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NDSC based Methods for Maximizing the Lifespan of Randomly Deployed Wireless Sensor Networks for Infrastructures Monitoring

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Abstract

This paper addresses the problem of wireless sensor network (WSN) lifetime maximization, under limited available energy constraint. The investigations have shown that the valid amount of energy was not used by the existing disjoint set covers (DSC) based scheduling method for WSNs' lifetime maximization, because of the DSC constraints. Instead, we suggest in this paper to schedule non-disjoint sets covers (NDSC) for maximizing WSNs' lifetime. Thus, we have formulated this problem, using the integer linear programming (ILP) mathematical model, then we developed an approach based on genetic algorithm GA to find the maximal lifespan. As main contributions, we investigated and designed a new method using the NDSC instead of the DSC. This approach removes the latter's constraint and gives the opportunity to a sensor to participate in more than one cover, and thereby improves significantly the WSNs' lifetime. We proposed an exact method and a genetic algorithms (GA) for the NDSC efficient scheduling for the WSN lifetime maximization. The exact method lies on the integer linear programming (ILP). For the GA based heuristics, we used a specific arrangement of chromosomes combining several crossover and mutation strategies for encoding the solutions. We provided experimental results for different instances involving sensors with non-identical amount of initial energy and power consumption. In addition, we provided comparative analysis results between the solutions obtained by our both methods and the existing methods based on DSC. The comparisons of the run times and the solutions' quality revealed the dominance of the solutions yielded by our methods based on the NDSC compared to those based on the DSC.

Keywords: Non-Disjoint Sets Covers, Wireless sensor network, Lifetime, Set covers, Maximization, Integer linear programming, Genetic algorithms

1. Introduction

Wireless sensors are small components with limited amount of energy and resources for processing, transmitting and receiving data. In a network, sensor nodes are used to sense, measure and gather data from the environment or from specific targets. A WSN typically has little or no infrastructure. It consists of several sensor nodes (few tens to thousands) working together to monitor and to collect data on a set of targets or in the environment in a given location [1]. On request, they can transmit

the sensed data to some decision support system. Sensor nodes may communicate not only with each other but also with a base station (BS) using their wireless radio, allowing them to send their data to remote systems for data processing, visualization, analysis, and storage. Involved sensors are often low-cost, low-power and multi-functional devices incorporating transceiver, processing unit, storage unit and electrical battery. The problem in this paper addresses embedded wireless sensor networks management of data collection for inspections, surveillances and degradations monitoring of long-life engineer-

applications of WSNs are intended to monitor a region or a set of targets. To ensure that the areas or targets of interest can be covered, sensors are randomly deployed in large numbers. Possible major states of a sensor in WSN can be either active or in sleep, where active state can belong to three possible modes: transmitting signal, receiving signal and idle (state which not engages to transmitting neither receiving signal).

The lifetime of a network is defined as the time elapses until any active set of sensors fails to satisfy the required coverage [3].

In order to extend the lifetime of a sensor network while maintaining coverage, a minimal subset of the deployed sensors is kept active while the other sensors can sleep. Then, the problem is to determine how long to use a given subset of sensors and which subset is to be used next in a scheduling approach [4]. This minimal subset of sensors could be noted as cover according to the following definition.



Definition 2. Cover of targets

Given a finite set $S = \{s_1, s_2, \dots, s_m\}$ of m sensors and a finite set $T = \{t_1, t_2, \dots, t_n\}$ of n targets, an element denoted C_l of the collection C of sensors subsets is a cover for the subset of targets denoted $T(C_l)$, if it can sense all the targets of $T(C_l) \subseteq T$, ($l \in \{1, \dots, q \leq m\}$), where:

- Each target t_j is covered by at least one sensor of S ,
- Each sensor s_i sense a subset $T(s_i) \subseteq T$ of targets.
- For all $i \neq j$, $T(s_i) \cup T(s_j) = T(s_i, s_j)$ is a subset of targets sensed by the pair (s_i, s_j) .
- A subset C_l is considered as a cover if $T(C_l) = T$

Thus, the WSNs lifetime could be optimized by finding the maximum number of covers with the maximal time that a cover could be used. The common method is to use each sensor in one cover for all its available energy and life according to a disjoint set covers (DSC) mode.

Definition 3. Disjoint Set Covers DSC [5]

Given a collection $C = \{C_1, C_2, \dots, C_q\}$ of subsets of S , a disjoint set cover $C_l \in C$ is a part of S denoted as $S(C_l)$ such that all element of S belongs to one and only one cover C_l ($l = 1, \dots, q$) and $Card[S(C_l)] \leq m$, i.e., for all $l \neq h$, $C_l \cap C_h = \emptyset$.

From the two above definitions, the WSNs lifetime maximization problem, based on energy consumption op-

2. Problem statement

The wireless sensors are often loaded with limited amount of energy and computational resources. The energy is stored on electrical batteries and once the batteries are exhausted, the sensor is considered to be dead. Most of the

timization, could be viewed as a combinatorial optimization problem, aiming at finding the best combinations of the sensors sets that maximizes the sensor network lifetime.

Many researchers have addressed the issue of energy consumption optimization through scheduling in generic wireless sensor networks. In these works, new constraints about sensing coverage have been introduced by their distributed sensing requirements [6].

Effective and popular optimal scheduling methods have emerged for solving complex engineering optimization problems in recent years. Approximative and bio-inspired optimization heuristics and metaheuristics, such as genetic algorithms (GAs), simulated annealing, ant colony, neural network and fuzzy logic have been exploited too. The optimizations problem are generally modeled by using related data, objective function and constraints [7].

