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**THÈSE DE DOCTORAT**  
**DE L'ÉTABLISSEMENT UNIVERSITÉ BOURGOGNE FRANCHE-COMTÉ**  
**PRÉPARÉE À L'UNIVERSITÉ DE FRANCHE-COMTÉ**

École doctorale n°37  
Sciences Pour l'Ingénieur et Microtechniques

Doctorat d'Informatique

par

**RANIA HAJ MANSOUR**

**Energy-efficiency and coverage quality management for wireless sensor networks**

Gestion de l'efficacité énergétique et de la qualité de la couverture pour les réseaux de capteurs sans fil

Thèse présentée et soutenue à Belfort, le 13 December 2021

Composition du Jury :

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# ABSTRACT

## Energy-efficiency and coverage quality management for wireless sensor networks

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Wireless sensor networks (WSNs) are widely used for monitoring in diverse fields of applications such as tracking, home security, tactical surveillance, health care, and so on. They are usually made of numerous devices, called sensor nodes, that work collaboratively or individually to collect information and to send the collected data to a remote base station. Nevertheless, WSNs present a number of shortcomings that may impact on the quality of the gathered data at the sink level, leading to imprecise diagnostics of the monitored targets. A major issue in WSNs is related to the limited amount of resources in terms of battery lifetime's sensor. Indeed, it is usually hard to recharge the battery of sensor after deployment, either because the number of sensor nodes is too large, or because the deployment area is hostile. Hence, the primary objective is to maximize the network lifetime while enhancing the WSN's QoS. Three critical and related issues, namely the energy consumption, coverage quality and network connectivity, need to be considered. In more detail, the aim is to divide the sensors into disjoint or non-disjoint cover sets that can independently monitor all the targets, and can therefore be sequentially activated one by one. In certain applications like forest fire detection and weather forecasting, the requirement of complete coverage may be too expensive or unnecessary. This type of coverage is called partial coverage. Most of the works in the literature consider homogeneous sensor networks with the same characteristics (same battery, same coverage range, same computing capacity,...). In reality, a network can contain heterogeneous sensors which make it more appropriate for real-life application requirements. In particular, the initial energy level of the battery and the energy consumption may differ from one sensor to another. In this thesis, centralized approaches for heterogeneous wireless sensor networks will be investigated to maximize network lifetime while maintaining the application

requirements such as energy saving, coverage quality and network connectivity.

First, the total coverage in a heterogeneous wireless sensor network was addressed. A mixed integer program has been proposed in this dissertation that allows getting a maximal number of disjoint cover sets. As the problem is an NP-hard, an approximate solution method based on a genetic algorithm has been proposed to deal with large size problems. This approximate method was compared to a simple local search method, the Hill Climbing method. The results show that 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.

Second, the partial coverage in a heterogeneous wireless sensor network was tackled. A linear integer program was proposed to solve the problem of partial coverage in a heterogeneous network. This model allows generating a maximal number of non-disjoint partial cover sets with fixed activation times. As opposed to the other suggested approaches, our model includes a new constraint which was called  $\beta$  constraint that forces a minimum coverage rate for each target over the total lifetime of the network, which makes it more suitable for the requirements of real applications. The model showed that the obtained network lifetime decreases under the  $\beta$  constraint contrary to the constraint proposed in the literature, which imposes that each target must be covered at least as well as the achieved one in the case of complete coverage. In addition, each target in partial coverage is not covered continuously, we have sought a scheduling for the cover sets returned by the model in order to distribute as well as possible the coverage and non-coverage periods of each target. This planning problem has been modeled as a p-dispersion and solved using a heuristic based on a genetic algorithm. The proposed heuristic could perform an efficient cover sets scheduling in order to fairly distribute the uncovered periods of the targets over the life of the network.

Finally, the partial coverage and the network connectivity in a heterogeneous wireless sensor network were studied. A mixed integer linear programming (MILP) was proposed to solve the problem of partial coverage in a heterogeneous network while maintaining connectivity and coverage constraints. This model allows generating the non-disjoint connected partial cover sets with variable activation times in contrast to what has been proposed in the second study, which is restricted to fixed activation periods. As in second study, it is also considered the  $\beta$  constraint in our proposed model for improving network's QoS. Since our problem is an NP-hard problem, the exact resolution of the MILP is limited to small problems. Then, an exact approach based on column generation to solve the problem at the optimum and in acceptable times was presented. As the column generation's subproblem is also NP-Hard, we propose a heuristic to solve the problem without the  $\beta$  constraint and adapt it when considering the  $\beta$  constraint. In addition, we proposed another exact method to solve the studied problem that applies an exact ILP formula-

tion when the heuristic fails to find an attractive column. The proposed heuristic based on column generation was able to find very competitive solutions when compared to the one recently proposed in the literature. A series of experiments are conducted and several QoS metrics are evaluated to show the usefulness of our proposals.

**KEYWORDS:** Sensor Networks, Lifetime Optimization, Total Coverage, Partial Coverage, Network Connectivity, Integer Linear Programming, Column Generation, Genetic Algorithms.



# RÉSUMÉ

## Gestion de l'efficacité énergétique et de la qualité de la couverture pour les réseaux de capteurs sans fil

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Université de Bourgogne Franche Comté, 2021

Encadrants: Karine Deschinkel, Mourad Hakem et Jean Claude Charr

Les réseaux de capteurs sans fil (WSN) sont largement utilisés pour la surveillance dans divers domaines d'application tels que le suivi, la sécurité domestique, la surveillance tactique, les soins de santé, etc. Ils sont généralement constitués d'un grand nombre de dispositifs, appelés capteurs, qui fonctionnent en collaboration ou individuellement pour collecter des informations et envoyer les données recueillies à une station de base distante. Néanmoins, ils présentent un certain nombre d'inconvénients qui peuvent avoir un impact sur la qualité des données recueillies au niveau du puits, conduisant à des diagnostics imprécis des cibles surveillées. Un problème majeur dans les WSNs est lié à la quantité limitée de ressources en termes de durée de vie des batteries des capteurs. En outre, il est généralement difficile de recharger la batterie du capteur après son déploiement, soit parce que le nombre de nœuds de capteurs est trop important, soit parce que la zone de déploiement est hostile. Par conséquent, l'objectif principal est de maximiser la durée de vie du réseau tout en améliorant la qualité de service du réseau. Trois problèmes critiques et connexes, à savoir l'économie d'énergie, la qualité de la couverture et la connectivité, doivent être pris en compte. Plus précisément, l'objectif est de diviser les capteurs en ensembles couvrant disjoints ou non-disjoints qui peuvent surveiller indépendamment toutes les cibles, et peuvent donc être séquentiellement activés les uns après les autres. La plupart des travaux dans la littérature considèrent des réseaux de capteurs homogènes avec les mêmes caractéristiques (même batterie, même zone de couverture, même capacité de calcul,...). En réalité, un réseau peut contenir des capteurs hétérogènes, ce qui le rend plus adapté aux exigences des applications réelles. En particulier, le niveau d'énergie initial de la batterie et la consommation d'énergie peuvent différer d'un capteur à l'autre. Dans cette thèse, les approches centralisées pour



les réseaux de capteurs sans fil hétérogènes seront étudiées afin de maximiser la durée de vie du réseau tout en maintenant les exigences de l'application telles que l'économie d'énergie, la qualité de la couverture et la connectivité du réseau.

Tout d'abord, la couverture totale dans un réseau de capteurs sans fil hétérogène a été abordée. Un programme mixte en nombres entiers est proposé dans cette thèse qui permet d'obtenir un nombre maximal d'ensembles couvrants disjoints. Comme le problème est NP-hard, une méthode de solution approximative basée sur un algorithme génétique est proposée pour traiter les problèmes de grande taille. Cette méthode approximative a été comparée à une méthode de recherche locale simple, la méthode Hill Climbing. Les résultats montrent que la différence de performance est plus significative pour les grandes dimensions (jusqu'à 146, 34% d'amélioration de la durée de vie du réseau) car l'espace de recherche pour ces dimensions est tout simplement trop grand pour cette méthode de recherche locale.

Deuxièmement, la couverture partielle dans un réseau de capteurs sans fil hétérogène a été étudiée. Un programme linéaire en nombre entier a été proposé pour résoudre le problème de la couverture partielle dans un réseau hétérogène. Ce modèle permet de générer un nombre maximal d'ensembles couvrants partiels non-disjoints avec des temps d'activation fixes. Contrairement aux autres approches proposées, notre modèle inclut une nouvelle contrainte qui a été appelée la contrainte  $\beta$  imposant un taux de couverture minimum pour chaque cible sur la durée de vie totale du réseau ce qui le rend plus adaptée aux exigences des applications réelles. Le modèle a montré que la durée de vie du réseau obtenue diminue sous la contrainte  $\beta$  contrairement à la contrainte proposée dans la littérature qui impose que chaque cible soit couverte moins autant qu'en couverture complète. Par ailleurs, chaque cible en couverture partielle n'est pas couverte en continu, nous avons cherché un ordonnancement pour les ensembles couvrants retournés par notre modèle afin de répartir au mieux les périodes de couverture et de non-couverture de chaque cible. Ce problème de planification a été modélisé comme un problème de p-dispersion et résolu en utilisant une heuristique basé sur l'algorithme génétique. L'heuristique proposée s'est avérée capable d'effectuer un ordonnancement efficace des ensembles couvrants afin de lisser équitablement les périodes non couvertes des cibles pendant la durée de vie du réseau.

Enfin, la couverture partielle et la connectivité du réseau dans un réseau de capteurs sans fil hétérogène ont été étudiées. Un programme linéaire en nombres entiers mixtes (MILP) a été proposé pour résoudre le problème de la couverture partielle dans un réseau hétérogène tout en maintenant les contraintes de connectivité et de couverture. Ce modèle permet de générer des ensembles couvrants non-disjoints partiels et connectés avec des temps d'activation variables, contrairement à ce qui a été proposé dans la deuxième étude, qui se limite à des périodes d'activation de durée fixe à l'avance.

Comme dans la deuxième étude, la contrainte  $\beta$  a également été prise en compte dans notre modèle proposé pour améliorer la qualité de service du réseau. Puisque notre problème est un problème NP-hard, la résolution exacte de MILP s'est limitée à des problèmes de petite taille. Ensuite, une approche exacte basée sur la génération de colonnes pour le résoudre à l'optimum et dans des temps acceptables, a été présentée. Comme le sous-problème de la méthode génération de colonnes est également NP-Hard, nous proposons une heuristique pour résoudre le problème sans la contrainte  $\beta$  et l'adaptions sous la contrainte  $\beta$ . En outre, nous proposons une autre méthode exacte pour résoudre le problème qui utilise une formulation ILP exacte lorsque l'heuristique ne parvient pas à trouver une colonne intéressante. L'heuristique proposée, basée sur la génération de colonnes, s'est montrée capable de trouver des solutions très compétitives par rapport à celle récemment proposées dans la littérature. Une série d'expériences sont menées et plusieurs métriques de QoS sont évaluées pour montrer l'utilité de nos propositions.

**Mots clés:** Réseaux de capteurs, Optimisation de la durée de vie, Couverture totale, Couverture partielle, Connectivité du réseau, Programmation linéaire en nombres entiers, Génération de colonnes, Algorithmes génétiques.



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# LIST OF ABBREVIATIONS

<b>ADC</b>	...	Analog to Digital Converter
<b>BILP</b>	...	Binary Integer Linear Programming
<b>BS</b>	...	Base Station
<b>CCP</b>	...	Connectivity Configuration Protocol
<b>CDMA</b>	...	Code Division Multiple Access
<b>CG</b>	...	Column Generation
<b>CG-GRASP</b>	...	Column Generation-Greedy Randomized Adaptive Search Procedure
<b>CG-MULTI</b>	...	Column Generation-MULTI
<b>CG-VNS</b>	...	Column Generation-Variable Neighborhood Search
<b>CMLP</b>	...	Connected Maximum Network Lifetime problem
<b>CSMA</b>	...	Carrier Sense Multiple Access
<b>CSSP</b>	...	Cover Sets Scheduling Problem
$R_c$	...	Communication Range
<b>DH</b>	...	Dedicated Heuristic
<b>DSC</b>	...	Disjoint Set Covers
<b>ECC</b>	...	Error Control Code
<b>ECG</b>	...	Exact Column Generation
<b>GA</b>	...	Genetic Algorithm
<b>GAMDSC</b>	...	Genetic Algorithm for Maximum Disjoint Set Covers
<b>GPS</b>	...	Global Positioning System
<b>GRASP</b>	...	Greedy Randomized Adaptive Search Procedure
<b>HCG</b>	...	Heuristic Column Generation
<b>HDSC</b>	...	Heterogeneous Disjoint Set Covers
<b>HNDPSC</b>	...	Heterogeneous Non-Disjoint Partial Set Cover
<b>HWSN</b>	...	Heterogeneous Wireless Sensor Network
<b>ILP</b>	...	Integer Linear Program

<b>LOX</b>	. . . . .	Linear Ordering Crossover
<b>LP</b>	. . . . .	Linear Program
<b>MAC</b>	. . . . .	Medium Access Control
<b>MCSC</b>	. . . . .	Minimum Connected Set Coverage Problem
<b>MILP</b>	. . . . .	Mixed Integer Linear Programming
<b>MLP</b>	. . . . .	Maximum Network Lifetime Problem
<b>NDSC</b>	. . . . .	Non-Disjoint Set Covers
<b>QoS</b>	. . . . .	Quality of Service
<b>NSGA-II</b>	. . . . .	Sorting Genetic Algorithm-II
<b>VNS</b>	. . . . .	Variable Neighborhood Search
<b>WSN</b>	. . . . .	Wireless Sensor Network
$\alpha$ - <b>CMLP</b>	. . . . .	$\alpha$ -Connected Maximum Network Lifetime Problem
$\alpha\beta$ - <b>CMLP</b>	. . . . .	$\alpha\beta$ -Connected Maximum Network Lifetime Problem
$\alpha$ - <b>MLP</b>	. . . . .	$\alpha$ -Maximum Network Lifetime Problem
$\alpha\beta$ - <b>MLP</b>	. . . . .	$\alpha\beta$ -Maximum Network Lifetime Problem



## DISSERTATION INTRODUCTION



# INTRODUCTION

This thesis focuses on advancing the state of the art of prolonging the lifetime of heterogeneous wireless sensor network, with a specific focus on saving energy, target coverage and the network connectivity. The presented research was carried out in the **Department of Informatics and Complex Systems (DISC in French) of FEMTO-ST** laboratory. Throughout the remainder of this thesis, the writer will be referred to as "**we**", rather than "**I**". The reason behind that is the thesis presents research performed in a collaborative setting in Belfort, France, as part of the AND research team.

This chapter provides an introduction to the work done in this thesis. It addresses the general context and the considered use cases, then presents briefly the contributions of this thesis.

## 1.1/ AN OVERVIEW OF WSN

In recent years, the paradigm of pervasive computing has become a reality and has gradually and surely imposed its presence in our daily lives. Today, the field of microelectronics and wireless communication technologies has allowed producing inexpensive sensor devices with low energy consumption and lower hardware costs. In addition, a wider variety of available sensors have expanded the application domain of wireless sensor networks that aims to collect physical quantities from their proximate environment (luminosity, movement, temperature, barometric pressure, etc.), and to process them if necessary. In the military field, sensor networks are used to analyze dangerous terrain or to monitor movements. Environmental applications are becoming more prevalent, for forest fire detection, volcanic or seismic activity monitoring, or even animal movement tracking. Sensor networks are also used for medical applications such as epidemiological monitoring, or for commercial purposes, to optimize storage processes, or in precision agriculture and the construction of smart houses. However, despite the diversity of applications of sensor networks, their success depends on their network lifetime. Indeed,



sensor nodes are constrained by their small size and by the deployment environment. In fact, the energy consumption of the sensors has an important role in the lifetime of the network which has become the predominant performance criterion in this field. The work done in this thesis addresses maximizing the lifetime of wireless sensor networks while ensuring the application requirements such as target coverage and network connectivity.

The purpose of this thesis is therefore to suggest solutions to numerous problems and challenges that exist in WSN applications. There are some applications that process heterogeneous data generated by different types of sensor nodes such as monitoring temperature and capturing image, which seems more realistic than homogeneous WSN. Thus, the contributions concentrate specifically on heterogeneous wireless sensor networks (HWSN) where the initial energy levels of nodes' batteries are different. The use case of optimizing the network lifetime of HWSN under the application requirements has been considered in this work.

## 1.2/ USE CASE: OPTIMIZING THE NETWORK LIFETIME OF HWSN

Latest technological advancements in the Wireless Sensor Network (WSN) have been conducted to address the network lifetime optimization problem. Actually, sensors are often widely deployed in hostile locations. They are subjected to a variety of environmental conditions. They may operate under high pressure on the ocean's floor, in harsh environments such as battlefields, in biologically or chemically contaminated fields, or even in extremely cold environments. Therefore, they must be able to operate unattended in geographically remote or inaccessible areas. Recharging the power sources is often too expensive and sometimes impossible. Therefore, the sensors must save energy as much as possible in order to be able to operate as long as possible. So, energy saving is one of the major issues in sensor networks.

For the reasons listed above, the study of network lifetime optimization has attracted a large number of researchers over the last few years. The need to improve the network's lifetime as much as possible has become the predominant performance criterion in many applications in various fields. Scheduling sensor activities is an effective way to prolong the lifetime of wireless sensor networks. This thesis considers the use case of optimizing network lifetime while maintaining application requirements such as target coverage and network connectivity.

## 1.3/ MAIN CONTRIBUTIONS OF THIS DISSERTATION

The main contributions in this dissertation fall within the requirements of an WSN application, namely energy saving, full/partial coverage and the network connectivity. The main contributions can be summarized as follows:

1. First, we investigate the problem of lifetime optimization for full coverage in heterogeneous sensor networks. The heterogeneity level of nodes' batteries in the case of Disjoint Set Covers (HDSC) based scheduling, is considered. To this end, we propose a novel mixed integer linear programming (MILP) formulation to solve optimally the HDSC problem for dense networks. This proposed model allowed to solve small instances of the problem to optimality. Next, we propose a genetic algorithm (GA) based approach to produce good approximate solutions for large instances in a reasonable time. The experimental results showed that the proposed GA approach can find the optimal solutions for small instances and for the bigger ones good quality solutions were discovered.
2. Second, we tackle the issue of lifetime optimization for partial coverage in heterogeneous sensor networks. In order to enhance the quality of coverage, a new local constraint, called  $\beta$  constraint, is included in our model. It requires each target to have a minimum coverage rate over the entire network lifetime. To perform this, we formulate the problem as a Binary Integer Linear Programming (BILP) and we solve it to optimality. The experimental results showed that applying the  $\beta$  constraint partially reduces the network's lifetime because it guarantees that each target will be covered for a minimum percentage of the network lifetime which makes it more appropriate for real-life applications requirements. Moreover, in this contribution, we show that the default covers' activation can lead some targets to be left uncovered for a long period of time. Therefore, we propose to formulate this scheduling problem as a *p-dispersion* problem and due to the NP-Completeness of the former, an efficient Genetic Algorithm (GA) based approach is proposed to achieve efficient covers' scheduling with minimal execution time. The experimental results showed that the obtained covers' scheduling effectively smooths the periods of uncovered targets throughout the network's lifetime.
3. The second study doesn't guarantee the network connectivity, which is a critical problem of WSNs. This issue was addressed in the third contribution of this thesis, in which a novel mathematical Mixed Integer Linear Programming (MILP) is proposed to solve to optimality the problem while respecting the *partial coverage* and the *network connectivity* constraints. This model outputs connected partial cover sets with variable activation time periods, in contrast to what has been proposed in the second study which is restricted to fixed activation time periods. Also, the

$\beta$  constraint presented in the second contribution is also considered in this study. The results showed that the resolution of this linear program with mixed variables becomes impracticable for large optimization problems. As the problem is NP-hard, we propose an exact method based on column generation (CG) to solve large instances. Due to the NP-Completeness of the subproblem of column generation, we also propose a dedicated heuristic (DH) based on the minimum connected set coverage problem (MCSC) to solve approximately the column generation's subproblem in each iteration without considering the  $\beta$  constraint and we adapted it when considering the  $\beta$  constraint. The results showed that the heuristic method based on the column generation approach returns very competitive solutions with lower execution time than the one proposed in the literature. Moreover, we propose another exact approach based on the CG framework to solve the problem in a low computational time. The method applies the proposed heuristic to find profitable solutions for the subproblem and only applies ILP formulation when the heuristic fails to find an interesting column.

## 1.4/ DISSERTATION OUTLINE

The rest of this dissertation is organized as follow: Chapter 2 presents the different components of a wireless sensor network (WSN), its limitations and its requirements. Chapter 3 presents the first contribution of this dissertation which deals with the complete coverage, which was published in an international conference under the title: "Optimizing the lifetime of heterogeneous sensors network under coverage constraint: MILP and genetic based approaches" [73]. Chapter 4 addresses the partial coverage, which has been presented in "Lifetime optimization for partial coverage in heterogeneous sensor networks" [78]. Chapter 5 addresses both the partial coverage and the network connectivity, which has been presented in "Partial Coverage and Network Connectivity in Heterogeneous Sensor Networks". Chapter 6 concludes the work that has been done in this thesis.



## WIRELESS SENSOR NETWORKS (WSNs)



This part presents the scientific background of the wireless sensor networks (WSNs) by discussing the recent advances in this area and the numerous challenges faced by WSN applications.



## GENERAL CONCEPT OF WSNs

WSNs have rapidly become an ubiquitous technology, supporting multiple applications in largely diverse contexts such as intrusion detection, traffic control, health monitoring and natural disasters forecasting. Moreover, WSNs are having a growing impact on our daily lives due to their expected integration with the "Internet of Things", where sensor nodes join the Internet dynamically, and use it to collaborate and accomplish their tasks. This chapter presents the benefits of WSNs, the different components of WSNs, the types of sensor networks, the WSN applications and the challenges and requirements that need to be addressed in these applications.

### 2.1/ INTRODUCTION OF WSNs

Typically, WSNs consist of a large number of small devices called sensor nodes. Sensor nodes monitor physical or environmental conditions (temperature, humidity, noise, vibration, pressure, motion, pollution, etc.), perform some computing, and share their data via wireless links to the main receiver. The WSNs include one (or more) base station(s), called sink(s), which serve as gateways between each WSN and the end users. A user can retrieve the necessary data from the information collected by this sink, and then analyze it to predict or anticipate certain phenomena. A typical wireless sensor network is illustrated in Figure 2.1.



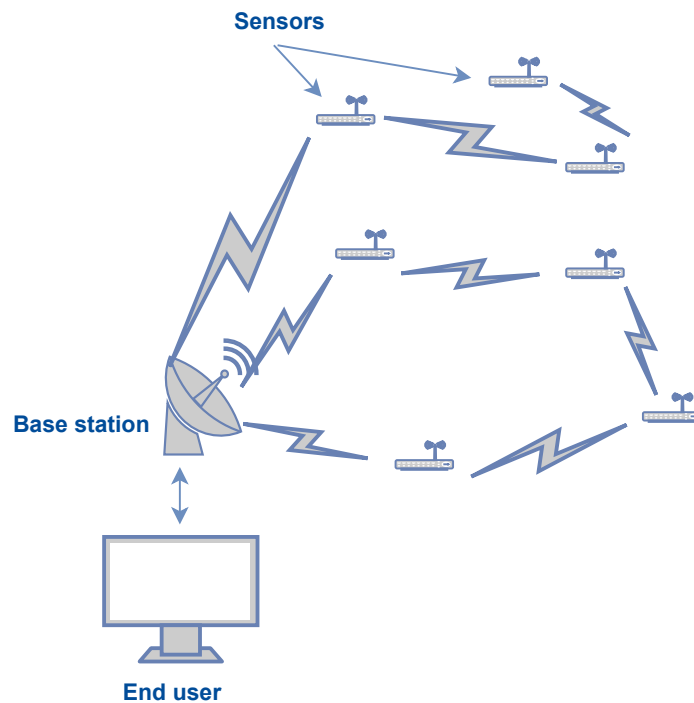


Figure 2.1: Wireless sensor network topology for environmental monitoring.

## 2.2/ BENEFITS OF WSNS

A sensor node has usually the following characteristics: it is energy-sufficient, low cost (and easy to deploy), easy to set up and has a small environmental impact. Sensors can operate immediately after deployment and do not require human intervention. Due to these reasons, WSNs offer many advantages, including:

- Due to its scalability, new devices or nodes can be added to the network in real-time.
- Cables and wires are not required.
- Due to its flexibility, physical partitions are possible.
- The technology can be applied on a large scale and in different domains, such as the military, healthcare, surveillance, etc.

## 2.3/ SENSOR NODE COMPONENTS

A wireless sensor node consists of four basic components (the acquisition unit, the processing unit, the communication unit and the energy source unit). Additionally, a sensor

can possess devices such as a unit driving one or more actuators and a geolocation system such as a GPS (Global Positioning System).

### 2.3.1/ THE ACQUISITION UNIT

Analog to Digital Converters (ADC) and sensors are the two sub-units of an acquisition unit. Sensors are responsible for measuring physical quantities. ADCs convert analog signals into digital data and send them to the processing unit.

### 2.3.2/ THE PROCESSING UNIT

Storage and computing are both included in the processing unit, which is generally a micro-controller. The data collection unit stores the collected environmental data. After that, the microprocessor processes the data.

### 2.3.3/ THE COMMUNICATION UNIT

The communication unit has a radio transmitter and a receiver (called a radio module) that transfers data wirelessly to the sink, if needed, through other sensor nodes.

### 2.3.4/ THE ENERGY SOURCE UNIT

The power source unit (batteries) usually provides all the other units with energy to perform the above mentioned tasks. Note that there are alternative energy sources (such as solar, vibration, etc.). According to these techniques, the sensors will collect energy from their environment through devices attached to them. Even though these techniques do not ensure continuous power supplies to the sensor nodes and are highly reliant on many environmental factors, they can be used to supplement all energy-saving techniques of WSNs.

## 2.4/ SENSOR NETWORK TYPES

There are five basic types of sensor networks, including terrestrial WSNs, underground WSNs, underwater WSNs, multimedia WSNs and mobile WSNs [39]. Hybrid types, such as terrestrial mobile or multimedia WSNs, also exist.

### 2.4.1/ TERRESTRIAL WSNS

Terrestrial WSNS contain many sensors that can be deployed in two different ways [35]:

- **The random deployment:** sensor nodes can be airdropped from an aircraft and randomly positioned in the target area.
- **The planned deployment:** nodes can be arranged in a grid, placed in an optimal location, etc.

The sensor nodes must be capable of transmitting data efficiently to the base station. Energy conservation is important for sensors since the battery is limited in energy and may not be rechargeable. Short transmission range, data aggregation, eliminating redundant data, minimization of delays, and duty-cycle operations can be used to conserve energy in terrestrial WSNS.

### 2.4.2/ UNDERGROUND WSNS

Underground WSNS consist of many sensors buried in a cellar or in a mine to survey underground conditions [33]. The sink node is usually positioned above or on the ground for the purpose of relaying information from the sensor nodes to the base station. The underground environments such as soil, rocks and other mineral containers present a challenge due to signal loss and attenuation. Like terrestrial WSN, underground sensor nodes are equipped with limited charge batteries and once deployed underground, it is difficult to recharge or replace a sensor's battery. As previously stated, a major goal is to optimize the lifetime of the network by reducing energy consumption.

### 2.4.3/ UNDERWATER WSNS

Underwater WSNS have vehicles and sensors deployed in a specific acoustic area for the purpose of conducting collaborative surveillance and data collection [15]. Acoustic waves are typically used for underwater wireless communications. As with terrestrial WSNS, underwater sensors are equipped with a battery that cannot be replaced or recharged. Under-water WSNS face many problems and challenges, such as high propagation delays, limited bandwidth, media access control, power constraints, etc.

### 2.4.4/ MULTIMEDIA WSNS

Multimedia WSNS are composed of a large number of nodes equipped with multimedia devices, such as cameras and microphones, that can record both video and audio data.

To ensure coverage, multimedia sensors are deployed in a planned manner in the environment. Multimedia WSNs have several problems and challenges such as high energy consumption, high bandwidth, guaranteed quality of service (QoS), cross-layer design, and data compression and processing techniques.

#### 2.4.5/ MOBILE WSNs

A WSNs is considered mobile if its sensors can independently move and interact with the physical environment [39]. Contrary to static nodes, mobile nodes also have the ability to reposition and organize themselves within a network. Another important difference is the distribution of the data. In a mobile WSN, dynamic routing is used instead of static routing. There are many problems and challenges associated with mobile WSNs, such as deployment, localization, self-organization, navigation, cover, energy, etc.

### 2.5/ FIELDS OF APPLICATION

Sensors offer new ways to manage information. By providing the user with information on physical events happening around him, they are a link with the real world. The facilities sensors offer have naturally attracted several fields of application. Here is a selection of these applications.

#### 2.5.1/ MILITARY DOMAIN

A sensor network offers some very valuable benefits for military applications. Since it can be set up quickly, dynamically and without any infrastructure, it offers a great asset to monitor enemy movements and communicate at a low cost between units.

#### 2.5.2/ ENVIRONMENTAL MONITORING

Sensors, due to their small size and relatively large computing and communication capabilities, can be placed in places that humans cannot or will not access, including large forests, volcanoes, deep oceans, polar regions, or even planets other than Earth [11]. WSNs can also be used to measure the quality of water or air.

#### 2.5.3/ MEDICAL DOMAIN

In the medical field, smart sensors have been used to provide home hospitalization, the integration of micro-sensors in the body, and emergency management [18]. A few useful

applications include remote monitoring of vital signs and activity levels in the homes of elderly or handicapped individuals, as well as remote monitoring of physiological data.

