Optimizing the Lifetime of Heterogeneous Sensor Networks Under Coverage Constraint : MILP and Genetic Based Approaches

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***Abstract*—Lifetime optimization in heterogeneous wireless sensor networks (HWSN) is investigated in this paper. This is a natural and important key issue which serves as a basis metric for QoS of the monitoring activity. To tackle this problem, nodes' clustering into Disjoint or Non Disjoint Cover Sets is the well-known technique that has been heavily studied in the literature. The objective is to organize the sensor nodes into a number of subsets of nodes that are activated successively. Only the nodes belonging to an active cover are responsible for targets' monitoring, while all other sensors are in a sleep mode. The presented paper is, to the best of our knowledge, the first work to consider the heterogeneity level of nodes' batteries in the case of Disjoint Set Covers (HDSC) based scheduling. To this end, first a novel mixed integer linear programming (MILP) formulation is proposed to solve optimally the HDSC problem, next we provide a genetic algorithm (GA) based approach to achieve approximate solutions but in polynomial time complexity. A comprehensive set of experimental results were conducted to assess the behavior of our proposals in terms of several QoS metrics.**

***Index Terms*—sensor networks, lifetime optimization, integer linear programming, genetic algorithms**

I. Introduction

With the technological progress, wireless sensor networks (WSN) emerge as an effective way of monitoring in diverse fields of applications such as pipeline and seismic monitoring, disaster prevention, oceanography, tactical surveillance, and so on. Nevertheless, they are constituted of a small sized nodes with limited resources in terms of battery lifetime, memory capacity, and computational power. Consequently, due to the conceptual constraints of WSN and without being able to recharge or replace exhausted batteries, especially in hostile and remote environments, there is an increasing need for designing techniques to improve the network's lifetime service.

In this paper, we focus on the case of Disjoint Set Covers (DSC) based scheduling in which sensors can participate in at most one cover and can interchange between idle and active modes. Unlike previous works that deal with homogeneous DSC, we consider heterogeneous networks, that is, the initial energy levels of nodes' batteries are different. The heterogeneous case seems to be more realistic than the homogeneous one for the following reasons :

i) wear-out rate : during the network service, the nodes' energy will be depleted at different rates leading to non homogeneous sensors' battery residual life.

ii) node failures: in large scale WSN, sensor failures are more likely to occur and network's reorganization will take place by adding non necessarily identical nodes to recover the failed ones.

iii) solar energy replenishment: if the sensor nodes are refillable by solar energy, then maintaining the network's homogeneity is far for being true.

In the following, we summarize the contributions of the presented work.

- Unlike earlier works, we deal with heterogeneous disjoint set covers (HDSC) based scheduling scheme to prolong the network's lifetime.
- A new mixed integer linear programming (MILP) formulation is proposed to tackle optimally the HDSC problem.
- An efficient genetic algorithm based approach is designed to achieve near optimal network's lifetime values with minimal computation time complexity.

The remainder of this paper is organized as follows. In Section II, we review the relevant lifetime optimization techniques that have been proposed in the literature. Section III describes the new MILP mathematical model. Section IV describes the genetic algorithm (GA) based approach for the heterogeneous DSC case. We report in Section V series of experimental results that assess the behavior of our proposals. Finally, we summarize the contributions of this work and draw some conclusions in Section VI.

II. Related works

The problem of lifetime optimization in wireless sensor networks has been formulated and studied in various ways. For instance, in order to save energy consumption under coverage requirement, some distributed algorithms have been proposed

*The authors are displayed in alphabetic order in [1] [2] [3] [4] [5] [6]. They seek to keep a maximal number of sensor nodes in a passive mode while guaranteeing the whole targets' coverage. The failed working nodes are replaced when needed based only on local neighbourhood decisions.

By and large, centralized nodes' clustering into disjoint or non disjoint set covers is by far the well-known approach that has been widely addressed in the literature [7] [8] [9] [10] [11] [12] [13] [14] [15] [16] [17]. There are two main approaches DSC and NDSC (for Non-Disjoint) as outlined in Table I.

	homogeneous	heterogeneous
NDSC	models : IP formulation [10]	models : LP formulation [8], [9]
	resolution methods : Heuristic [10]	resolution methods : Heuristic [12] GA [11]
DSC	models : IP formulation [14]	models : No model
	resolution methods : Heuristic, GA [13]	resolution methods : No resolution method

TABLE I: A synthesis of fundamental WSN's lifetime optimization approaches in the literature.