Mathematical programming, including (integer) linear programming based methods, and metaheuristic approaches are two highly suitable streams for solving combinatorial optimization problems (COPs). These two approaches have been worked out by different research communities more or less isolated from each other. The available methods for solving COPs may roughly be classified into two main categories: exact and heuristic algorithms. Exact methods can find an optimal solution and its optimality can be proved for every instance of a COP. But, their running-time can dramatically be huge for large size problem instances. Consequently, only small or moderately-sized instances can be practically solved to optimality. For larger instances, the only possibility is usually to turn to heuristic algorithms to ensure a reasonable compromise between solution quality and computation time [8].

In this context, many works have been in particular elaborated on evolutionary methods. As an example, for the GAs, the term chromosome typically refers to a candidate solution to a problem, often encoded as a string of characters, or numbers or bits. The genes are either single bits or short blocks of adjacent bits or characters that encode a particular element of the candidate solution [9].

In this paper, the ILP based method in [10] and the GA based method introduced in [11] are extended, improved, evaluated and compared to another method from the literature. The proposed methods have been used to solve the

problem of randomly deployed wireless sensors network lifetime optimization, formulated as set covers scheduling problem.

3. Related works

This section mainly introduces the techniques used for sensors activity scheduling and for the optimization of a sensor network lifetime. There are several methods used to solve this problem, and one will notice that most of them rely on approaches using the DSC as a decision meta-variable. The investigated methods could be gathered into two categories of lifetime maximization: 1) exact mathematical programming methods, 2) heuristics based on DSC approach. In this paper, we formulate the problem using NDSC as a meta-variables and we propose a mathematical programming formulation. We found the exact solution using this model. In addition, we sought the optimal solution in reasonable time using the genetic algorithm.

3.1. Exact methods of the lifetime maximization

Exact methods can lead to an optimal solution if we are given a sufficient time. As stated earlier, a simple enumeration is out of question, and consequently exact methods must use more clever techniques. The worst case running time for NP-hard problems are still going to be high though [12]. In [13], the problem of maximizing the sensors network lifetime has been formulated as a linear programming problem, considering the energy cost for data sensing, receiving and transmitting. The linear programming technique has been used to compute the maximum lifetime of the WSN and a workload matrix. Then, the workload matrix has been decomposed into a sequence of schedule matrices to achieve the maximum lifetime. In [14], the linear programming has been used to figure out the state of each individual sensor node either active or sleep, while preserving the network coverage and minimizing energy consumption. A search in 2^n possible combinations is necessary to find the schedulings with the lowest energy solution for this NP-hard problem, where n is the number of sensors. The authors have demonstrated that linear programming can find the minimum number of nodes in working condition and can achieve the maximum network coverage. Authors in [15] have used the integer

programming and some greedy heuristics to maximize the lifetime of a WSN with adjustable sensing ranges. They observed that adjustable sensing ranges have a great impact on the network lifetime. Sensors with two coverage ranges and the possibility for a sensor to be included in more than one cover have been considered.

The ILP has been used in [16] to formulate the maximum lifetime broadcasting problems in WSNs. The authors have showed that a model like ILP, often regarded as over-theoretical and unrealistic, is indeed a suitable framework to solve some problems in energy consumption and communication in WSNs. In [17], an ILP approach has been used alone and with GA approach as ILP+GA to address the problem of lifetime maximization of directional sensor networks. The authors have found that the ILP+GA approach is about 4.74 times faster in average over all instances than the approach based on ILP alone.

3.2. Heuristic and metaheuristics based on DSC

The problem of WSNs lifetime maximization is widely solved by a transformation to a DSC maximization problem which is defined as it follows.

Consider a set $S = \{s_1, s_2, \dots, s_m\}$ of sensors used to monitor a set $T = \{t_1, t_2, \dots, t_n\}$ of targets. The objective function is the number of disjoint set covers as a representation of the network lifetime under the following restrictions:

- A sensor can be included into one set covers at most.
- Sensors in each disjoint set cover should be able to monitor all the targets.

The DSC problem has been proved to be NP-Complete in [5], on the basis of partition properties in sets theory. From all our investigations, all those methods leave a number of viable sensors out-of all covers, and thus unused over the network lifetime. Example 1 in Section 4 shows that the DSC does not yield an optimal energy consumption in all cases. In [3], a period iteration and sequential assignment heuristics have been developed to maximize the network lifetime by using the maximum number of DSC, based on the sensors deployment and the sink node mobility. The authors in [5] observed that the number of disjoint set covers increases when the number

of sensors and the sensing range increase. They transformed the problem of disjoint set covers maximization into maximum-flow problem (MFP) for maximizing the number of DSC. In [18], authors have used the genetic algorithm to find the maximum number of DSC, and they have determined an upper bound by using critical targets. The sensors were randomly clustered as coverage candidates subsets. A genetic algorithm, with a reconfiguration operator and a fitness function, were used to find satisfactory solutions and enhance WSNs lifetime [19]. Using the binary integer programming formulation and heuristics, authors in [20] maximized the number of disjoint set covers for extending the WSNs lifetime. In [21], the targets system is an indoor area divided into fields of points according to a finite resolution, where each sensor can cover one or more fields. The authors extracted k -DSC set and had developed a heuristic for this problem.