#### 2.5.4/ URBAN AND HOME AUTOMATION FIELDS

Sensors are becoming an increasingly important part of our daily lives. Sensors are already used in the urban environment for bus localization, electronic tickets, and security. A good example of this involves monitoring road traffic with sensor networks deployed on highways [41]. Moreover, homes, buildings, and offices equipped with smart intelligent sensors enable the development of omnipresent information systems [10].

### 2.6/ NETWORK LIFETIME SENSOR NETWORKS

Prolonging network lifetime is one of the most difficult problems to solve in WSNs, which defines how long a deployed WSN is able to perform its assigned task(s). In the literature, the WSN lifetime has been defined differently based on various assumptions. According to [4] [26], the network lifetime is given as the period of time from the network's initial deployment to the first sensor node dies because of energy depletion. The sensor nodes in the network perform their assigned tasks with a high degree of redundancy. Therefore, the network can continue to function after the first sensor node dies. In [24], another more practical definition of network lifetime is the period from the network's initial deployment to the time when WSN can no longer meet the requirements of the assigned tasks. In this thesis, we define the network lifetime as the duration until either the coverage or connectivity requirement is not satisfied.

### 2.7/ CHALLENGES FOR QUALITY OF SERVICE (QoS) SUPPORT IN WSNs

Sensors in WSNs sense and forward data from the surrounding environment to a remote and resourceful node called sink or base station. As a result, QoS provisioning in WSN has some important challenges. Here are a few example of such challenges.

#### 2.7.1/ CHALLENGES IN POWER MANAGERMENTS

WSNs face technical challenges due to the low intrinsic resources of the sensor nodes. The nodes have limited energy, short communication range, limited throughput, low memory and storage capacity, and low computing power. The sensor nodes are sometimes

not rechargeable or replaceable and once they are deployed, they must be operational for long periods of time at large sites without fixed infrastructure. This requires efficient energy management, self-organizing capability to cope with changing radio links, and redundancy in the topology to compensate for the failure of some nodes. This thesis focuses specifically on energy saving. There have been numerous energy saving schemes studied by different WSNs research communities to minimize the energy consumption of the nodes and thus enhance the network lifetime [44] [40] [50] [63] [55] [54]. The proposed solution must reduce the causes and effects of energy overconsumption in order to ensure an efficient energy saving. Different energy saving protocols exist, including duty cycle, energy efficient routing, energy efficient medium access control (MAC), data aggregation, cross layer design and error control code (ECC). Sleep/wake scheduling sensor activities is adopted by the duty cycle approach to reduce the active time of the nodes and save their energy. The routing and MAC protocols use suitable energy efficient algorithms for energy saving. Through data aggregation, we can reduce the number of transmissions, which will save energy. As part of this thesis, we study Sleep-Awake scheduling sensor activities in order to reduce the node's energy consumption and, in turn, increase the lifetime of the network.

### 2.7.2/ REDUNDANT DATA

Due to the dense deployment of sensors in a terrain of interest, the majority of data generated by sensor nodes is redundant. However, the energy wasted by this redundancy contributes to the reliability and fault tolerance of the WSNs. Data aggregation or data fusion removes this redundancy.

### 2.7.3/ HETEROGENEITY OF THE SENSOR NODES

WSNs face another challenge: handling heterogeneous data generated by different types of sensor nodes. There are some applications that require different types of sensors such as monitoring temperature, pressure and humidity of the surrounding environment, capturing image or video of moving objects. These sensors generate data at different rates depending on the QoS constraint and delivery models. Therefore, these types of diversified sensor network can pose significant challenges to QoS. Sensor nodes in a heterogeneous wireless sensor network might have different specifications, such as different computing power, different battery life, different sensing and communication ranges. In this thesis, heterogeneous WSNs are considered rather than homogeneous WSNs, in particular, the initial energy levels of nodes' batteries differ. For the following reasons, heterogeneous networks seem more realistic than homogeneous networks:

- **wear-out rate:** during the network service, the nodes' energy will be depleted at different rates leading to non homogeneous sensors' battery residual life.
- **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.
- **solar energy replenishment:** if the sensor nodes are rechargeable using solar energy, then maintaining the network's homogeneity is almost impossible.

#### 2.7.4/ MULTIPLE SINKS OR BASE STATIONS

Although most sensor networks have only one sink or base station, there may be multiple sink nodes depending on the application requirements. WSNs must be able to maintain a diverse level of QoS support associated with multiple sinks or base stations.

### 2.8/ WSNS REQUIREMENTS

Target coverage and network connectivity are fundamental requirements for the vast majority of sensor network applications.

#### 2.8.1/ TARGET COVERAGE

Coverage is one of the key aspects of WSNs, which determines how well sensors monitor a phenomenon of interest (area or target). Each sensor node can detect a phenomenon within a specific sensing area. Any point within the sensing area of a sensor is considered to be covered by the sensor. A sensor's sensing area is typically described as a disk with the sensor in the center. A disk's radius is known as its sensing range. As a general rule, there are three types of coverage [7], categorized by what needs to be covered :

- **Area coverage:** This means that every point in the area of interest is covered with active sensors.
- **Discrete points coverage (target coverage):** This usually applies to a small number of discrete target surveillance scenarios.
- **Barrier coverage(linear coverage):** Aims to detect intrusion attempts into protected areas.

Both the area coverage and target coverage are based on a binary model for sensing capacity. However, in barrier coverage [7], the sensing capability of a sensor is presented as

the probability of detecting a phenomenon, which is supposed to depend on some other factors such as the distance between the sensor and the phenomenon. Moreover, the area coverage problem could be easily and accurately transformed into a target coverage problem [22]. In this dissertation, the problem of target coverage is addressed, which is useful for applications such as environmental monitoring or data collection that need to monitor static points and locations.

### 2.8.2/ THE NETWORK CONNECTIVITY

When implementing WSNs, maintaining network connectivity is another important consideration. The connectivity of a WSN refers to the ability for each sensor to find a path to reach the designated data sink. Data collected by a sensor node cannot be processed if there is no path to the data sink. If two sensors are within the same communication range, they are considered neighbors. The communication area of a sensor is normally shaped like a disk, with the sensor in the center. The radius of the disk is known as the communication range. WSN connectivity is usually studied using a graph associated with the network. A vertex corresponds to a sensor, while an edge linking two vertices indicates that the sensors corresponding to the vertices can directly communicate. When this associated graph is connected, a network is said to be connected. The purpose of this thesis is to keep the WSN connected when carefully selecting the active subset of sensors.

## 2.9/ SCHEDULING SENSOR ACTIVITIES

Sleep-Awake scheduling sensor activity is the most common and well-known technique, which turns sensors to On and Off according to the application requirements in order to save energy consumption and extend the network lifetime. In the scheduling problem, nodes are divided into cover sets that are activated successively. Nodes in an active cover set are responsible for monitoring all targets, while all other sensors are in sleep mode. There are two kinds of cover sets:

- Non-Disjoint Set Covers (NDSC) problem in which sensors can participate to more than one cover set.
- Disjoint Set Covers (DSC) problem in which sensors can participate only in one cover set.

The problem of Sleep-Awake scheduling sensor activities while maintaining target coverage has been extensively studied in the literature [22] [25] [28]. Sleep-Awake scheduling



sensor activities while maintaining connectivity has been studied in the literature [9][12] [20]. The problem of Sleep-Awake scheduling sensor activities while maintaining both coverage and connectivity has been studied in the literature [21][31] [32] [13].

## 2.10/ CONCLUSION

This chapter presented an overview of WSNs and highlighted some of their challenges and requirements. The emphasis of the following works presented in this dissertation is optimizing the network lifetime under the application requirements, including target coverage and network connectivity.



## CONTRIBUTIONS



This part examines the main contributions in this thesis. As discussed in the previous chapter, the proposed approaches and methods are designed to solve different challenges in lifetime optimization for full/partial coverage of a WSN application.



# LIFETIME OPTIMIZATION FOR TOTAL COVERAGE IN HWSNS

Lifetime optimization for total coverage in heterogeneous wireless sensor networks (HWSN) is investigated in this work. 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 presented work 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.

## 3.1/ 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. Due to the conceptual constraints of WSN and without being able to recharge or replace exhausted batteries, there is an increasing need for designing techniques to improve the network's lifetime service.

In this work, 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 which are more realistic than homogeneous networks, that is, the initial energy levels of nodes' batteries are different.

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.

### 3.2/ RELATED WORK

In the last two decades, the Maximum Network Lifetime Problem (MLP) in wireless sensor networks had considerable attention from researchers. In [45, 53, 59, 67, 74, 71], exact methods and heuristics were proposed to either solve small instances of the problem to optimality or produce good solutions for large instances in a reasonable time. Solving the MLP consists in finding subsets of sensors that can cover all the targets for the longest possible time period. The MLP was shown to be NP-complete by a polynomial time reduction from the well known problem 3-SAT [23]. For instance, in order to save energy consumption under coverage requirement, some distributed algorithms have been proposed in [56][43] [48] [64] [37][62]. 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 [69] [61] [16] [24] [71] [47] [36] [46] [22] [65] [77]. There are two main approaches DSC and NDSC (for Non-Disjoint) as outlined in Table 3.1.

In [16], 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 [61] 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 [24], 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

	homogeneous	heterogeneous
NDSC	models : IP formulation [24]	models : LP formulation [61], [16]
	resolution methods : Heuristic [24]	resolution methods : Heuristic [47] GA[71]
DSC	models : IP formulation [46]	models : No model
	resolution methods : Heuristic, GA [36]	resolution methods : No resolution method

Table 3.1: A synthesis of fundamental WSN's lifetime optimization approaches in the literature.

sensor nodes into a maximal number of non-disjoint cover sets. In [47], 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 [8]. 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 [71]. 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 [36]. 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.

### 3.3/ 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.

#### 3.3.1/ NOTATIONS

In the rest of this work, 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 =  $\{s_1, \dots, s_n\}$
- $T$  : set of targets =  $\{t_1, \dots, t_m\}$
- $E_i$  : 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 [17], 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:

$$K = \min_{j=1..m} |S_j| \quad (3.1)$$

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  $L_{max}$ :

$$L_{max} = \min_{j=1..m} \sum_{i \in S_j} E_i \quad (3.2)$$

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:

$$d_k = \min_{i \in C_k} E_i \quad (3.3)$$

### 3.3.2/ EXAMPLE

Let consider a simple network (see Figure 3.1) 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  $C_5 = \{2, 4\}$ . These five sets are shown in the figure 3.2. 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 heteroge-

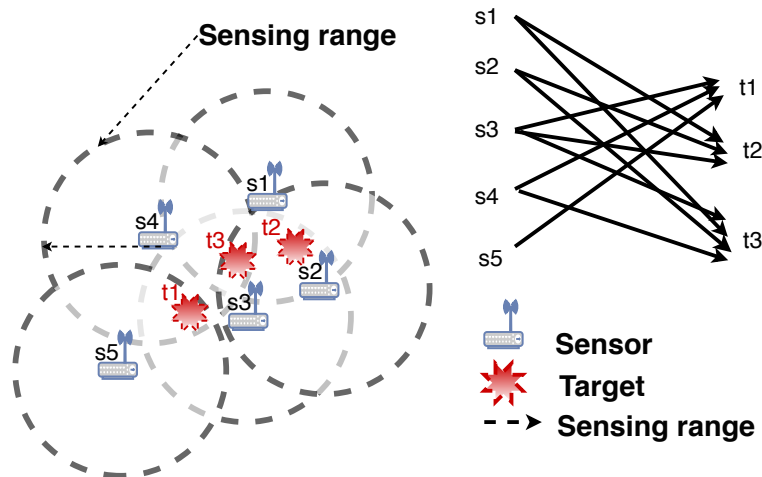


Figure 3.1: A network with 5 sensors and 3 targets

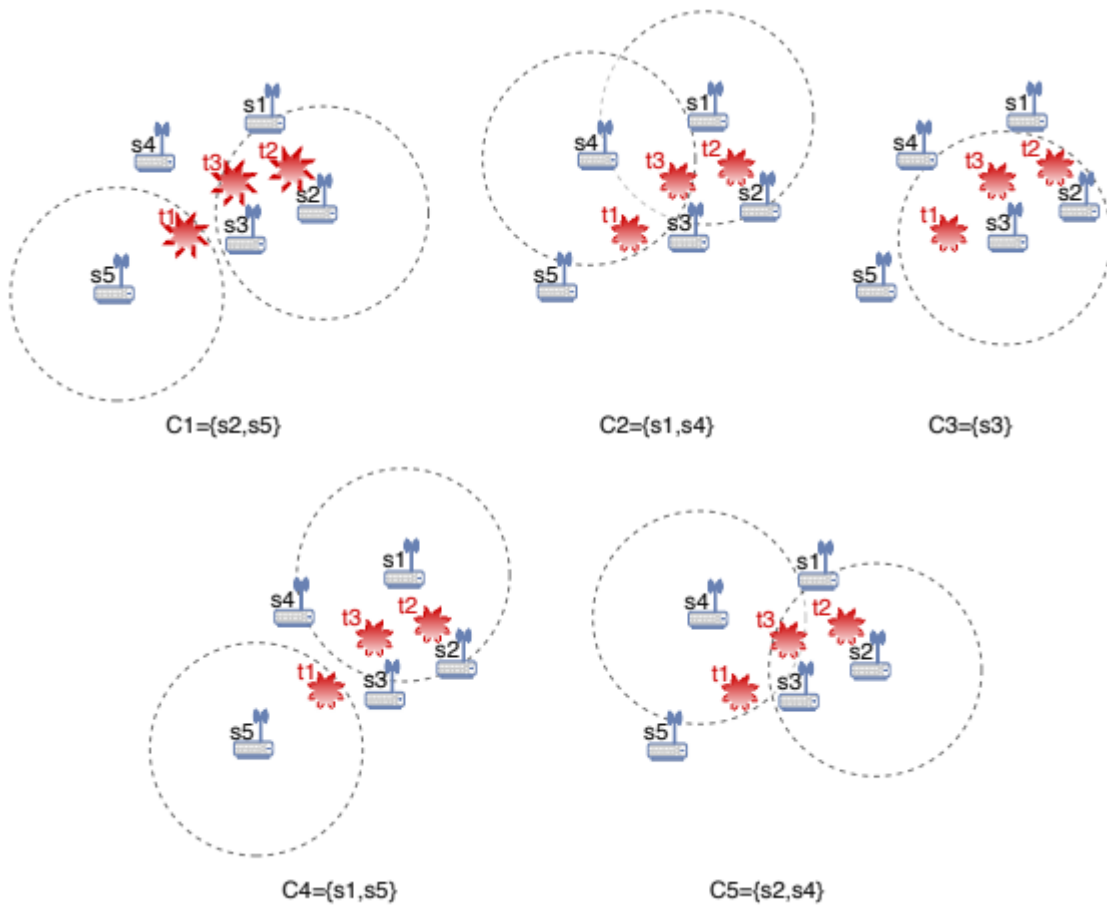


Figure 3.2: Possible cover sets for the example shown in Figure 3.1

neous 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  $d_1 + d_2 + d_3 = \min(E_2, E_5) + \min(E_1, E_4) + E_3 = 20 + 2 + 15 = 37$ .

### 3.3.3/ 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,  $\forall k \in \llbracket 1, K \rrbracket$  where  $K$  is the upper bound defined by (5.1)
- 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.

$$\text{Max} \sum_{k=1}^K d_k \quad (3.4)$$

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:

$$M1(1 - x_{i,k}) + E_i x_{i,k} \geq d_k \quad \forall i \in \llbracket 1, n \rrbracket, \forall k \in \llbracket 1, K \rrbracket \quad (3.5)$$

The constant  $M1$  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  $M1 \geq d_k$  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:

$$\sum_{i \in S_j} E_i x_{i,k} \geq d_k \quad \forall j \in \llbracket 1, m \rrbracket, \forall k \in \llbracket 1, K \rrbracket \quad (3.6)$$

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:

$$\sum_{k=1}^K x_{i,k} \leq 1 \quad \forall i \in \llbracket 1, n \rrbracket \quad (3.7)$$

Other additional constraints can be added:

$$d_k \leq \max_{i \in S} E_i \quad \forall k \in \llbracket 1, K \rrbracket \quad (3.8)$$

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.

$$\sum_{i \in S} x_{i,k} \leq M2d_k \quad \forall k \in \llbracket 1, K \rrbracket \quad (3.9)$$

The constant  $M2$  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.

### 3.4/ PROPOSED GENETIC ALGORITHM

Among the well-known meta-heuristics, adequate for solving optimization problems, the so-called evolutionary genetic algorithm, firstly proposed by Holland [1], 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.

#### 3.4.1/ 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 run

time 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 3.2, forms two cover sets ( $\{1, 3\}$  and  $\{2, 4\}$ ) that have a total network lifetime equal to 4.

---

**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  $C_1, \dots, C_k$ )

$k \leftarrow 0$  ;

$L \leftarrow 0$  ;

**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**

---

### 3.4.2/ 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.

### 3.4.3/ THE CROSSING AND MUTATION OPERATORS

Among several types of crossing operators, the LOX (Linear Ordering Crossover) [1] linear crossing was used because it has been shown in [27] that it is adapted for linear permutation problems. The LOX operator, illustrated in 3.3, works as follows:

- Two cut-off points are randomly selected.
- Each parent transfers its sub-sequence located between the 2 cut-off points to a child.
- The sequence of each child is completed with genes from the other parent. Starting from the beginning of both sequences, the genes are copied from the parent to the child if they do not already exist in that child.

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

### 3.5/ EXPERIMENTAL SETUP

This section describes the performance and the quality of the solutions given by the proposed Genetic Algorithm were evaluated in a series of experiments. To do so, 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,

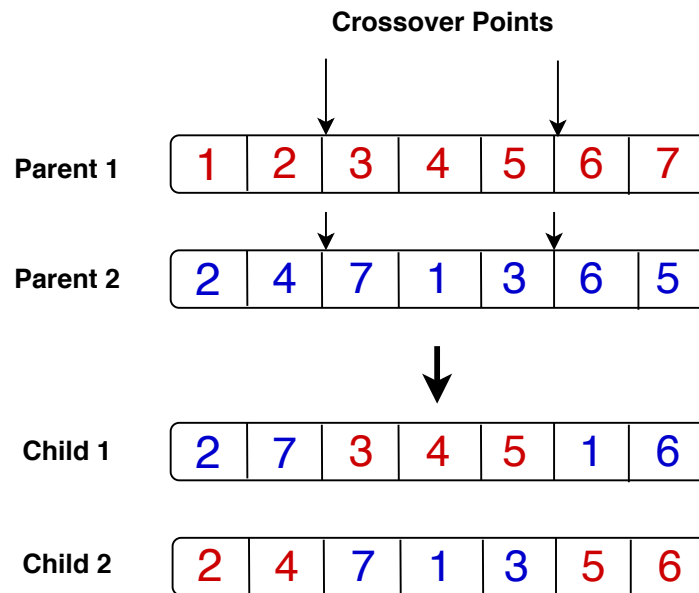


Figure 3.3: Applying the LOX crossover operator on 2 parents.

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.

### 3.6/ EXPERIMENTAL RESULTS AND ANALYSIS

This section describes the results of the experiments conducted to validate the solution proposed in this chapter. The performance of the genetic algorithm is evaluated with fixed parameters described in table 3.2. 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  $n$ .

#### 3.6.1/ THE IMPACT OF THE INITIAL POPULATION SIZE ON THE PERFORMANCE OF THE GA

The first step in a GA consists of generating the initial population. There are two parameters to consider for the population: the number of individuals in the population and their quality. In [75], it is shown that an appropriate population size parameter allows the GA to give better results. In the proposed GA, the size of the population do not change during the whole iterative process. Figure 3.4 shows the evolution of the average network lifetime for 10 instances according to the size of the initial population. The network consisted



of 40 sensors and 40 targets and the GA executed 100 generations. Although these results are problem dependent, it can be noticed that the average lifetime was significantly increased when the initial population size was increased from 10 to 50 individuals and afterwards it stagnates. For the same parameters, Figure 3.5 presents the evolution of the GA's execution time according to the size of its population.

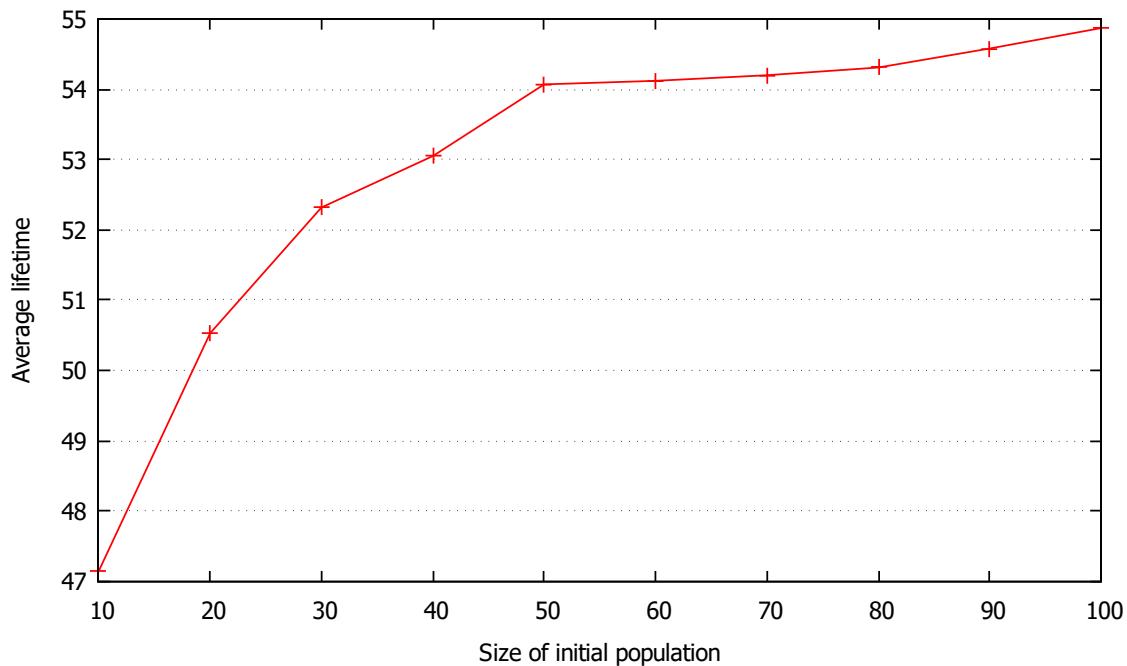


Figure 3.4: The lifetime of the network ( $n=40$ ,  $m=40$ ) while varying the population size.

It can be noticed that the relationship between the execution time and the population size is linear. While the growth of the population size raises the chances of the GA to find good solutions, it also increases the number of operations to execute at each generation and thus raises the overall execution time. Therefore, the chosen size of the initial population must maximize the GA's chances of finding good solutions while minimizing the execution time of the GA. This parameter is problem and instance dependent. Experimental results can help find out what is a good population size for a given instance. In the examples shown in Figures 3.4 and 3.5, ( $n = 40$ ,  $m = 40$ ), the population size equal to 50 individuals, gives the best trade-off between average lifetime and execution time. In the rest of the work, the population size of the GA is fixed to 100 individuals for all the small and large instances in order to eliminate the influence of this parameter on the results of the experiments.

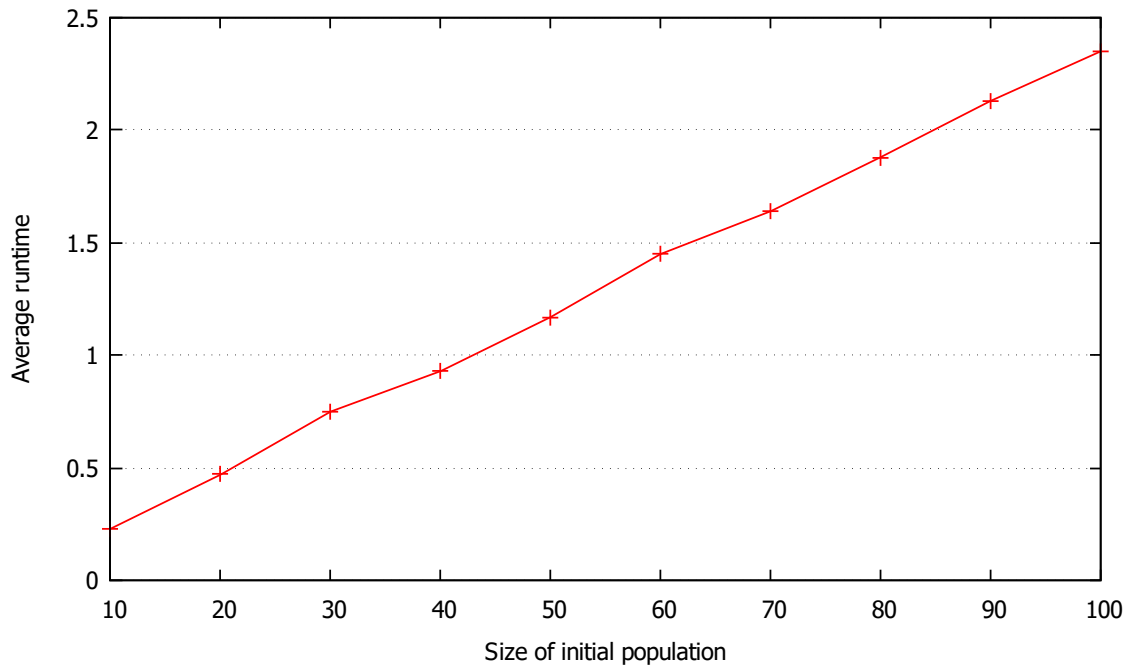


Figure 3.5: The execution time of the GA for the same instance and while varying the population size.

### 3.6.2/ THE IMPACT OF THE INITIAL POPULATION QUALITY ON THE PERFORMANCE OF THE GA

Figure 3.6 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.

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

Table 3.2: List of parameters for GA

### 3.6.3/ THE GA VERSUS THE EXACT METHOD

Table 3.3 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

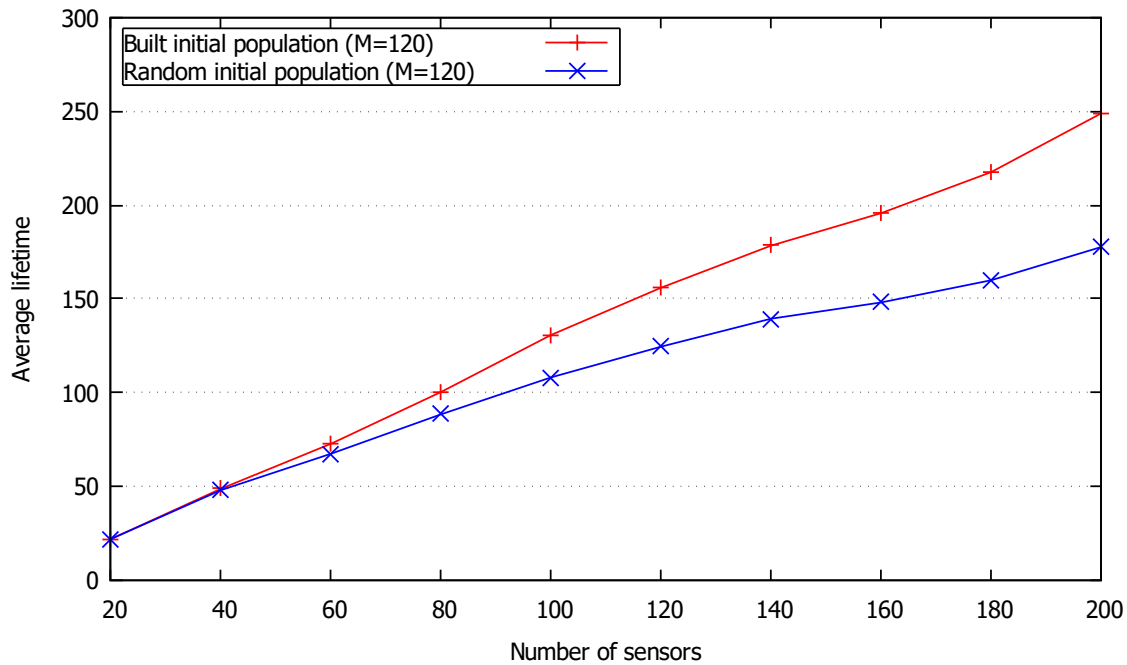


Figure 3.6: Average lifetime returned by the GA with different initial populations

with a good quality initial population composed of 100 individuals and executes 100 generations. Table 3.3 shows that the exact method can only compute 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 computed with the GA is given in Table 3.3. 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.

### 3.6.4/ 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 [52] 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

$n$	$m$	Exact Method		Genetic algorithm	
		$L_{opt}$	Rt(s)	Gap(%)	Rt(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 3.3: The lifetime, execution time for different networks computed with the exact method and the GA.

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. 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 3.7 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.

