Genetic Algorithm-Driven Cover Set Scheduling for Longevity in Wireless Sensor Networks

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***Abstract*—This paper aims to develop an efficient scheduling approach based on Genetic Algorithms to optimize energy consumption and maximize the operational lifetime of Wireless Sensor Networks (WSNs). Effective energy management is crucial for prolonging the operational lifespan of wireless sensor networks (WSNs) that include a substantial number of sensors. Simultaneously activating all sensors results in a fast depletion of energy, thus diminishing the overall lifespan of the network. To address this issue, it is necessary to schedule sensor activity in an effective manner. This task, known as the maximum coverage set scheduling (MCSS) problem, is highly complex and has been demonstrated to be NP-hard. This article presents a customized genetic algorithm designed to tackle the MCSS problem, aiming to improve the longevity of Wireless Sensor Networks (WSNs). Our methodology effectively detects and enhances combinations of coverage sets and their corresponding schedules. The program incorporates key criteria such as the detection ranges of individual sensors, their energy levels, and activity durations to optimize the overall energy efficiency and operational sustainability of the network. The performance of the suggested algorithm is assessed through simulations and compared to that of the Greedy algorithm and the Pattern search algorithm. The results indicate that our genetic algorithm not only maximizes network lifetime but also enhances the efficiency and efficacy of solving the MCSS problem. This represents a significant improvement in managing the energy consumption in WSNs.**

Keywords*—*Maximum network lifetime; wireless sensor network; coverage; sets scheduling; genetic algorithm; pattern search algorithm

I. Introduction

The rapid expansion of network applications has driven the development of specialized network systems tailored to specific domains. Among, these Wirelesse Sensor Networks (WSNs) stand out as a criticle technology. WSNs consist of numerous sensors that work together to monitor and measure physical environments [1]. These networks are widely employed in divers fields, including weather monitoring, climate surveillance, industrial automation, healthcare, and topographic analysis. In a WSNs, the sensors collect data and transmit it to a central node (Sink node), which then relays the data though systems, such as the Internet or satellites to the base station [2].

WSNs comprise numerous low-power sensors, leading to extensive research to improve their effectiveness and efficiency in regions with coverage challenges [3]. Energy consumption is a critical concern that greatly impacts the lifespan of a WSN [2]. Continuing research is focused on optimizing the lifespan of networks, particularly in situations where sensors are scattered throughout the designated target area [4].

Due to the limited detection range and battery capacity of individual sensors, it is common to have overlapping coverage areas among multiple sensors. As a result, all sensors don't need to detect all targets simultaneously. Several sensors provide a feature that allows for temporary deactivation, which helps to save battery life and prolong their operational duration [5].

This study addresses one of the most significant challenges in WSNs: the Maximum Network Lifetime Problem (MLP). The MLP revolves around maximizing the duration for which a network can remain operational by strategically managing the activity of its sensors. Since each sensor node has a finite energy supply, the key is to organize sensors into groups that can take turns monitoring targets. By activating these groups sequentially, the network can maintain functionality for an extended period. Many modern sensors are equipped with a temporary disable feature, allowing them to conserve energy when not in use. This specific challenge, often referred to as the Maximum Lifetime Coverage Problem (MLCP), involves selecting and scheduling sensor groups to ensure continuous coverage while adhering to strict energy constraints.

To address the MLCP, this study explores advanced scheduling techniques for sensor activation, focusing on the interplay between sensing ranges, activation durations, and energy limitations. A central innovation of this research is the application of a Genetic Algorithm (GA), a computational approach inspired by natural selection [6]. GAs are particularly well-suited for solving complex, NP-hard problems like the MLCP due to their ability to efficiently navigate large solution spaces and adapt to intricate constraints. By leveraging a GA, this study aims to develop an optimized scheduling strategy that balances coverage requirements with energy efficiency, ultimately extending the network's operational lifespan.

The primary objective of this research is to design an energy-efficient scheduling framework using a GA, with a focus on maximizing network longevity. This involves carefully considering sensor parameters such as sensing ranges, available energy, and activation durations. Additionally, the framework will enforce strict energy constraints to prevent premature battery depletion, ensuring uninterrupted coverage of all targets. We intend to achieve this by identifying the optimal combinations of sensor coverage sets and their operational schedules for the Maximum Coverage Set Scheduling (MCSS) problem [7]. The findings are expected to contribute valuable insights into prolonging the operational lifespan of sensor networks, offering a significant step forward in the field of WSN optimization.