In a more general context, heuristics are typical methods that can relatively quickly select a better candidate from feasible solutions with reasonable quality. There are no guarantees about the solution quality, which can be bad. The heuristics are tested empirically and the conclusions can be made about the quality of the their solutions, based on these experiments. Heuristics were typically used for solving real-life problems because of their speed and their ability to handle large instances [12]. Optimal algorithm and heuristics were used in [7] for sensors activation/deactivation considering the coverage constraint and the target system health condition monitoring, to maximize the targets monitoring time. GA in [22] and graph based heuristic algorithm in [20] were used to optimize WSNs lifetime by using DSC. Authors in [22] showed the possibility to find near-optimal solutions within polynomial computation time. The more sensor covers can be found, the longer sensor network lifetime can be prolonged. Authors in [23] used the greedy algorithm for scheduling targets coverage with directional sensor networks (DSN). The authors addressed the lifetime maximization issue via the maximum set covers for DSN. Then, they presented their targets coverage scheme. Authors in [24] introduced a heuristic procedure for solving this problem. They developed two greedy-based algorithms for solving the targets coverage problem in WSNs with adjustable sensing ranges. They used the critical targets as a bottleneck for the network lifetime to identify an

upper bound on the maximum operation time of the network. In [25], the authors presented some greedy-based heuristic approaches and an exact approach. They considered an upper bound similar to that used in [24].

4. Problem formulation

This section explains the WSNs lifetime maximization problem by the maximization of DSC and their optimal scheduling. As notations, $S = \{s_1, s_2, \dots, s_m\}$ is a set of sensors, $T = \{t_1, t_2, \dots, t_n\}$ is a set of targets, $S(t_j)$ is a set of sensors that can cover target j , $T(s_i)$ is a set of targets allocated in the coverage area of sensor i , E_i is the initial energy of sensor i , C_l is a subset of sensors that can cover all targets and L is the network lifetime to be maximized. The following basic properties can be observed.

Property 1. Given the previous notations, the WSN lifetime is extendable if and only if $T(S) = T(s_1, \dots, s_m) = T$.

Property 2. Solving the WSNs lifetime optimization problem as DSC problem amounts to finding the maximum number of DSC for S .

Proof. With definition 1 and assuming property 1, $T = \cup_p T(s_p) = T(s_1, \dots, s_m)$, and from Definition 2, $S = \cup_l C_l$ where the C_l are partitions of S . It is then obvious that the set of all the sensors can sense all the targets on only one time period, while consuming the energy of all the sensors. Assume now that there is a partition of S into two covers C_1 and C_2 such that $T(C_1) = T(C_2) = T$ with $T(C_1) \cap T(C_2) = \emptyset$, then the covers C_1 and C_2 can be scheduled to sense all the targets during two distinct time periods. Thus, increasing the number of disjoint set covers will correspondingly increase the number of period of operation of disjoint subsets of sensors. ■

Consider the WSNs lifetime optimization problem formulated as DSC maximization problem. All the methods introduced earlier and used to solve it don't always result in an optimal energy utilization and the maximum lifetime of the network. Indeed, these methods often leave a number of viable sensors unused, due to the DSC constraint. Besides, the sensors must be initially loaded with the same energy quantity and consume it at the same rate. In this work, we proposed, investigated and designed an NDSC based approach that relying on covers finding and

scheduling methods, which allows improving existing solutions to this problem. Solving this problem using NDSC removes the DSC constraint and gives the opportunity to a sensor to participate in more than one cover. This allows to maximize the energy utilization and to extend the lifetime of a WSN. This approach offers: 1) the possibility to prolong the WSNs lifetime using suitable algorithms, 2) the possibility for the algorithms to be implemented for not-identical sensors that can be involved in more than one cover, and 3) the possibility to reduce a sensor failure effect on the network lifetime and to maximize the network availability. The contribution of this work could be seen behind the formulation of the WSNs lifetime maximization as a scheduling problem, the mathematical modeling and the methods developed to solve it using a NDSC-based approach compared to existing DSC-based ones. The difference between the DSC-based approaches, and the NDSC-based approach proposed in this paper is the promising possibility of the latter to prolong the WSN lifetime and to be tolerant to some sensors failure. Such a possibility is illustrated starting with Example 1.

Example 1: NDSC illustration

Let $T = \{t_1, t_2, t_3, t_4\}$ and $S = \{s_1, s_2, s_3\}$, where $T(s_1) = \{t_1, t_2, t_4\}$, $T(s_2) = \{t_2, t_3, t_4\}$ and $T(s_3) = \{t_1, t_3, t_4\}$. Clearly, the maximum number of DSC is 1 and therefore the network lifetime is 1 monitoring season with one sensor not included. By cons, if the sensors operated in NDSC "regardless of DSC constraint" as it follows: s_1, s_2 for 0.5 unit of time, s_2, s_3 for 0.5 unit of time, and s_1, s_3 for 0.5 unit of time, the lifetime is 1.5 time unit [26] as depicted in Figure 2.

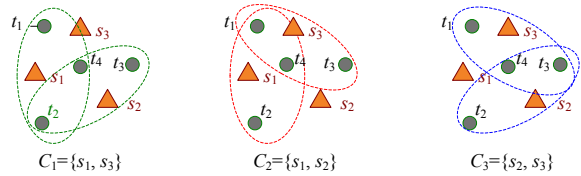


Figure 2: Sensors selection in covers.

Therefore, the schedule of sensors can be formulated as: $S = \{s_1, s_2, s_3\}$ and $T = \{t_1, t_2, t_3, t_4\}$, with $T(s_1) = \{t_1, t_2, t_4\}$, $T(s_2) = \{t_2, t_3, t_4\}$ and $T(s_3) = \{t_1, t_3, t_4\}$. The maximum possible number

of covers $q = 3$ as in Figure 2. These NDSC can be scheduled as in Figure 3.

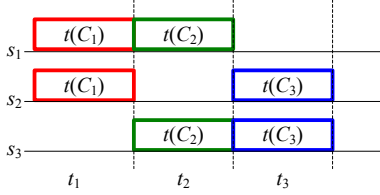


Figure 3: Covers scheduling.