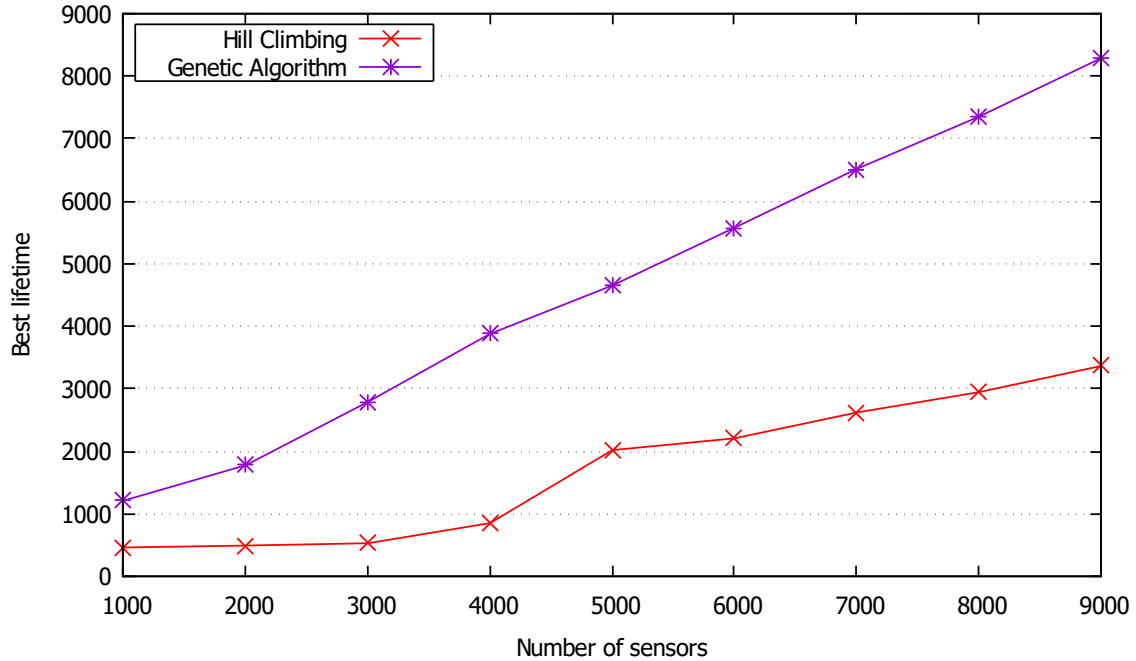


Figure 3.7: Lifetime of the best found solutions for different problem sizes and using the GA or the Hill climbing method.

### 3.7/ CONCLUSION

In this work, 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.

## LIFETIME OPTIMIZATION FOR PARTIAL COVERAGE IN HWSNS

In certain applications such as fire detection, the full coverage discussed in Chapter 3 is not a critical requirement. Therefore, we investigate in this chapter the problem of lifetime optimization for partial coverage in heterogeneous sensor networks. This problem which is NP-Hard in its general form is known under the name of  $\alpha$ -coverage, where  $\alpha$  refers to a prescribed level of coverage threshold that we need to maintain. Sleep-Awake scheduling has been heavily studied in the literature to deal with energy management under coverage constraint. The question is how to orchestrate the clustering of the sensor nodes into disjoint or non-disjoint covers, and to schedule these covers, so that the total network's lifetime is maximized. Unlike earlier works, we consider both global (whole targets) resp. local (individual target) monitoring thresholds to improve the coverage quality rather than dealing with a single global leveling threshold as in the literature. In addition, instead of employing a default covers' activation which may lead to the starvation phenomenon, where targets may remain uncovered for a long time period, we provide a clairvoyant scheduling for the obtained covers to ensure fair smoothing for the cumulated target's uncovered time periods during the network's service. First, a novel mathematical Binary Integer Linear Programming (BILP) is proposed to solve the  $\alpha$ -coverage problem to optimality. Then, provable guarantees of the upper bound for the number of partial cover sets are given. Next, we formulate the covers' planning as a  $p$ -dispersion problem and due to the NP-Completeness of the former, an efficient Genetic Algorithm (GA) based approach is designed to achieve efficient covers' scheduling with minimal execution time complexity. Finally, a series of experiments are conducted and several QoS metrics are evaluated to show the usefulness of our proposals.

## 4.1/ INTRODUCTION

Energy consumption and target coverage are two main critical and related issues that need to be considered to improve the network's QoS.

While some very sensitive applications require the complete coverage of all the targets during the whole lifetime of the network, others can bear less strict monitoring. Depending on the nature and the sensitivity of the monitored targets, partial coverage, where some targets may remain uncovered for a limited time period, could be tolerated in order to prolong the network's lifetime. For instance, since the probability of a forest fire occurring in the rainy season is significantly lower than in the dry season, monitoring at each time period a few random regions in the forest could be sufficient to prevent the forest from taking fire. This partial coverage would also lead to activating at each time period a smaller number of sensors than in full-coverage which would drastically reduce the sensors' energy consumption and increase the network's overall lifetime [38]. Pollution monitoring systems can also make do with partial coverage of the monitored area. Excluding, at each time period, some random regions and computing the average pollution level using a percentage of the measurements, would not practically affect the final results [53].

Although, both energy saving and coverage requirement have been studied in the literature, to the best of our knowledge, none of the existing research works has considered, at the same time, both **global** (whole targets) and **local** (individual target) monitoring level threshold constraints nor the **starvation phenomenon** that may occur if the obtained cover sets are not scheduled in a suitable way. Going further, it is usually assumed that the lifetime of the partial coverage must be at least as well as the achieved one in the case of complete coverage. We strongly conjecture that this assumption is a weaker condition and it is far from being sufficient to provide reliable targets' coverage.

In this work, we bring answers to the aforementioned shortcomings of the previous works in the literature. We target the case of Non-Disjoint Set Covers (NDSC) problem in which sensors can participate to more than one cover set and can interchange between idle and working modes. We consider heterogeneous networks where the initial energy levels of nodes' batteries are different. The aim of this work is to deal with energy saving subject to a prescribed leveling threshold of the coverage quality that we have to ensure during the network's activity. To this end, two main and distinct optimization problems are investigated: i) the construction of the  $\alpha$ -cover sets (by the exact resolution of a binary integer linear program) and ii) the planning of the generated  $\alpha$ -cover sets (in which order they should be activated successively?). The output of the former is the input of latter.

In the following, we summarize the contributions and the novelties of of the presented study:

- A new mathematical Binary Integer Linear Programming (BILP) formulation is proposed to solve to optimality the Heterogeneous Non-Disjoint Partial Set Cover (HNDPSC) problem with fixed activation time periods.
- We provide *necessary* and *sufficient* global and local coverage constraints to achieve an efficient trade-off between energy and coverage performance related objectives during the network's service. The findings of our research study reveal that, when dealing with partial coverage under energy constraint, local (individual target) coverage constraint plays a crucial role on the achieved global performances of the network's monitoring activity (See Section 4.3 for more details on these constraints called resp.  $\alpha$  for the global constraint and  $\beta$  for the local one).
- We give provable guarantees for two upper bounds for the number of non-disjoint cover sets that can be constructed when dealing with partial coverage under fixed activation time periods in heterogeneous sensor networks. This drastically reduces the number of variables which is a key factor when solving linear and nonlinear optimization problems. That is to say that these bounds allow practical gains and enable us to solve the  $\alpha$ -coverage problem in a single stage in contrast with what was previously proposed in the literature.
- To avoid the starvation phenomenon, instead of considering a default activation of the resulting cover sets, we provide an efficient scheduling to fairly smooth the target's uncovered time periods during the network's lifetime. To this end, first we formulate the dispersion of uncovered time periods of a target throughout the network's lifetime as a *p-dispersion* problem. Then, we derive a generalization of the *p-dispersion* problem where the dispersion of the uncovered time periods for all the monitored targets should be optimized at the same time. Two criteria were adopted to reflect how well the uncovered time periods of all targets are balanced (See Section 4.4 for more details on these criteria). Due to the NP-completeness of the *p-dispersion* problem and its generalization, an efficient GA was designed to achieve near optimal solutions in polynomial time complexity.

## 4.2/ RELATED WORK

Several derived problems from the MLP were proposed to adapt it to different contexts. Some of them address coverage connectivity [60][57], reliability [58], or consider sensors with adjustable coverage range [34] [70]. Another interesting variant of the problem, studied in [53, 70, 59] and [67], is the  $\alpha$ -Maximum Network Problem ( $\alpha$ -MLP), in which a



given portion  $((1 - \alpha)$  percent) of the targets could be uncovered in each cover set. In [53] and [59], the authors demonstrated that in some cases, it is preferred to partially cover the targets for a longer period instead of providing full coverage for a short one. They have also provided a formulation of the problem as a linear program where the objective function is the maximization of the  $\alpha$ -Lifetime of the WSN. This formulation first requires the generation of all possible feasible  $\alpha$ -covers. For a given  $\alpha \in [0, 1]$ , an  $\alpha$ -cover is a subset of the sensors that covers at least  $\alpha \times |T|$  targets (where  $|T|$  is the total number of targets in the monitored area). Once all the  $\alpha$ -covers have been generated, the resolution method have to find out how much time each  $\alpha$ -cover has to be activated. Therefore, the linear program's variables are the activation times of all the feasible  $\alpha$ -covers and its objective function is the maximization of the sum of their activation times while ensuring that the battery lifetime of each sensor is not exceeded.

Since the number of potential  $\alpha$ -covers increases exponentially with the number of sensors, especially for lower values of  $\alpha$ , the authors applied a Column Generation (CG) approach to be able to find the optimal solutions for small instances of the problem in reasonable times. The same approach was already proposed in [51] to solve the MLP. At each iteration of the CG method, a Restricted Master Problem, with only a subset of the feasible  $\alpha$ -covers, is solved. Then a specific optimization problem (generally called subproblem) is solved which either produces an attractive cover to be considered while solving the Master Problem in the next iteration or guarantees that the last found solution found is the optimal one.

In [53] the subproblem was formulated as a integer linear program (ILP) and solved to optimality. In [59], the authors attempted to heuristically solve the subproblem by using a genetic meta-heuristic. In both works, an additional constraint was added to the Restricted Master problem such that each target is at least covered as in the complete coverage problem (with  $\alpha = 1$ ). Therefore, before solving the  $\alpha$ -MLP for a given instance, the complete coverage problem must be solved for the same instance in order to find out what is the minimal coverage time to respect for each target. The need to go through this preliminary step is one of the major disadvantages of this approach. The authors also proposed in the same work a greedy approach, called  $\alpha$ -greedy, to find feasible  $\alpha$ -covers and to initialize the Column Generation procedure. They assigned a predefined activation time to each generated  $\alpha$ -cover. Their heuristic iteratively constructs each  $\alpha$ -cover by adding to it the sensor with the highest residual energy and at the same covering the largest number of uncovered targets. In [70], another greedy algorithm for partial coverage of WSNs was proposed as well. In this work, the nodes have different sensing and communication ranges but the same amount of initial energy. The proposed algorithm guarantees the connectivity of the nodes while constructing the  $\alpha$ -covers. The covers sets are then successively activated during a fixed amount of time  $\lambda$  such that a sensor could participate in several cover sets. However, this approach does not guarantee that

each target will be sufficiently monitored over the entire lifetime of the network.

In [67], a heuristic that provides the maximum number of  $\alpha$ -cover sets, was presented. These cover sets were activated one by one for a fixed time period. As in [53] and [59], a minimal coverage time per target, equal to their coverage time in the complete coverage problem, was ensured. Therefore, this approach also requires the pre-calculation of the minimum coverage level for each target. The authors of this work claim that it is possible to extend the network lifetime by wisely selecting the targets to be uncovered in each cover set. However, their approach and simulations are limited to homogeneous sensors (all the sensors have one initial energy unit) and therefore each sensor can at most be involved in two cover sets (the activation time of a cover set is fixed to 0.5 unit). Even though the network's lifetime is extended in most cases, for some instances some targets are monitored less than 20% of the network lifetime which can be potentially dangerous.

The work presented in [71] is the closest one to our study because it also proposes an exact method for solving the coverage problem in a heterogeneous wireless sensor network (sensors with non-identical amount of initial energy and power consumption). The authors of [71] present an Integer Linear Programming (ILP) mathematical model for maximizing the network lifetime. Their goal is to find out how many times each possible cover set should be activated during a fixed amount of time. Their model can be easily extended to partial coverage. More details about this technique are given in section 4.3.4. But the major drawback of this method, as shown in our experiments in Section 4.5.2, is that it requires two time-consuming preliminary steps in order to generate all the possible cover sets. The authors of [53, 59, 67, 70, 71] proposed exact or heuristic methods for solving the  $\alpha$ -MLP but none of them took into account the fact that the coverage period for each target may be too short when compared to the total lifetime of the network. Therefore, in our approach, although the network lifetime is partially reduced, we guarantee that each target will be covered for a minimum percentage of the network lifetime, which is more appropriate to real-life applications requirements. Note that we deal with the case of the Non-Disjoint  $\alpha$ -cover sets problem which is restricted to fixed activation period, in contrast to what have been proposed in Chapter 5 which removes this limitation and deals with variable activation period. In addition, to the best of our knowledge, no method is proposed in the literature for scheduling  $\alpha$ -cover sets once they have been generated. This is why we provide a judicious way to schedule the  $\alpha$ -cover sets in order to avoid excessively long periods of time during which some targets are not monitored.

### 4.3/ PROBLEM FORMULATION

In this section, we define more formally the  $\alpha$ -Maximum Lifetime problem and in order to solve it, it is modeled as a Binary Integer Linear Programming (BILP) problem.

#### 4.3.1/ NOTATIONS

Before getting in details, we need some notations that have not yet been defined throughout this thesis:

- $C_k$  :  $\alpha$ -cover set  $k$
- $d$  : Fixed activation time of a partial cover set  $C_k$ .

In the partial coverage context, for a given  $\alpha \in (0, 1]$ ,  $C_k \subseteq S$  is an  $\alpha$ -cover set if its sensors cover at least  $T_\alpha = \lfloor \alpha \times m \rfloor$  targets. The  $\alpha$ -cover sets can be non-disjoint which means a sensor can participate to more than one cover set if it has enough energy. In this work, we assume that all the cover sets have the same activation time  $d$ . Therefore, improving the lifetime of the network amounts to maximizing the number of constructed  $\alpha$ -cover sets. As in other models [67][70] in the literature, the activation time is a fixed parameter. Its value should be long enough to hide the system control overhead and short enough to minimize the negative effects in case of node failures. In this work, to concentrate our efforts on the introduction of new types of constraints to prevent some targets from being uncovered during a long time period in the case of partial coverage, we have assumed that the duration of the activation time is fixed. Concerning the choice of the value of the fixed activation time  $d$ , it is correlated to the type of the considered application and the sensors initial energies.

When the coverage is partial, all the targets do not have the same coverage rate which can lead to very poor coverage of some individual targets. Therefore, it is appropriate to add additional constraints to ensure for each target a minimum coverage rate over the total lifetime of the network. We introduce a new parameter  $\beta$  which defines the minimal ratio between the time of coverage of one target and the network lifetime. We denote this parameter  $\beta$  as a "Target Monitoring Ratio" applied to each target whereas the coverage ratio  $\alpha$  is applied to each cover set. Therefore, the new objective of the  $\alpha$ -Maximum Lifetime Problem is to form as many  $\alpha$ -cover sets as possible while meeting coverage and energy constraints.

### 4.3.2/ BILP: MODEL FORMULATION

The search for the optimal solution to the  $\alpha$ -MLP, can be formulated as a Binary integer linear programming (BILP) problem. Since all the cover sets have a fixed activation time, the goal of the BILP is to construct the maximum number of  $\alpha$ -cover sets. The upper bound of the possible number of  $\alpha$ -cover sets for a given instance can be denoted by  $K$  and its calculation is discussed in section 4.3.3.

The variables used to define the problem are the following:

- Binary variables  $x_{i,k}$ ,  $\forall i \in \llbracket 1, n \rrbracket$  and  $\forall k \in \llbracket 1, K \rrbracket$ ;  $x_{i,k} = 1$  means that the sensor  $s_i$  is active in the cover set  $C_k$ .
- Binary variables  $y_{j,k}$ ,  $\forall j \in \llbracket 1, m \rrbracket$  and  $\forall k \in \llbracket 1, K \rrbracket$ ;  $y_{j,k} = 1$  means that the target  $t_j$  is covered by the cover set  $C_k$ .
- Binary variables  $z_k$ ,  $\forall k \in \llbracket 1, K \rrbracket$ ;  $z_k = 1$  means that  $C_k$  is an  $\alpha$ -cover set.

#### 4.3.2.1/ OBJECTIVE

The objective is to maximize the number of  $\alpha$ -cover sets.

$$\text{Max} \sum_{k=1}^K z_k \quad (4.1)$$

#### 4.3.2.2/ GLOBAL COVERAGE CONSTRAINTS

If the sensor  $s_i$  is active in the cover set  $C_k$ , the set of targets ( $T_i$ ) that it monitors will be covered in the cover set  $C_k$ . A target  $t_j$  is covered if there is at least one sensor  $s_i \in S_j$  that monitors it in the set  $C_k$ . This is mathematically formulated by the following two types of constraints:

$$y_{j,k} \geq x_{i,k} \quad \forall j \in \llbracket 1, m \rrbracket, \quad \forall k \in \llbracket 1, K \rrbracket, \quad \forall i \in S_j \quad (4.2)$$

$$\sum_{i \in S_j} x_{i,k} \geq y_{j,k} \quad \forall j \in \llbracket 1, m \rrbracket, \quad \forall k \in \llbracket 1, K \rrbracket \quad (4.3)$$

Constraint (4.2) forces the variable  $y_{j,k}$  to be equal to 1 if one sensor of  $S_j$  is activated in the  $\alpha$ -cover. Constraint (4.3) allows the variable  $y_{j,k}$  to be equal to 1 only if at least one of the sensors monitoring it is active in the cover set  $C_k$ .

Each  $\alpha$ -cover set must cover at least  $T_\alpha$  targets. This results in the following constraints:

$$\sum_{j \in T} y_{j,k} \geq T_\alpha \times z_k \quad \forall k \in \llbracket 1, K \rrbracket \quad (4.4)$$

#### 4.3.2.3/ TARGET'S COVERAGE CONSTRAINTS

As explained above, our model includes a new type of constraints that limits the network lifetime according to the parameter  $\beta$  (Target Monitoring Ratio) such that the total coverage time of each target is greater than or equal to  $\beta$  percent of the network lifetime. Moreover, in some applications such as forest fires, it is necessary to monitor the coverage of the targets that have been affected by the fires. These targets must have a higher monitoring ratio than the others and then each target  $j$  has its own monitoring ratio  $\beta_j$ . This constraint is called in this work  $\beta$  constraint and it can be expressed as follows :

$$\sum_{k=1}^K y_{j,k} \geq \beta_j \times \sum_{k=1}^K z_k \quad \forall j \in \llbracket 1, m \rrbracket \quad (4.5)$$

$\sum_{k \in K} y_{j,k}$  represents the number of  $\alpha$ -cover sets which cover the same target  $t_j$ , and  $\sum_{k \in K} z_k$  is the total number of generated  $\alpha$ -cover sets.

The  $\beta$  constraint differs from those usually proposed in the literature for partial coverage. Authors of [53], [59] and [67] have proposed the  $w_{min}$  constraint which imposes that each target must be covered at least as well as the achieved one in the case of complete coverage. This kind of constraint requires the resolution of the model with  $\alpha = 1$  beforehand to provide a common minimum coverage bound  $w_{min}$  for the whole targets and it can be expressed as follows :

$$\sum_{k=1}^K d \times y_{j,k} \geq w_{min} \quad \forall j \in \llbracket 1, m \rrbracket \quad (4.6)$$

#### 4.3.2.4/ ENERGY CONSTRAINTS

In the non-disjoint case, a sensor might belong to several  $\alpha$ -cover sets if it has enough energy. The following constraint ensures that the total energy consumed by a sensor does not exceed its initial energy:

$$\sum_{k=1}^K d \times x_{i,k} \leq E_i \quad \forall i \in \llbracket 1, n \rrbracket \quad (4.7)$$

#### 4.3.2.5/ ADDITIONAL CONSTRAINTS

To make the model consistent and ensure that the sets that do not respect the  $\alpha$ -cover set conditions (i.e  $z_k$  is equal to 0), are empty, the following constraint has been added to the model:

$$\sum_{i \in S} x_{i,k} \leq n \times z_k \quad \forall k \in \llbracket 1, K \rrbracket \quad (4.8)$$

This constraint forces the variables  $x_{i,k}$  to be equal to zero if  $C_k$  is not an  $\alpha$ -cover set.

#### 4.3.2.6/ OPTIONAL CONSTRAINTS

By construction, the total coverage time of a target cannot exceed the total time of the sensors capable of monitoring it. This constraint can be formulated as follows:

$$\sum_{k=1}^K d \times y_{j,k} \leq \sum_{i \in S_j} E_i \quad \forall j \in \llbracket 1, m \rrbracket \quad (4.9)$$

This constraint is not mandatory but we have noticed that by adding this extra constraint, the resolution time of the Branch-and Bound method for the BILP is significantly reduced. This constraint can be seen as a cutting plane in the resolution process.

Considering cover sets of fixed duration  $d$ , a Coverage Ratio  $\alpha$  and a Target Monitoring Ratio  $\beta$ , a new mathematical formulation of the  $\alpha$ -Maximum Lifetime Problem can be given as follows:

$$\left\{ \begin{array}{ll} \max \sum_{k=1}^K z_k & \\ \text{subject to :} & \\ y_{j,k} \geq x_{i,k} & \forall j \in \llbracket 1, m \rrbracket, \forall i \in S_j, \\ & \forall k \in \llbracket 1, K \rrbracket \\ \sum_{i \in S_j} x_{i,k} \geq y_{j,k} & \forall j \in \llbracket 1, m \rrbracket, \forall k \in \llbracket 1, K \rrbracket \\ \sum_{j \in T} y_{j,k} \geq T_\alpha \times z_k & \forall k \in \llbracket 1, K \rrbracket \\ \sum_{k=1}^K d \times x_{i,k} \leq E_i & \forall i \in \llbracket 1, n \rrbracket \\ \sum_{k=1}^K y_{j,k} \geq \beta \times \sum_{k=1}^K z_k & \forall j \in \llbracket 1, m \rrbracket \\ \sum_{i \in S} x_{i,k} \leq n \times z_k & \forall k \in \llbracket 1, K \rrbracket \\ \sum_{k=1}^K d \times y_{j,k} \leq \sum_{i \in S_j} E_i & \forall j \in \llbracket 1, m \rrbracket \end{array} \right. \quad (4.10)$$

It's worthwhile to note that the number of variables is  $(n + m + 1) \times K$ . The number of constraints is bounded by  $mnK + mK + 2K + n + 2m$ . Consequently, it is not surprising that the resolution of this linear program with binary variables becomes impracticable for large optimization problems.

#### 4.3.3/ THE UPPER BOUND OF THE NUMBER OF $\alpha$ -COVER SETS, $K$

In this section, we give two upper bounds of the number of  $\alpha$ -cover sets for the problem of partial coverage in WSN where each  $\alpha$ -cover set is activated during a fixed time period (called slot) of  $d$  time units. First, we start by computing the general upper bound  $K$ , next we derive a tighter one  $K' \leq K$  and prove its attainability. Finally, we shall express a bound

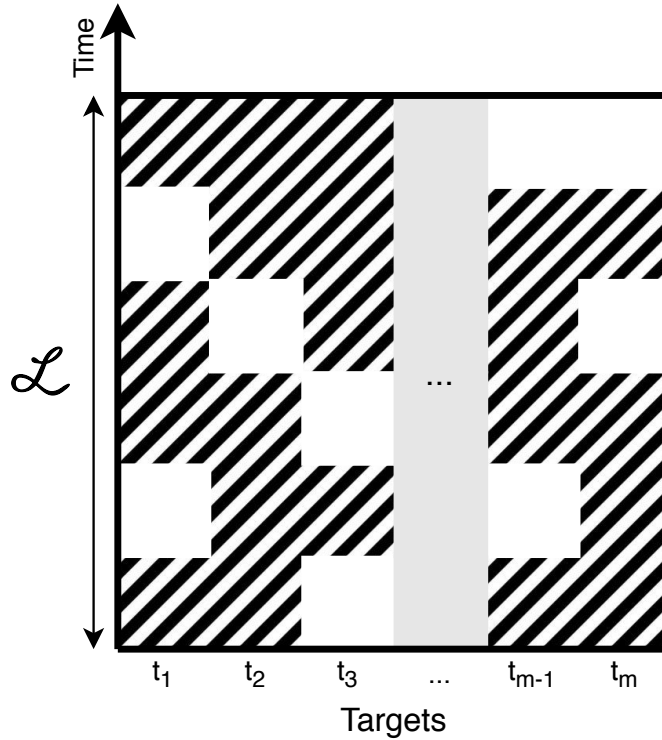


Figure 4.1: The cumulated idle and coverage time slots of the  $m$  targets.

on the maximum number of  $\alpha$ -cover sets in the special case where a Target Minimum Ratio,  $\beta$ , is required for each target.

**Proposition 1.** *The number of cover sets for the  $\alpha$ -coverage problem is upperbounded by*

$$K = \left\lfloor \frac{\sum_{\ell=1}^m \sum_{i \in S_{\ell}} E_i}{\alpha \times m \times d} \right\rfloor$$

*Proof.* Consider the clustering illustrated in Figure 4.1. Since we deal with partial coverage, at any time step in the network's activity, some targets are covered and some others are not. Let  $\mathcal{I}$  and  $\mathcal{C}$  be the cumulated Idle time slots, resp. the cumulated Coverage time slots of the  $m$  targets throughout the lifespan of the network.

Intuitively, we have:

$$\mathcal{I} + \mathcal{C} = \mathcal{L} \times m$$

where  $\mathcal{L}$  is the Upper Bound of the achieved network's lifetime. Since, the cover's duration time is the same for all the constructed covers, we obtain:

$$\mathcal{I} + \mathcal{C} = K \times d \times m$$

Moreover, we can observe that:

$$C = K \times d \times m \times \alpha$$

In this way we deduce:

$$K = \left\lfloor \frac{C}{\alpha \times m \times d} \right\rfloor = \left\lfloor \frac{\sum_{\ell=1}^m \sum_{i \in S_\ell} E_i}{\alpha \times m \times d} \right\rfloor$$

□

**Proposition 2.** *Let  $\Delta > 0$  be the cumulated residual energy that cannot be used to form new covers, then the Upper Bounded  $K$  can be reduced down to*

$$K' = K - \varepsilon$$

where,  $\varepsilon$  is within

$$\left\lfloor \frac{\Delta}{\alpha \times m \times d} \right\rfloor$$

*Proof.* We need to prove that  $K' \leq K$  holds. According to the *Greedy-Procedure's* policy (see Algorithm 2), a cover set is built if and only if it remains enough energy that could be assigned to  $\alpha \times m$  targets. Let  $\lambda$  be the remaining cumulated energy in the time slot at the  $i$ 'th iteration,  $1 \leq i \leq K$ . Then, the number of constructed cover sets at the time step  $i$  during the clustering process is:

$$i - 1 + \left\lfloor \frac{\lambda}{\alpha \times m \times d} \right\rfloor \leq K$$

Now, we consider the worst case where all the computed covers are holding the needed value of  $\alpha \times m$  targets except for the last one which cannot be retained owing to the condition pointed above. In this configuration, the whole amount of the residual energy, denoted as  $\Delta$ , that will no longer be usable before reaching the final number of cover sets will be

$$\begin{aligned} K' &= \left\lfloor \frac{\sum_{\ell=1}^m \sum_{i \in S_\ell} E_i - \Delta}{\alpha \times m \times d} \right\rfloor \\ &\leq \left\lfloor \frac{\sum_{\ell=1}^m \sum_{i \in S_\ell} E_i}{\alpha \times m \times d} \right\rfloor + \left\lfloor \frac{-\Delta}{\alpha \times m \times d} \right\rfloor + 1 \end{aligned}$$

$$\begin{aligned} \text{decreased from the global energy of the network. Thus,} &= \left\lfloor \frac{\sum_{\ell=1}^m \sum_{i \in S_\ell} E_i}{\alpha \times m \times d} \right\rfloor - \left\lfloor \frac{\Delta}{\alpha \times m \times d} \right\rfloor + 1 \\ &= K - \left\lfloor \frac{\Delta}{\alpha \times m \times d} \right\rfloor + 1 \\ &\implies K' \leq K + 1 - \left\lfloor \frac{\Delta}{\alpha \times m \times d} \right\rfloor \end{aligned}$$

We have two scenarios:



1.  $0 < \Delta \leq \alpha \times m \times d \implies K' = K$
2.  $\Delta > \alpha \times m \times d \implies K' < K$

$$(1) \text{ and } (2) \implies K' \leq K$$

Hence a result,

$$K' = K - \varepsilon \wedge \varepsilon \leq \left\lfloor \frac{\Delta}{\alpha \times m \times d} \right\rfloor$$

□

**Proposition 3.** *The bound  $K'$  is attainable.*

*Proof.* To see that this bound is really attainable, consider a network of two sensors ( $n = 2$ ) which are deployed to cover two targets ( $m = 2$ ). Assume a one-to-one scenario where each sensor is assigned to a separate target. Let  $\alpha = 0.5$ ,  $E_1 = E_2 = 1$  and  $T_1 \cap T_2 = \phi$ . It's straightforward to check that the achieved lifetime is  $L = 2$  with  $K' = 2$  covers. This result is optimal and cannot be improved. □

---

**Algorithm 2** Compute the upper bound of the number of cover sets in the proposed linear program: The *Greedy-Procedure*

---

**Require:**

$CT_j = \sum_{i \in S_j} E_i$  : the cumulative time units for each target

$K' = 0$

**while**  $\exists \lfloor m \times \alpha \rfloor$  targets with  $CT_j > d$  **do**

Decrement by  $d$  the residual cumulative time units  $CT_j$  of the  
 $\lfloor m \times \alpha \rfloor$  targets with the highest residual cumulative time units.

$K' = K' + 1$

**end while**

**return**  $K'$

---

In our BILP formulation, when the Constraint (4.5) with the Target Minimum Ratio  $\beta_j$  is applied, the maximum number of non-disjoint  $\alpha$ -cover sets of a fixed activation time period  $d$ , is bounded by the least covered target and  $\beta_j$ . Thus, this upper bound can be computed as the following:

$$K = \min_{j \in T} \left\lfloor \frac{\sum_{i \in S_j} E_i}{\beta_j \times d} \right\rfloor \quad (4.11)$$

For the sake of comparison, we present in the following section, the description of an existing network's lifetime optimization approach introduced in [71] which is, as far as we know, the closest work to the one addressed in this work.