The subsequent sections of this paper are structured as follows: Section II outlines the effort directly relevant to the survey. Section III explains the formulation of the MCSS issue.

Section IV showcases the simulation results. Finally, in Section V, this work concludes.

II. Related Work

Various approaches have been employed to address the sensor deployment problem in wireless sensor networks (WSNs). This section outlines several techniques that are particularly relevant to our study. The scenario discussed requires sensors to remain active during specific periods, referred to as operating time slots, to cover various locations within a designated geographic area. The study also derives an upper bound for the maximum network lifetime in this context and proposes a genetic algorithm to determine a near-optimal schedule for sensor node activity [8].

The study presented in [9] introduces a mathematical model focused on optimizing the density of active sensor nodes within a wireless sensor network (WSN) by leveraging geometric principles. Through the use of concentric hexagonal tessellations and the concept of coverage contribution areas, the paper proposes an algorithm capable of generating the largest possible set of mutually exclusive sensor nodes. This approach offers an optimal solution to the k-coverage problem, where the goal is to ensure that every target area is covered by at least k sensors.

In [10], the authors propose a recursive neighborhood-based estimate of distribution algorithm (NEDA) tailored to address the k-coverage challenge. In this approach, each entity within NEDA represents a coverage strategy that selectively activates sensors to monitor designated targets. To enhance network longevity, the study introduces a linear programming (LP) model designed to optimally distribute activation times among different strategies within the population, thereby extending the overall network lifespan.

The research discussed in [11] explores a routing strategy aimed at managing incoming traffic within a WSN. This strategy integrates the hybrid energy-efficient distributing (HEED) algorithm with a fuzzy logic-based approach to enhance both node lifetime and energy efficiency. The FLH-P proposal algorithm consists of two main components: first, WSN clustering is initiated using the stable election mechanism of the HEED method. Subsequently, criteria such as residual energy, minimum hop counts, and node traffic are evaluated using a combination of fuzzy inference and the low-energy adaptive clustering hierarchy (LEACH) method.

In the study conducted by researchers [12], they introduce an academic model called Efficient Topology-driven Cooperative Self-Scheduling (TDCSS). This model employs a hybrid strategy rather than a centralized scheduling approach for network node management. The TDCSS technique dynamically adjusts its scheduling approach based on current conditions to minimize the overhead in control packet transmission. This is accomplished by periodically exchanging node statistics. The research conducted by the scholars [13] primarily focuses on addressing the Maximum α-Lifetime Problem, aiming to develop a heuristic solution that maximizes the lifetime of the network while satisfying coverage requirements. They achieve this objective by selectively activating and deactivating groups of sensors while still maintaining the necessary coverage rate.

In [14] presents a population-based iterated greedy algorithm that aims to solve the maximum disjoint dominating sets problem in wireless sensor networks. The algorithm assigns sensors to disjoint node sets and incorporates a sleep-wake cycling mechanism. This mechanism ensures that only the active nodes from one set are active at a time, while the others remain dormant. In simpler terms, only the nodes from one of these sets are active at any given time, while the others remain inactive.

In the scholarly research conducted by these authors [15], a two-phase solution is proposed to tackle coverage and connectivity issues. The proposed solution incorporates a combination of the Greedy algorithm with Linear Programming (GLA) for Phase I and the Clustering algorithm with the graph Max Flow Approach (CMFA) for Phase II. To evaluate the effectiveness of these algorithms, multiple datasets are employed and compared against baseline methods (ESSNP in Phase I; CCMFA and FCSA in Phase II).

The [16] addresses the maximum network lifetime problem (MLP) in wireless sensor networks under connectivity and coverage constraints. It considers two variants: $\alpha - coverage$ and $\beta{-}coverage$ or $\beta{-}constraint$. The problem is called $\alpha\beta$-Connected Maximum Lifetime Problem ($\alpha\beta - CMLP$) and considers both global and local monitoring level thresholds. The authors propose dividing sensor nodes into non-disjoint subsets and scheduling covers with variable activation time periods to optimize the network's lifetime. They present a novel mathematical Mixed Integer Linear Programming (MILP) to solve the problem but propose a new exact approach based on column generation for large optimization problems. They also propose a dedicated Heuristic for the CG subproblem.