Thus, the sum of $t(C_l)$ is the objective function, considering the sum of energy consumption $E_i(C_l)$, where sensor i is included " $x_{il} = 1$ " and the energy of each sensor i must not exceeds E_i .

$$L = \sum_{l=1}^3 t(C_l) \quad (1)$$

subject to:

$$\begin{aligned} \sum_{l=1}^3 x_{il} E_i(t(C_l)) &\leq E_i \text{ for } i = 1, 2, \text{ and } 3 \\ E_1(t(C_1)) + E_1(t(C_2)) &\leq E_1 \\ E_2(t(C_1)) + E_2(t(C_3)) &\leq E_2 \\ E_3(t(C_2)) + E_3(t(C_3)) &\leq E_3 \end{aligned} \quad (2)$$

When the schedule satisfies these constraints, then the WSN lifetime is:

$$L = \sum_{l=1}^3 t(C_l) = t(C_1) + t(C_2) + t(C_3) \quad (3)$$

The optimal solution is

$$L = 1.5E \text{ with } t(C_1) = t(C_2) = t(C_3) = 0.5E.$$

When the DSC are used, it is clear that the maximum number of DSC (and the network lifetime) is $1E$ with one sensor never included.

Example 1 gives an indication that the lifetime can be extended by better using NDSC than DSC. This is possible if there are one or several sensors, which can use

parts of their lifetime and their energy in a cover, and then use the remaining parts of their lifetime and their energy in other joint covers. The proposed methods consider all possible covers to find out the optimal scheduling solution with the possibility for all sensors to be included in one or more covers.

To solve the lifetime maximization problem using NDSC, one must find first the maximum number of NDSC, then the optimal period of time to be scheduled for each NDSC so as to maximize the WSN lifetime. To find the NDSC, we worked out a method based on binary coverage relations matrix; then we developed an ILP mathematical model for NDSC scheduling for the lifetime maximization. We used the basic ILP model to find an exact solution and a GA to search for a near-optimal solution in a reasonable computation time. The next section explains our methods proposed for WSNs lifetime optimization using NDSC.

5. The proposed methods

This Section presents the approach for identifying the NDSC used in the methods introduced in this paper. First, Subsection 5.1 details the construction approach of sensors coverage relations matrix, used for finding the NDSC by the available sensors. Those relations link sensors and targets into covers. Then, in Subsection 5.2, the ILP mathematical model of the problem is derived using the entries of the coverage relations matrix. Then, the Subsection 5.3 proposes an exact method of NDSC scheduling based on the ILP model for maximizing the network lifetime. Lastly, the Subsection 5.4 develops the heuristic that we proposed from the NDSC based ILP model and a GA of scheduling the covers for WSNs lifetime maximization. For purposes of comparison and evaluation, Subsection 5.5 recalls the GA suggested by authors in [18] for scheduling DSC and maximization of WSN lifetime.

5.1. The binary coverage relations matrices

These matrices are used for sorting the randomly deployed network to find all possible covers. The first matrix, denoted Δ , describes the coverage relations for individual sensors. Indeed, after random deployment of the sensors, each sensor $s_i \in S$ is localized through coordinates (x_i, y_i) , just as is each target $t_j \in T$ by coordinates

(x_j, y_j) . Therefore, t_j is covered by s_i if the distance between them is less than or equal to the coverage range d of s_i . For a random distributed set S of sensors and set T of targets to be monitored, each sensor s_i can cover a set of targets $T(s_i) \leq T$. Assume a set of q covers could be found from randomly deployed sensors set S and a set T of targets. Then one can find the q covers through the coverage relations matrix denoted V , using the individual coverage relations matrix Δ , in two steps as it follows:

1. Create the individual cover relations matrix Δ :

$$\Delta = (\delta_{ij}) = \begin{pmatrix} \delta_{11} & \delta_{12} & \dots & \delta_{1n} \\ \delta_{21} & \delta_{22} & \dots & \delta_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \delta_{m1} & \delta_{m2} & \dots & \delta_{mn} \end{pmatrix}$$

$$\delta_{ij} = \begin{cases} 1 & \text{if sensor } i \text{ can cover target } j \\ 0 & \text{otherwise} \end{cases}$$

In this matrix, a row i includes the set $T(s_i)$ of targets that sensor s_i covers and each column j includes the set $S(T_j)$ of sensors that can cover target t_j .

2. Create the set covers matrix V , which models the relations between sensors and covers for m sensors and q covers:

$$V = (v_{li}) = \begin{pmatrix} v_{11} & v_{12} & \dots & v_{1m} \\ v_{21} & v_{22} & \dots & v_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ v_{q1} & v_{q2} & \dots & v_{qm} \end{pmatrix}$$

$$v_{li} = \begin{cases} 1 & \text{if sensor } i \text{ is included in cover } l \\ 0 & \text{otherwise} \end{cases}$$

Due to the binary relations of sensors into covers, the total number of possible covers is $q = 2^m - 1$. In this matrix V , a row is a potential cover. The solutions set will include this cover if the latter can cover all the targets as a constraint. The following steps intend to find from V the set covers that can meet the total coverage constraint.

- 1) Thus, for each row in V , the set of targets covered by the included sensors must be equal to T .

Now, finding a set cover with minimum number of sensors in V is possible. From the previous step, each row with a set of sensors covering totally all targets is a candidate cover. The summation of each row in V gives the number of sensors in this cover.

- 2) Thus, finding the cover with minimum sensors is finding the row with minimum sum.

Recall back the DSC, when the covers are found, there is no additional efforts required for scheduling and finding the optimal energy distribution through the covers because there is no shared sensor among DSC. Now removing the DSC constraint, a sensor has the opportunity to join more than one cover. To maximize lifetime, we solved a second subproblem consisting of determining the maximum time a sensor from S must spend with each cover. The following subsection summarizes the mathematical model of this problem and presents an exact method and a heuristic for solving it.