In [9], the authors formulate the energy saving problem as a linear packing problem, then use Garg-Könemann algorithm to achieve sub-optimal solutions. An approximation algorithm is also proposed for q-coverage case problem where only a partial region have to be monitored. This work is borrowed in [8] to deal with non disjoint set covers scheduling. Due to the exponentiality of the number of feasible cover sets, Column Generation is used to alleviate the induced cost time. The main idea is that only a restricted number of set covers is built and other ones are generated when needed by solving an auxiliary problem formulated as an integer linear programming (ILP) problem.

In [10], the authors model the network lifetime problem as a maximum set covers problem. They prove its NP-Completeness by a polynomial reduction from the so called 3-SAT problem, and provide two efficient heuristics, using a linear programming (LP) formulation and a greedy approach, respectively, to enhance the network's lifetime by clustering the sensor nodes into a maximal number of non-disjoint cover sets. In [12], an efficient approach which is called High-Energy-First is introduced to solve targets' coverage problem in HWSN. The clustering process into Non Disjoint Cover Sets is performed greedily by prioritizing sensors having high battery residual life. Numerical results show that the proposed heuristic achieves better performances compared to other works in the literature.

Energy consumption using DSC based scheme is also investigated in [18]. The authors' work consists of a sequence of two main refinement steps. The first step, identifies the fields of points that are covered by the same sensor nodes set, while the second one assigns nodes into mutually exclusive independent set covers. Its effectiveness is evaluated through a variety of test-beds simulated scenarios.

Optimizing targets' motoring in heterogeneous WSN based on NDSC is addressed in [11]. The authors present first an Integer Linear Programming (ILP) model to achieve optimal network's lifetime solutions and next, they provide a genetic algorithm based method. The chromosome's encoding solution relies on the battery lifespan by using an integer representation. Each gene represents the number of periods to be scheduled for each potential cover set. The main drawback of this method is that the chromosome's length is exponential in the number of sensor nodes. This leads to heavier computation times even for reasonable networks' sizes.

A genetic algorithm based technique which is called GAMDSC is also proposed in [13]. The energy saving is achieved by organizing sensor nodes into Disjoint Set Covers. The authors use integer representation for the encoding scheme where each gene indicates the cover's index to which a sensor belongs. The adopted chromosomes' representation ensures that, at each iteration step, the whole genotypic space corresponds to feasible solutions. The chromosome's length is equal to the network's size and the gene's value is bounded by the optimum number of cover sets which is equal to the straightforward number of nodes able to monitor the sparsely covered target. Simulation results show that the proposed evolutionary algorithm exhibits good performances compared to the ones obtained by the MILP's solver.

III. Problem Formulation

In this section, the problem of maximizing the lifetime of a network, consisting of sensors with heterogeneous energy levels, is presented. The objective is to divide the sensors into disjoint cover sets where each set covers all the targets. The disjoint cover sets are then activated successively. The activity of the network nodes is thus planned in advance for the entire life of the network.

In the literature, the network is mostly considered to be homogeneous, that is, the sensors have the same characteristics and in particular, the same initial energy level. In this case, only the target coverage objective guides the construction of the cover sets. The problem of maximizing the network's lifetime is then reduced to the problem of building a maximum number of cover sets, all of which can stay activated for the same duration. In the heterogeneous case, the problem becomes more complex and it is necessary to take into account the difference in energy levels between the sensors when forming the cover sets. The cover sets may not have the same activation time period in the heterogeneous case.

A. Notations

In the rest of this paper, we will use the following notations to present the problem of maximizing the lifetime of a heterogeneous sensor network (denoted by HDSC for Heterogeneous Disjoint Sets Cover):

- N : number of sensors
- M : number of targets
- S : set of sensors = $\{s_1, ..., s_N\}$
- T : set of targets = $\{t_1, ..., t_M\}$

- E_i : number of time units during which s_i can be continuously activated
- T_i : set of targets covered by the sensor i
- S_j : set of sensors that cover the target j
- C_k : set of indexes of sensors forming the k^{th} cover set
- d_k: activation time of the k^{th} cover set

In the considered coverage model, it is assumed that target j is covered by sensor i if and only if the distance (Euclidean distance) between j and i is less than the sensing radius of sensor i. To focus only on the coverage problem, it is also assumed that the communication range of the sensors, R_c, is at least twice higher than their sensing range R_s ($R_c \geq 2 \cdot R_s$). This strong hypothesis makes it possible to affirm, as in [19], that a complete coverage of a convex region implies the connectivity of the active nodes.