The [17] discusses the Lifetime Maximization of Range Adjustable Sensors (LM-RAS) in Wireless Sensor Networks (WSNs) [25], an essential component of the Internet of Things (IoT) [26]. The goal is to optimize the lifetime of WSNs while simultaneously monitoring all targets and limiting the sensor activation time. A novel meta-heuristic called Shuffled ARSH-FATI is proposed, which divides the problem into two sub-problems: creating energy-efficient coverage schemes and scheduling these schemes. The method uses a Linear Programming model to generate optimal schedules, but its performance depends on the quality of the coverage schemes.

The study [18] proposes a Genetic Lavrentyev Paraboloid Lagrange Support Vector Machine-based (GLPL-SVM) multiclass classification method to optimize Wireless Sensor Networks (WSN) performance in dynamic situations. The method uses Genetic Lavrentyev Regularized Machine Learning for sensor node placement, Quadrant Count Event for efficient data collection, and Paraboloid Lagrange Multiplier SVM for dynamic network coverage. The method improves scheduling time, network lifetime, energy consumption, and classification accuracy when compared to existing methods.

The research [19] examines the Lifetime Effective Movement Algorithm, a unique heuristic for wireless sensor network lifetime. The study discusses a mobile sensor network concept that continuously monitors fixed targets. The method considers sensor node movement to maximize network lifetime and target coverage.

Graph theory is crucial to solving WSN challenges, hence

[20] proposes a vertex coloring-based sensor scheduling and deployment technique to maximize sensor covers and optimize sensor location. To evaluate the algorithm's efficiency, the mathematical upper bound is estimated and the highest number of covers obtained is compared to it. Existing random, cuckoo search, and genetic algorithms are used with the suggested approach.

A wireless sensor network coverage hole detection and recovery approach is presented in [21]. The suggested method cellulates the network first and assigns agents to each cell. Sensor nodes are scheduled by calculating the degree of neighbor overlap of each node's sensing area. Node overlap information helps the cell agent determine cell coverage and holes. Hole recovery is completed by mobile nodes and grasshopper optimization. Despite the various methodologies proposed in previous studies to optimize the scheduling of sensors and extend the lifetime of Wireless Sensor Networks (WSNs), most existing approaches rely on heuristic or mathematical optimization techniques that do not fully exploit evolutionary search strategies. Traditional algorithms, such as Greedy-based and Pattern Search methods, often suffer from premature convergence and suboptimal scheduling decisions, limiting the network's performance. Moreover, many of these studies focus primarily on maximizing the coverage without explicitly considering the energy efficiency of the scheduling process. In contrast, our work introduces a Genetic Algorithm-based approach that dynamically optimizes both sensor activation schedules and energy consumption. By integrating evolutionary operators, our method efficiently explores the search space, leading to improved sensor scheduling and network longevity. Our approach bridges the gap by providing a balance between maximum coverage and energy-efficient scheduling, outperforming existing solutions in terms of adaptability and efficiency.

III. The MCSS Problem Definition and Formulation

A. Problem Definition

The Maximum Coverage Set Scheduling Problem (MCSSP) is a combinatorial optimization challenge that arises in the context of wireless sensor networks. In this problem, a set of sensors is deployed in a region to monitor certain events or phenomena, and the goal is to schedule the sensors in a way that maximizes the coverage of the entire area. A set of sensors is strategically placed in a given geographic area to monitor specific events or collect data. Each sensor has a limited operational lifespan, and the scheduling problem involves determining the optimal activation and deactivation times for each sensor to maximize the overall coverage during the network's lifetime. The coverage of a sensor refers to its ability to detect or monitor events within its sensing range. The coverage function is a measure of how effectively a sensor can sense or monitor the environment.

The primary objective of the MCSS problem is to find an optimal schedule for activating and deactivating sensors over time to maximize the coverage of the entire region throughout the network's operational lifetime. The problem is computationally challenging because it involves finding the best combination of activation and deactivation times for each sensor to achieve the maximum coverage. This is often an NP-hard problem, requiring the application of heuristic or metaheuristic optimization techniques.

In this context, Our focus is on using Genetic Algorithms, a type of evolutionary algorithm, to address the MCSS problem. Genetic Algorithms involve evolving a population of potential solutions over multiple generations to find an optimal or near-optimal solution to a given problem, making them suitable for tackling complex optimization problems like the MCSS problem.