5.2. The mathematical model

For a set $S = \{s_1, s_2, \dots, s_m\}$ of sensors used to cover a set $T = \{t_1, t_2, \dots, t_n\}$ of targets, the problem of the network lifetime maximization consists in finding subsets from S that can cover all the targets in T . Finally, the problem amounts to finding a maximum number of cover subsets that must be optimally scheduled to maximize the number of periods during which the targets will be covered and so for the maximum lifetime.

5.2.1. The objective function

Assume the cover C_l is scheduled to monitor the targets T on a number of period k of time units equal to y_l and the maximum possible number of covers is q , then, to maximize the lifetime is expressed as:

$$\text{Maximize } \sum_{l=1}^q y_l \quad (4)$$

5.2.2. The constraints

The total energy consumed by each sensor s_i cannot exceed its initial energy reserve E_i . So, if the total energy consumed by a sensor s_i on the period of time k is $E_i(k)$ and sensor s_i can be included in every cover C_l , which can be scheduled for a number of periods y_l , ($l = 1, \dots, q$ and $v_{il} = 1$), then the energy constraint is expressed as:

$$\sum_{l=1}^q v_{il} E_i(y_l) \leq E_i \quad i = 1, 2, \dots, m \quad (5)$$

where

$$v_{il} = \begin{cases} 1 & \text{if sensor } i \text{ is included in cover } l \\ 0 & \text{otherwise} \end{cases}$$

Therefore, the optimal solution is that can give the values of y_1, y_2, \dots, y_q with a maximum sum, while not exceeding the sensors initial energy E_i . We used the ILP and GA respectively for exact and heuristic methods to solve this problem as described in the next subsections.

5.3. The ILP based method

Let's recall that the ILP refers to the class of combinatorial constrained optimization problems with integer variables, where the objective function is a linear function and the constraints are linear inequalities [27]. Based on subsection 5.1, we can determine the number q of covers that must be scheduled to maximize the lifetime. As mentioned earlier, different methods are used in the literature to maximize the lifetime, based on DSC with various strategies and genetic algorithms. We designed a linear programming model for the lifetime as an objective function to be maximized and the energy consumption for each sensor as constraints to not be exceeded as in subsection 5.2.

If a cover C_l is scheduled to monitor the targets T for a number of periods of time y_l with k units of time for each period, and if the maximum possible number of covers is q , then the lifetime is expressed as:

$$L = k \sum_{l=1}^q y_l \quad (6)$$

Assume that a sensor s_i consumes $E_i(k)$ as energy on the time period k and each sensor $s_i \in S$ can be included in every cover C_l , then the sensor s_i consumes as energy, $E_i(y_l)$ on all periods where covers C_l were scheduled.

Now, consider that the total of energy consumed cannot exceed its initial reserve of energy E_i then:

$$\sum_{l=1}^q v_{il} E_i(y_l) \leq E_i \quad i = 1, 2, \dots, m \quad (7)$$

Consider now a WSN with m sensors and q possible covers. Equation 7 can be used to generate m linear inequality constraint equations with q unknowns. Therefore, the linear programming optimization technique can

be used to find out the values of the unknowns that optimize the linear objective function L in Equation 6.

When each sensor $s_i \in S$ has a constant initial energy E_i and consumes a constant amount of energy $E_i(k)$ on the period of time k , the maximum possible number of utilization periods for sensor s_i and so for cover $l \in \{1, 2, \dots, q\}$ that includes sensor i is $E_i/E_i(k)$. Therefore, the number of periods y_l on which cover C_l can be scheduled is bounded for all cover $l \in \{1, 2, \dots, q\}$, as

$$0 \leq y_l \leq E_i/E_i(k) \quad l = 1, 2, \dots, q \quad (8)$$

When the number of covers increases, the number of unknowns increases. The simplification method in [10] is used to enhance the performance of the algorithms.

5.4. The GA based method

In evolutionary algorithms, genetic programming began as a general approach of adaptive process, but has since become effective optimization strategy [28]. By the end of subsection 5.1, we obtain a number q of covers that should be scheduled to maximize the network lifetime. As mentioned earlier, different methods are used in the literature to solve the lifetime maximization problem using DSC and linear programming, with many strategies. We developed a simple effective scheduling method using genetic algorithm as follows:

1. *Coding.* A chromosome represents the battery lifespan by using a vector of integer values, lying between zero and the initial energy E_i divided by the energy cost of activation on the period of time k ($E_i(k)$) of sensors. Each gene represents the number of scheduling periods for each cover, where the number of genes, which is the vector length, is equal to the number q of covers.
2. *Initialization.* Randomly generate the initial population of limited number of chromosomes and calculate the sum of genes for each chromosome, as in Figure 4. The sum of genes in the chromosome represents the total number of periods that all covers are scheduled. Thus, for each chromosome, the lifetime can be calculated by the sum of genes in the chromosome multiplied by the period time length k .

Periods for C_1	Periods for C_2	...	Periods for C_q
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Figure 4: Genetic algorithm chromosome illustration.

3. *Fitness.* The fitness aims to ensure that all sensors in the candidate solution did not exceed the energy constraint. For a sensor $s_i \in S$, the total energy consumed through all covers in a schedule must not exceed the initial energy E_i , which discard schedule that not meet this constraint from the population.
4. *Selection.* From the fit population members, select the best two schedules with the maximum lifetime (sum of genes) as parents.
5. *Crossover.* A suitable crossover is applied to generate children and update the population. We used single and dual crossovers with randomly selected crossover genes.
6. *Mutation.* A suitable mutation is applied to enhance the children. One or more genes can be updated. We consider that the enhancement increases the genes value, and thus, increases the sum of the chromosome. The mutation genes are selected randomly. We investigated two increasing strategies: 1) deterministic by adding a constant value to the previous value of the selected gene, and 2) randomized by adding a randomly generated value.
7. *Children fitness.* Regarding the energy consumption in Equation (5), the fitness of the children (new chromosomes) is applied again to make sure that no sensor exceeds its initial energy and the parents are updated if new enhanced children are better.