Intuitively, the maximum number K of disjoint cover sets that can be built is bounded by the minimum number of sensors monitoring a target:

$$K = \min_{j=1..M} |S_j| \tag{1}$$

Indeed, each cover set must cover all targets and a sensor can only belong to one cover set.

Each sensor i has a battery level B_i and an energy consumption per unit of time equal to e_i. Consequently, the number of time units during which sensor i can be continuously activated is equal to $E_i = \frac{B_i}{e_i}$. The maximum network lifetime is then limited by the value L_{max}:

$$L_{max} = \min_{j=1..M} \sum_{i \in S_j} E_i \tag{2}$$

The problem of maximizing the lifetime of a heterogeneous sensor network is then reduced to maximizing the sum of the activation times of the formed disjoint cover sets. The activation time of a set cover C_k can be noted by:

$$d_k = \min_{i \in C_k} E_i \tag{3}$$

B. Example

Let consider a simple network (see Figure1) consisting of 5 sensors monitoring 3 targets with $S_1 = \{s_3, s_4, s_5\}$, $S_2 = \{s_1, s_2, s_3\}$, $S_3 = \{s_1, s_2, s_3, s_4\}$. For this example, there are five possible cover sets: $C_1 = \{2, 5\}$, $C_2 = \{1, 4\}$, $C_3 = \{3\}$, $C_4 = \{1, 5\}$ and $C_5 = \{2, 4\}$. There are two possible scheduling for the disjoint case. The first solution is to form the cover sets C_4, C_5 and C_3. The second one is to activate successively cover sets C_1, C_2 and C_3. In the homogeneous case, the two solutions are equivalent with three disjoint cover sets in each solution. In the heterogeneous case with different sensors activation times, solutions with the same number of cover sets may result in different network lifetimes. For example, suppose that $E_1 = 2$, $E_2 = 20$, $E_3 = 15$, $E_4 = 2$ and $E_5 = 20$. The first solution gives a network lifetime equal to $d_4 + d_5 + d_3 = \min(E_1, E_5) + \min(E_2, E_4) + E_3 = 2 + 2 + 15 = 19$ while the second scheduling returns a network lifetime equal to $d_1 + d_2 + d_3 = \min(E_2, E_5) + \min(E_1, E_4) + E_3 = 20 + 2 + 15 = 37$.

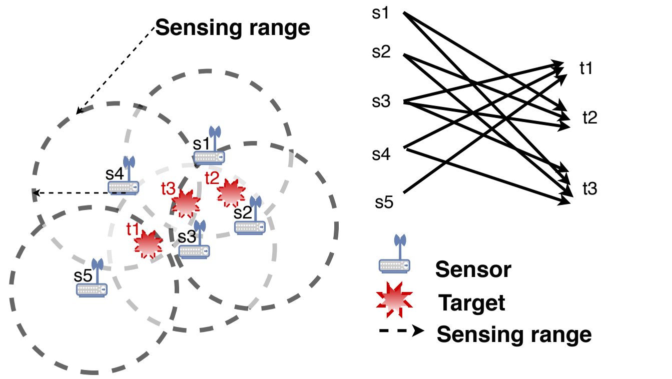

Fig. 1: A network with 5 sensors and 3 targets

C. MILP: model formulation

The search for the optimal solution which maximizes the lifetime of the network while preserving the total coverage of the targets, can be formulated as a mixed integer linear programming (MILP) problem. The variables used to define the problem are the following:

- Continuous variable $\mathbf{d_k}$: $\mathbf{d_k} > 0$ means that C_k is a cover set, $\forall k \in [\![1, K]\!]$ where K is the upper bound defined by (1)
- Binary variable $\mathbf{x_{i,k}}$: $\mathbf{x_{i,k}} = 1$ indicates that the sensor i is active in the cover set C_k

The objective is to maximize the sum of the duration of the activation times of the cover sets.

$$Max \sum_{k=1}^{K} d_k \tag{4}$$

The activation time of a sensor i belonging to a cover set C_k is greater than or equal to the activation time d_k. This constraint is expressed by:

$$\alpha(1 - x_{i,k}) + E_i x_{i,k} \geq d_k \ \forall i \in [\![1, N]\!], \forall k \in [\![1, K]\!] \tag{5}$$