B. Problem Formulation

In a hypothetical scenario, let's imagine a flat region defined by two well-defined dimensions. The next step involves the random distribution of wireless sensors in this region. This set of sensors, denoted by $S = \{s_i\}, i \in \{1, ..., m\}$, comprises a collection of m sensors, each of which is capable of switching between active and standby states. The maximum time a sensor can remain active is represented by the value b_i.

The main objective of our research is to develop an optimal scheduling strategy for coverage sets in this spatial domain, denoted by $C = \{C_j\}, j \in \{1, ..., n\}$. Each coverage set C_j , constitutes a group of sensors collectively providing complete coverage for all the p targets listed in the set $T = \{t_1, ..., t_p\}$.

In addition, our scheduling strategy aims to maximise the activity time of the coverage sets, between 1 and n. Each sensor has a limited battery life and a specific detection range dictating the range of targets, denoted by $R = \{r_{i,k}\}, k \in \{0, ..., q\}$ and $i \in \{1, ..., m\}$, it can effectively monitor. Our research aims to maximise the total duration of activity of the cover sets within C, while taking into account the constraint that only one cover set can be active at any given time. This research is essential for improving the efficiency and longevity of wireless sensor networks in various applications.

In conjunction with a primary power source b_i , each individual sensor s_i possesses $q + 1$ distinct sensing range alternatives, denoted as $\{r_{i,0}, r_{i,1}, ..., r_{i,q}\}$, that correspond to various levels of energy consumption $\{ e_{i,0}, e_{i,1}, ..., e_{i,q} \}$, where $r_{i,0} = 0$ and $e_{i,0} = 0$ signifies a state of inactivity. There is an underlying assumption that:

$$e_{i,k} = e_{i,q} \left(\frac{r_{i,k}}{r_{i,q}} \right)^2 \tag{1}$$

Where $e_{i,k}$ quadratic function represents the energy consumption rate $e_{i,q}$ of the largest sensing range $r_{i,q}$ within the interval $r_{i,k}$ [22].

The energy consumption of each sensor s_i upon activation with sensing ranges r_k during a given time interval is $e_{i,k} * LifeTime_j$. In the scheduling strategy, the aggregate energy consumption and the cumulative active time slots for each sensor must be both constrained to be no greater than their respective initial active time slots b_i .

The problem of the MCSS can be mathematically represented as an integer linear programming (ILP) formulation, which is as follows:

$$max \sum_{j=1}^{n} LifeTime_j \tag{2}$$

Subject to:

$$\sum_{j=1}^{n} (\delta_{i,j} LifeTime_j) \leq b_i, \forall s_i \in S \tag{3}$$

$$\sum_{j=1}^{n} (e_{i,j} LifeTime_j) \leq b_i, \forall s_i \in S \tag{4}$$

Where $e_{i,j}$ is the energy that sensor s_i consumes in a feasible coverage set $C_j = (\{s_i, r_k\})$. Moreover, $\delta_{i,j}$ is a binary variable as follows:

$$\delta_{i,j} = \begin{cases} 1, & \text{if } s_i \in C_j \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

C. The Proposed Approach for Solving the MCSS Problem

In this section we presented a novel approach based on a genetic algorithm for solving the MCSS problem. Developing a scheduling approach for the cover sets in C, ensuring that only one cover set is activated at a time while maximizing their total active duration, has the potential to significantly improve the network's lifespan. In this section, we will delineate the fundamental components and provide a full explanation of the entire procedure involved in deploying the Genetic Algorithm (GA).

1) The Main elements of the GA proposal:

a) Chromosome representation: In the context of Genetic Algorithms (GA), a chromosome is an essential element that contains a possible solution to the optimization problem at hand. In this specific GA, which is tailored for scheduling cover sets, the chromosome acts as a plan for a particular scheduling strategy. The chromosome's objective is to outline a viable sequence for gathering these cover sets, guaranteeing that the solution meets the problem's limitations. Let's consider a situation where the objective is to fully assemble a collection of cover sets C. Each gene within the chromosome corresponds to a unique cover set C_j. Hence, the chromosome can be expressed mathematically as: $C = C_1, C_2, \ldots, C_j, \ldots, C_n$.

