, 250\}$.

| $MO - ARSC$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| $Test\#$ | $n$ | $m$ | Number of set covers | | Residual energy | | Reliability | |
| | | | $r_1 = 150$ | $r_1 = 250$ | $r_1 = 150$ | $r_1 = 250$ | $r_1 = 150$ | $r_1 = 250$ |
| 1 | 10 | 100 | 21.6000 | 18.6000 | 0.9889 | 0.9889 | 0.3595 | 0.4433 |
| 2 | | 125 | 30.8000 | 20.8000 | 0.9912 | 0.9912 | 0.3882 | 0.4609 |
| 3 | | 150 | 32.8000 | 20.6000 | 0.9937 | 0.9937 | 0.3790 | 0.4583 |
| 4 | 15 | 100 | 21.4000 | 15.5000 | 0.9828 | 0.9840 | 0.4847 | 0.5668 |
| 5 | | 125 | 24.6000 | 19.1000 | 0.9851 | 0.9843 | 0.4946 | 0.5921 |
| 6 | | 150 | 27.5000 | 20.8000 | 0.9858 | 0.9882 | 0.5310 | 0.5975 |
| 7 | 20 | 100 | 18.0000 | 14.2000 | 0.9733 | 0.9738 | 0.5287 | 0.6541 |
| 8 | | 125 | 21.8000 | 18.2000 | 0.9815 | 0.9800 | 0.5178 | 0.6387 |
| 9 | | 150 | 23.5000 | 20.5000 | 0.9822 | 0.9812 | 0.5359 | 0.6832 |
| 10 | 25 | 100 | 16.6000 | 11.9000 | 0.9669 | 0.9728 | 0.5740 | 0.6801 |
| 11 | | 125 | 19.4000 | 13.1000 | 0.9734 | 0.9747 | 0.6048 | 0.7325 |
| 12 | | 150 | 20.8000 | 14.4000 | 0.9761 | 0.9805 | 0.6000 | 0.6848 |

## 6. Conclusion

This paper introduces a new set covers optimization problem to solve two main design issues in WSNs. Both network's lifetime and coverage reliability are the main parameters that reflect the design of the proposed adjustable range set covers (ARSC) optimization model. The proposed model adds to the existing ARSC models an additional parameter: the sensing model of the sensors. While all of the existing ARSC models assume the traditional Boolean sensing model, the proposed model concerns with more realistic sensing model. The proposed model is formulated as a multi-objective optimization problem (MO-ARSC) and solved using one of the well known multi-objective evolutionary algorithms (MOEA/D). Moreover, the general layout of MOEA/D is suggested to operate in multi-wise layers. The quality of set covers generated from the proposed multi-layer MOEA/D are quantified in terms of their cardinality, residual energy, and coverage reliability. Moreover, the evaluations consider the impact of varying total number of sensors, and varying their sensing abilities. The results report that the behavior of the proposed MO-ARSC model matches expectation by means of increasing total number of sensors and/or increasing sensing ranges.

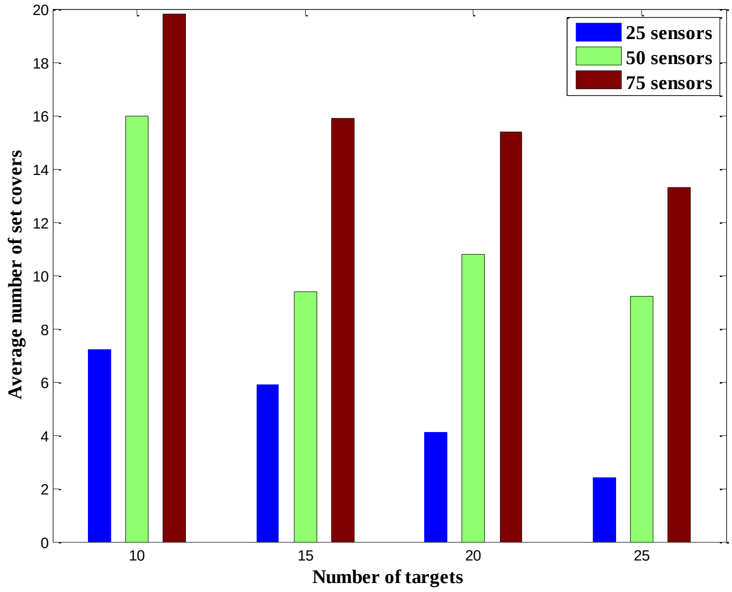


**Figure 1-** Average number of set covers when number of targets $n = \{10, 15, 20, 25\}$, number of sensors $m = \{25, 50, 75\}$, and $r_1$ =150.