New generations may be obtained by continuously repeating the above stages until a specific upper bound or the specified number of generations is reached.

5.5. The DSC-GA method in [18]

Authors in [18] have proposed a GA for maximum DSC (DSC-GA), where the chromosome representation, selection, crossover and mutation, in addition to operator called scattering, are applied to the offspring.

- Initialization: each sensor randomly joins a group among prescribed groups.

- Selection: a group forms a cover if it can cover all targets.
- Upper Bound: they considered that if a target is only covered by k sensors as minimum, it is impossible to find more than k disjoint covers. Thus, the number of the prescribed groups is used as an upper bound (ub) of the number of covers.
- Fitness: the fitness of a chromosome is defined as the number of DSC that can be found by grouping combinations represented by the chromosomes.
- Crossover: uniform crossover exchanges each gene of the two parents.
- Mutation: mutation changes a randomly selected gene by a random value from 1 to ub to generate a new solution.

6. Simulation and results

In this section, we describe the simulation environment for the ILP-based exact method and the GA-based heuristic. Experimental results for each method on different instances are described. Then, the results obtained by the GA based heuristic results are compared to those obtained by the ILP-based exact method on the same instances. Additional results and comparisons to DSC-GA as an existing method from the literature are also provided.

6.1. The GA based heuristic

The methods is coded in the C language on Widows7 and Intel inside core TM^{i7} EliteBook computer. The primary scheduling data (number of sensors, number of covers, set cover matrix V , initial energy E_i and energy consumption rate $E_i(k)$ for a given period k) are required to run the program in addition to the randomly deployed sensor network.

Based on the results of this network deployment and initialization, the program runs the genetic algorithm for a given number of generations to obtain the NDSC schedule with the maximum lifetime.

We considered for our study by simulation, as in Table1, a WSNs where 10 sensors monitoring 5 targets are deployed randomly in a 10×10 area. The initial energy of each sensor is E_i unit and the energy consumption for a specified period k unit of time is $E_i(k)$. The possible number of covers found is 644. Each cover can be

scheduled for zero or more times and the sum of scheduled periods of all covers are generated as column lifetime in the table. Therefore, the lifetime is computed by multiplying the value in this column by k as mentioned earlier. Table 1 displays the maximum lifetime for 160 units initial energy with different rates of energy consumption. GAs with single crossover point and a single mutation point (GA11), a single crossover point and dual mutation point (GA12), dual crossover point and a single mutation point (GA21) and dual crossover point and dual mutation point (GA22) with deterministic and randomized mutation strategies were tested. While the population size can affects the performance of GA [28], small size population of 50 to 1200 generations and larger size population of 100 to 1200 generations were investigated.

A simple comparison is made between the mutation strategies regarding the number of generations and the nearness of the solution to the optimal. One remarks that the GA12 results are better than GA11 for the same number of generations as in Figure 5. The GA12 takes 1250 generation to obtain the best solution while GA11 takes 2250.

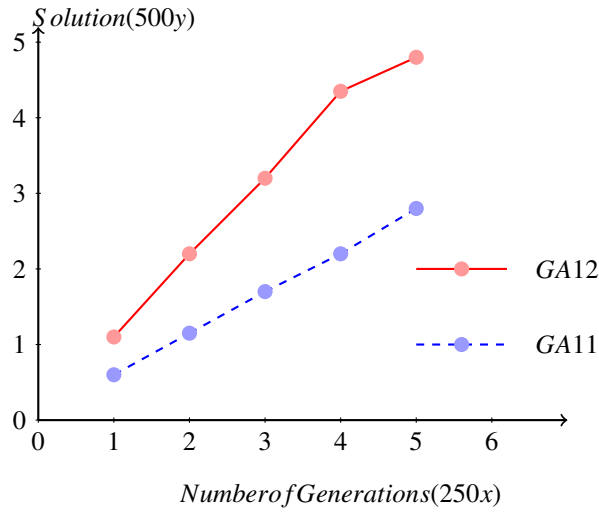


Figure 5: GA11 via GA12.

Consider now the deterministic and randomized mutation strategies. We made a simple comparison between them regarding the number of generations and the nearness of the solution to the optimal. One notices that the

randomized GA11 yields better results than the deterministic GA11 for the same number of generations as in Figure 6. The deterministic GA11 took 1250 generation to obtain the best solution while the randomized GA11 took 2250.

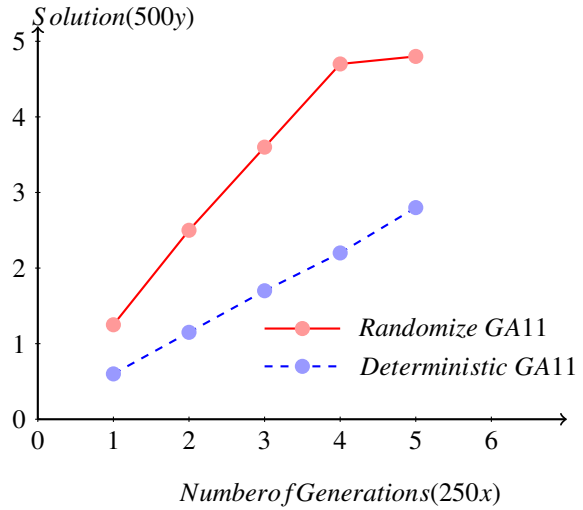


Figure 6: Deterministic vs Randomize GA11.