Where:

- C_j represents the j cover set.
- n denotes the total number of genes in the chromosome, which usually correlates to the number of cover sets that require scheduling.

Every chromosome in the population represents a possible solution inside the solution field. The representation scheme is essential because it guarantees that each chromosome represents a unique schedule, which enhances the variety of solutions and facilitates the exploration of the search field. The specific design of the chromosome's structure caters to the unique requirements of the cover set scheduling problem, enabling the genetic algorithm to progress towards an optimal or nearly optimal solution efficiently.

b) Fitness function: The genetic algorithm mainly depends on the fitness function to evaluate the quality of each chromosome. The fitness function quantifies the degree to which a specific solution meets the objectives of the optimization issue. The suggested Genetic Algorithm (GA) attempts to enhance the network's lifespan by improving the scheduling of cover sets. The fitness function is designed to consider both energy efficiency and coverage restraints. The fitness function is a mathematical expression used to assess the effectiveness of a solution in an optimization issue.
The fitness function is designed to ensure that the scheduling approach achieves an optimal balance of energy utilization among all sensors, while still satisfying the required coverage criteria. More specifically, the fitness function is bound by two fundamental constraints:

- The first constraint ensures that each sensor s_i in the set S must have a cumulative active time across all cover sets in the schedule that is not over a predetermined active slot b_i.

$$f(C_j) = \sum_{j=1}^{n} (\delta_{i,j} LifeTime_j) \leq b_i, \forall s_i \in S \tag{6}$$

- The second constraint states that the total energy consumed by each sensor, which is defined by the detection range r_k during each time interval $1 \leqslant k \leqslant q$), must not exceed the initial energy capacity of the sensor.

$$g(C_j) = \sum_{j=1}^{n} (e_{i,j} LifeTime_j) \leq b_i, \forall s_i \in S \tag{7}$$

c) Selection: Selection is the process by which the chromosomes of the parents of the current population are chosen to produce the offspring of the next generation. The selection mechanism has a direct impact on the rate of convergence of the GA and on the quality of the solution.

In the proposed GA, the selection process consists of choosing the two most promising chromosomes in the population, in pairs, on the basis of their fitness values, focusing on the chromosomes with the longest lifespan. These best-performing chromosomes are then designated as parents for the crossover process. By selecting the fittest individuals, the aim is to ensure that their advantageous characteristics are passed on to the next generation, thereby improving the overall quality of the population.

$$max \sum_{j=1}^{n} LifeTime_j \tag{8}$$

d) Crossover: The proposed GA uses the following crossing techniques: The single point crossover technique involves selecting a random crossover point in the parent chromosomes. Segments from both parents are then exchanged at this point, producing two offspring that inherit genetic material from both parents. The probability of crossover, denoted by P_c [23], determines the likelihood of this operation occurring.

In addition, multipoint crossing allows several segments to be exchanged between the parent chromosomes, generating offspring with a more varied genetic composition. Multi-point crossover is particularly effective in improving the efficiency of the evolutionary process, as it allows a wider range of potential solutions to be explored.

The offspring generated by these crossing techniques are then added to the population, contributing to the genetic diversity needed by the GA to avoid premature convergence.

e) Mutation: The mutation is a fundamental genetic operator that introduces random mutations into the chromosomes. The main purpose of this is to prevent the population from becoming too similar, thus minimizing the chance of reaching local optimal solutions.

The crossover phase produces children with mutations in the suggested genetic algorithm (GA). The mutation operator randomly chooses one or more genes inside a chromosome and modifies their values. This modification can entail increasing or decreasing gene values, thus altering the chromosome's fitness. A mutation rate regulates the frequency of mutations.

The new population subsequently integrates the mutated chromosomes, ensuring that each successive generation brings novel genetic material.

2) Description of the whole GA proposal process: In the following paragraphs, we will outline the steps involved in the process of GA (Fig. 1).