#### 4.3.4/ AN EXISTING INTEGER LINEAR FORMULATION

In this section, we discuss a mathematical formulation for the Maximal Lifetime Problem in WSN designed in [71] and we present an adaptation of this method to solve  $\alpha$ -MLP. In this way, we will be able to compare this approach to the one proposed in this work. To solve the MLP problem, the authors in [71] proposed a method using the three following steps :

1. Construct all possible cover sets (at most  $2^n - 1$  where  $n$  is the number of sensors). Retain only the cover sets where the coverage conditions are satisfied (all targets are covered in the case of complete coverage,  $\lfloor \alpha * m \rfloor$  targets are covered in the case of partial coverage). You get  $L'$  cover sets said valid.
2. Among the valid  $L'$  cover sets, retain those which are elementary (where there are no superfluous sensors) and thus with a smaller number of sensors. We get  $L$  valid and elementary cover sets. Construct the matrix  $A$  of binary coefficient  $a_{i,l}$  which is equal to 1 if the sensor  $i$  is in the cover set  $C_l$ , 0 otherwise.
3. Write the associated Integer Linear Program and solve it.

Let  $u_l$  be the number of times the cover set  $C_l$  is activated during a fixed activation time  $d$ . The mathematical model, designed by the authors of [71], can be formulated with the notation used in this work as the following Integer Linear Program (ILP).

$$\begin{cases} \max \sum_{l=1}^L d \times u_l \\ \text{subject to :} \\ \sum_{l=1}^L d \times a_{i,l} \times u_l \leq E_i \quad \forall i \in \llbracket 1, n \rrbracket \end{cases} \quad (4.12)$$

The objective function expresses the network lifetime. As constraint (4.7), the constraints in this formulation guarantee that the total consumed energy by a sensor cannot exceed its initial reserve of energy (here expressed as a number of available time units  $E_i$  for a sensor  $i$ ). To introduce the  $\beta$  constraint in this model, it is necessary to build the matrix  $B$  where the binary coefficient  $b_{j,l}$  is equal to 1 if the target  $j$  is monitored in the cover set  $C_l$ , 0 otherwise. The  $\beta$  constraint for this model can be formulated as the following:

$$\sum_{l=1}^L b_{j,l} \times u_l \geq \beta_j \sum_{l=1}^L u_l \quad \forall j \in \llbracket 1, m \rrbracket \quad (4.13)$$

Although this formulation seems to be simple as it involves only one type of variables and two types of constraints, its construction process is composed of two preliminary complex steps which are very time-consuming. We have called this method the 3-steps method to distinguish it from our approach (called all-in-one method) for which the construction

of the covers sets and the computation of their activation times are performed in a single model. In part 5.6, our approach is compared to the 3-steps method and the results show that our mathematical formulation outperforms the latter.

#### 4.4/ COVER SETS SCHEDULING PROBLEM

The optimal solution obtained from the BILP consists of  $K_{opt}$   $\alpha$ -cover sets that have a fixed activation time period  $d$ . These cover sets should be activated successively to cover the targets during the lifetime of the WSN. In the case of partial coverage, a target might be covered in a non continuous mode.

Let  $\Theta$  be the coverage binary matrix for a given solution such that  $\theta_{j,k}$  is equal to 1 if target  $t_j$  is covered in the cover set  $C_k$  and 0 otherwise, see matrix (4.14).

$$\Theta = \begin{pmatrix} \theta_{1,1} & \theta_{1,2} & \cdots & \theta_{1,K_{opt}} \\ \theta_{2,1} & \theta_{2,2} & \cdots & \theta_{2,K_{opt}} \\ \vdots & \vdots & \ddots & \vdots \\ \theta_{m,1} & \theta_{m,2} & \cdots & \theta_{m,K_{opt}} \end{pmatrix} \quad (4.14)$$

In some cases, when the cover sets are not properly scheduled, we may have situations where targets remain continuously uncovered during many successive cover sets. For example, in matrix (4.15), target 1 is not covered for three consecutive periods.

$$\begin{array}{c} C_1 \quad C_2 \quad C_3 \quad C_4 \quad C_5 \quad C_6 \quad C_7 \quad C_8 \quad C_9 \quad C_{10} \\ \begin{matrix} t_1 \\ t_2 \\ t_3 \end{matrix} \begin{pmatrix} 1 & 1 & 1 & 0 & 0 & 0 & 1 & 1 & 1 & 1 \\ 1 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 1 & 1 \end{pmatrix} \end{array} \quad (4.15)$$

To avoid this issue which can be viewed as a starvation phenomenon, we provide in this section a meta-heuristic that searches for a good approximation of the most favourable scheduling of the obtained cover sets. For each target and as much as possible, the new scheduling should smooth fairly, during the whole lifetime of the network, the periods where a target is not covered. In other words, the new order should disperse, for every target, the zeros in the coverage matrix,  $\Theta$ .

As was mentioned in the introduction section, to measure the dispersion rate of the uncovered periods for a given covers' schedule, we use two key criteria, namely: the p-dispersion and the coefficient of variation criteria.

## 4.4.1/ THE FIRST CRITERION: MEASURE OF DISPERSION (P-DISPERSION)

Dispersing elements in a set has been already tackled in the literature and it is called the p-dispersion problem. Unfortunately, this problem is known to be NP-hard [2] in the general case and heuristics are required to achieve sub-optimal solutions but in polynomial time complexity.

**Definition 4.4.1.** p-dispersion Problem

Given  $p$  elements and a set of  $n$  locations where  $p < n$ , the objective of this problem is to select  $p$  locations where the  $p$  elements would be as dispersed as possible which amounts to maximizing the minimum distance (MAX-MIN) between any pair of the  $p$  elements [81] [3] [72].

Let  $N$  and  $U$  be respectively the set of candidate locations (of size  $n$ ) and the solution vector (of size  $p$ ). Considering a metric space where the distance between two elements  $u_i$  and  $u_j$  is denoted by  $dis(u_i, u_j)$  and the identity of indiscernible, symmetry and triangle inequality properties are satisfied, the discrete p-dispersion problem can be stated as the following:

$$\begin{cases} \max(f(U)) \\ \text{Subject to:} \\ f(U) = \min(dis(u_i, u_j) : 1 \leq i < j \leq p) \\ U \subset N, |U| = p \end{cases} \quad (4.16)$$

In our case, for a given target  $t_i$ , the indexes of the vector  $(\theta_{i,1}, \dots, \theta_{i,K_{opt}})$  are the locations and the  $p$  elements to disperse in these locations are the coefficients of that vector that are equal to 0. The distance between two elements is equal to the absolute value of the difference between their indexes minus 1,  $dis(\theta_{i,x}, \theta_{i,y}) = |x - y| - 1$ , with  $x \neq y$ . For example, if  $\theta_i = (1, 1, 0, 1, 1, 0, 1, 1, 1, 0, 1)$ ,  $dis(\theta_{i,3}, \theta_{i,6}) = 2$ ,  $dis(\theta_{i,5}, \theta_{i,9}) = 3$  and the minimum distance between the coefficients equal to 0,  $\min(dis)$ , is equal to 2. To well disperse the uncovered periods of a target, the minimum distance should be maximized. Moreover, in order to not always have the first and last periods uncovered, the extremities of the vector could be assumed as uncovered periods and thus, in the last example, the minimum distance between the coefficients equal to 0 or the extremities, is equal to 1. The best dispersion of the uncovered periods in this example is the following:  $\theta_i = (1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1)$  where  $\min(dis) = 2$ .

The p-dispersion problem should be applied to each target in order to disperse, along the whole lifetime of the network, the periods where a target is not covered. A cover set in the solution, obtained by solving the BILP optimization problem, represents, for a given activation time period, which target is covered or not. Then modifying the cover's schedule

to disperse the uncovered time periods of one target might jeopardize the dispersion rate of the other targets' uncovered time periods. Therefore, in this case the objective should be maximizing the minimum of the minimum distances for each target. The problem can be stated as the following:

$$\left\{ \begin{array}{l} \max(\min_{l=1}^m (f(U_l))) \\ \text{Subject to:} \\ f(U_l) = \min(\text{dis}(u_i, u_j) : 1 \leq i < j \leq p) \\ N = \theta_l \\ U_l = \{\theta_{l,j}/\theta_{l,j} = 0, j = 1, \dots, K_{opt}\} \end{array} \right. \quad (4.17)$$

From this formulation, it can be seen that the minimum of the minimum distances between the uncovered periods for each target in the coverage matrix (4.15), is equal to 0. If the same covers are scheduled as in the coverage matrix (4.18), the minimum of the minimum distances is equal to 1.

$$\begin{array}{c} C_9 \quad C_2 \quad C_8 \quad C_4 \quad C_1 \quad C_6 \quad C_7 \quad C_3 \quad C_5 \quad C_{10} \\ t_1 \left( \begin{array}{cccccccccc} 1 & 1 & 1 & 0 & 1 & 0 & 1 & 1 & 0 & 1 \end{array} \right) \\ t_2 \left( \begin{array}{cccccccccc} 1 & 0 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 1 \end{array} \right) \\ t_3 \left( \begin{array}{cccccccccc} 1 & 1 & 1 & 1 & 0 & 1 & 0 & 1 & 1 & 1 \end{array} \right) \end{array} \quad (4.18)$$

The same covers can also be ordered as in the coverage matrix (4.19) which has the minimum of the minimum distances also equal to 1. To differentiate between two solutions with same minimum of the minimum distances, as in the previous two coverage matrices, another criterion must be used. In the next subsection, the coefficient of variation criterion is presented.

$$\begin{array}{c} C_9 \quad C_6 \quad C_8 \quad C_4 \quad C_1 \quad C_2 \quad C_7 \quad C_3 \quad C_5 \quad C_{10} \\ t_1 \left( \begin{array}{cccccccccc} 1 & 0 & 1 & 0 & 1 & 1 & 1 & 1 & 0 & 1 \end{array} \right) \\ t_2 \left( \begin{array}{cccccccccc} 1 & 1 & 1 & 1 & 1 & 0 & 1 & 0 & 1 & 1 \end{array} \right) \\ t_3 \left( \begin{array}{cccccccccc} 1 & 1 & 1 & 1 & 0 & 1 & 0 & 1 & 1 & 1 \end{array} \right) \end{array} \quad (4.19)$$

#### 4.4.2/ THE SECOND CRITERION: COEFFICIENT OF VARIATION

Two distinct solutions having the same minimum of the minimum distances (first criterion) does not imply that both solutions have the same dispersion rate for the uncovered periods. Moreover, solutions giving the same minimum of the minimum distances is very common especially when the ratio of the maximum number of uncovered periods per target to the number of periods ( $\max_{i=0}^m (p_i)/K_{opt}$ ) is high. The number of uncovered periods

per target,  $p_i$ , depends on  $\beta$ . To differentiate such solutions, we propose to use the average of the coefficients of variation (CV) criterion. Indeed, if the uncovered periods of one target are well dispersed, the distances between its successive uncovered periods should be very close to the average of these distances. Therefore, if the CV of a target is low, these distances are very close to their average and the uncovered periods are well dispersed. The coefficient of variation was used instead of the standard deviation, because the number of uncovered periods might be different from one target to the other. The relative value of the CV allows its comparison to the CVs of other targets.

The CV of the distances between the successive uncovered periods of a target,  $t$ , with the coverage vector  $\theta_t = (\theta_{t,1}, \dots, \theta_{t,K_{opt}})$  can be computed as follows:

Let  $I = (i_1, \dots, i_p)$  be an ordered set containing the indexes of the coefficients equal to 0 in  $\theta_t$  and  $|I| = p_t$ .

Let  $D = (d_0, \dots, d_p)$  be the set of distances between the coefficients equal to 0 in  $\theta_t$ .  $d_0 = i_1 - 1$  is the distance between the left extremity and the first coefficient equal to 0. For  $k = 1, \dots, p - 1$ ,  $d_k$  is the distance between the coefficients of indexes  $i_k$  and  $i_{k+1}$ .  $d_p$  is the distance between the last coefficient which is equal to 0 and the right extremity. CV is equal to the standard deviation to the mean of the vector  $D$ .

For example, for  $\theta_t = (1, 1, 0, 1, 1, 0, 1, 1, 1, 0, 1)$ , the CV of target  $t$  can be computed as follows:

$$\begin{aligned}\mu_t &= (2 + 2 + 3 + 1)/4 = 2 \\ \sigma_t^2 &= (2 - 2)^2 + (2 - 2)^2 + (3 - 2)^2 + (1 - 2)^2 = 2 \\ CV_t &= \sigma_t/\mu_t = \sqrt{2}/2\end{aligned}$$

To consider the dispersion of uncovered periods for all the targets in a solution, the average of the CVs of all the targets is computed. When two solutions have the same value for the first criterion, the one having the lowest average CVs is considered to have more dispersed uncovered periods than the other. The scheduling 4.18 and 4.19 give the same value for the first criterion. Their respective average CVs are equal to 0.87 and 1.06 and therefore the first scheduling is considered to have well balanced uncovered time periods than the second one.

#### 4.4.3/ METHOD OF RESOLUTION: GENETIC ALGORITHM

Since, the cover sets scheduling problem is a hard problem and some solutions could consist of a large number of cover sets, we present in this section a genetic algorithm (GA) to find good solutions to this problem in a reasonable time and maximize the dispersion of the uncovered periods in the optimal solution obtained by the BILP. Before going into in details, we first pay a little attention on the rationale of our choice for GA metaheuristic [1] in order to tackle the second optimization problem addressed in this

work. Indeed, broadly speaking, other metaheuristics optimization algorithms may be more efficient than GA in terms of performances and convergence speed, but the metaheuristics suitability relies on the amount of knowledge and the kind of the problem that we are facing. It was shown, in the literature, that GAs are prevalent and natural candidates for ordering optimization problems like job scheduling, vehicle routing problem (VRP) or the well-known, a special case of the later, travelling salesman problem (TSP). They are often able to achieve better trade-offs between the solution's quality and the induced computing time. Moreover, the chromosomes' representation ensures that, at each iteration step, the whole genotypic space corresponds to feasible solutions. In our study, it turns out that the second optimization problem of covers' planning, in particular the *p-dispersion* problem and its generalization for all the monitored targets can be seen as an ordering optimization problem. Hence the rationale of our choice.

In the following paragraphs the different steps of the genetic algorithm are described.

#### 4.4.3.1/ ENCODING

The Cover Sets Scheduling Problem (CSSP) is considered as the scheduling of  $K_{opt}$   $\alpha$ -cover sets and the search space corresponds to the  $K_{opt}!$  possible ordering of these cover sets. A solution of this ordering problem, called a chromosome in the GA, can be naturally represented by an ordered sequence (*OS*) of the  $K_{opt}$   $\alpha$ -cover sets where each gene corresponds to the index of an  $\alpha$ -cover set as outlined in Figure 4.2.



Figure 4.2: Representation of a solution as an ordered sequence.

#### 4.4.3.2/ FITNESS FUNCTION

It evaluates the quality of a solution according to the first and second criteria presented in the previous sections. Assigning a score to a solution allows its comparison to other solutions. If two solutions have the same minimum distance between the uncovered periods for all the targets, the average coefficient of variation for both solutions are compared and the one with the lowest average coefficient of variation has a better uncovered periods dispersion rate. Therefore, the fitness function returns two values for a given *OS*: i) the minimum distance between the uncovered periods and ii) the average coefficient of variation for all targets.

4.4.3.3/ CROSSOVER OPERATOR

Since, the cover sets scheduling problem is a linear permutation problem, we use the LOX operator which is already presented in the section 3.4.3.

4.4.3.4/ MUTATION OPERATOR

The mutation operator consists of modifying one or more genes of a solution to improve its fitness. The swap mutation operator which consists in selecting two genes to swap them was adopted. Instead of randomly selecting the two genes to swap, the implemented operator selects, as the first gene, one of the cover sets that gives the smallest distance between the uncovered periods. A search method is then used to discover which other cover set would give the best improvement when swapped with the first selected gene. Figure 4.3 shows an example of applying the mutation operator on one parent to generate a new child solution. In the example, target  $t_1$  has the least dispersed uncovered periods due to three successive uncovered periods in cover sets  $C_4, C_5$  and  $C_6$ . To increase the distance between successive uncovered periods, it is obvious that  $C_5$  should be swapped with a cover set that does cover target  $t_1$ . Therefore, all the possible swaps are evaluated and as seen in the figure,  $C_8$  gives the highest distance when swapped with  $C_5$ . Therefore, the mutation operator swaps these two cover sets and generates a new solution with a better dispersion rate of uncovered periods.

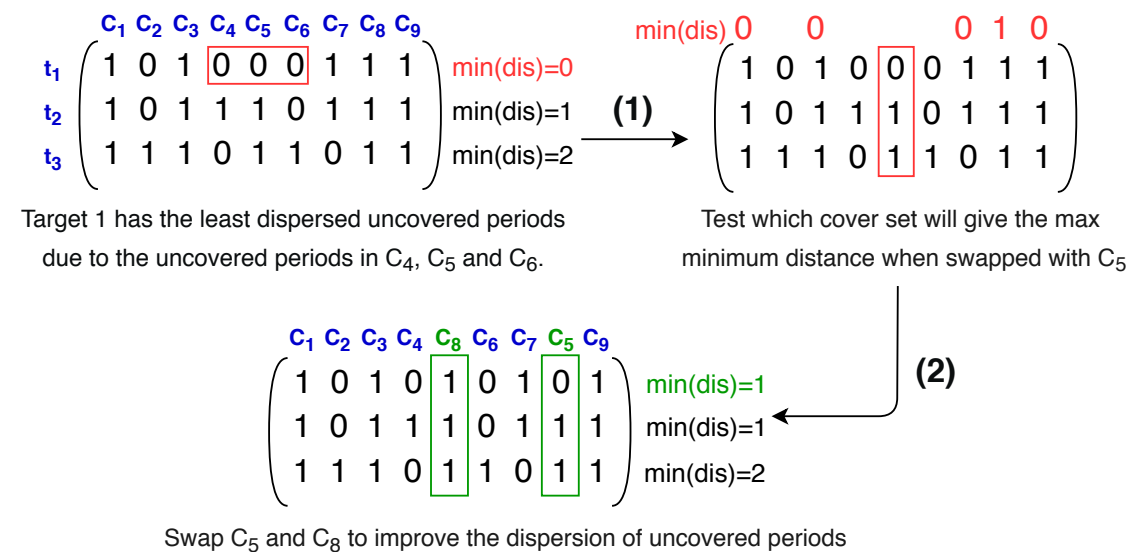


Figure 4.3: The mutation operator applied on one individual to generate a better solution.

Figure 4.4 illustrates the flow chart of the proposed genetic approach to obtain good solutions for the cover sets scheduling problem. At the beginning of the algorithm, a set of



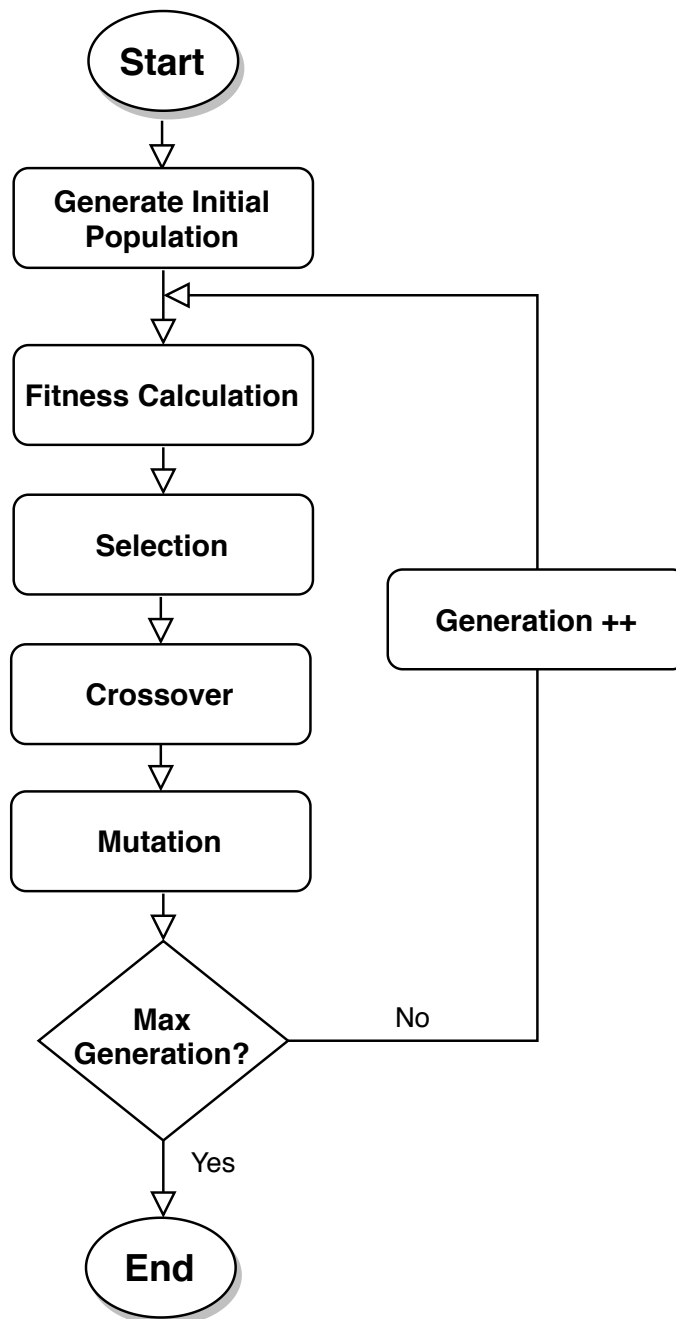


Figure 4.4: General flow chart of the proposed genetic approach.

solutions, represented by chromosomes and known as the initial population, is generated and the fitness of each solution is computed. At each generation of the genetic algorithm, the individuals in the population with the best fitness values are selected. The crossover and mutation operators are then applied on the selected individuals to generate new solutions. At the end of a generation, the new solutions are added to the population and in order to keep the size of the population fixed, the worst individuals in the population are removed. The iterative process is stopped when the maximum number of generations is

reached.

The results of the experiments evaluating the performance of this genetic algorithm are presented in Section 4.5.3.1.

## 4.5/ EXPERIMENTS AND RESULTS

In this section, we present the experiments conducted to assess the performance of our proposals. As mentioned in the introduction, two main optimization objectives are considered, namely: i) the network's lifetime optimization and the cover sets scheduling. The former seeks to solve the  $\alpha$ -coverage problem to optimality by proposing a novel BILP mathematical model, whereas the later focuses on the suitable planning way of the set covers obtained by the BILP's solver to smooth fairly the cumulated targets' uncovered time periods during the network's service. In subsection 4.5.1, the results of solving to optimality many instances of the  $\alpha$ -MLP are presented. In these experiments, we evaluate the effects of considering the  $\beta$  constraint instead of the  $w_{min}$  constraint, on the obtained network lifetime and target's coverage ratio. We also assess the quality of the upper bound of the number of  $\alpha$ -cover sets by comparing it for many instances with the numbers of  $\alpha$ -cover sets in the optimal solutions. Finally the results obtained by our method are compared to those obtained by an existing 3-steps method proposed in [71]. In subsection 4.5.3, we compare the results obtained by default from solving the BILP to the ones provided by the proposed Genetic Algorithm and demonstrate that this GA can improve the quality of the solutions for the Cover Set Scheduling Problem. All these experiments were coded in JAVA and executed over an Intel(R) i7-8650U processor with 16GB of RAM. Note that the experimental set up and the parameters used in our study are chosen in such a way that they are representative and are in line with those used in the literature ((see for example [53], [59] and [67]).

### 4.5.1/ RESULTS FOR $\alpha$ -MLP

IBM ILOG CPLEX 12.5 was used to solve the considered instances of the BILP, presented in Section 4.3.2. All these instances consisted of networks with 15 targets and 10 to 40 sensors. In each instance, the  $n$  sensors and  $m$  targets were randomly deployed in a  $500 \times 500$  sqm two-dimensional area. Each target was at least covered by  $n/4$  sensors. All the deployed sensors could communicate directly with the base station and had the same 300m sensing range. Note that the sensing range value will not affect the BILP's performances. It is a system parameter which specifies which targets are monitored by each sensor. At the start of the surveillance, they had heterogeneous initial energy, varying between 1 to 12 energy units. One unit of energy allows a sensor to stay active

during one unit of time and to cover during that time all the targets in its range. All the presented experiments' results are averages of 10 randomly generated instances. Four values for the activation time  $d$ , equal to 2, 3, 4 or 6 time units, were considered in the first set of the experiments and then it was fixed to 3 time units for the rest of them. Four values of  $\alpha$  equal to 1, 0.85, 0.75 and 0.5 were also considered and therefore, each partial cover set had to survey at least  $T_\alpha = 15, 13, 11$  and 8 targets respectively. All the parameters of the experiments for the  $\alpha$ -MLP are listed in Table 4.1.

Parameter	Description
Area	500 × 500 sqm
Number of sensors ( $n$ )	10-40
Number of targets ( $m$ )	15
Sensing range ( $R_s$ )	300 m
Initial energy of sensor ( $E_i$ )	1-12 unit
Activation time for $\alpha$ - cover set ( $d$ )	2, 3, 4, 6
Values of $\alpha$	1, 0.85, 0.75, 0.5
Values of $T_\alpha$	15, 13, 11, 8

Table 4.1: Simulation Parameters for  $\alpha$ -MLP

#### 4.5.1.1/ THE NETWORK LIFETIME FOR DIFFERENT VALUES OF ACTIVATION TIME

This first experiment was conducted to evaluate the influence of the activation time on the network lifetime, obtained by solving the BILP, while varying the value of  $\alpha$ . The following activation times were tested: 2, 3, 4 and 6 time units where sensors can at most participate to 6, 4, 3 or 2 cover sets respectively.

Figure 4.5 presents the average lifetime of a network composed of 20 sensors for different activation times and  $\alpha$  values. As expected, with the partial coverage constraint the lifetime of the network is higher than with the complete coverage constraint. As more targets are neglected in the cover sets ( $\alpha$  is decreased), the lifetime of the network increases. For example, with the activation time  $d = 2$ , the obtained network lifetime is largely improved from 14.45% ( $\alpha = 0.85$ ,  $T_\alpha = 13$ ) to 96.98% ( $\alpha = 0.5$ ,  $T_\alpha = 8$ ) when compared to the network lifetime obtained under full coverage ( $\alpha = 1$ ). Figure 4.5 also shows that the network lifetime increases when the cover set activation time is decreased. This is due to the fact that as the activation times are decreased, a sensor can participate in more  $\alpha$ -cover sets and can fully consume its energy, while with larger activation times, a sensor can be active in a small number of cover sets and it will waste a lot of its energy. For example, with  $\alpha = 0.5$ , the network lifetime increases by 57.97% when considering an activation time equal to two time units ( $d = 2$ ) instead of six time units ( $d = 6$ ).

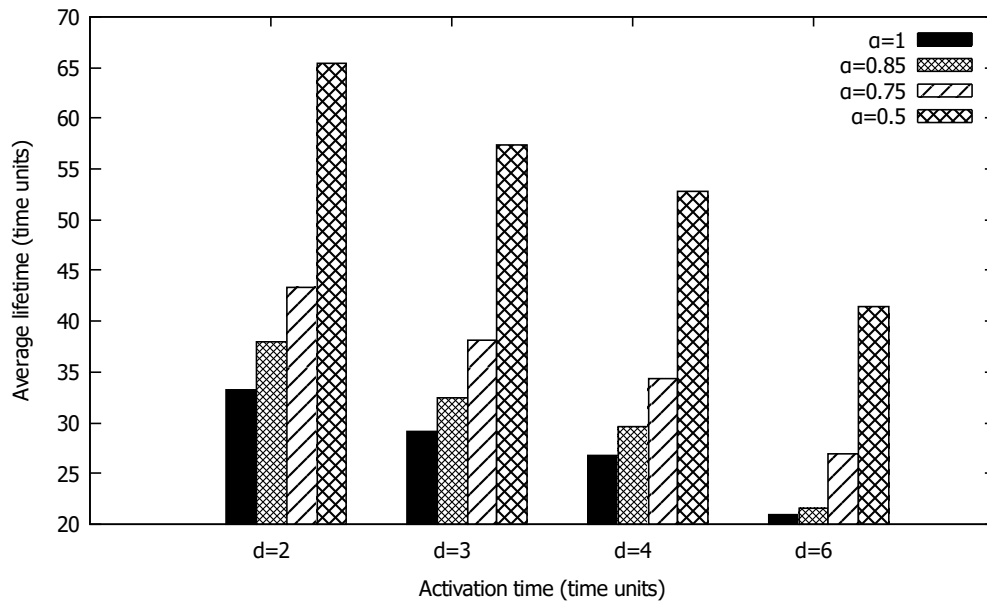


Figure 4.5: Average network lifetime obtained by solving the BILP for different activation time period values under constraint  $\beta$ .

4.5.1.2/ THE EXECUTION TIME FOR DIFFERENT VALUES OF ACTIVATION TIME

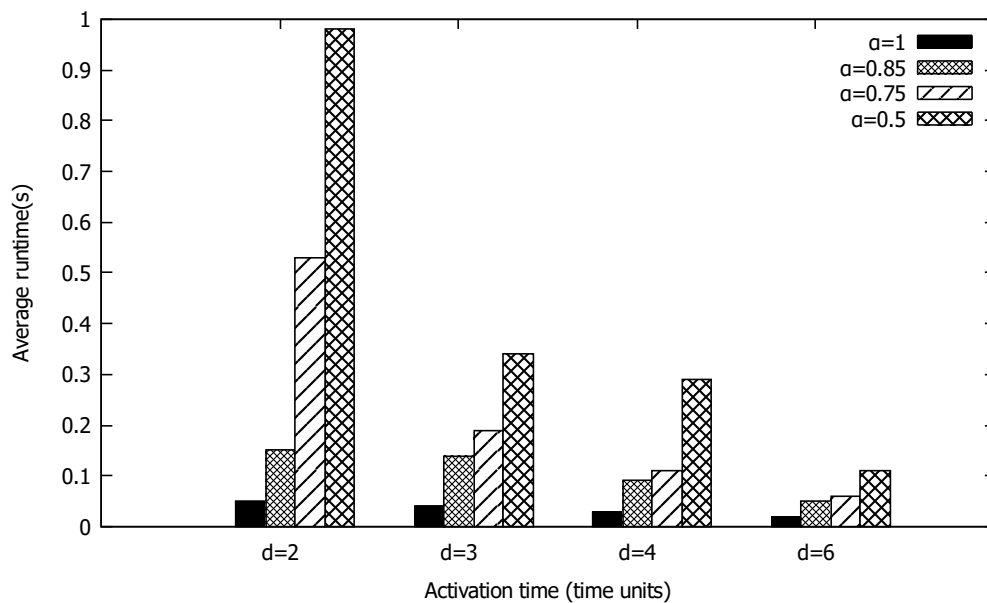


Figure 4.6: Average runtime to solve the BILP for different values of activation time under constraint  $\beta$ .