The constant α is chosen large enough so that the inequality is satisfied regardless of the value of $x_{i,k}$. If sensor i does not belong to the cover set C_k, then $x_{i,k} = 0$ and the inequality $\alpha \geq d_k$ is satisfied. If the sensor i belongs to the cover set C_k, then $x_{i,k} = 1$ and the inequality $E_i \geq d_k$ must be satisfied. The coverage of all targets in each cover set is modelled by the following constraint:

$$\sum_{i \in S_j} E_i x_{i,k} \geq d_k \ \forall j \in [\![1, M]\!], \forall k \in [\![1, K]\!] \tag{6}$$

Among all the sensors used to cover a target j, at least one must be present in the cover set for the inequality to be satisfied. On the other hand, a sensor can only belong to one and only one cover set in the disjoint case, this results in the following constraint:

$$\sum_{k=1}^{K} x_{i,k} \leq 1 \ \forall i \in [\![1, N]\!] \tag{7}$$

Other additional constraints can be added:

$$d_k \leq \underset{i \in S}{max} E_i \ \forall k \in [\![1, K]\!] \quad (8)$$

This constraint indicates that the activation time of any cover set will necessarily be less than or equal to the activation time of the sensor with the shortest lifetime.

$$\sum_{i \in S} x_{i,k} \leq \beta d_k \ \forall k \in [\![1, K]\!] \quad (9)$$

The constant β is chosen large enough so that the inequality is satisfied regardless of the values of $x_{i,k}$. This constraint makes the cover set of zero duration to be empty. The number of variables is $K + NK$. The number of constraints is equal to $MK + NK + NK + N + 2K$. The resolution of this linear program with mixed variables becomes impracticable for large problems. Heuristics and meta-heuristics are more suitable for large problems and they are able to find sub-optimal solutions in a reasonable execution time.

IV. Proposed genetic algorithm

Among the well-known meta-heuristics, adequate for solving optimization problems, the so-called evolutionary genetic algorithm, firstly proposed by Holland [20], has been applied to many scientific areas and is proving to be very effective. This section presents the proposed Genetic Algorithm (GA) that is used to solve the HDSC based scheduling problem.

A. Encoding and fitness

To keep the representation of the solutions simple, the HDSC problem is considered as a permutation of N sensors and the search space corresponds to the $N!$ possible ordering of these sensors. The natural representation of the chromosome consists then of an ordered sequence (OS) of the N sensors and each gene corresponds to the index of a sensor.

In this case, the fitness function plays a dual role, that of building the disjoint cover sets from a given OS and calculating the maximum lifetime of the network represented by the OS. The fitness function is detailed in Algorithm 1. It builds greedily the cover sets by considering the sensors according to their order in the sequence. Each time a cover set is formed (it contains enough sensors to cover all targets), its activation time which corresponds to the shortest lifetime of the sensors that compose it, is calculated. The network lifetime L is the sum of the activation times of the cover sets. The worst-case runtime complexity of the fitness calculation is $O(MN^2)$. As an illustration to how this algorithm operates, its application on the chromosome $\|1, 3, 4, 2, 5\|$ of the example presented in the section III-B, forms two cover sets ($\{1, 3\}$ and $\{2, 4\}$) that have a total network lifetime equal to 4.

B. The initial population

The quality of the initial population has a major influence on the capacity of the GA to achieve approximate solutions and it might increase its convergence rate. A good quality initial population does not only consist of good quality individuals but should also contain diverse chromosomes in order to allow the GA to explore different regions of the search space and not be limited to a single region with a local optimum. The generation of individuals with a good quality is in general problem dependent. For the targets coverage problem with sensors having heterogeneous initial energy, the main idea for increasing the lifetime of the network is to maximize the activation period of each cover set. Since the activation period of a given set is limited by the sensor with the smallest energy in the set, it would be careful to try to put sensors with similar initial energies in the same set. This heuristic can be used to generate a good quality of initial population; however, its individuals tend to be very similar. In order, to keep the initial population diversified and of good quality, half of the individuals are randomly generated and the other half according to the heuristic described previously.