- The first is initialization: A starting population is generated with a limited number of chromosomes, chosen at random. The chromosomes are assessed using a fitness function. The C chromosome represents a planning strategy for a collection of cover sets, and its lifetime can be determined by summing the time slots $LifeTime_j$ of the genes within the chromosome.
- The second requirement is related to Fitness: Every candidate solution sensor mustn't exceed the energy limit. For future GA processes to utilize the candidate schedule from the population, it must meet this specific requirement. Furthermore, the optimization process proceeds to the third step.
- The third step is Selection: the selection process is carried out to determine the top two tournaments (parents).
- In the fourth step, new populations are created using crossover and mutation operators, which are part of the Reproduction process.
- The fifth aspect to consider is children's fitness: Once reproduction occurs, the chromosomes in the new population undergo evaluation using the fitness function. This evaluation is crucial to ensure no sensor exceeds its initial energy level. Parents are informed when their children improve their genetic makeup or life expectancy.
- Furthermore, once the steps from the third to the fifth are completed, a new population for the next generation is established. The optimization process goes back to the second step and starts another generation of evolution.

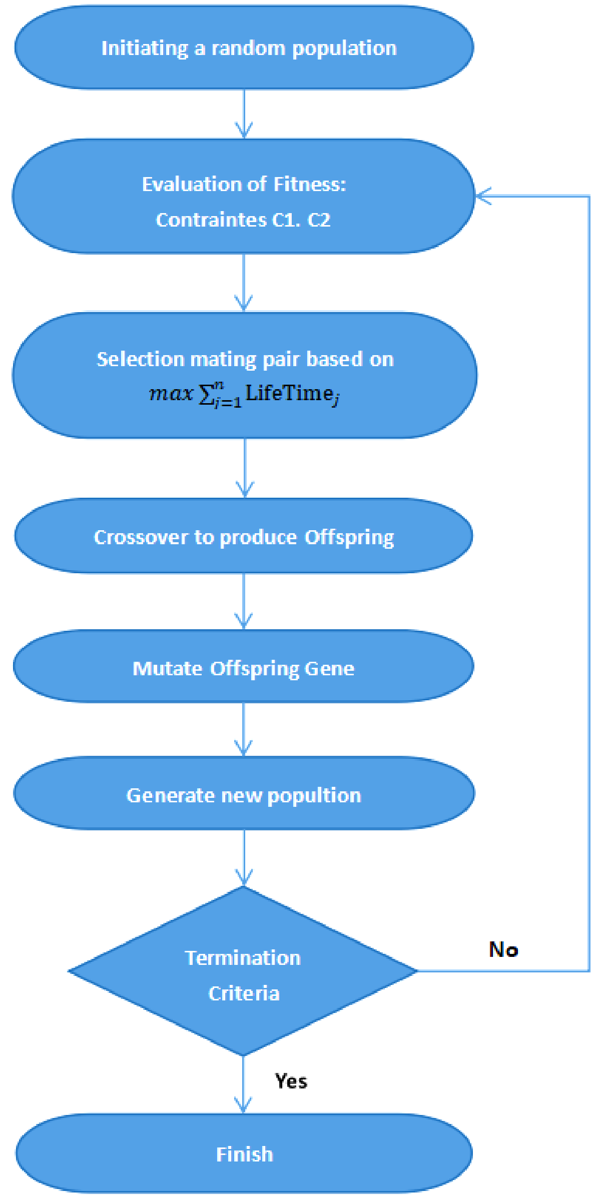

Fig. 1. The Process of genetic algorithm.

3) Explanation overview: To elucidate the algorithmic approach, let's consider a basic scenario involving five sensors $S = \{s_1, s_2, s_3, s_4, s_5\}$, and four targets. Each sensor is assigned a stochastic time slot for operation. Let represent the active time slots with corresponding durations $\{2, 3, 1, 4, 3\}$.

Additionally, we define $Cs_1 = \{s_1, s_2, s_3\}, Cs_2 = \{s_2, s_3\}, Cs_3 = \{s_2, s_4\}$, $Cs_4 = \{s_1, s_2, s_3\}$, $Cs_5 = \{s_1, s_2, s_4, s_5\}$,$Cs_6 = \{s_2, s_3, s_4\}$, $Cs_7 = \{s_1, s_3, s_4, s_5\}$, and $C = \{Cs_1, Cs_2, Cs_3, Cs_4, Cs_5, Cs_6, Cs_7\}$. Since Cs_1 is a segment of Cs_5, Cs_1 is a segment of Cs_7, and Cs_2 is a segment of Cs_6, it follows that Cs_5, Cs_6, and Cs_7 have been excluded from C, as illustrated in Fig. 2. Consequently, the coverage set is represented as $C = \{Cs_1, Cs_2, Cs_3, Cs_4\}$, wherein each coverage set encompasses sensors capable of fully covering all targets.