Figure 4.6 presents the average execution times for solving the BILP under constraint  $\beta$  for different activation time values. It can be noticed that as the activation time is increased the execution time is decreased. This is due to the fact that the upper bound of the

number of cover sets,  $K$  is inversely proportional to the activation time. As  $K$  increases, the complexity of the BILP and the search space increases. For example, with  $\alpha = 0.5$ , the execution time is increased by 790.9% when considering ( $d = 2$ ) instead of ( $d = 6$ ). Figure 4.6 also shows that as more targets are neglected ( $\alpha$  decreased), the execution time increases because more cover sets can be constructed and the upper bound  $K$  grows which complexifies the BILP and widens the search space. For example, for  $d = 3$  the execution time increases by 142.85% when considering  $\alpha = 0.5$  instead of  $\alpha = 0.85$ .

#### 4.5.1.3/ THE UPPER BOUND VERSUS THE OPTIMAL VALUE FOR THE NUMBER OF $\alpha$ -COVER SETS UNDER $w_{min}$ AND $\beta$ CONSTRAINT

The upper bound of the possible number of  $\alpha$ -cover sets  $K$  computed in part 4.3.3 is used to size the BILP presented in (5.16). In this paragraph, we investigate whether this  $K$  value is often attainable on the set of processed instances and we measure the deviation between this value and the optimal number of  $\alpha$ -cover sets (denoted by  $K_{opt}$ ) obtained after resolution of the BILP. This value  $K_{opt}$  corresponds to the number of non-zero  $z_k$  variables in the optimal solution. We distinguish two cases, the case where the  $w_{min}$  constraint is applied, and the case where the  $\beta$  constraint is applied. Table 4.2 presents the upper bound  $K$  and the obtained  $\alpha$ -cover sets  $K_{opt}$  of the BILP formulated previously under either the constraint  $w_{min}$  or the constraint  $\beta$ . The activation time is fixed to 3 time units.

$\alpha$	$n=10$				$n=20$				$n=30$				$n=40$			
	$w_{min}$		$\beta$		$w_{min}$		$\beta$		$w_{min}$		$\beta$		$w_{min}$		$\beta$	
	$K$	$K_{opt}$	$K$	$K_{opt}$	$K$	$K_{opt}$	$K$	$K_{opt}$	$K$	$K_{opt}$	$K$	$K_{opt}$	$K$	$K_{opt}$	$K$	$K_{opt}$
1	4.9	4.0	4.9	4.0	11.9	9.7	11.9	9.7	23.3	19.7	23.3	19.7	26.2	21.7	26.2	21.7
0.85	12.0	8.8	5.5	4.2	25.9	16.6	14.0	10.8	44.5	30.7	27.2	22.5	54.4	37.3	30.6	25.1
0.75	17.1	10.5	6.5	4.9	34.2	22.1	16.0	12.7	56.2	36.5	31.1	25.9	70.1	47.7	34.8	28.6
0.5	24.6	14.2	9.9	8.0	48.3	29.0	24.3	19.1	78.1	46.2	46.9	38.9	98.5	-	52.5	43.3

Table 4.2: The upper bound  $K$  and the obtained  $\alpha$ -cover sets  $K_{opt}$  for different networks under either  $w_{min}$  constraint or  $\beta$  constraint

Table 4.2 shows that the upper bounds are higher when using the  $w_{min}$  constraint instead of the  $\beta$  constraint. For example, with  $n = 30$  and  $\alpha = 0.75$ , the upper bound is 80.7% higher with the  $w_{min}$  constraint than with the  $\beta$  constraint. This is due to the fact that the constraint  $\beta$  limits the network's lifetime according to the parameter  $\beta$  and consequently the upper bound of the number of cover sets is also tighter. Moreover, it can be noticed that as less targets are covered in the cover sets ( $\alpha$  is decreased), the upper bound increases under either constraint  $\beta$  or constraint  $w_{min}$ . For example, with  $n = 20$ , the upper bound under constraint  $\beta$  increases by 73.57% when considering  $\alpha = 0.5$  instead of  $\alpha = 0.85$ . Nevertheless, the quality of the obtained upper bounds considerably reduces the number of variables and constraints in the BILP and allows us to solve to optimality

larger instances than before.

#### 4.5.1.4/ $w_{min}$ CONSTRAINT VERSUS $\beta$ CONSTRAINT

Table 4.3 presents the execution time and lifetime of the BILP formulated previously under either the constraint  $w_{min}$  or the constraint  $\beta$  for the same instances as those presented in table 4.2. As under the  $\beta$  constraint and for the same reasons, when partial coverage is considered instead of complete coverage, the network lifetime also increases under the  $w_{min}$  constraint. For example, Table 4.3 shows that for the instance with  $n = 30$ , the average network lifetime under constraint  $w_{min}$  significantly improved from 55.83% with  $\alpha = 0.85$  to 134.51% with  $\alpha = 0.5$  when compared to the network lifetime under full coverage ( $\alpha = 1$ ). Moreover, it can be noticed that for some instances considering constraint  $\beta$  instead of constraint  $w_{min}$  might decrease the network lifetime. For example, for the instances with  $n = 30$  and  $\alpha = 0.75$ , when constraint  $\beta$  is considered instead of constraint  $w_{min}$ , the average network lifetime decreased by 29.04%. This decrease in lifetime under the  $\beta$  constraint was expected because contrary to the  $w_{min}$  constraint, it imposes a minimum coverage level per target which makes it more appropriate for real-life applications requirements. On the other hand, Table 4.3 shows that the execution times are higher when using constraint  $w_{min}$  instead of constraint  $\beta$ . For example, with  $n = 40$  and  $\alpha = 0.75$ , the execution time is 120,516% higher with  $w_{min}$  instead of constraint  $\beta$ . This is due to the fact that the upper bound of the number of cover sets  $K$  is smaller under the  $\beta$  constraint than under the  $w_{min}$  constraint and the complexity of the BILP is directly related to the value of  $K$ . Finally, with either constraints,  $w_{min}$  or  $\beta$ , only the optimal solutions of small networks can be computed in a reasonable time because it is an NP-hard problem. The results of instances with  $n = 40$  and  $\alpha = 0.5$  under constraint  $w_{min}$  are not displayed in Table 4.3 because they could not be solved in a reasonable time.

$\alpha$	$T_\alpha$	$n=10$				$n=20$				$n=30$				$n=40$			
		$w_{min}$		$\beta$		$w_{min}$		$\beta$		$w_{min}$		$\beta$		$w_{min}$		$\beta$	
		L	Rt(s)	L	Rt(s)	L	Rt(s)	L	Rt(s)	L	Rt(s)	L	Rt(s)	L	Rt(s)	L	Rt(s)
1	15	12	0.017	12	0.017	29.1	0.042	29.1	0.042	59.1	0.084	59.1	0.084	65.1	0.13	65.1	0.13
0.85	13	26.4	0.05	12.6	0.02	49.8	1.38	32.4	0.14	92.1	49.78	67.5	0.49	111.9	157.79	75.3	0.78
0.75	11	31.5	0.01	14.7	0.02	66.3	103.21	38.1	0.18	109.5	973.53	77.7	0.77	143.1	1399.15	85.8	1.16
0.5	8	42.6	0.24	24	0.04	87	6.95	57.3	0.35	138.6	305.27	116.7	29.43	-	-	129.9	615.24

Table 4.3: The lifetime and execution time for different networks under either  $w_{min}$  constraint or  $\beta$  constraint

After comparing the effects of considering  $\beta$  constraint instead of the  $w_{min}$  constraint in terms of execution time and network lifetime, in this paragraph, we compare their influence on the target's coverage percentage over the total lifetime of the network. In these

experiments, the considered instances have 20 sensors and the activation time of the cover sets is fixed to 3 time units. For the sake of simplicity, all targets have the same monitoring ratio  $\beta$  which is equal to  $\alpha$ . Figures 4.7, 4.8 and 4.9 show for  $\alpha$  equals to 0.85, 0.75 and 0.5 respectively, the percentage of coverage for each target over the total lifetime of the network under either  $\beta$  constraint or  $w_{min}$  constraint. The results reveal that under the  $\beta$  constraint each target is on average covered for a period equal or superior to the one under the  $w_{min}$  constraint.

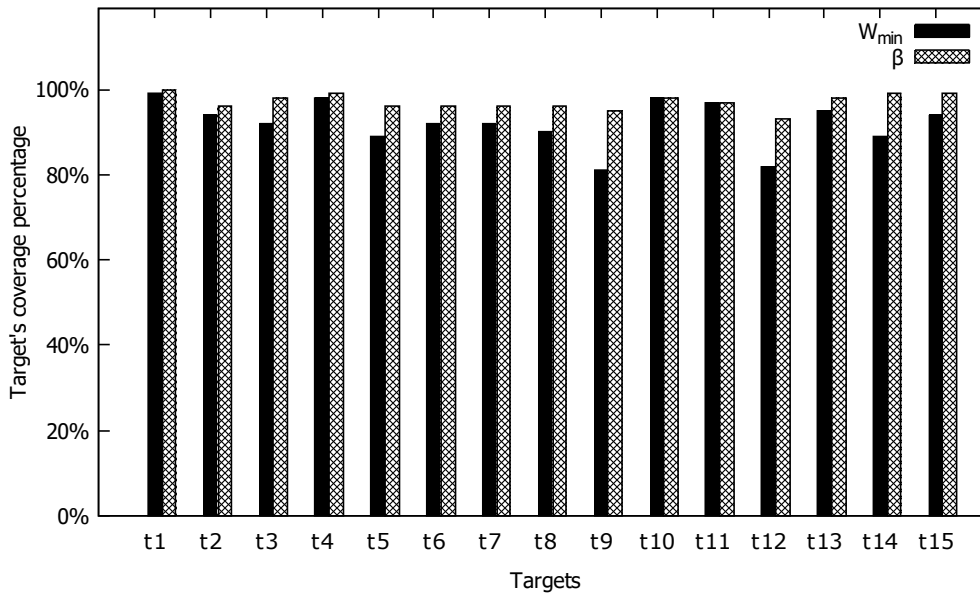


Figure 4.7: The target's coverage percentage over the total lifetime of the network for  $\alpha - MLP$  under  $\beta$  constraint,  $w_{min}$  constraint with  $\alpha = 0.85$ ,  $n = 20$ ,  $\beta = \alpha = 0.85$

To prove that the  $w_{min}$  constraint is not sufficient to impose an appropriate global covering for each target, we have solved 10 instances of the  $\alpha - MLP$  under the  $w_{min}$  constraint and counted the number of targets that were not covered appropriately. A target is considered as not being covered properly, if its coverage ratio is less than  $\alpha$ . The activation time was fixed to 3 time units and each instance had 15 targets to monitor. Table 4.4 shows the results of this experiment and it can be noticed that a high number of targets is under-covered with the  $w_{min}$  constraint. Therefore, constraint  $w_{min}$  is not sufficient to guarantee a good coverage quality for the monitored targets. For example, for  $\alpha = 0.75$ , 37 of the 150 targets (15 targets for 10 instances) were covered for periods smaller than the desired level. On the other hand, when considering the  $\beta$  constraint and when setting  $\beta = \alpha$ , the global and local coverage levels are always satisfied.

Moreover, for the same experiment, Table 4.5 presents the target's minimum coverage ratio under either the  $w_{min}$  constraint or the  $\beta$  constraint. The results show that when only considering the  $w_{min}$  constraint, the target's minimum coverage ratio is very low which means that some targets are extremely under-covered during the network's lifetime. For

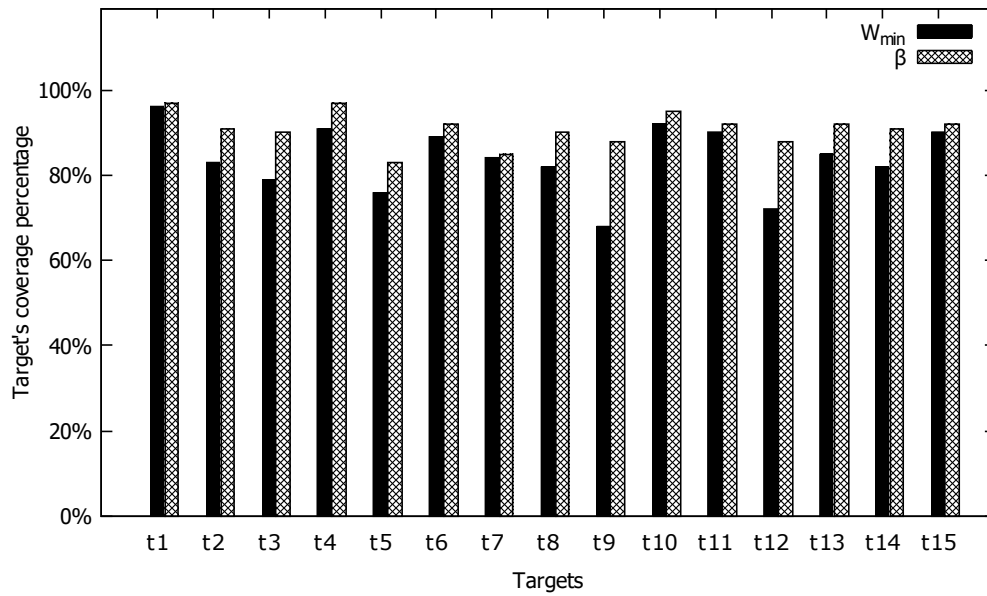


Figure 4.8: The target's coverage percentage over the total lifetime of the network for  $\alpha - MLP$  under  $\beta$  constraint ,  $w_{min}$  constraint with  $\alpha = 0.75$ ,  $n = 20$ ,  $\beta = \alpha = 0.75$

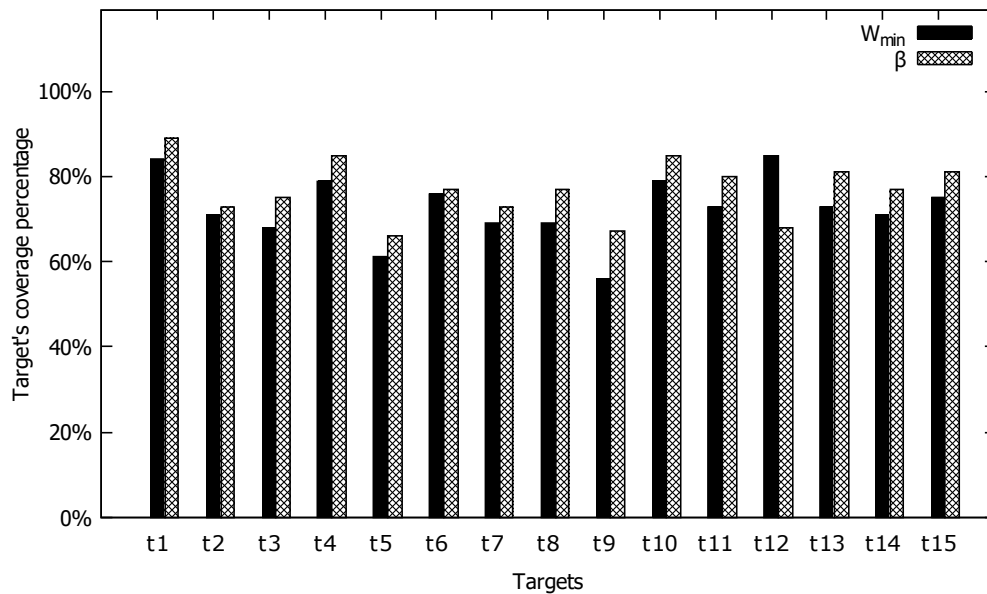


Figure 4.9: The target's coverage percentage over the total lifetime of the network for  $\alpha - MLP$  under  $\beta$  constraint ,  $w_{min}$  constraint with  $\alpha = 0.5$ ,  $n = 20$ ,  $\beta = \alpha = 0.5$

	$\alpha=0.85$	$\alpha=0.75$	$\alpha=0.5$
Constraint $w_{min}$	29	37	22

Table 4.4: Number of targets in 10 instances with a coverage rate inferior to  $\alpha$  under the  $w_{min}$  constraint

example, for  $\alpha = 0.5$ , the experiment showed that at least one target is just covered during



15% of the network's lifetime. On the other hand, under the  $\beta$  constraint, each target is at least covered during  $\beta \times 100\%$  of the network's lifetime. For example, replacing in the experiment constraint  $w_{min}$  by constraint  $\beta$ , improves the target's minimum coverage rate from 0.2 to 0.75 for  $\alpha = \beta = 0.75$ .

	$\alpha = \beta = 0.85$	$\alpha = \beta = 0.75$	$\alpha = \beta = 0.5$
Constraint $w_{min}$	0.27	0.2	0.15
Constraint $\beta$	0.85	0.75	0.5

Table 4.5: Target's minimum coverage ratio using constraint  $w_{min}$  or constraint  $\beta$

#### 4.5.1.5/ THE RELATIVE TARGET'S COVERAGE GAIN UNDER CONSTRAINT $\beta$

This section presents for each target how much its coverage would increase if the partial coverage mode under the  $\beta$  constraint is adopted instead of the complete coverage mode. The relative coverage gain per target was computed as follows:

$$\frac{\sum_{k=1}^K (y_{j,k} \times d) - w_{min}}{w_{min}} \times 100$$

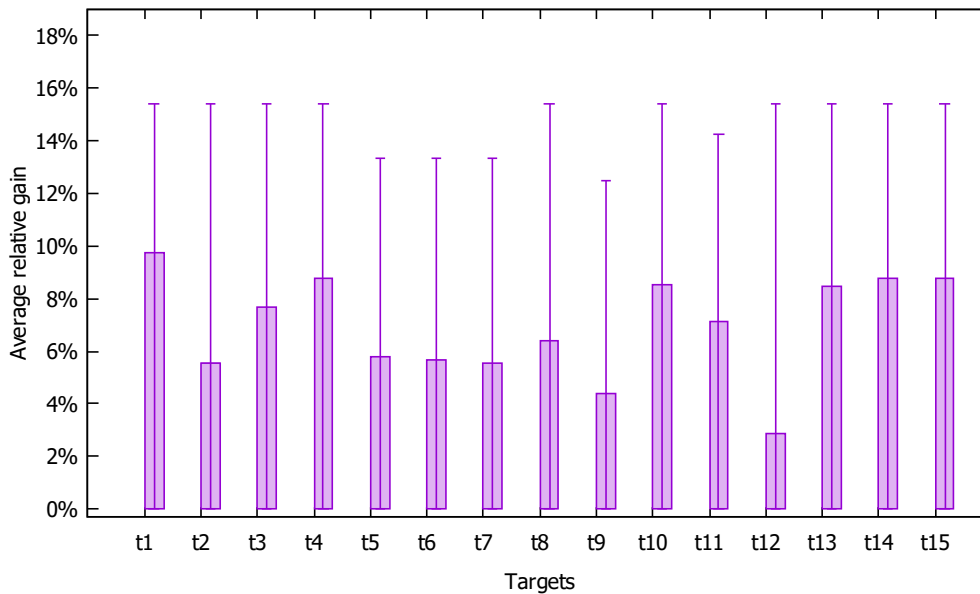


Figure 4.10: The average coverage relative gain for each target under partial coverage and with  $\alpha = \beta = 0.85$ .

Figures 4.10, 4.11 and 4.12 present, for each target, the average coverage relative gain under partial coverage and for  $\alpha$  equal to 0.85, 0.75 and 0.5 respectively. They also display the 100% confidence interval. In this experiment, the number of sensors was fixed to 20 and the activation time for each cover set was also set to 3 time units. These figures

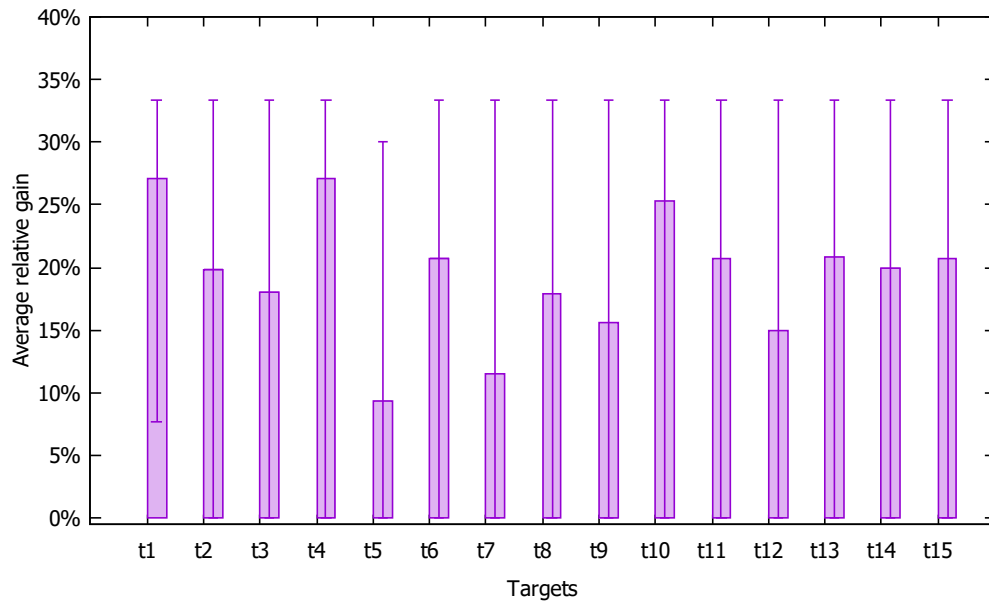


Figure 4.11: The average coverage relative gain for each target under partial coverage and with  $\alpha = \beta = 0.75$ .

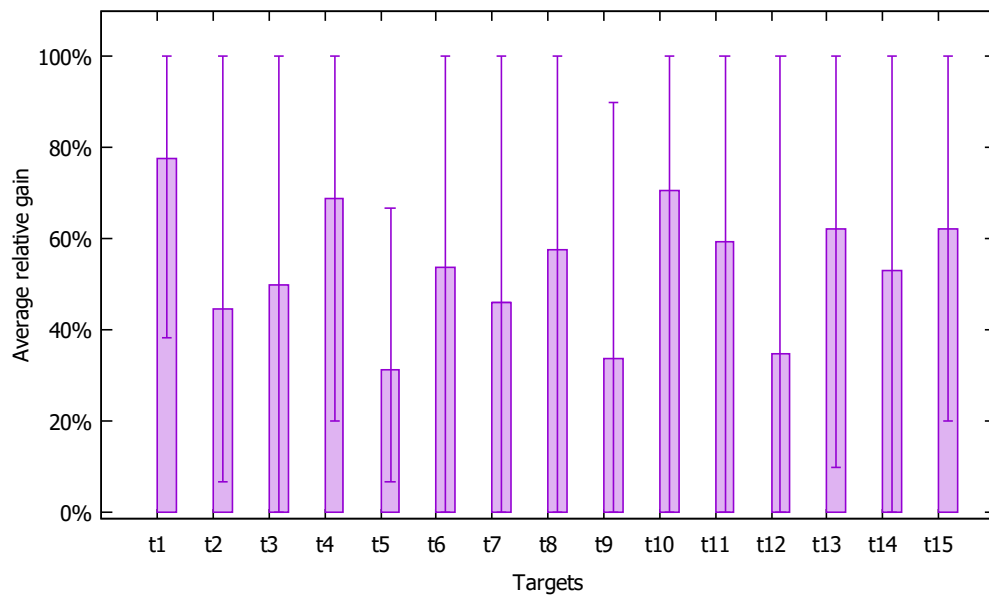


Figure 4.12: The average coverage relative gain for each target under partial coverage and with  $\alpha = \beta = 0.5$ .

show that with partial coverage and under the  $\beta$  constraint each target is at least covered for a time period equal or bigger than the network's lifetime under the complete coverage constraint because all the coverage gain values are null or positive. On average the target's coverage is improved by 6.94%, 19.3% and 53.79% for  $\alpha = 0.85$ , 0.75 and 0.5 respectively. Therefore, the  $\beta$  constraint can advantageously replace the  $w_{min}$  constraint because it imposes for each target a coverage level equal or superior to the one required

by the  $w_{min}$  constraint without computing  $w_{min}$ .

#### 4.5.2/ PERFORMANCE COMPARISON BETWEEN OUR ALL-IN-ONE METHOD AND THE 3-STEPS METHOD

In Table 4.6, we compare the performance of our all-in-one method with the 3-steps method, proposed in [71]. We applied both methods on smaller instances than in the previous experiments because the 3-steps method took too much time to solve to optimality larger instances including 30 or more sensors. The comparison results show that our method outperforms the 3-steps method in all the tested instances besides the very small ones. For example, with  $n = 25$  and  $\alpha = 0.5$ , the execution time of our method is on average 99.52% lower than the 3-steps method's execution time for the 10 tested instances. This is due to the time complexity of the two first steps of the 3-steps method where all the valid and elementary cover sets are enumerated. The number of possible cover sets is equal to  $2^n - 1$  which is an exponential function of  $n$  and each time the number of sensors is increased by 1, the number of possible cover sets doubles. For this reason, the 3-steps method cannot solve in a reasonable time an instance including more than 25 sensors. It took around four hours to solve an instance with  $n = 30$  and  $\alpha = 1$ .

Moreover, as  $\alpha$  decreases in the partial coverage case, the number of the enumerated valid and elementary  $\alpha$ -cover sets,  $NVC$ , increases. For each valid and elementary  $\alpha$ -cover set, a constraint is added to the linear model in the third step of the 3-steps method. Therefore, as  $NVC$  increases the model takes more memory and becomes harder to solve by the IBM ILOG CPLEX which imposes a size limit on the model. On the other hand, our method can compute the optimal solution for larger instances, up to  $n = 40$ , with an execution time inferior to 10 minutes as shown in Table 4.3.

In conclusion, our approach outperforms the 3-steps method and can solve larger instances.

$\alpha$	$T_\alpha$	$n=10$			$n=15$			$n=20$			$n=25$		
		NVC	Rt (3-steps method)	Rt (all-in-one method)	NVC	Rt (3-steps method)	Rt (all-in-one method)	NVC	Rt (3-steps method)	Rt (all-in-one method)	NVC	Rt (3-steps method)	Rt (all-in-one method)
1	15	12	0.034	0.042	22.5	0.383	0.036	29.1	9.062	0.084	46.8	378.145	0.059
0.85	13	12.6	0.039	0.02	24.9	0.476	0.064	32.4	8.92	0.14	53.4	499.964	0.301
0.75	11	14.7	0.078	0.02	29.1	0.417	0.084	38.1	9.55	0.18	61.2	521.282	0.394
0.5	8	24	0.046	0.04	44.7	0.463	0.139	57.3	9.72	0.35	91.5	408.854	1.957

Table 4.6: Comparison of the two methods in terms of running time (Rt) in seconds.

### 4.5.3/ RESULTS FOR CSSP

In this section, we evaluate the proposed genetic algorithm to optimize the scheduling of the cover sets of the solutions obtained by the resolution of the BILP. The crossover and the mutation rates of the GA were set to 80% and 20% respectively. As described in Section 4.4.3, a chromosome represents the order of the  $\alpha$ -cover sets in a given solution and its size is always equal to  $K_{opt}$ . All the experiments' results are averages for 10 randomly generated instances. All the GA's parameters are listed in Table 4.7.

Parameter	Description
Number of generations	100
Population size	100
Probability of crossover	0.8
Probability of mutation	0.2

Table 4.7: The genetic algorithm's parameters

#### 4.5.3.1/ THE GA VERSUS THE EXHAUSTIVE SEARCH METHOD FOR COVER SETS SCHEDULING PROBLEM ON SMALL NETWORKS

Solving the cover sets scheduling problem seeks to plan efficiently the cover sets of a given solution in order to smooth fairly the targets' uncovered periods throughout the network's lifetime. To show the usefulness of our proposal, two scheduling approaches were compared in this section: the exhaustive (brute-force) search method and the proposed GA. Their results were also compared to the default scheduling obtained by solving the BILP. Due to the factorial time complexity of the brute-force search, this method can only be applied to small instances and therefore the experiments of this section are limited to solutions including 6 to 11 partial cover sets.

$K_{opt}$	Default scheduling		Exhaustive search method		GA	
	min(dis)	Average CV	min(dis)	Average CV	min(dis)	Average CV
6	0.3	0.63	0.9	0.32	0.9	0.32
7	0	1.56	0.5	0.62	0.4	0.64
8	0.3	1.27	0.9	0.44	0.9	0.44
9	0	2.38	0	1.06	0	1.21
10	0.1	0.6	1.9	0.15	1.8	0.17
11	0.5	0.39	2.7	0.06	2.6	0.07

Table 4.8: Minimum of the minimum distances and average coefficient of variation for cover sets scheduling returned by the BILP (default), the exhaustive search method and the GA.