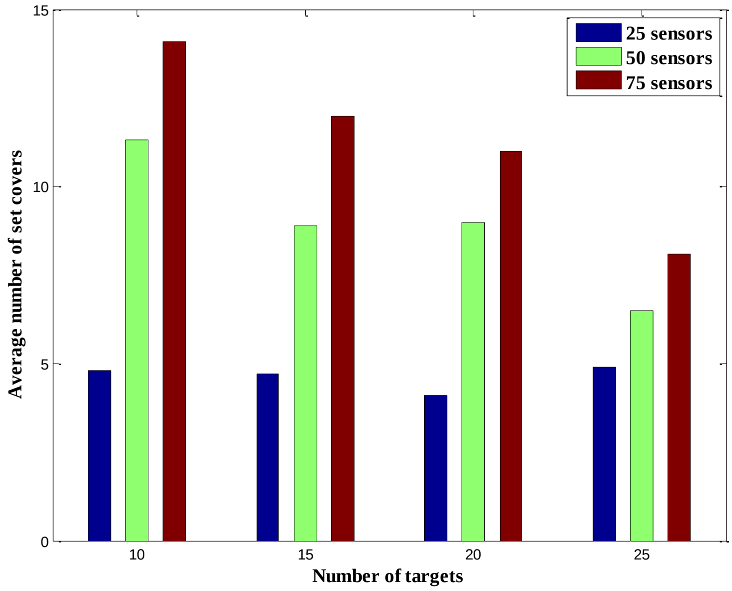


**Figure 2-**Average number of set covers when number of targets $n = \{10, 15, 20, 25\}$, number of sensors $m = \{25, 50, 75\}$, and $r_1$ =250.

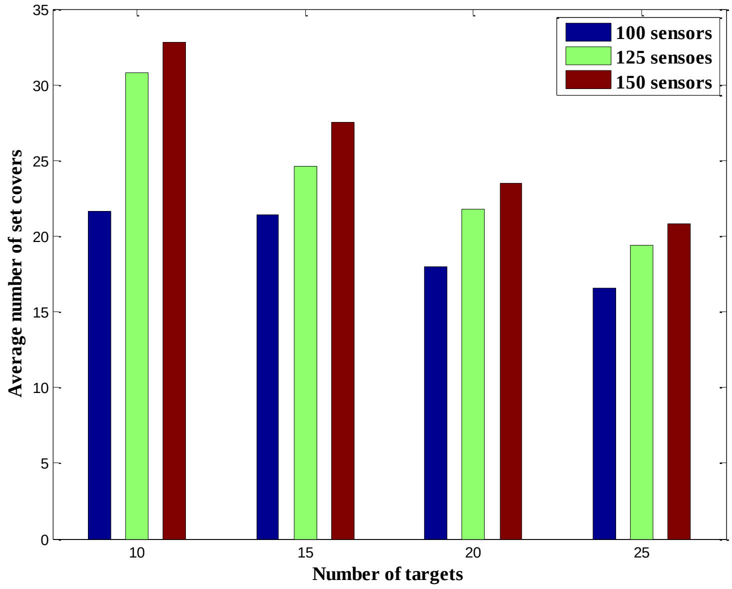


**Figure 3-**Average number of set covers when number of targets $n = \{10, 15, 20, 25\}$, number of sensors $m = \{100, 125, 150\}$, and $r_1$ =150.

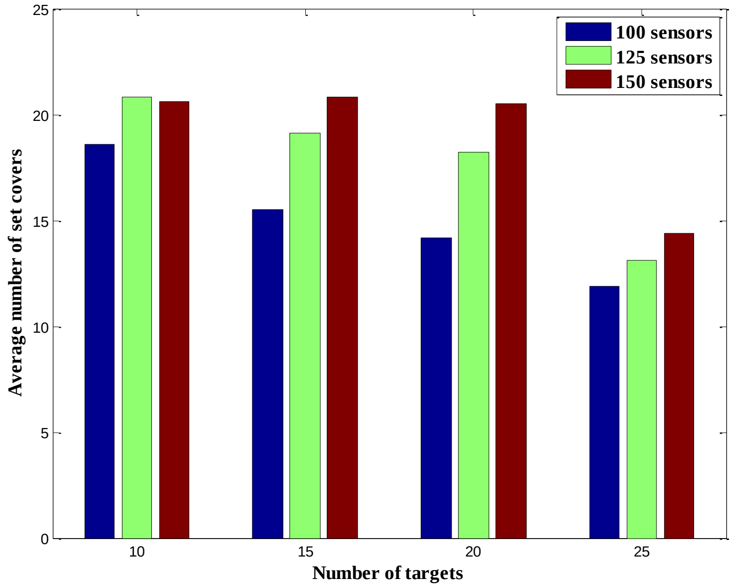


**Figure 4-** Average number of set covers when number of targets $n = \{10, 15, 20, 25\}$, number of sensors $m = \{100, 125, 150\}$, and $r_1$ =250.

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