Moreover, let's designate the duration of the cover set's activity as j, satisfying the condition $1 \leqslant j \leqslant 4$. The sensing range options are defined as $R = \{0, 2, 4\}$, where each sensor offers three distinct sensing range options denoted as $r_{i,0}, r_{i,1}, r_{i,2}$, which correspond to energy consumptions $e_{i,0}, e_{i,1}, e_{i,2}$. It is noteworthy that $r_{i,0} = 0$ and $e_{i,0} = 0$ signify the inactive state. The energy consumptions can be calculated using Eq. 1, where $0 < k < 2$. The values of $r_{i,k}$ are given as $\{2, 4, 2, 4, 3\}$, and the values of $e_{1,k}, e_{2,k}, e_{3,k}, e_{4,k}$ and $e_{5,k}$ are given as $\{0, 1/2, 2\}$, $\{0, 1, 4\}, \{0, 1/2, 2\}, \{0, 1, 4\}$, and $\{0, 3/4, 3\}$, respectively.

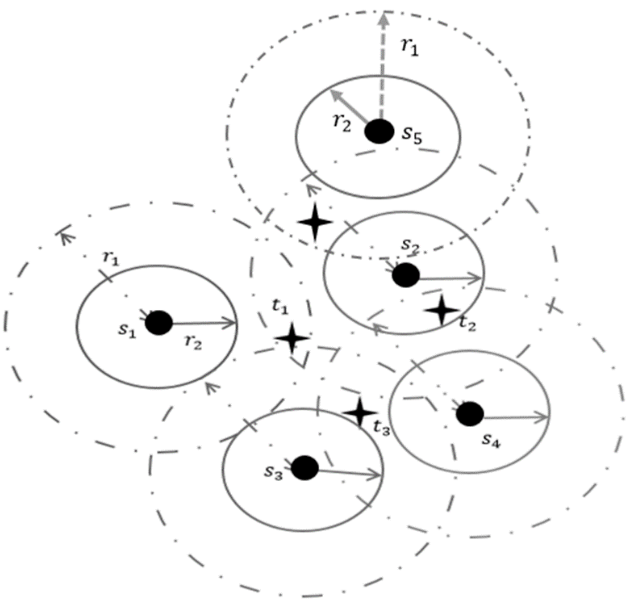

Fig. 2. A Sample illustration.

In this scenario, we establish $X_j = LifeTime_j$, where X_j denotes the activity time of the cover set C_j. Our primary goal is to maximize the overall lifetime of the network, and to achieve this objective, we employ the genetic algorithm detailed in the preceding section. The objective function, guiding the optimization process, is defined as follows:

$$max(\sum_{j=1}^{4} X_j) = max(\sum_{j=1}^{4} LifeTime_j) \tag{9}$$

Subject to

$$\sum_{j=1}^{4}(\delta_{i,j} X_j) \leq b_i, \forall s_i \in S \Longrightarrow \begin{cases} X_1 + X_4 \leq b_1 \\ X_2 + X_3 + X_4 \leq b_2 \\ X_2 + X_4 \leq b_3 \\ X_1 + X_3 \leq b_4 \end{cases} \tag{10}$$

Where $\delta_{i,j}$ is a binary variable equal to 1 if $s_i \in S$ and 0 otherwise.

$$\sum_{j=1}^{4}(e_{i,j} X_j) \leq b_i, \forall s_i \in S \Longrightarrow \begin{cases} 2X_1 + 2X_4 \leq b_1 \\ 4X_2 + X_3 + 4X_4 \leq b_2 \\ 2X_2 + \frac{1}{2}X_4 \leq b_3 \\ 4X_1 + 4X_3 \leq b_4 \end{cases} \tag{11}$$

IV. Results and Discussions

To comprehensively evaluate the effectiveness of the proposed Genetic Algorithm (GA), simulations were carried out on a network consisting of N sensors that were randomly dispersed around a predetermined region. The network's main purpose is to identify 10 targets, which are also randomly located inside the area. The sensors were programmed with three distinct sensing range values: 0, 2, and 4 units. To guarantee the dependability of the outcomes, we computed the average of each test based on 100 simulation runs. The simulations were conducted using MATLAB R2020, which offers a strong and versatile platform for modeling and analysis (Table I).