In Section 4.4, two criteria were proposed to compare the solutions returned by the search

methods: p-dispersion and coefficient of variation. Table 4.8 presents the minimum of the minimum distances between uncovered periods ( $\min(dis)$ ) and the coefficient of variation of these distances (CV) for the best solutions found by each of the three methods with the number of cover sets varying from 6 to 11. It can be noticed that as expected the exhaustive search method always returns the solutions with highest  $\min(dis)$  and CV, which are the best solutions according to the chosen criteria. It can also be seen that the  $\min(dis)$  and CV of the solutions returned by the GA are very close to the ones returned by the exhaustive search method. For some instances, like when  $K_{opt}$  is equal to 6 or 8, the GA finds the optimal scheduling for the cover sets. For the other instances, the difference between the  $\min(dis)$  of the optimal solution and the one returned by the GA is less than or equal to 0.1. In all the instances, the GA improves the default scheduling returned by the BILP. Table 4.8 also shows that in some cases, as with  $K_{opt} = 9$ , the  $\min(dis)$  criterion is not sufficient to compare the obtained solutions and the second criterion, CV, must be considered. As a consequence, the results in Table 4.8 highlight that if the obtained  $\alpha$ -cover sets are scheduled a a suitable way, we can achieve in a reasonable time a well-balanced smoothing of the targets' uncovered periods throughout the network's lifetime.

#### 4.5.3.2/ THE PERFORMANCE OF THE PROPOSED GA ON LARGE NETWORKS

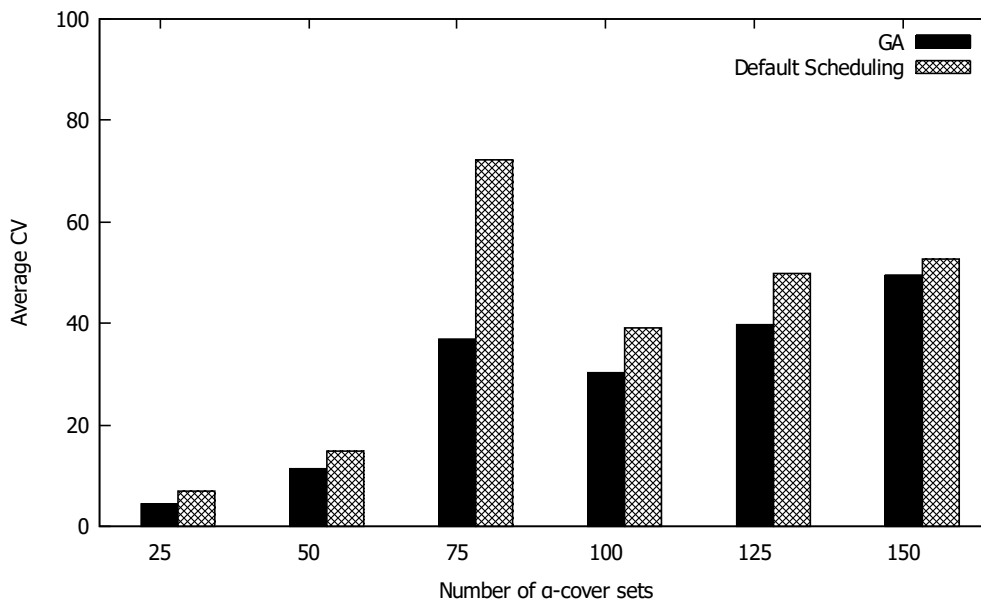


Figure 4.13: Average coefficient of variation for solutions of different problem sizes returned by the BILP (default) or the GA.

In order to evaluate the performance of the proposed GA on large networks and since the exhaustive search cannot solve them in a reasonable time, the scheduling returned by the GA was only compared to the default scheduling. 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 partial cover sets to schedule varied between 25 and 150. When the ratio of the maximum number of uncovered periods per target to the number of periods is high, most of the solutions give the same minimum of the minimum distances, the first criterion is not sufficiently discriminatory. For this reason, we only focus on the second criterion in this section. Hence, Figure 4.13 only presents the average coefficient of variation of the solutions returned by default or by the GA for different numbers of  $\alpha$ -cover sets. It can be noticed that the scheduling returned by the GA is better than the one returned by default for all the considered configurations. The improvement over the default scheduling varies from one instance to the other and it is hard to quantify this improvement because it also depends on the quality of the default scheduling. For example, the obtained improvement is equal to 49.05% for  $K_{opt} = 75$  where the default scheduling is probably very poor and there is a lot of room for improvement. On the other hand, for the 150 cover sets case, the GA does not significantly improve over the default scheduling which is already of good quality.

## 4.6/ CONCLUSION

In this chapter, we have addressed the problem of partial coverage in heterogeneous sensor networks. The aim is to organize the sensor nodes into a number of non-disjoint subsets nodes that are scheduled successively to improve the network's QoS under the constraints of energy saving and partial coverage. To this end, a novel mathematical BILP is proposed to solve to optimality the  $\alpha$ -coverage problem. Moreover, provable guarantees of the upper bound for the number of cover sets that can be built are given. Unlike earlier works in the literature, to improve the coverage quality of the network while prolonging its lifetime, we provided necessary and sufficient condition constraints to meet, at the same time, both **global** and **local** monitoring quality thresholds. Another important contribution of this work is the design of an efficient cover sets scheduling to fairly smooth the targets' uncovered periods during the lifetime of the network. Different scenarios were studied and the obtained results corroborate the merits of our proposals.



# LIFETIME OPTIMIZATION FOR PARTIAL COVERAGE AND CONNECTIVITY IN HWSNs

The network connectivity is a critical problem of WSNs which is not addressed in both Chapter 2 and 3. Therefore, the maximum network lifetime problem (MLP) in heterogeneous wireless sensor networks under connectivity and coverage constraints is addressed in this chapter. Two main variants of the studied problem are considered. The first variant is  $\alpha$ -**coverage** where a portion  $((1 - \alpha)$  percent) of the targets are allowed to be left uncovered. The second one is called  $\beta$ -**coverage** or  $\beta$ -**constraint** where each target has a minimum coverage rate  $\beta$  during the network's lifetime service. When the two variants are considered at the same time, the problem is called  $\alpha\beta$ -Connected Maximum Lifetime Problem ( $\alpha\beta$ -CMLP) where we consider both global (whole targets) resp. local (individual target) monitoring level thresholds to improve the coverage quality of the deployed WSN. Unlike earlier works devoted to only  $\alpha$  coverage, we deal with both local ( $\alpha$ ) and global ( $\beta$ ) coverage leveling thresholds under network connectivity constraint. One approach to optimize the network's lifetime is to divide the sensor nodes into Non-Disjoint subsets of sensors, or cover sets, and to schedule these covers with variable activation time periods, so that the global time lifespan of the network is optimized. To this end, we provide both exact and heuristic approaches in this study. First, a novel mathematical Mixed Integer Linear Programming (MILP) is presented to solve the  $\alpha\beta$ -**coverage** with **network connectivity** requirement to optimality. Unfortunately, due to the NP-Completeness of the addressed problem, the MILP's resolution becomes impracticable for large optimization problems. To remedy this and to cope with large instances, we propose a new exact approach based on column generation able to achieve optimal solutions in reasonable time. In addition, since the CG's subproblem resolution is also an NP-Hard problem, a new dedicated Heuristic (DH) is designed to solve the CG's subproblem in polynomial time complexity. Moreover, we propose an exact ILP formulation



for the CG's subproblem if the DH heuristic fails to compute an attractive solution in each iteration of the CG computation process. Finally, several experiments are performed to evaluate the performances of our proposals.

## 5.1/ INTRODUCTION

One of the well-known and most important problems in WSN is Maximum Network Lifetime Problem (MLP) where the objective is to organize the sensor nodes into disjoint or non-disjoint covers, and to schedule these covers, so that the total network's lifetime is maximized. Note that when the network connectivity is taken in account, the problem is designed under the name of Connected Maximum Network Lifetime problem (CMLP).

Ensuring connectivity among the sensors and the base station (BS) is an important metric to measure the network QoS. The network remains connected so that the collected information within the network can be routed toward to the Base Station (BS). Recall that two sensors are considered to be connected if the distance between them is less than the communication range  $R_c$ . That is, the sensors of the same active set cover are able to both monitor targets and forward the sensed information to the BS. In the same way, network's lifetime and target coverage quality are important related issues that need to be addressed to enhance the network's QoS. Indeed, in some applications like fire detection, the complete coverage of all the targets during the whole network lifetime is not a critical requirement. For instance, during the summer season, the entire forest area must be monitored while during the other seasons covering only part of the region might be sufficient. To cope with this scenario, CMLP is extended to consider the case in which a fraction of the targets can be tolerated to be uncovered for a limited time period in order to prolong the network's lifetime. This new problem is called  $\alpha$ -coverage, where  $\alpha$  refers to a prescribed level of coverage threshold that should be maintained. However, in the case of partial coverage, the coverage rate for all targets is not the same which can lead to very poor coverage of some individual targets. Thus, a local threshold can be defined as the minimum coverage rate over the entire lifetime of the network, i.e. each target is covered at least  $\beta$  (percent) during the network's service [78].

In this chapter, we focus on the  $\alpha\beta$ -CMLP optimization problem where both global (whole targets) resp. local (individual target) monitoring thresholds are considered.

We deal with the case of the Non-Disjoint  $\alpha$ -cover sets problem with variable activation time periods under network connectivity constraint, in contrast to what have been proposed in [78] which is restricted to fixed activation periods.

The contributions and the novelties of the presented study are summarized as follows:

- A new mathematical Mixed Integer Linear Programming (MILP) formulation is proposed to solve to optimality the  $\alpha\beta$ -CMLP problem with variable activation time periods.
- To speedup the time resolution of the  $\alpha\beta$ -CMLP problem, an upper bound is given for the maximum number of non-disjoint cover sets that can be constructed when dealing with partial coverage under variable activation time periods in heterogeneous sensor networks.
- A new column generation based approach for  $\alpha\beta$ -CMLP is proposed to process large instances in contrast to MILP model which is applicable to smaller instances.
- Due to the NP-Completeness of both  $\alpha$ -CMLP and  $\alpha\beta$ -CMLP optimization problems addressed in this work, a new efficient heuristic is designed to solve the column generation's subproblem in polynomial time complexity.

## 5.2/ RELATED WORK

In this section, we provide an overview on the state-of-art of connected maximum network lifetime problem (CMLP) in wireless sensor networks. Many efforts have been devoted to energy saving and coverage problems and most of them focus on the total coverage problem ([66], [14], [5],[9] ,[60], [57],[76], [6], [70]) which consists in maximizing the lifetime of WSN while guaranteeing both full coverage and connectivity constraint. For instance, in [76], the authors propose an efficient Genetic Algorithm (GA) for CMLP problem to achieve the full coverage of the monitoring targets. The connectivity constraint between the sensors belonging to the same active cover set is taken into account to forward the sensed data to the BS. A fitness function is designed to deal with four conflicting objectives, namely the selection of the minimum number of sensor nodes, full coverage, connectivity, and the residual level of energy of the selected sensor nodes.

A similar work is conducted in [79] where a Non-dominated Sorting Genetic Algorithm-II (NSGA-II) with modified dominance is proposed to solve the CMLP problem. It consists of four conflicting objectives which are, as in the preceding work, the selection of minimum number of sensors, coverage requirement, network connectivity and the selection of sensors with higher remaining energy. In both [76] and [79], the problem is also formulated as an integer linear programming (ILP) to compute the optimal solutions for small instances of in reasonable time complexity.

An efficient randomized and distributed algorithm which is called SPAN for CMLP problem is designed in [6] to ensure the network's connectivity. Some nodes are scheduled to sleep while the remaining active nodes provide continuous monitoring service. The

coordinators election process is based on a round robin policy. The objective is to reduce the number of sensor nodes that remain active without diminishing the system capacity or the network's connectivity. The numerical results show that SPAN algorithm achieves better performances compared to other works in the literature in terms of system capacity preservation, energy consumption, and communication latency.

An integrated coverage and connectivity configuration protocol (CCP) to solve CMLP problem that guarantees both connectivity and coverage was presented in [14]. The resolution of the *one*-coverage problem was also extended to solve the *q*-coverage problem which requires that each target must be covered by at least *q* sensors instead of one sensor. In addition, the CCP is integrated within SPAN introduced in [6] to ensure both *q*-coverage and *p*-connectivity. This provides fault tolerance and high system capacity through multi-path connectivity. The authors in [30] have proved that if the communication range of the sensors ( $R_c$ ) is twice higher than their sensing range ( $R_s$ ), then full network coverage implies network connectivity ( $R_c \geq 2R_s$ ). However, even though this condition holds for complete coverage, when partial coverage is considered, this hypothesis is not sufficient to ensure connectivity.

Some works were conducted to address  $\alpha$ -CMLP. For instance, in [70], the authors propose a greedy algorithm for  $\alpha$ -CMLP problem. In this work, nodes have different sensing and communication ranges but the same amount of initial energy. The proposed algorithm guarantees the connectivity between sensor nodes. The cover sets are scheduled during a fixed amount of time  $\lambda$  and each sensor can participate in several cover sets.

In [57], both exact and heuristics were proposed to deal with  $\alpha$ -CMLP optimization problem. The exact approach is based on Column Generation method. To speedup the resolution process, two heuristics called GRASP and VNS are embedded in the used CG approach and are involved sequentially in a multistage scheme. An Integer Linear Programming (ILP) resolution model is applied if the two embedded heuristics are unable to find an attractive solution for the CG's subproblem. The experimental results show that the proposed multilevel technique improves the results significantly.

The  $\alpha$ -CMLP problem was also addressed in [66] by using a Column Generation method as in [57] and [70]. It differs from other works in the sense that it makes use of a Genetic Algorithm to overcome the difficulty of the subproblem's resolution to optimality. To take into account the network's connectivity requirement, a Steiner Tree Heuristic is embedded within the column generation framework. Exact solutions were also provided by solving an exact ILP formulation when the used metaheuristic fails to compute attractive columns in each iteration of the resolution process. As far as we know, the authors study is the closest work to the one presented in this chapter. However, the constraint  $\beta$  is not considered to ensure for each target a minimum level of coverage during the network's service. We conjecture that this leveling threshold constraint turns out to be a key factor

to enhance the QoS of the deployed WSN.

We note that the works in [66], [57] and [70] are based on a column generation approach. They deal only with  $\alpha$ -CMLP problem and do not consider  $\beta$  constraint as addressed in this chapter.

## 5.3/ PROBLEM FORMULATION

In this section, a formal definition of the  $\alpha\beta$ - Connected Maximum Lifetime Problem ( $\alpha\beta$ -CMLP) is presented. It is then modeled as a Mixed Integer Linear Programming (MILP) problem.

### 5.3.1/ NOTATIONS

We consider an undirected graph  $G = (S, E)$ , such that the communication link  $(s_i, s_j) \in E$  exists if and only if the distance between  $s_i$  and  $s_j$  is less than the communication range  $R_c$ . The  $\alpha$ -cover set  $C_k$  is connected if and only if its subgraph  $G' = (C_k, E(C_k))$  is connected, that is, for each sensor  $s_i \in C_k$ , there exist a path of communication that links the sink node (in our case  $s_0$ ) to  $s_i$  in  $G'$ . Each sensor  $s_i \in C_k$  is able to monitor, collect, and forward the sensed information to the base station  $s_0$ . The  $\alpha$ -cover sets can be non-disjoint which means that a sensor can participate to more than one cover set if it has enough energy.

We consider the case of variable activation time periods of the resulting cover sets which is more practical in terms of flexibility when we deal with heterogeneous sensor networks. Unlike earlier works in the literature, both global (whole targets) and local (individual target) leveling threshold constraints are considered at the same time to improve the coverage quality of the network. The objective of the new  $\alpha\beta$ -CMLP optimization problem is to maximize the whole lifetime of the network service while guaranteeing  $\alpha$ -coverage,  $\beta$ -coverage, and network connectivity.

In the following, we give an application example to highlight the effect of the different variants of coverage on the network's lifetime.

### 5.3.2/ EXAMPLE:

Consider a network of 3 heterogeneous sensors with different initial energy levels deployed to cover 4 targets:  $t_1, t_2, t_3, t_4$  as presented in Figure 5.1. Three variants of coverage are examined: total coverage, partial coverage under only  $\alpha$  constraint as in the literature and partial coverage under both  $\alpha$  and  $\beta$  constraints as considered in this chapter. Let  $E_1 = 5$ ,  $E_2 = 2$ ,  $E_3 = 1$ ,  $\alpha = 0.75$ , and  $\beta = 0.5$ . In the former case of total coverage,

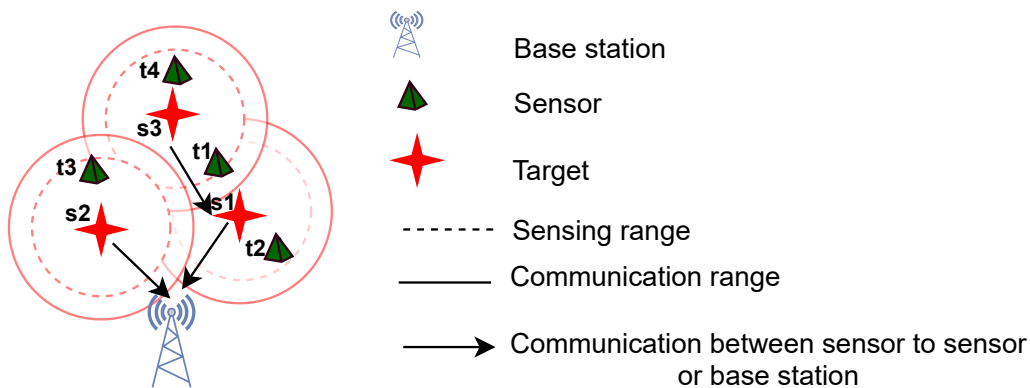


Figure 5.1: An example network completely covered and connected.

the connected cover set  $C = \{s_1, s_2, s_3\}$  can be built leading to an activation time period of 1 ut which is equal to the minimum energy level of its constituent sensors. The second variant refers to the case of partial coverage where only  $\alpha$  constraint is considered as in the literature. This constraint would lead to activating, at each time period, fewer sensors than in the total coverage, which would significantly reduce the energy consumption of the sensors and thus increase the overall lifetime of the network. Consequently, for  $\alpha = 0.75$ , the cover set obtained for the case of full coverage can be split into two subsets  $C_1 = \{s_1, s_2\}$  and  $C_2 = \{s_1, s_3\}$  with activation time periods of 2 ut and 1 ut respectively. With this, the network lifetime will be improved until 3 ut compared to the one obtained in full coverage. However, we can observe that the target  $t_4$  has a poor coverage rate of 33% during the whole network service. In order to alleviate this problem, constraint  $\beta$  which reflects the target's leveling coverage threshold must be taken into account in contrast to what have been studied in the literature. The upshot of this is to achieve efficient trade-off between global ( $\alpha$ ) and local ( $\beta$ ) related constraints during the monitoring activity of the network. This case is described by the third variant of this example where  $\alpha = 0.75$  and  $\beta = 0.5$ . With these settings, we obtain the same cover sets, as in the second variant, but with an activation time period of 1 ut each and a network lifetime span of 2 ut. Obviously, this slight decrease of the network lifetime is predictable since we guarantee a minimum level threshold for each target in the network. To conclude this example, we can notice that  $\beta$  constraint plays a crucial role on the overall performance of the network's monitoring service.

### 5.3.3/ MILP: MODEL FORMULATION

The search for the optimal solution for the  $\alpha\beta - CMLP$  can be formulated as a mixed integer linear programming (MILP) problem. All the cover sets have a minimum activation time  $d_{min}$  and the goal of the MILP is to maximize the whole lifetime of the network service.

In our MILP formulation, when the local monitoring threshold  $\beta_j$  is applied, the maximum number of non-disjoint  $\alpha$ -cover sets of a variable activation time period  $d_k$  is bounded by the least covered target and constraint  $\beta$  as in [78]. Thus, this upper bound can be computed as the following:

$$K = \min_{j \in T} \left\lfloor \frac{\sum_{i \in S_j} E_i}{\beta_j \times d_{min}} \right\rfloor \quad (5.1)$$

The variables used to define the problem are the following:

- Binary variables  $x_{i,k}$ ,  $\forall i \in \llbracket 1, n \rrbracket$  and  $\forall k \in \llbracket 1, K \rrbracket$ ;  $x_{i,k} = 1$  means that the sensor  $s_i$  is active in the cover set  $C_k$ .
- Continuous variables  $v_{i,k}$ ,  $\forall i \in \llbracket 1, n \rrbracket$  and  $\forall k \in \llbracket 1, K \rrbracket$ : activation period of the sensor  $i$  in the cover set  $C_k$ .
- Continuous variables  $w_{j,k}$ ,  $\forall j \in \llbracket 1, m \rrbracket$  and  $\forall k \in \llbracket 1, K \rrbracket$ : coverage time of the target  $j$  in the cover set  $C_k$ .
- Continuous variables  $d_k$ ,  $\forall k \in \llbracket 1, K \rrbracket$ : the duration of the activation time of the cover set  $C_k$ .

### 5.3.3.1/ OBJECTIVE

The objective is to maximize the sum of the duration of the activation times of the  $\alpha$ -cover sets.

$$\text{Max} \sum_{k=1}^K d_k \quad (5.2)$$

### 5.3.3.2/ GLOBAL COVERAGE CONSTRAINTS

If the sensor  $s_i$  is active in the cover set  $C_k$ , the set of targets ( $T_i$ ) that it monitors will be covered in the cover set  $C_k$ . A target  $t_j$  is covered if there is at least one sensor  $s_i \in S_j$  that monitors it in the set  $C_k$ . This is mathematically formulated by the following two types of constraints:

$$w_{j,k} \geq v_{i,k} \quad \forall j \in \llbracket 1, m \rrbracket, \quad \forall k \in \llbracket 1, K \rrbracket, \quad \forall i \in S_j \quad (5.3)$$

$$\sum_{i \in S_j} v_{i,k} \geq w_{j,k} \quad \forall j \in \llbracket 1, m \rrbracket, \quad \forall k \in \llbracket 1, K \rrbracket \quad (5.4)$$

Constraints (5.3) force the variable  $w_{j,k}$  to be different than 0 if one sensor of  $S_j$  is activated in the  $\alpha$ -cover. Constraints (5.4) allow the variable  $w_{j,k}$  to be different from 0 only if at least one of the sensors monitoring it is active in the cover set  $C_k$ .

The following constraints impose that at least  $T_\alpha$  targets are covered in each  $\alpha$ -cover set:

$$\sum_{j \in T} w_{j,k} \geq T_\alpha \times d_k \quad \forall k \in \llbracket 1, K \rrbracket \quad (5.5)$$

### 5.3.3.3/ TARGET'S COVERAGE CONSTRAINTS

As previously explained, our model includes a new type of constraints that limits the network lifetime according to the parameter  $\beta$  such that the total coverage time of each target is superior or equal to  $\beta$  percent of the network lifetime.

Moreover, in some applications such as forest fires, it is efficient to monitor targets with the highest risk probabilities of being infected by fire. These targets must have a higher monitoring ratio than the others and then each target  $j$  has its own monitoring ratio  $\beta_j$ . This local level threshold is called  $\beta$  constraint in [78] and it can be expressed as follows:

$$\sum_{k=1}^K w_{j,k} \geq \beta_j \times \sum_{k=1}^K d_k \quad \forall j \in \llbracket 1, m \rrbracket \quad (5.6)$$

### 5.3.3.4/ CONNECTIVITY CONSTRAINTS

We present the following three constraints based on single-commodity flows proposed in [49] that ensure the connectivity of the obtained  $\alpha$ -cover sets.

$$\sum_{(s_0, s_i) \in E} f_{k,0,i} = \sum_{i \in S} x_{i,k} \quad \forall k \in \llbracket 1, K \rrbracket \quad (5.7)$$

$$\sum_{(s_i, s_j) \in E} f_{k,i,j} - \sum_{(s_j, s_i) \in E} f_{k,j,i} = x_{i,k} \quad \forall s_i \in S \setminus \{s_0\}, \forall k \in \llbracket 1, K \rrbracket \quad (5.8)$$

$$x_{i,k} \leq \sum_{(s_j, s_i) \in E} f_{k,j,i} \leq (|S| - 1) \times x_{i,k} \quad \forall s_j \in S \setminus \{s_0\}, \forall k \in \llbracket 1, K \rrbracket \quad (5.9)$$

$$f_{k,i,j} \in \mathbb{Z}^+ \cup \{0\} \quad \forall (s_i, s_j) \in E \quad (5.10)$$

Where  $f_{ij} \quad \forall (s_i, s_j) \in E$  are flow variables. Constraints (5.7) impose the amount of flow produced by the base station to be equal to the number of activated sensors. Constraints (5.8) are the flow conservation constraints. Constraints (5.9) impose all sensors with ingoing positive flow to be activated in each  $\alpha$ -cover set.

### 5.3.3.5/ ENERGY CONSTRAINTS

In the non-disjoint case, a sensor might belong to several  $\alpha$ -cover sets if it has enough energy. The following constraints ensure that the total energy consumed by a sensor

does not exceed its initial energy:

$$\sum_{k=1}^K v_{i,k} \leq E_i \quad \forall i \in \llbracket 1, n \rrbracket \quad (5.11)$$

The activation time of a sensor  $i$  that belongs to a  $\alpha$ -cover set  $C_k$  is greater than or equal to the activation time  $d_k$ . This constraint is expressed in the form:

$$\max_{i \in S} E_i \times (1 - x_{i,k}) + v_{i,k} \geq d_k \quad \forall i \in \llbracket 1, n \rrbracket, \forall k \in \llbracket 1, K \rrbracket \quad (5.12)$$

If the sensor  $i$  does not belong to the  $\alpha$ -cover set  $C_k$ , then  $x_{i,k} = 0$  and the inequality  $\max_{i \in S} E_i \geq d_k$  is satisfied. Otherwise,  $x_{i,k} = 1$  and the inequality  $v_{i,k} \geq d_k$  must be satisfied.

The coverage time of the target  $j$  in  $\alpha$ -cover set  $C_k$  must be less than or equal to the activation time  $d_k$ . This results in the following constraints:

$$w_{j,k} \leq d_k \quad \forall k \in \llbracket 1, K \rrbracket \quad \forall j \in \llbracket 1, m \rrbracket \quad (5.13)$$

The sensor  $i$  must belong to  $\alpha$ -cover set ( $x_{i,k} = 1$ ) when its activation time in this cover is non-zero. This results in the following constraints:

$$v_{i,k} \leq \max_{i \in S} E_i \times x_{i,k} \quad \forall k \in \llbracket 1, K \rrbracket \quad \forall i \in \llbracket 1, n \rrbracket \quad (5.14)$$

The activation time of the sensor  $i$  must be superior to the minimal activation time  $d_{min}$  when the sensor  $i$  is active ( $x_{i,k} = 1$ ), this results in the following constraint:

$$v_{i,k} \geq d_{min} \times x_{i,k} \quad \forall k \in \llbracket 1, K \rrbracket \quad \forall i \in \llbracket 1, n \rrbracket \quad (5.15)$$

Considering cover sets of variable durations  $d_k$  with both global and local leveling threshold  $\alpha$  and  $\beta$ , a new mathematical model of the  $\alpha\beta$ - Connected Maximum Lifetime Problem



( $\alpha\beta$  – CMLP) can be formulated as follows:

$$\left\{ \begin{array}{ll}
 [P] \max \sum_{k=1}^K d_k & \\
 \text{subject to:} & \\
 w_{j,k} \geq v_{i,k} & \forall j \in \llbracket 1, m \rrbracket, \\
 & \forall k \in \llbracket 1, K \rrbracket, \forall i \in S_j \\
 \sum_{i \in S_j} v_{i,k} \geq w_{j,k} & \forall j \in \llbracket 1, m \rrbracket \forall k \in \llbracket 1, K \rrbracket \\
 \sum_{j \in T} w_{j,k} \geq T_\alpha \times d_k & \forall k \in \llbracket 1, K \rrbracket \\
 \sum_{k=1}^K w_{j,k} \geq \beta_j \times \sum_{k=1}^K d_k & \forall j \in \llbracket 1, m \rrbracket \\
 \sum_{(s_0, s_i) \in E} f_{k,0,i} = \sum_{i \in S} x_{i,k} & \forall k \in \llbracket 1, K \rrbracket \\
 \sum_{(s_i, s_j) \in E} f_{k,i,j} - \sum_{(s_j, s_i) \in E} f_{k,j,i} = x_{i,k} & \forall s_i \in S \setminus \{s_0\}, \forall k \in \llbracket 1, K \rrbracket \\
 x_{i,k} \leq \sum_{(s_j, s_i) \in E} f_{k,j,i} \leq (|S| - 1) \times x_{i,k} & \forall s_j \in S \setminus \{s_0\}, \forall k \in \llbracket 1, K \rrbracket \\
 \sum_{k=1}^K v_{i,k} \leq E_i & \forall i \in \llbracket 1, n \rrbracket \\
 \max_{i \in S} E_i \times (1 - x_{i,k}) + v_{i,k} \geq d_k & \forall i \in \llbracket 1, n \rrbracket, \forall k \in \llbracket 1, K \rrbracket \\
 w_{j,k} \leq d_k & \forall k \in \llbracket 1, K \rrbracket \forall j \in \llbracket 1, m \rrbracket \\
 v_{i,k} \leq \max_{i \in S} E_i \times x_{i,k} & \forall k \in \llbracket 1, K \rrbracket \forall i \in \llbracket 1, n \rrbracket \\
 v_{i,k} \geq d_{\min} \times x_{i,k} & \forall k \in \llbracket 1, K \rrbracket \forall i \in \llbracket 1, n \rrbracket
 \end{array} \right. \quad (5.16)$$

The resolution of this linear program with mixed variables becomes impracticable for large optimization problems. Thus, heuristics and meta-heuristics are more suitable for large problems and they are able to find sub-optimal solutions in a reasonable execution time. It's worthwhile to note that our MILP model is very useful and has a lot of interest when considering  $\beta$  constraint to initialize the restricted master problem of CG with a starting set of columns as it will be shown in Section 5.6.2.2.