It is clear from these results that the performance of the GA does not critically depend on the strategy of crossover and mutation when the number of generations is “greater than 2500” for example. Indeed, one can observe that the single mutation provides the best results for a small size population, while the results of the randomized mutation gives longer lifetime than the deterministic mutation for a large size population as in Table 1.

Consider now the effect of a great number of generations on the running time. This number with reasonable running time, which gives acceptable solution, can be found for all strategies. The number of generation required for GA11 to get the best solution is not less than 2250 and 1250 for GA12. In addition, further ways of crossover and mutation can be investigated in addition to different ways to initializing and generating the chromosomes for more enhancements, in order to derive the best strategy for solving this problem.

Network			Deterministic Mutation								Random Mutation			
			Population Size=50 Lifetime = ($\times k$)				Population Size=100 Lifetime = ($\times k$)				Population Size=100 Lifetime = ($\times k$)			
Sens.	E_i	$E_i(k)$	GA11	GA12	GA21	GA22	GA11	GA12	GA21	GA22	GA11	GA12	GA21	GA22
10	160	2	310	279	308	296	307	284	296	270	302	305	287	283
10	160	4	153	150	148	135	153	154	157	147	154	157	150	155
10	160	6	99	94	103	95	101	92	101	92	96	103	103	100
10	160	8	74	76	77	73	77	77	75	71	75	80	70	76
10	160	10	59	64	57	64	62	58	62	59	60	58	62	63

Table 1: Different GA crossover and mutation strategies

6.2. The exact ILP based methods

Computational experiments have been carried out on networks generated randomly, with $Card[S] \in \{5, 10, 20\}$ and $Card[T] = 5$. Fourteen instances have been investigated, with the initial energy $E_i \in \{60, 50, 40, 30, 20, 10\}$ and energy consumption of sensors for periods k $E_i(k) \in \{16, 8, 4, 2\}$. Eclipse supported with the linear optimization libraries of Cplex and Java Development Kit (JDK) were used to design the linear optimization algorithm on Widows7 and Intel inside core TM^{i7} EliteBook computer for WSNs with different numbers of sensors and different energy situations. For $S = \{s_1, s_2, s_3, s_4, s_5\}$ and $T = \{t_1, t_2, t_3, t_4, t_5\}$ randomly deployed in a 10×10 area, that is $m = 5$ and $n = 5$, with the coverage relations matrix as follows:

$$\Delta = \begin{pmatrix} 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 & 1 \\ 1 & 1 & 0 & 1 & 0 \\ 0 & 1 & 1 & 0 & 0 \end{pmatrix}$$

There are $2^5 - 1 = 31$ sensors possible arrangements into covers distribution, but only 15 of them are covers. Therefore, the objective function from Equation 4 becomes

$$L = k \sum_{l=1}^{15} y_l \quad (9)$$

Subject to

$$\sum_{l=1}^{15} v_{il} E_i(y_l) \leq E_i \quad i = 1, 2, \dots, 5 \quad (10)$$

The problem is expressed with an objective function and 5 inequality constraints involving 15 unknowns.

Therefore, it can be formulated linearly as “to maximizing a linear objective function subjected to 15 linear constraints.”

For all covers $l \in \{1, 2, \dots, 15\}$, y_l is bounded as

$$0 \leq y_l \leq E_i/E_i(k) \quad l = 1, 2, \dots, 15$$

Applying this enhancements and taking advantage from the V matrix, each row covers completely the targets. Thus, one can find the covers with the minimum number of sensors. The sum of each row in V gives the number of sensors in this cover. Therefore, finding the cover with minimum sensors is finding the row with minimum sum. When a cover is selected, this cover cannot be included in next covers, which discards covers that include small size covers as the Lemma 1 stated.

For $S = \{s_1, s_2, s_3, s_4, s_5\}$ and $T = \{t_1, t_2, t_3, t_4, t_5\}$ randomly deployed in a 10×10 area, that is $m = 5$ and $n = 5$, as in Example 2, the cover relations matrix V becomes

$$V = \begin{pmatrix} 1 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 1 & 1 \end{pmatrix}$$

The objective function from Equation 4 becomes

$$L = k \sum_{l=1}^4 y_l \quad (11)$$

Subject to

$$\sum_{l=1}^4 v_{il} E_i(y_l) \leq E_i \quad i = 1, 2, \dots, 5 \quad (12)$$

Let's call SILSOM this simplified integer linear scheduling and optimization method, and let's apply it, in parallel with the integer linear scheduling and optimization method without using the V matrix denoted ILSOM, to the same instances, as displayed in Table 2. It is clear that the enhancement has simplified the problem without affecting the optimal solutions.

Sensor Network			SILSOM		ILSOM	
Sens.	E_i	$E_i(k)$	Cov.	Opt.	Cov.	Opt.
5	160	2	4	160	15	160
5	160	4	4	80	15	80
5	160	8	4	40	15	40
5	160	16	4	20	15	20

Table 2: SILSOM and ILSOM

Now, $S = \{s_1, s_2, \dots, s_{10}\}$ and $T = \{t_1, t_2, t_3, t_4, t_5\}$ are randomly deployed in 10×10 area, that is $m = 10$ and $n = 5$, one will find only 784 covers among $2^{10} - 1 = 1023$ possibilities of sensors sets distribution, according to the ILSOM method. Therefore, this problem is formulated linearly with an objective function, 10 inequality constraints and 784 unknowns. This problem was solved and the optimal lifetime for different energy situations are displayed in Table 3 according to the ILSOM method.