Algorithm 1 Fitness Algorithm

Require: An ordered sequence OS representing a permutation of n sensors
Ensure: The lifetime L (cumulative duration of the activation times of the cover sets $C_1, .., C_k$)
  $k \leftarrow 0$;
  $L \leftarrow 0$;
  while ($OS \neq \emptyset$) **do**
    $p \leftarrow 1$;
    $T' \leftarrow T$;
    $C_k \leftarrow \emptyset$;
    (*While a cover set has not yet been formed and there are still elements in the sequence that were not examined yet*)
    while ($T' \neq \emptyset \wedge p \leq |OS|$) **do**
      $i \leftarrow OS[p]$;
      if ($T_i \cap T' \neq \emptyset$) **then**
        $C_k \leftarrow C_k \cup \{i\}$;
        $OS \leftarrow OS - \{i\}$;
        for all targets $j \in T_i$ **do**
          $T' \leftarrow T' - \{j\}$;
        end for
      else
        $p \leftarrow p + 1$;
      end if
    end while
    if ($T' = \emptyset$) **then**
      $k \leftarrow k + 1$;
      $d_k \leftarrow \min_{i \in C_k} E_i$;
      $L \leftarrow L + d_k$;
    else
      $OS \leftarrow \emptyset$;
    end if
  end while

C. The crossing and mutation operators

Among several types of crossing operators, the LOX (Linear Ordering Crossover) [20] linear crossing was used because it has been shown in [21] that it is adapted for linear permutation

Parameter	GA
Number of Generations	100
Population Size	100
Probability of Mutation	0.1
Probability of Crossover	0.9

TABLE II: List of parameters for GA

problems. A simple mutation operator was used, it consists of randomly selecting two genes and swapping them.

V. Experiments and Results

The performance and the quality of the solutions given by the proposed Genetic Algorithm were evaluated in a series of experiments. All experiments were run on an Intel(R) i7-8650U processor with 16GB RAM. Different parameters of the GA, such as the population size and quality, and the number of generations, were tested in order to examine their impact on the final solutions. Moreover, the GA was applied to networks with different number of sensors N, and different numbers of targets M. In each instance of a network, the N sensors and M targets were randomly deployed in a 500X500m two-dimensional area. Each target had to be at least covered by $N/4$ sensors. All the deployed sensors can communicate directly with the base station and have the same 300m cover range but they start the surveillance with heterogeneous initial energy, varying between 1 to 10. One unit of energy allows a sensor to stay active during one unit of time and cover during that time all the targets in its range.

In this section, the performance of the genetic algorithm is evaluated with fixed parameters described in table II. In all these experiments, the crossover and the mutation rates were equal to 90% and 10% respectively and a two-point crossover operator was used. As described above, a chromosome represents the order of the sensors in a given solution and its size is always equal to N.

Figure 2 compares the average lifetime of the solutions returned by the GA after 100 generations while starting with a good quality initial population and a random one. The GA returns better solutions when initialized with a good quality solution than with a random one, especially for large networks that have a large search space.

A. The GA versus the exact method

Table III compares the GA's execution time and solutions quality to those of the exact method formulated previously. The displayed values are the averages of 10 executions over 10 instances for each considered network's size. For each instance, the GA starts with a good quality initial population composed of 100 individuals and executes 100 generations. Table III shows that the exact method can only computes the optimal solution for small networks in a reasonable time. Its execution time increases exponentially to the size of the network. However, the optimal solutions obtained by this exact method can be used to evaluate the quality of the solution returned by the GA for small networks. The gap between the lifetime obtained by the exact method (L_{opt}) and the lifetime

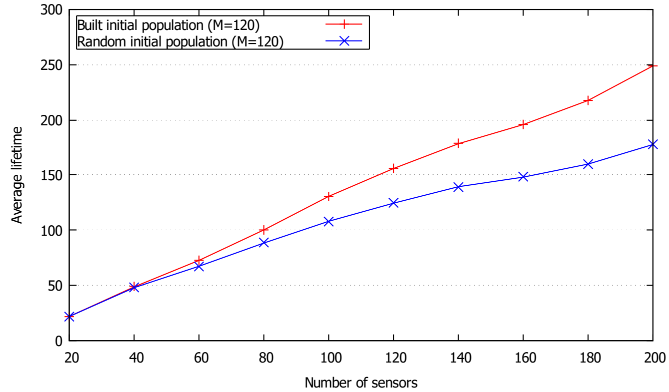

Fig. 2: Average lifetime returned by the GA with different initial populations

computed with the GA is given in Table III. On the other hand, the execution times of the GA are relatively small, less than 10 seconds. For small networks, ($N \leq 30$), the GA was able to find the optimal solution. For dense networks with larger search spaces, only good quality solutions were found because the GA was limited to 100 generations and had a population of just 100 individuals. Therefore, it explored the same number of solutions, 10^4, regardless of the size of the network.