## 5.4/ COLUMN GENERATION METHOD FOR $\alpha\beta$ -CMLP

Since the mixed linear programming formulation is a hard problem and some solutions could consist of a large number of variables, we present in this section a Column Generation based approach (CG) to find optimal solutions to this problem in a reasonable time. The CG is one of the most optimization decomposition methods that enables to reduce the amount of variables (columns) for MILP problems. The CG is first formulated as a restricted master problem (RMP), with few subset of its original columns, which will be solved to optimally. Next, the CG considers the subproblem to construct an attractive new column(subset) which could improve the current solution. This subproblem is solved and if its objective value (reduced cost) is negative (in case of maximization problems), an incumbent solution is already optimal, otherwise, the attractive column is introduced in the [RMP] and the process is repeated until no more columns can be added to the [RMP].

### 5.4.1/ RESTRICTED MASTER PROBLEM [RMP ]

The  $\alpha\beta$ -CMLP problem consists in finding a collection of pairs  $(C_k, d_k)$  where each  $C_k \subseteq S$  is a feasible cover set and each  $d_k \geq 0$  is an amount of activation time for which  $C_k$  is activated. Each sensor  $i$  is in an active state for an amount of activation time that does not exceed its initial energy and each target  $j$  has a minimum coverage time period over the total the network's lifespan (own monitoring ratio  $\beta_j$ ) so that the sum of the whole covers' activation times is maximized.

Let  $a_{i,k}$  be a given binary values which is equal to 1 if  $s_i$  is active in the  $\alpha$ -cover set and 0 otherwise. Let  $b_{j,k}$  be a given binary value which is equal to 1 if  $t_j$  is covered in the  $\alpha$ -cover set and 0 otherwise. The restricted master problem [RMP] is formulated as following:

$$\begin{aligned} \text{[RMP]} \quad & \max \sum_{k=1}^{K'} d_k \\ & \text{subject to:} \end{aligned} \quad (5.17)$$

$$\sum_{k=1}^{K'} a_{i,k} d_k \leq E_i \quad \forall s_i \in S \setminus \{s_0\} \quad (5.18)$$

$$\sum_{k=1}^{K'} b_{j,k} d_k \geq \beta_j \times \sum_{k=1}^{K'} d_k \quad \forall j \in \llbracket 1, m \rrbracket \quad (5.19)$$

The objective function (5.17) aims to maximize the sum of the activation time periods and thus the network lifetime. Note that only a limited number of cover sets are considered in the RMP, noted  $K'$ , which is less than or equal to the upper bound  $K$ . Constraints (5.18) ensure that the total energy consumed by a sensor does not exceed its initial energy.

In partial coverage, the  $\beta$  constraint must be introduced in our [RMP] master problem. The constraints (5.19) ensure that each target is at least covered with a rate  $\beta$  of the whole lifetime of the network. These constraints (5.19) can be simplified as follows:

$$\sum_{k=1}^{K'} p_{j,k} d_k \leq 0 \quad \forall j \in \llbracket 1, m \rrbracket \quad (5.20)$$

where,

$$p_{j,k} = \beta_j - b_{j,k} \quad (5.21)$$

### 5.4.2/ REDUCED COST

The question that arises when we consider  $\beta$  constraint is how to analyze and calculate the reduced cost  $r$ . Let  $\pi_i, \forall s_i \in S \setminus \{s_0\}$  and  $\rho_j, \forall t_j \in T$ , be the dual prices associated to constraints (5.18) and constraints (5.20) in the incumbent solution respectively.

Recall that without considering  $\beta$  constraint,  $r$  is computed as follows:

$$r = 1 - \sum_{i \in S} a_{i,k} \pi_i$$

To take  $\beta$  constraint into account,  $r$  is rewritten as follows:

$$\begin{aligned} r &= 1 - \sum_{i \in S} a_{i,k} \pi_i - \sum_{j \in T} p_{j,k} \rho_j \\ &= 1 - \sum_{i \in S} a_{i,k} \pi_i - \sum_{j \in T} (\beta_j - b_{j,k}) \rho_j \\ &= 1 - \sum_{i \in S} a_{i,k} \pi_i - \sum_{j \in T} \beta_j \rho_j + \sum_{j \in T} b_{j,k} \rho_j \end{aligned}$$

A new cover set is attractive (can improve the incumbent solution) if its reduced cost is positive ( $r > 0$ ). Thus, if

$$\begin{aligned} 1 - \sum_{i \in S} a_{i,k} \pi_i - \sum_{j \in T} \beta_j \rho_j + \sum_{j \in T} b_{j,k} \rho_j &> 0 \\ 1 - \sum_{j \in T} \beta_j \rho_j &> \sum_{i \in S} a_{i,k} \pi_i - \sum_{j \in T} b_{j,k} \rho_j, \end{aligned}$$

the attractive  $\alpha$ -cover set will be added to the restricted master problem [RMP] in the next iteration. Otherwise, the incumbent solution is optimal and the procedure ends.

### 5.4.3/ SUBPROBLEM [SP]

We search for a new attractive cover set with positive reduced cost. This search can be formulated as an optimization problem called subproblem. Some notations used to define the subproblem [SP] are given in the following:

Let  $act_i$  and  $cov_j$  be binary variables which define resp. how a cover set is built and which targets are covered. We are looking for a cover set  $C_k$  which minimizes the total value:  $\sum_{i \in S} act_i \pi_i - \sum_{j \in T} cov_j \rho_j$ . If this sum is less or equal than  $(1 - \sum_{j \in T} \beta_j \rho_j)$ , the cover set  $C_k$  is an attractive column. The variables used to define the subproblem are the following:

- Binary variable  $act_i$ ,  $\forall i \in \llbracket 1, n \rrbracket$ ;  $act_i = 1$  means that the related sensor  $i$  is chosen to be in the attractive  $\alpha$ -cover set.
- Binary variable  $cov_j$ ,  $\forall j \in \llbracket 1, m \rrbracket$ ;  $cov_j = 1$  stands for that the related target is covered in the attractive  $\alpha$ -cover set.

The following formulation represents the subproblem [SP] to solve in the global  $\alpha\beta$ -CMLP optimization problem:

$$[SP] \quad \min(\sum_{i=1}^n act_i \times \pi_i - \sum_{j=1}^m cov_j \times \rho_j) \quad (5.22)$$

subject to:

$$\sum_{s_i \in S \setminus \{s_0\}} \delta_{i,j} \times act_i \geq cov_j \quad \forall j \in \llbracket 1, m \rrbracket \quad (5.23)$$

$$\sum_{j \in T} cov_j \geq T_\alpha \quad (5.24)$$

$$\sum_{(s_0, s_i) \in E} f_{0,i} = \sum_{i \in S} act_i \quad (5.25)$$

$$\sum_{(s_i, s_j) \in E} f_{i,j} - \sum_{(s_j, s_i) \in E} f_{j,i} = act_i \quad \forall s_i \in S \setminus \{s_0\} \quad (5.26)$$

$$act_i \leq \sum_{(s_j, s_i) \in E} f_{j,i} \leq (|S| - 1) \times act_i \quad \forall s_j \in S \setminus \{s_0\} \quad (5.27)$$

$$f_{i,j} \in \mathbb{Z}^+ \cup \{0\} \quad \forall (s_i, s_j) \in E \quad (5.28)$$

Constraints (5.23) ensure that at least one of the sensors that can cover target  $j$  is activated, While constraint (5.24) guarantees that at least  $T_\alpha$  targets are covered. Constraint (5.25) imposes the amount of flow produced by the base station to be equal to the number of activated sensors. Constraints (5.26) are the flow conservation constraints which indicate that, for each sensor  $s_j \in S \setminus \{s_0\}$ , the difference between ingoing and outgoing flow is equal to 1 if the sensors belongs to the new cover, and 0 otherwise. Constraints (5.27) impose that all sensors with ingoing positive flow have to be activated in each  $\alpha$ -cover set. If the objective function value of [SP] is less than  $1 - \sum_{j \in T} \beta_j \rho_j$ , the generated attractive  $\alpha$ -cover set is added to the restricted master problem [RMP], otherwise the procedure stops.

As the subproblem resolution is NP-Hard [57], an efficient heuristic based approach to solve this problem in a reasonable execution time is presented in the next section.

## 5.5/ A DEDICATED HEURISTIC TO ADDRESS THE COLUMN GENERATION'S SUBPROBLEM

In this section, a new heuristic that generates attractive columns to add to the master problem of the column generation's method, is presented. This heuristic is called DH (Dedicated Heuristic) and inspired from the greedy algorithm given in [42] (Algorithm 2

page 814) for the minimum connected set cover problem (MCSC). It builds a minimum connected  $\alpha$ -cover set. However, the  $\alpha$ -cover set generated by DH may have redundant coverage, thus, an additional step is used to remove from the  $\alpha$ -cover set the surplus sensors while respecting the coverage and the connectivity constraints. DH was integrated to both heuristic and exact methods, namely  $CG_{DH}$  and  $CG_{MIXT}$ . On one hand, the  $CG_{DH}$  approach produces approximate solutions by solving the column generation's subproblem [SP] using DH and it stops as soon as DH fails to find an attractive  $\alpha$ -cover. On the other hand, the  $CG_{EXACT}$  approach gives the optimal solution by solving an exact ILP formulation for the column generation's subproblem [SP]. Finally, the exact method  $CG_{MIXT}$  gives the optimal solution by solving the column generation's subproblem through the ILP formulation if the DH heuristic fails. The ILP resolution ensures that there is no more attractive cover set and it certifies optimality for the incumbent solution.

### 5.5.1/ DH'S ALGORITHM

CMLP optimization problems addressed in this section. Before starting the algorithm, we need to define the following definition:

**Definition 5.5.1.** A sensor  $s_i$  is considered as graph-adjacent to a cover set  $C_k$ , if and only if there exists a path in the graph that connects  $s_i$  to at least one sensor of  $C_k$ .

The DH heuristic is detailed in Algorithm 3. Let weighted directed graph  $G^d = (S, E^d)$  be the directed version of the connectivity graph  $G = (S, E)$ , where  $E^d$  contains both  $(s_i, s_j)$  and  $(s_j, s_i)$  for each communication link  $(s_i, s_j) \in E$ . We define a function which assigns to each edge of  $E^d$  a weight is equal to  $\pi_i$  corresponding to dual variable of sensor  $s_i$  is associated to all arcs incoming in  $s_i$ . DH takes as input the wireless sensor network  $WSN = (S, T)$ , its connectivity graph  $G = (S, E)$ , the  $T_\alpha$  value and the dual multipliers  $\pi_i$  for each sensor obtained from the last iteration of the [RMP]. DH first builds a cover set  $C_k$  that contains only the base station  $s_0$ . Then, the sensors are iteratively added to the  $C_k$  to form an attractive cover set that respects both coverage and connectivity constraints. At each iteration, the algorithm creates a restricted candidate list of sensors containing only the sensors which are graph-adjacent with a sensor in  $C_k$ . The objective is to add to the cover set in construction in priority sensors with low dual values and covering a maximum of targets while maintaining connectivity. To do this, we choose sensors with a path  $P_s$  for which the  $CO(P_s)$  value is minimal. This cost  $CO(P_s)$  is the ratio between the length of the shortest path and the minimum between the number of additional covered targets on this path and the number of targets that remain to be covered ( $T_\alpha \setminus T_{cov}$ ). We observed that the effect of taking into account the number of targets that remain to be covered ( $T_\alpha \setminus T_{cov}$ ) when dealing with partial coverage greatly improves our heuristic. The selected sensor is added to  $C_k$ . The iterative process stops when either the required coverage level  $\alpha$  is

**Algorithm 3** Pseudocode of  $DH(\pi_i, T_\alpha)$ 


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**Require:** The dual multipliers  $\pi_i$  for each sensor  $i \in S$   
**Ensure:** A minimum connected cover set  $C_k$  and the associated reduced cost  $r$

- 1:  $C_k \leftarrow s_0$
- 2:  $T_{cov} \leftarrow \emptyset$
- 3:  $r \leftarrow 0$
- 4: **while** ( $|T_{cov}| < T_\alpha$ ) && ( $|S| > 0$ ) **do**
- 5:   **for all**  $s \in S \setminus C_k$  which is graph-adjacent with a sensor in  $C_k$  **do**
- 6:     Compute the value  $v(P_s)$  of a shortest path  $P_s$  from  $C_k$  to  $s$  using only edges in  $E(S)$
- 7:     Compute  $T(P_s)$  the set of targets of  $T \setminus T_{cov}$  which are covered by sensors on  $P_s$
- 8:     Define and compute  $CO(P_s)$  the cost of the shortest path  $P_s$ :  

$$CO(P_s) = \frac{v(P_s)}{\min(|T_\alpha \setminus T_{cov}|, |T(P_s)|)}$$
- 9:   **end for**
- 10:   Choose  $s^* \in S$  such that  $CO(P_{s^*})$  is minimum
- 11:   Add all sensors on  $P_{s^*}$  into  $C_k$
- 12:   Remove all sensors on  $P_{s^*}$  from  $S$
- 13:    $T_{cov} \leftarrow T_{cov} \cup T(P_{s^*})$
- 14: **end while**
- 15: **if** ( $|T_{cov}| \geq T_\alpha$ ) **then**
- 16:   **for all**  $s \in C_k$  **do**
- 17:      $r \leftarrow r + \pi_s$
- 18:   **end for**
- 19:    $r \leftarrow 1 - r$
- 20: **else**
- 21:    $r \leftarrow -\infty$
- 22: **end if**

---

reached or the cover set  $C_k$  cannot be created. In the first case, the reduced cost  $r$  for the cover set  $C_k$  is calculated. DH returns the obtained cover set that corresponds to an attractive column for the restricted master problem, and the associated reduced cost  $r$ . Otherwise,  $r$  takes any negative value to end the algorithm.

## 5.5.2/ EXAMPLE

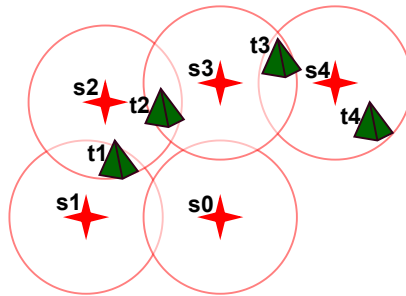


Figure 5.2: An example of a sensor network with 4 sensors and 4 targets

To illustrate Algorithm 3, it is applied on a simple network consisting of four sensors and four targets. It was assumed that the communication and sensing ranges are equal for all sensors. Figure 5.2 shows the wireless sensor network where  $T = \{t_1, t_2, t_3, t_4\}$  is the set of targets and  $S = \{s_0, s_1, s_2, s_3, s_4\}$  is the set composed of the sensors and the base station  $s_0$ .

From this network a communication graph  $G = (S, E)$  can be deduced such that the communication link  $(s_i, s_j) \in E$  if and only if  $s_i$  can directly communicate with  $s_j$ . This graph is drawn in Figure 5.3.

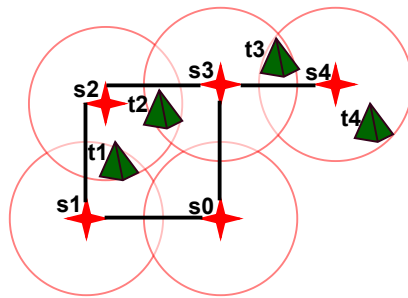


Figure 5.3: The corresponding communication graph  $G$

Each edge is split into two oriented edges and the weight of each edge is calculated as previously described. Figure 5.4 gives a representation of the new weighted directed graph.

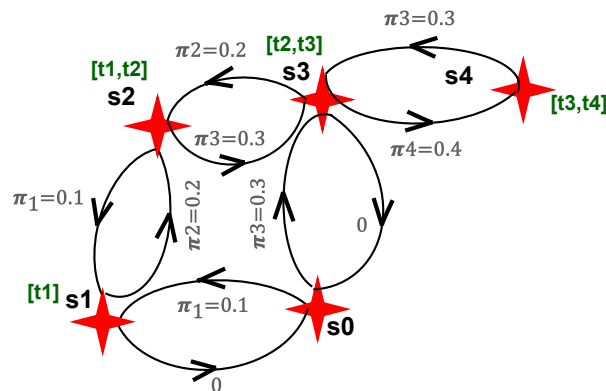


Figure 5.4: The corresponding weighted directed graph

In this example, it was assumed that the partial cover set  $C_k$  must cover at least three targets ( $|T_\alpha| = 3$ ). The steps of the algorithm applied to this example is described as the following. At the initialization phase, the cover set  $C_k$  contains only the base station  $s_0$  ( $C_k = \{s_0\}$ ), the covered targets  $T_{cov}$  is empty, the available sensors  $S$  are  $\{s_1, s_2, s_3, s_4\}$  and the reduced cost  $r$  is set to 0.

For the first iteration, the sensors  $s_1, s_2, s_3$  and  $s_4$  are graph-adjacent with a sensor in  $C_k$

## 5.5. A DEDICATED HEURISTIC TO ADDRESS THE COLUMN GENERATION'S SUBPROBLEM 93

and one of them will be added to  $C_k$ . Their cost values are calculated as follows:

- Sensor  $s_1$ : shortest path  $(s_0, s_1)$ , value of the path  $v(P_{s_1}) = 0.1$ , new set of covered targets  $\{t_1\}$ ,  $|T(P_{s_1})| = 1$ , uncovered targets  $|T_\alpha \setminus T_{cov}| = 3$ ,  $CO(P_{s_1}) = \frac{0.1}{1} = 0.1$ .
- Sensor  $s_2$ : shortest path  $(s_0, s_1, s_2)$ , value of the path  $v(P_{s_2}) = 0.1 + 0.2 = 0.3$ , new set of covered targets  $\{t_1, t_2\}$ ,  $|T(P_{s_2})| = 2$ , uncovered targets  $|T_\alpha \setminus T_{cov}| = 3$ ,  $CO(P_{s_2}) = \frac{0.3}{2} = 0.15$ .
- Sensor  $s_3$ : shortest path  $(s_0, s_3)$ , value of the path  $v(P_{s_3}) = 0.3$ , new set of covered targets  $\{t_2, t_3\}$ ,  $|T(P_{s_3})| = 2$ , uncovered targets  $|T_\alpha \setminus T_{cov}| = 3$ ,  $CO(P_{s_3}) = \frac{0.3}{2} = 0.15$ .
- Sensor  $s_4$ : shortest path  $(s_0, s_3, s_4)$ , value of the path  $v(P_{s_4}) = 0.3 + 0.4 = 0.7$ , new set of covered targets  $\{t_2, t_3, t_4\}$ ,  $|T(P_{s_4})| = 3$ , uncovered targets  $|T_\alpha \setminus T_{cov}| = 3$ ,  $CO(P_{s_4}) = \frac{0.7}{3} = 0.23$ .

As the sensor  $s_1$  has the minimum cost value, it is added to  $C_k$ . Then, the cover set  $C_k$  contains  $\{s_0, s_1\}$ , its covered targets are  $\{t_1\}$  and the available sensors are  $\{s_2, s_3, s_4\}$ . The new graph is represented in figure 5.5.

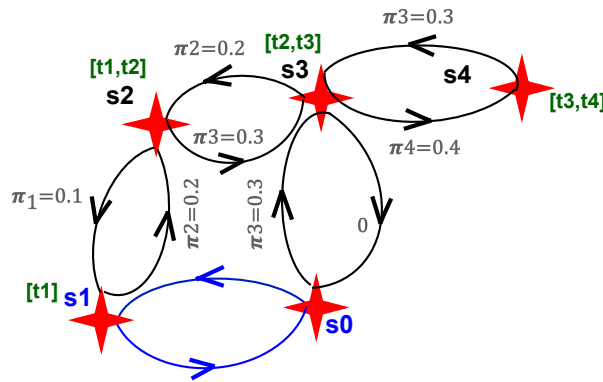


Figure 5.5: The corresponding graph after the first iteration where the sensors added to  $C_k$  are colored in blue.

The algorithm continues to the next iteration because the number of covered targets in  $C_k$  has not yet reached  $|T_\alpha|$ .

For the second iteration, the sensors  $s_2$ ,  $s_3$  and  $s_4$  are graph-adjacent with a sensor in  $C_k$  and one of them will be added to  $C_k$ . Their cost values are calculated as follows:

- Sensor  $s_2$ : shortest path  $(s_1, s_2)$ , value of the path  $v(P_{s_2}) = 0.2$ , new set of covered targets  $\{t_2\}$ ,  $|T(P_{s_2})| = 1$ , uncovered targets  $|T_\alpha \setminus T_{cov}| = 2$ ,  $CO(P_{s_2}) = \frac{0.2}{1} = 0.2$ .
- Sensor  $s_3$ : shortest path  $(s_0, s_3)$ , value of the path  $v(P_{s_3}) = 0.3$ , new set of covered targets  $\{t_2, t_3\}$ ,  $|T(P_{s_3})| = 2$ , uncovered targets  $|T_\alpha \setminus T_{cov}| = 2$ ,  $CO(P_{s_3}) = \frac{0.3}{2} = 0.15$ .



- Sensor  $s_4$ : shortest path  $(s_0, s_3, s_4)$ , value of the path  $v(P_{s_4}) = 0.3 + 0.4 = 0.7$ , new set of covered targets  $\{t_2, t_3, t_4\}$ ,  $|T(P_{s_4})| = 3$ , uncovered targets  $|T_\alpha \setminus T_{cov}| = 2$ ,  $CO(P_{s_4}) = \frac{0.7}{2} = 0.35$ .

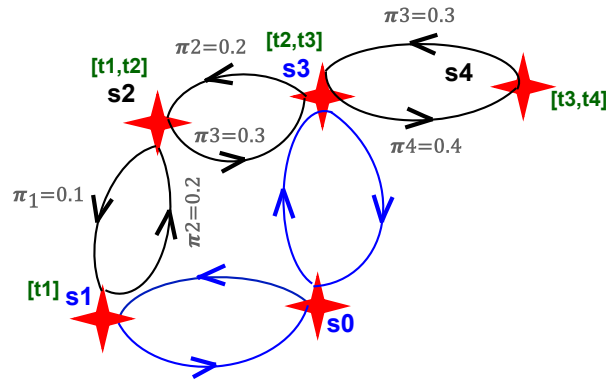


Figure 5.6: Graph obtained after two iterations.  $\{s_0, s_1, s_3\}$  are in the cover set  $C_k$ . The desired number of covered targets is reached.

As the sensor  $s_3$  has the minimum cost value, it is added to  $C_k$ . Then, the cover set  $C_k$  contains  $\{s_0, s_1, s_3\}$ , its covered targets are  $\{t_1, t_2, t_3\}$  and the available sensors are  $\{s_2, s_4\}$ .

The new graph is represented in figure 5.6. The iterative process stops because the number of covered target has reached  $|T_\alpha|$  and the reduced cost of this connected cover set is computed. In this example,  $r = 1 - \pi_1 - \pi_3 = 1 - 0.1 - 0.3 = 0.6 > 0$ . In this case, this building attractive cover set is added to the [RMP].

### 5.5.3/ ADAPTING ALGORITHM 3 TO RESPECT CONSTRAINT $\beta$ AND SOLVE THE $\alpha\beta$ -CMLP PROBLEM

To ensure a local coverage quality for each target, two modifications were made as follows:

- For  $CO(P_s)$  the sum of the dual variables ( $\rho_j$ ) associated with the additional targets covered ( $T(P_s)$ ) by the sensors which are part of the path, are subtracted. This modification can be expressed in algorithm 3 (after line 6) as follows:

---

```

for all  $j \in T(P_s)$  do
     $v(P_s) \leftarrow v(P_s) - \rho_j$ 
end for
    
```

---

- For  $r$  both the sum of the dual variables ( $\rho_j$ ) associated with the targets covered ( $T(C_k)$ ) by the sensors into  $C_k$  and the sum of the multiplication of the dual variables

$(\rho_j)$  and  $\beta_j$  associated with the targets covered ( $T(C_k)$ ) into  $C_k$ , are also subtracted. This modification can be expressed in algorithm 3 (after line 3 and 18 respectively) as follows:

---

```

 $r' \leftarrow 0$ 
for all  $j \in T(C_k)$  do
   $r' \leftarrow r' + (\beta_j \times \rho_j)$ 
end for

```

---

```

for all  $j \in T(C_k)$  do
   $r \leftarrow r - \rho_j$ 
end for
 $r \leftarrow 1 - r' - r$ 

```

---

#### 5.5.4/ AN EXISTING GENETIC ALGORITHM TO ADDRESS THE COLUMN GENERATION'S SUBPROBLEM

For the sake of comparison, we present in this subsection, a genetic algorithm (GA) introduced in [66] and that also solves the column generation's subproblem for  $\alpha$ -CMLP. To our knowledge, this is the closest work to the one addressed in this chapter. The GA based approach is called  $CG_{GA}$  in this chapter to distinguish it from our approach  $CG_{DH}$ . The GA heuristic consists of the following steps:

1. Construct the initial population of chromosomes  $P$  which represents feasible  $\alpha$ -cover sets. Each chromosome  $C$  is formed by applying three operators namely the cover feasibility operator, the connect feasibility operator and the redundancy removal operator to ensure feasibility in terms of coverage, connectivity and non-redundant coverage (no superfluous sensors), respectively.
2. Build iteratively new chromosomes by applying first the crossover operator and then the mutation operator.
3. Perform the cover feasibility operator, the connect feasibility operator and the redundancy removal operator to guarantee the feasibility of new chromosomes.
4. Calculate the fitness function of the resulting chromosome which is equal to  $\sum_{i \in C} act_i \pi_i$
5. If the resulting chromosome does not already belong to the population, then it will replace an older chromosome that is randomly selected from the  $|P|/2$  chromosomes with the worst fitness values.

6. The GA terminates once the stopping criterion is reached.

The GA only returns the chromosomes ( $\alpha$ -cover sets) in the population that have a fitness value lower than 1.

The GA approach differs from our objectives in the following points.

1. The  $\beta$  constraint is not considered which leads to solutions where some targets are almost never covered.
2. The GA builds an attractive  $\alpha$ -cover set through 3 different steps, first ensuring the cover feasibility, then the connectivity feasibility and finally removing redundant sensors.

In the next section, our approach is compared to the  $CG_{GA}$  heuristic.

## 5.6/ EXPERIMENTS AND RESULTS

In this section, the experiments conducted to assess the performance of the proposed optimization methods for different studied problems, are presented and are summarized in Table 5.1. All these experiments were coded in JAVA and executed over an Intel(R) i7-8650U processor with 16GB of RAM. All the implemented approaches make use of the IBM ILOG CPLEX 12.5 to solve the mathematical formulations. The main objective of the proposed methods is to maximize the network's lifetime while ensuring both  $\alpha$ -coverage and network connectivity.

### 5.6.1/ FIXED VERSUS VARIABLE COVER SET'S ACTIVATION TIME PERIOD

In this part, the effects of considering fixed or variable activation time periods on the obtained network's lifetime and the model's resolution time, are evaluated. As opposed to the mathematical Binary Integer Linear Programming (BILP) published in [78], the proposed MILP can return a solution to the  $\alpha\beta$ -MLP problem including cover sets with variable activation time periods. The variability in the cover set's activation time period might impact the overall network's lifetime. To evaluate it, both models, BILP and MILP, were used to solve a set of instances used in [78].  $s_0$  was considered as the base station and it could not monitor any target. The considered instances have 15 targets and either 10 or 20 sensors. In each instance, the sensors and targets were randomly deployed in a two-dimensional area measuring  $500 \times 500$  sqm. Each target was at least covered by  $n/4$  sensors where  $n$  is the total number of sensors. All the deployed sensors had the same 300m sensing range. At the start of the surveillance, they had heterogeneous initial

	Explication
<i>MLP</i>	The Maximum Network Lifetime Problem.
<i>CMLP</i>	The Connected Maximum Network Lifetime Problem.
$\alpha - CMLP$	An extension of <i>CMLP</i> problem which consists in replacing the full coverage requirement by a constraint for enforcing a minimum quality of service.
$\alpha\beta - CMLP$	An extension of $\alpha - CMLP$ problem which consider $\beta$ constraint that has been proposed in [78] that guarantees that each target will be covered for a minimum percentage of the network lifetime.
<i>BILP</i>	The mathematical Binary Integer Linear Programming that solves the process of nodes' clustering to optimally in the case of NDSC based scheduling that ensures partial coverage.
<i>MILP</i>	The mathematical Mixed Integer Linear Programming that solves the process of nodes' clustering to optimally in the case of NDSC based scheduling that ensures both partial coverage and network connectivity.
<i>DH</i>	A Dedicated Heuristic based on the minimum connected set coverage problem (MCSC) that solves the column generation's subproblem.
<i>CG<sub>GA</sub></i>	An approximate method based on CG that solves the subproblem by GA approach. <i>CG<sub>GA</sub></i> stops as soon as the GA fails to find an attractive $\alpha$ -cover.
<i>CG<sub>DH</sub></i>	Our approximate method based on CG that solves the subproblem by DH approach. <i>CG<sub>DH</sub></i> stops as soon as the DH fails to find an attractive $\alpha$ -cover.
<i>CG<sub>EXACT</sub></i>	An exact method based on CG that solves the column generation's subproblem by an exact ILP formulation [SP].
<i>CG<sub>MIXT</sub></i>	An exact method based on CG that solves the column generation's subproblem by the ILP formulation [SP] whenever our heuristic <i>DH</i> fails.