Sensors Network			ILSOM	
Sensors	E_i	$E_i(k)$	Covers	Optimal ($\times k$)
10	10	2	784	15
10	20	2	784	30
10	30	2	784	45
10	40	2	784	60
10	50	2	784	75

Table 3: ILSOM for 10 sensors

Using the SILOM for the 10 same sensors, the objective function was computed for maximizing the sum of the 26 unknowns. Thus, the constraints reduce to 10 inequalities with the 26 unknowns. Considering the initial energy E_i and the energy consumption $E_i(k)$, y_l cannot exceed $E_i/E_i(k)$, which is bounded as

$$0 \leq y_l \leq E_i/E_i(k)$$

The problem is now very simple, compared to the one composed of an objective function and 10 inequality constraints with 784 unknowns. For $S = \{s_1, s_2, \dots, s_{20}\}$ and

$T = \{t_1, t_2, t_3, t_4, t_5\}$ randomly deployed in a 10×10 area, with $m = 20$ and $n = 5$ as in Example 2, one will find $2^{20} - 1 = 1048576$ possibilities of sensors sets arrangements, involving 910336 covers according to Definition 1. This problem was solved and the maximum lifetime for different energy situations are shown in Table 4 according to the ILSOM method.

Sensors Network			ILSOM	
Sensors	E_i	$E_i(k)$	Covers	Optimal ($\times k$)
20	10	2	910336	15
20	20	2	910336	30
20	30	2	910336	45
20	40	2	910336	60
20	50	2	910336	75

Table 4: ILSOM for 20 sensors

6.3. The NDSC-GA method vs the DSC-GA in [18]

Consider the randomly deployed sensors and targets which allowed q covers. We compare the DSC-GA (DSC implemented within the GA-based scheduling heuristic presented in Subsection 5.5), and our NDSC-GA (GA-based scheduling heuristic involving a GA-based NDSC maximization), both applied to maximize the WSN lifetime. The method in [18] was implemented to maximize the lifetime for the same instances with our method as in Table 5. The average of results of the GA11, GA12, G21 and GA22 strategies, for the NDSC-GA, is compared to average of results obtained by the DSC-GA.

m	E_i	$E_i(k)$	DSC-GA	NDSC-GA	percentage
10	160	2	240	298	24.17
10	160	4	120	146	21.67
10	160	6	80	98	22.5
10	160	8	60	75	25
10	160	10	48	61	27.08
Average					24.08

Table 5: DSC-GA and NDSC-GA

The NDSC based GA brought out an average enhancement of about 24.08% compared to the GA based on DSC.

6.4. Results discussion

Table 6 provides a simple comparison between the NDSC-GA based heuristic and the ILP based exact

method using eight instances with $S \in \{5, 10\}$ and energy consumption cost $E_i(k) \in \{2, 4, 8, 16\}$, coverage range $r = 3$ and initially charged with 160 energy units used to monitor 5 targets. The computation time in seconds and the optimal lifetime as multiples of k are obtained using both methods for all instances.

The NDSC-GA based heuristic found the optimal solution for 5 out of 8 instances and 97.5% in the worst case is (117 of 120). Consider the running time for both methods and the nearness of the optimal percentage for NDSC-GA-based heuristic, the experimental results lead to the following observations:

- It is possible to get the optimal solution using all suggested GA strategies but with different numbers of generations, and so different computation time.
- It is possible to extend the WSN size and lifetime when the number of sensors increases, with an increase of the running time. The computation time increased from 0.02 to 6.04 seconds when the number of sensors increased from 5 to 20.
- Additional time is required for the WSN randomly deployed for sorting to build the matrix V . It is the same for the linear model loading time, which increased from 0.02 to 2.53 seconds when the number of sensors increased from 5 to 20.

Instances $S, T, r, E_i, E_i(k)$	Lifetime = (optimal value $\times k$)			
	ILP		NDSC-GA	
	Rt	Opt.	Rt	Opt.
5, 5, 3, 160, 16	0.03	20	0.010	20
5, 5, 3, 160, 8	0.02	40	0.010	40
5, 5, 3, 160, 4	0.02	80	0.010	80
5, 5, 3, 160, 2	0.02	160	0.010	160
10, 5, 3, 160, 16	0.02	30	0.051	30
10, 5, 3, 160, 8	0.02	60	0.041	59
10, 5, 3, 160, 4	0.02	120	0.055	117
10, 5, 3, 160, 2	0.02	240	0.068	238

Table 6: Comparison of ILP based and NDSC-GA methods (Rt: Runtime)

7. Conclusion

The paper addressed the problem of lifetime maximization in WSNs for data collection and monitoring of long-life engineering infrastructures. It considered the WSN

random deployment, then, it composed subsets of sensors that can completely cover all targeted elements to be monitored. In overall, the paper proposes an ILP model and a scheduling heuristic based on genetic algorithms to maximize the network lifetime. Different crossover and mutation operators were used to enhance solutions represented into chromosomes. In addition, linear programming based exact solution is obtained. Different instances were investigated in the experimental results. To summarize, our NDSC-GA yields better solutions compared to DSC-GA for the same instances. Referring to the best solution obtained using NDSC-GA based heuristic and the exact methods, the NDSC-GA based heuristic found the optimal solution in 5 out of 8 instances with 97.5% of nearness for the worst case. Moreover, our new encoding method and mathematical model can be used as a basic for more advanced investigations to enhance the performance of the NDSC-GA based method. In addition, our ILP method can be used as an exact method to evaluate new heuristics for the randomly deployed WSNs lifetime maximization problem. In future works, other ways of chromosome composition, crossover and mutation will be investigated for more enhancements, while the exact solution will be used to evaluate new heuristics for this problem. Comparative studies to our methods will be conducted to evaluate the efficiency of these approaches. Also, the investigations will consider the sensors energy consumption profiles and the degradation dynamics functions in terms of failure rates or reliability and remaining useful life whatever the energy available.

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