		Exact Method		Genetic algorithm	
N	M	L_{opt}	Runtime(s)	Gap(%)	Runtime(s)
20	40	25.2	1.71	0.00	0.84
	60	23.9	2.37	0.00	1.35
	80	22.5	1.87	0.00	1.94
	100	22.5	1.73	0.00	2.64
	120	22.2	1.04	0.00	3.35
25	40	36.0	4.64	0.00	1.08
	60	33.7	4.43	0.29	1.77
	80	32.4	4.76	0.00	2.57
	100	31.8	4.32	0.00	3.51
	120	30.5	4.40	0.00	4.56
30	40	40.8	38.28	0.00	1.38
	60	37.2	12.20	0.26	2.23
	80	36.1	24.68	0.00	3.22
	100	35.1	35.06	0.00	4.25
	120	34.0	5.76	0.00	5.40
35	40	45.5	82.24	0.43	1.75
	60	43.3	149.12	0.00	2.89
	80	42.5	84.37	0.23	4.05
	100	40.9	7.85	0.24	5.40
	120	40.6	9.27	0.24	6.92
40	40	56.7	2175.20	0.52	2.20
	60	53.0	1011.15	0.75	3.51
	80	52.9	1474.60	1.32	5.01
	100	52.3	947.26	0.76	6.58
	120	51.5	587.96	1.74	8.47

TABLE III: The lifetime, execution time for different networks computed with the exact method and the GA.

B. The GA versus the Hill Climbing method

In order to evaluate the performance of the proposed GA on large networks and since the exact method cannot solve them in a reasonable time, the GA was compared to a simple local search method, the Hill Climbing method. The Hill

Climbing method [22] starts from one initial solution and at each iteration it searches its local neighborhood for a better solution. In this comparison the neighborhood of a solution X is defined as the set of solutions reachable by a two genes swap in the X. The GA's parameters, crossover and mutation rates, and initial population size, were kept the same as in the previous experiments. On the other hand, the number of targets was fixed to 1000 and the number of sensors varied between 1000 and 9000.

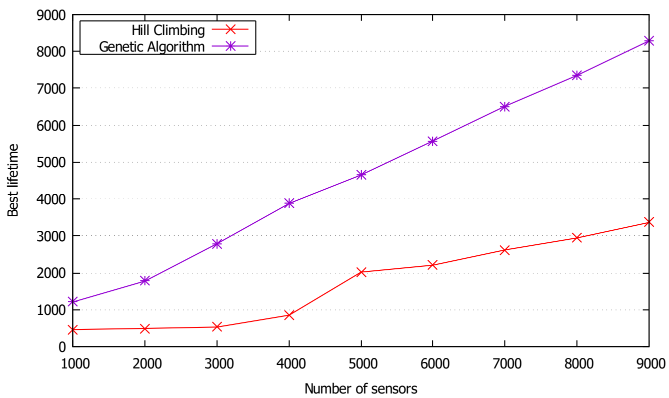

Fig. 3: Lifetime of the best found solutions for different problem sizes and using the GA or the Hill climbing method.

To fairly compare those two optimization methods, both were executed for just one hour and only the best found solutions with each method was considered. Figure 3 shows the lifetime of the best found solutions with each method and for different numbers of sensors. It can be noticed that the proposed GA outperforms the local search methods for all the considered configurations. The performance difference is more significant for large dimensions (up to 146.34% network's lifetime improvement) because the search space for such dimensions is just too large for this local search method.

VI. Conclusions

In this paper, we have studied the problem of energy management under targets' coverage requirement in heterogeneous WSN. The heterogeneity stems for the fact that the initial energy levels of the nodes in the network are different. Major achievements include: i) a new mixed integer linear programming (MILP) formulation to tackle optimally the process of nodes' clustering in the case of DSC based scheduling, and ii) a genetic algorithm (GA) based approach which is able to achieve efficient solutions compared the MILP's optimal ones. Based on a comprehensive set of experiments, it was shown, that obtained results corroborate the merits of our proposals in terms of several QoS metrics.

Our future work will explore other possible chromosomes' representations of the encoding solutions as well as the GA's backbone design in order to achieve more efficiency with minimal execution time complexity.

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