Table 5.1: The list of abbreviations.

energy, varying between 3 to 12 energy units. One unit of energy allows a sensor to stay active during one unit of time and to cover during that time all the targets in its range. All the presented experiments' results are averages of 10 randomly generated instances. The activation time was fixed to 3 time units in the BILP model. Four values of  $\alpha$  equal to 1, 0.85, 0.75 and 0.5 were also considered and therefore, each partial cover set had to survey at least  $T_\alpha = 15, 13, 11$  and 8 targets respectively. Table 5.2 presents the execution

		$n=10$						$n=20$					
		BILP[78]		MILP				BILP[78]		MILP			
$\alpha$	$T_\alpha$	without connectivity		Without connectivity		with connectivity		without connectivity		Without connectivity		with connectivity	
		L	Rt(s)	L	Rt(s)	L	Rt(s)	L	Rt(s)	L	Rt(s)	L	Rt(s)
1	15	12.60	0.03	14.70	0.11	10.80	0.27	33.30	0.06	38.30	0.71	29.80	1780.47
0.85	13	13.20	0.04	16.43	0.20	11.12	0.81	37.80	0.17	45.06	1.82	-	-
0.75	11	15.60	0.04	19.16	0.18	13.87	0.57	43.20	0.30	51.06	1.55	-	-
0.5	8	25.20	0.07	29.40	0.21	21.10	0.77	66.60	0.74	76.60	7.70	-	-

Table 5.2: Presents the execution time and lifetime of both the BILP and the MILP problems

time and lifetime obtained by the resolution of both the BILP[78] and the MILP, to solve the  $\alpha\beta$ -MILP. As expected, with the partial coverage constraint the network lifetime obtained by both models is higher than with the complete coverage constraint. As more targets are neglected in the cover sets ( $\alpha$  is decreased), the lifetime of the network increases. For example, with  $n = 10$ , the network lifetime obtained by the MILP when considering network

connectivity is largely improved from 2.96% ( $\alpha = 0.85$ ,  $T_\alpha = 13$ ) to 95.37% ( $\alpha = 0.5$ ,  $T_\alpha = 8$ ) when compared to the network lifetime obtained under full coverage ( $\alpha = 1$ ). Table 5.2 also shows that with variable activation time periods (MILP), the obtained lifetime is higher than with fixed activation time periods (BILP). For example ( $n = 10$ ,  $\alpha = 0.75$  and  $T_\alpha = 11$ ), the lifetime obtained by the MILP resolution is largely improved by 22.82% when compared to the lifetime obtained by the BILP. It can be noticed that the addition of the connectivity constraint to the MILP ( $\alpha\beta$ -CMLP), decreases the network's lifetime. This is due to the fact that more sensors are activated in the cover sets to satisfy the connectivity constraint. For example with  $n = 10$ ,  $\alpha = 0.85$  and  $T_\alpha = 13$ , the network's lifetime decreased by 32.31% when respecting the connectivity constraint.

Table 5.2 also shows that the resolution time of the MILP increases exponentially with the number of sensors and especially for lower values of  $\alpha$ . For example, the results of instances with  $n = 20$  and  $\alpha = 0.85$  under connectivity constraint are not displayed in Table 5.2 because they could not be solved in a reasonable time. The resolution of this linear program with mixed variables becomes impracticable for large problems. This is due to the fact that the number of constraints is bounded by the upper bound of the number of cover sets  $K$ , the number of constraints and the number of variables. As the later increases, the complexity of the MILP and the search space increases. For this reason, we opted for a column generation approach which is more suitable to solve larger instances in a reasonable time. In the next section, our column generation approach  $CG_{DH}$  is compared to  $CG_{GA}$  which was proposed in [66].

## 5.6.2/ EVALUATION OF THE COLUMN GENERATION BASED APPROACHES

The experiments were carried out on the benchmark instances used in [66]. The size of the wireless network in these instances varies between 100 to 500 sensors to cover 15 or 30 targets. All the sensors have the same communication range  $R_c$  equal to 125m, while their sensing range  $R_s$  was equal to 100m. Furthermore, all sensors have the same initial battery life, normalized to 1 time unit. Different coverage levels, represented by the  $\alpha$  value which varies in the set 0.7, 0.85, 1, were considered. The results of the experiments for solving the  $\alpha$ -CMLP and the  $\alpha\beta$ -CMLP problems are presented in the following subsections. Each presented value is an average of 4 instances. Similarly to [66], a 3600 seconds time limit for each scenario was considered and the best found solution is reported once the time limit is reached.

### 5.6.2.1/ RESULTS OF THE $\alpha$ -CMLP

In this experiment,  $CG_{DH}$  and  $CG_{GA}$  are compared while solving the  $\alpha$ -CMLP problem and varying the desired coverage level. The parameters of the genetic algorithm were fixed

as follows:

- The population size  $SizeP$  was fixed to 100 chromosomes.
- The initial population generation stopping criterion  $maxInitDup$  was chosen to be equal to 100. If more than  $maxInitDup$  chromosomes already existing in the population are consecutively generated, the initial population generation process is stopped and the current population size is considered instead of  $SizeP$ .
- The maximum number of iterations without improvements in the fitness value  $MaxIT$  was limited to 100 iterations.
- The stopping criterion  $MaxDUP$  was chosen to be equal to 100. If more than  $MaxDUP$  chromosomes already existing in the population are consecutively generated, the GA is stopped.

Since  $CG_{GA}$  is a non-deterministic heuristic, each instance was executed 5 times. In Table 5.3, the  $L_{MAX}$  column reports the maximum lifetime obtained in the 5 executions. The  $L$  column shows the average lifetime values in time units, while the  $T(s)$  column presents the average execution time in seconds and the  $\#CS$  column gives the number of  $\alpha$ -cover sets injected in the master problem. The last two columns in Table 5.3 show in percentage the lifetime gap and the execution time gap between the two approaches. The gaps were computed as follows:

$$Gap\ on\ L = 100 * \frac{L(CG_{DH}) - L(CG_{GA})}{L(CG_{GA})} \quad (5.29)$$

$$Gap\ on\ Rt = 100 * \frac{Rt(CG_{GA}) - Rt(CG_{DH})}{Rt(CG_{GA})} \quad (5.30)$$

Table 5.3 shows that the lifetime gap between  $CG_{DH}$  and  $CG_{GA}$  varies between  $-1.06\%$  and  $6.54\%$ . Therefore,  $CG_{DH}$  finds very competitive solutions when compared to the other heuristic. Even when considering  $L_{MAX}$  instead of  $L$  to compute the lifetime gap,  $CG_{DH}$  outperforms the other heuristic in many instances. For example, with  $n = 400$ ,  $m = 15$  and  $\alpha = 0.7$ , the gap remains positive and slightly decreases by  $0.22\%$  when considering  $L_{MAX}$  instead of  $L$ .

On the other hand, Table 5.3 also shows that  $CG_{DH}$  was on average faster than  $CG_{GA}$  in 29 out of 30 instance types. In the only instance type ( $n = 500$ ,  $m = 30$  and  $\alpha = 0.85$ ) where  $CG_{DH}$  took more time than the other heuristic, it gave a solution with a lifetime higher by  $6.54\%$ . The GA's parameters, such as the population size and the number of generations, surely have an influence on its execution time and therefore its execution time could be improved if the optimal parameters are used. However, it is very hard to guess beforehand the optimal GA parameters for every instance type.

$n$	$m$	$\alpha$	$CG_{GA}$				$CG_{DH}$			Gap(%)	
			L	$L_{MAX}$	Rt(s)	#CS	L	Rt(s)	#CS	L	Rt(s)
100	15	0.7	6.88	6.88	10.53	2434.65	6.87	3.25	123.50	-0.14	69.13
		0.85	6.60	6.64	15.43	3148.00	6.53	5.75	204.50	-1.06	62.73
		1	4.00	4.00	7.51	2467.30	4.00	3.00	71.00	0.00	60.05
100	30	0.7	7.00	7.00	20.97	2726.05	7.00	4.75	120.00	0.00	77.34
		0.85	6.42	6.44	19.21	3268.70	6.45	11.25	265.00	0.46	41.43
		1	4.00	4.00	17.26	2676.00	4.00	10.00	97.50	0.00	42.06
200	15	0.7	16.23	16.25	215.98	6519.65	16.18	18.75	337.00	-0.30	91.31
		0.85	15.35	15.37	148.62	7362.65	15.39	38.25	646.50	0.26	74.26
		1	10.25	10.25	87.16	6306.05	10.25	20.25	221.25	0.00	76.76
200	30	0.7	16.25	16.25	291.79	6722.75	16.25	20.25	318.25	0.00	93.06
		0.85	15.00	15.04	155.79	8042.20	15.41	90.00	877.25	2.73	42.22
		1	8.75	8.75	69.69	5415.90	8.75	36.00	215.75	0.00	48.34
300	15	0.7	18.25	18.25	880.21	9034.50	18.25	30.75	293.00	0.00	96.50
		0.85	18.25	18.25	514.45	10244.90	18.25	53.25	393.00	0.00	89.64
		1	15.00	15.00	268.42	9797.15	15.00	66.25	377.75	0.00	75.31
300	30	0.7	18.25	18.25	508.36	9269.95	18.25	34.50	287.00	0.00	93.21
		0.85	18.25	18.25	304.51	10016.00	18.25	75.25	432.50	0.00	75.28
		1	13.25	13.25	182.01	8024.90	13.25	110.50	390.25	0.00	39.28
400	15	0.70	31.51	31.55	2244.10	16169.60	31.62	297.75	1044.50	0.34	86.73
		0.85	29.19	29.24	1194.51	15651.95	29.53	400.00	1216.00	1.16	66.51
		1	18.25	18.25	497.57	11448.70	18.25	128.00	458.75	0.00	74.27
400	30	0.7	30.21	30.23	1476.63	14720.50	30.87	692.50	1129.25	2.18	53.10
		0.85	27.48	27.55	818.63	15136.40	28.19	708.00	1590.25	2.58	13.51
		1	18.00	18.00	427.79	11148.65	18.00	244.00	552.75	0.00	42.96
500	15	0.7	45.86	46.44	2935.65	21600.25	48.58	1492.75	2498.75	5.93	49.15
		0.85	41.74	41.94	2521.53	24825.35	43.36	2449.25	3488.00	3.88	2.86
		1	29.00	29.00	890.75	17547.60	29.00	483.50	837.25	0.00	45.71
500	30	0.7	47.21	47.46	2693.90	21323.15	49.12	1481.75	2330.00	4.04	44.99
		0.85	39.55	39.55	2063.22	21504.60	42.14	2787.25	3426.50	6.54	-35.09
		1	26.25	26.25	914.20	15528.95	26.25	625.00	834.50	0.00	31.63

Table 5.3: The results of solving the  $\alpha$ -CMLP problem with  $CG_{GA}$  and  $CG_{DH}$  in homogeneous sensor networks

Moreover, for example with  $n = 100$ ,  $m = 15$  and  $\alpha = 1$ , Table 5.4 presents the average number of  $\alpha$ -cover sets (#CS) and those with null activation time (#NCS) obtained by both  $CG_{GA}$  and  $CG_{DH}$ . It can be noticed that a high number of cover sets that were generated by  $CG_{GA}$  have null activation time. The difference between the #NCS returned

	#CS	#NCS
$CG_{GA}$	2467.30	2430.50
$CG_{DH}$	71.00	45.75

Table 5.4: Average number of cover sets and those with null activation time.

by both  $CG_{GA}$  and  $CG_{DH}$  is very high.  $CG_{DH}$  returns on average only 45.75 null cover sets whereas the solutions returned by  $CG_{GA}$  contained on average 2430.5 null cover sets. The high number of #NCS generated by  $CG_{GA}$  makes the size of the problem bigger without any benefit and then it increases the execution time of the [RMP].

The same experiment was conducted on instances consisting of sensors with heteroge-

neous initial energy levels. To obtain these instances, the initial energy of each sensor in the previous benchmark instances was affected a random integer value varying between 3 to 12 energy units. Table 5.5 presents the results of this experiment and shows that  $CG_{DH}$  gave solutions with very competitive network's lifetime when compared to the ones returned by  $CG_{GA}$ . The lifetime gap between both heuristics varies between  $-0.67\%$  and  $6.67\%$ . On the other hand, Table 5.5 also shows that  $CG_{DH}$  is on average faster than  $CG_{GA}$  in 28 out of 30 scenarios with an execution time gap up to  $95.77\%$ . In both scenarios where  $CG_{DH}$  took more time than  $CG_{GA}$ , it gave solutions with a better lifetime.

$n$	$m$	$\alpha$	$CG_{GA}$			$CG_{DH}$			Gap(%)	
			L	Rt(s)	#CS	L	Rt(s)	#CS	L	Rt(s)
100	15	0.7	44.44	30.83	2641.50	44.14	3.25	181.25	-0.67	89.45
		0.85	39.37	29.96	3407.50	39.34	4.75	209.50	-0.07	84.14
		1	23.12	18.15	2795.00	23.12	3.00	73.00	0.00	83.47
100	30	0.7	44.01	34.29	3202.50	44.12	6.25	186.25	0.24	81.77
		0.85	33.92	26.33	3154.00	35.55	11.00	239.50	4.80	58.47
		1	21.33	18.06	2645.50	21.33	7.50	83.25	0.00	94.08
200	15	0.7	107.00	232.59	6334.00	107.00	13.75	292.75	0.00	82.41
		0.85	103.66	171.98	8578.00	103.69	30.25	592.25	0.02	78.50
		1	69.25	108.14	7292.25	69.25	23.25	256.75	0.00	93.61
200	30	0.7	107.00	273.98	6831.50	107.00	17.50	285.75	0.00	45.9
		0.85	102.69	166.36	8959.50	104.66	90.00	856.50	1.91	45.90
		1	57.75	84.99	6390.50	57.75	43.75	258.25	0.00	48.52
300	15	0.7	121.00	751.76	9887.00	121.00	31.75	302.75	0.00	95.77
		0.85	121.00	438.52	10641.00	121.00	53.50	402.25	0.00	87.79
		1	98.00	269.03	10845.00	98.00	69.25	399.25	0.00	74.25
300	30	0.7	121.00	586.27	9148.00	121.00	87.50	316.25	0.00	85.07
		0.85	121.00	308.47	10295.00	121.00	109.50	444.25	0.00	64.50
		1	88.50	190.89	8494.75	88.50	120.25	406.75	0.00	37.00
400	15	0.7	226.52	1698.69	15740.25	227.52	296.25	1052.50	0.44	82.56
		0.85	209.97	1161.38	15808.00	212.40	449.00	1322.75	1.15	61.33
		1	127.00	502.65	11802.75	127.00	129.25	499.00	0.00	74.28
400	30	0.7	215.81	1291.23	14254.00	220.42	381.25	1015.00	2.13	70.47
		0.85	192.97	833.34	1567.50	201.48	861.00	1962.00	4.41	-3.31
		1	114.25	414.94	10893.75	114.25	249.0	557.25	0.00	39.99
500	15	0.7	344.71	2763.73	24441.00	352.55	1574.50	2736.75	2.27	43.02
		0.85	297.53	2432.43	25709.50	309.04	2375.25	3400.00	3.86	2.35
		1	208.5	1000.72	19465.75	208.50	410.25	912.75	0.00	59.00
500	30	0.7	341.72	2479.63	21895.50	354.00	1764.00	2727.75	3.59	28.86
		0.85	280.55	2017.36	86100.00	299.29	2788.75	3585.75	6.67	-38.23
		1	199.50	1120.84	17548.25	199.5	989.75	1180.00	0.00	11.69

Table 5.5: The results of solving the  $\alpha$ -CMLP problem with  $CG_{GA}$  and  $CG_{DH}$  in heterogeneous sensor networks.



5.6.2.2/ RESULTS OF THE  $\alpha\beta$ -CMLP IN HETEROGENEOUS NETWORKS

In this subsection, the CG based approaches were applied to the  $\alpha\beta$ -CMLP problem. For the sake of simplicity, it was assumed that all targets have the same monitoring ratio  $\beta$  which is equal to  $\alpha$  ( $\beta = \alpha$ ). The same heterogeneous instances described in the previous subsection were used in this experiment. For the initialization of CG, the MILP was used to generate a set of  $\alpha$ -cover sets that satisfy the  $\beta$  constraint. It is indeed easy to generate cover sets that satisfy the  $\alpha$  constraint but not so simple to ensure that the  $\beta$  constraint is satisfied. Thus, at the beginning of  $CG_{DH}$ ,  $CG_{EXACT}$  and  $CG_{MIXT}$ , a preliminary execution of the MILP is used to initialize the restricted master problem with two feasible cover sets such that the  $\alpha$  and  $\beta$  constraints are satisfied. In Table 5.6, the  $\#opt$  column reports the number of optimal solutions found in the scenario over one hour. The two last columns show in percentage the lifetime gap and the execution time gap between  $CG_{MIXT}$  and  $CG_{DH}$ . Table 5.6 shows that both  $CG_{EXACT}$  and  $CG_{MIXT}$

$n$	$m$	$\alpha$	$CG_{DH}$		$CG_{EXACT}$			$CG_{MIXT}$			Gap(%)	
			L	Rt(s)	L	Rt(s)	#opt	L	Rt(s)	#opt	L	Rt(s)
100	15	0.7	41.81	10.50	44.21	479.75	4	44.21	230.25	4	-5.42	95.43
		0.85	37.16	13.50	38.87	1051.25	3	39.00	950.00	3	-4.71	98.57
		1	23.12	12.50	23.12	17.50	4	23.12	13.25	4	0.00	5.66
100	30	0.7	41.47	16.25	42.83	1284.00	3	42.90	950.25	3	-3.33	98.28
		0.85	33.70	25.50	34.41	1289.50	3	34.60	920.50	3	-2.60	97.22
		1	21.33	24.25	21.33	32.25	4	21.33	25.75	4	0.00	5.82
200	15	0.7	105.80	93.75	105.66	1184.00	3	106.27	119.50	4	-0.44	21.54
		0.85	101.76	110.25	99.55	2275.00	2	102.50	1520.5	3	-0.72	92.74
		1	69.25	65.00	69.25	253.50	4	69.25	70.50	4	0.00	7.80
200	30	0.7	106.34	161.75	104.77	1398.50	3	106.34	162.25	4	0.00	0.30
		0.85	99.78	249.25	94.59	2775.25	1	99.93	2517.25	1	-0.15	90.09
		1	57.75	168.00	57.75	483.50	4	57.75	169.75	4	0.00	1.03

Table 5.6: The results of solving the  $\alpha\beta$ -CMLP problem with  $CG_{DH}$ ,  $CG_{EXACT}$  and  $CG_{MIXT}$ .

are unable to find the optimal solutions of dense networks in a reasonable time (less than 3600 seconds) because it is an NP-hard problem. However, it can be noticed that  $CG_{MIXT}$  is more effective than  $CG_{EXACT}$ , because  $CG_{MIXT}$  is able to produce quickly most of the needed cover sets, avoiding whenever possible the expensive exact resolution of the subproblem. For example, with  $n = 200$ ,  $m = 15$  and  $\alpha = 0.7$ , the time limit is not reached by  $CG_{MIXT}$  for all instances, as opposed to only 3 out of 4 instances by  $CG_{EXACT}$ . Therefore, it is obvious that the average lifetime obtained by  $CG_{MIXT}$  will be higher than the one obtained by  $CG_{EXACT}$ . For example, with  $n = 200$ ,  $m = 15$  and  $\alpha = 0.7$ , the network lifetime obtained by  $CG_{MIXT}$  is largely improved by 0.57% when compared to the network lifetime obtained by  $CG_{EXACT}$ .

Regarding the execution time, it can be noticed that  $CG_{DH}$  is always faster than  $CG_{MIXT}$  for all scenarios, with the execution time gap varying between 0.3% and 98.57%. This is obvious because  $CG_{MIXT}$  uses the same  $DH$  heuristic as  $CG_{DH}$  but in addition the

subproblem's resolution is invoked when  $DH$  fails to find an attractive cover set. Moreover, the lifetime obtained by  $CG_{MIXT}$  is slightly higher than the one obtained by  $CG_{DH}$ , with a solution gap that varies between  $-5.42\%$  and  $0\%$ . In conclusion, the heuristic  $CG_{DH}$  gives near optimal solutions for the  $\alpha\beta$ -CMLP problem in a reasonable time and can be used to solve large instances of this problem.

## 5.7/ CONCLUSION

In this chapter, we have investigated the problem of lifetime optimization for partial coverage under connectivity constraint in heterogeneous sensor networks. To our knowledge, this is the first study to consider, under connectivity requirement, both  $\alpha$  and  $\beta$  constraints to improve the coverage quality rather than dealing with only  $\alpha$  leveling threshold as in the literature. To this end, both exact and heuristic approaches were provided in this chapter. First, a novel mathematical Mixed Integer Linear Programming (MILP) is presented to solve the  $\alpha\beta$ -coverage problem to optimality. Next, to cope with large optimisation instances, we propose another exact approach based on column generation (CG) to tackle the studied problem in reasonable time. Due to the NP-Completeness of the CG's subproblem resolution, a new dedicated heuristic (DH) is designed to speedup the time resolution process. Finally, we gave an exact ILP formulation for the CG's subproblem resolution if the introduced DH heuristic fails to compute attractive columns in each iteration of the CG scheme. Different test-bed scenarios and QoS metrics were considered and the obtained results corroborate the merits of our proposals.



# IV

## CONCLUSION & PERSPECTIVES



## CONCLUSION & PERSPECTIVES

### 6.1/ CONCLUSION

In this thesis, the problem of maximizing the lifetime of heterogeneous wireless sensor networks has been addressed. The target coverage and the network connectivity have been studied as two key factors for improving the network's QoS. This dissertation is composed of two parts: the first part covers the scientific background of WSNs, whereas the second one presents the contributions that have been made in this thesis.

The first part began by presenting some WSN applications, including military domain, medical domain, environmental monitoring and urban and home automation fields. Afterward, we discussed issues such as energy consumption, coverage quality and network connectivity that need to be addressed in such applications.

The second part of this dissertation presented the contributions in three sections. The first one focused on the problem of the total coverage in heterogeneous sensor networks. The objective was to organize the sensor nodes into a number of disjoint subsets nodes that were scheduled successively to improve the network's QoS under the constraints of energy saving and total coverage. To do this, a new mixed integer linear programming (MILP) formulation was proposed in this work to optimize the network's lifetime by organizing the sensor nodes into a maximal number of disjoint cover sets. The resolution of the model with mixed variables becomes impracticable for large optimization problems. Its execution time increased exponentially to the size of the network. In order to achieve good solutions in polynomial time complexity, a genetic algorithm (GA) based approach was proposed. It was able to achieve optimal solutions for small networks, but it was only able to get good quality solutions for larger ones.

The second part concentrated on the issue of partial coverage ( $\alpha$ -coverage) in heterogeneous sensor networks. The goal was to maximize the network lifetime by an adaptive scheduling that divided sensors into a number of non-disjoint subsets nodes. We have proposed a novel mathematical Binary Integer Linear Programming (BILP) to tackle the

$\alpha$ -coverage problem to optimality. This model could only achieve optimal solutions in a reasonable time for small instances. Additionally, provable guarantees of the upper bound for the number of cover sets that can be built have been given. Moreover, not all targets have the same coverage rate in partial coverage, which can result in very poor coverage for some targets. For this reason, a new constraint, namely the  $\beta$  constraint has been introduced in this work. It ensures that each target is covered for at least a given percentage of the network's lifetime, thus enhancing the quality of the network's coverage and extending its lifetime. When using a default covers' activation in the case of partial coverage, some targets might remain uncovered for a long time period. In order to accomplish this, we proposed an Genetic Algorithm (GA) based approach that can efficiently schedule cover sets in order to fairly smooth the time period of the uncovered targets during the network's lifetime.

The last part focused on the problem of lifetime optimization for partial coverage and network connectivity in heterogeneous sensor networks. To improve the network's QoS, the  $\beta$  constraint was also considered. One of the main approaches that allowed sensors to operate alternatively to extend the network lifetime is to divide the sensor nodes into Non-Disjoint subsets of sensors and to organize these subsets with variable activation time periods. A novel mathematical Mixed Integer Linear Programming (MILP) has been developed to solve the  $\alpha$ -coverage problem with the connectivity requirement. Due to the NP-Hard of the studied problem, the resolution of MILP becomes impracticable for large networks. Therefore, we have proposed a column generation approach (CG) to find the exact solution in an acceptable time compared to the time taken by the resolution of the MILP by a classical Branch&Bound method. As the resolution of the CG subproblem was also an NP-Hard problem, a new heuristic was designed to generate new attractive columns without considering  $\beta$  constraint and then we adapted it to take into account the  $\beta$  constraint. In addition, another exact method which used an exact ILP formulation for the CG's subproblem resolution was proposed in case of a fail of computation of an attractive solution in each iteration of the CG computation process by the heuristic. Finally, performance evaluation results were performed to verify our proposals.

We believe that the solutions given in this thesis for various challenges in WSN applications related to energy saving, full/partial coverage and the network connectivity can serve as additional and efficient solution choices or tools to address the aforementioned challenges.

## 6.2/ PERSPECTIVES

There are many perspectives to consider in an environment that is constantly evolving and has the potential to impact people's lives. The key focus of this thesis was to maximize

the lifetime of HWSN. Different possible works that emerge from the research presented in each chapter remain for future research.

In Chapter 3, a genetic algorithm (GA) based approach to achieve efficient solutions, was provided. The chromosome's encoding solution relies on the battery lifetime by using an integer representation. Nevertheless, other representations of the chromosomes' encoding solutions as well as the GA's backbone design can be further studied to improve the network lifetime with minimal execution time complexity.

Our proposals in Chapter 4 are tested and evaluated with small networks. Future studies should address the case of large-scale networks, where nodes must decide cooperatively and in a distributed manner whether to remain in sleep or active mode while ensuring that a minimum level of coverage quality is achieved.

To extend the network's QoS, coverage and connectivity are two important issues that need to be addressed. The work done in Chapter 5 targeted applications where the one-coverage and the one-connectivity are required. Possible future research should focus on  $p$ -connectivity [29] [19] and  $q$ -coverage [80] [68] to improve the network's reliability. It would also be interesting to investigate other metaheuristics as well as their hybridizations to analyse and compare the behavior of the column generation subproblem resolution process proposed in Chapter 5 on the achieved global performances.

Finally the work done in this thesis opens up limitless perspectives in various research lines. One of the future work is to study the mobile WSN where sensors are mobile. Due to the dynamic changes of events and hostile environments, a traditional static WSN has limitations on supporting multiple missions and handling different situations when network conditions change. Introducing mobility to WSNs would be interesting for future research, as it can significantly improve the network capability. Further study could also consider other performance metrics such as the delay, reliability and data security.





# PUBLICATIONS

## JOURNAL PAPERS

- CHARR, Jean-Claude, DESCHINKEL, Karine, MANSOUR, Rania Haj, et al. Lifetime optimization for partial coverage in heterogeneous sensor networks. *Ad Hoc Networks*, 2020, vol. 107, p. 102264.

## CONFERENCE PAPERS

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## SUBMITTED PAPERS

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**Title:** Energy-efficiency and coverage quality management for wireless sensor networks

**Keywords:** Sensor networks, Lifetime optimization, Full coverage, Partial coverage, Connectivity, Integer linear programming, Genetic algorithms, Column generation

**Abstract:**

In recent years, wireless sensor networks (WSNs) are widely used in various applications areas such as military, environmental, home automation, medical, etc. They consist of a large number of nodes deployed to cover, collect, process and transmit environmental data to one or more sinks. These nodes are generally considered homogeneous with the same characteristics. However, a network may have different specifications, such as different computing power, different battery life, different sensing and communication ranges. In particular, the initial battery energy level and energy consumption may vary from one sensor to another. Some very sensitive applications require the complete coverage of all the targets during the whole lifetime of the network, others can bear less strict monitoring. For instance, since the probability of a forest fire occurring in the rainy season is lower

than in the dry season, monitoring at each time period a few random regions in the forest could be sufficient to prevent the forest from taking fire. This is called partial coverage. Unfortunately, despite the diversity of applications of sensor networks, their success depends on their lifetime. Indeed, sensor nodes are highly dependent on energy consumption due to their very small size and the deployment environment.

This thesis mainly focuses on energy consumption as well as coverage quality in order to improve the quality of service of heterogeneous wireless sensor networks (HWSN). To do so, centralized approaches (optimization models and resolution heuristics for these different cases: heterogeneity, partial coverage, connectivity) have been studied to orchestrate the trade-off between energy saving and coverage optimization.

**Titre :** Energy-efficiency and coverage quality management for wireless sensor networks

**Mots-clés :** Réseaux de capteurs, Optimisation de la durée de vie, Couverture totale, Couverture partielle, Connectivité, Programmation linéaire en nombres entiers, Algorithmes génétiques, Génération de colonnes.

**Résumé :**

Ces dernières années, les réseaux de capteurs sans fil (WSN) sont largement utilisés dans divers domaines d'applications tels que militaire, environnementale, domotique, médicale, etc. Ils sont constitués de nœuds déployés en grand nombre en vue de couvrir, collecter, traiter et transmettre des données environnementales vers un ou plusieurs puits. Ces nœuds sont généralement considérés homogènes avec les mêmes caractéristiques. Cependant, un réseau peut avoir des spécifications différentes, telles qu'une puissance de calcul différente, une batterie différente, une portée de détection et de communication différente. En particulier, le niveau d'énergie initial de la batterie et la consommation d'énergie peuvent varier d'un capteur à l'autre. Certaines applications très sensibles exigent une couverture complète de toutes les cibles pendant toute la durée de vie du réseau, tandis que d'autres peuvent supporter une surveillance moins stricte. Par exemple, la probabilité qu'un incendie de forêt se produise pendant la saison des pluies

étant plus faible que pendant la saison sèche, la surveillance à chaque période de quelques régions aléatoires de la forêt pourrait suffire à empêcher la forêt de brûler. On parle alors de la couverture partielle. Malheureusement, malgré la diversité des applications des réseaux de capteurs, leur succès dépend de leur durée de vie. En effet, les nœuds capteurs sont soumis à une forte contrainte de consommation d'énergie en raison de leurs dimensions très réduites ainsi qu'à l'environnement de déploiement.

Cette thèse se focalise principalement sur la consommation d'énergie ainsi que sur la qualité de la couverture afin d'améliorer la qualité de service des réseaux de capteurs sans fil hétérogènes (HWSNs). Dans cet ordre d'idées, des approches centralisées (des modèles d'optimisation et des heuristiques de résolution pour ces différents cas de figure: hétérogénéité, couverture partielle, connectivité) ont été étudiées pour orchestrer la relation de compromis entre l'économie d'énergie et l'optimisation de la couverture.