The simulations were conducted on a gaming laptop featuring an AMD Ryzen 9 5900HX processor with a clock speed of 3.3 GHz and 16 GB of RAM. This hardware configuration ensured that the simulations ran smoothly and efficiently, without any interruptions. Providing these hardware and software specifications is essential for reproducibility, as it allows others to understand the computational resources necessary to replicate the study's results. This, in turn, helps to further validate the effectiveness of the proposed Genetic Algorithm (GA) in optimizing network lifetime for wireless sensor networks (WSNs).

TABLE I. Parameters of Simulations

Parameters	Values
Length of chromosome	The scheduling strategy of the collection of cover sets C
population size (Number of coverages sets)	20
Crossover probability	0.5 [24]
Mutation probability	0.2 [24]
Iteration	150
R (Sensing range of each sensor node)	0, 2 and 4
Coverage sets	10

In this section, simulations are performed to compare the results of the genetic algorithm with those of the search algorithm. In addition, simulations are performed to evaluate how algorithm parameter changes influence the proposed method's performance.

In the initial experiment, shown in Fig. 3, we compared the lifetimes of our approach with those of the Greedy algorithm and Pattern search algorithm by gradually varying the active time slots (b_i) of the sensors from 5 to 30. The results demonstrate the superiority of the genetic algorithm over the author algorithms in terms of efficiency for calculating lifetimes.

The results show that the Genetic algorithm consistently achieves the longest network lifetimes across all time slots. The robust search capabilities of the GA enable it to effectively explore the solution space and avoid premature convergence pit-

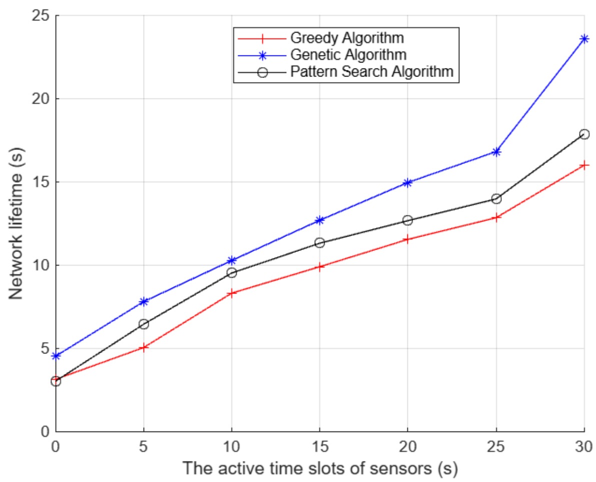

Fig. 3. Network lifetime by the active time slots.

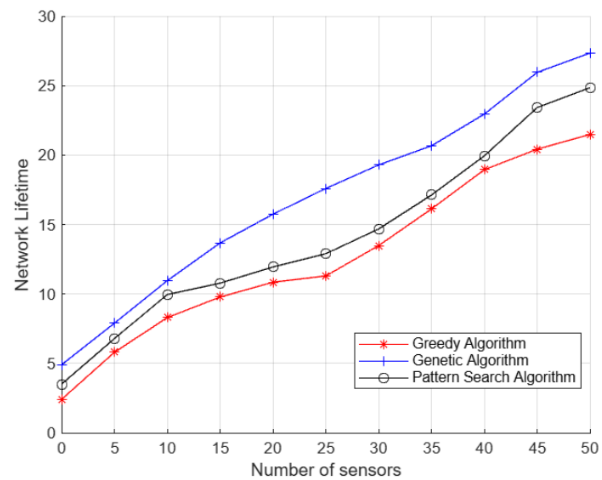

Fig. 4. Network lifetime by the number of sensors.

falls that often hinder other algorithms, contributing to its superior performance. The GA's evolutionary techniques—such as selection, crossover, and mutation—enable it to generate high-quality offspring with favorable traits, leading to more optimal scheduling and extended network operation.

In comparison, the Greedy algorithm consistently produces the shortest network lifetimes, reflecting its tendency to make locally optimal decisions that do not necessarily translate into globally optimal solutions. The Pattern Search algorithm, while performing better than the Greedy approach, still falls short of the Genetic algorithm's performance. Although the Pattern Search method effectively explores the solution space, its vulnerability to local optima limits its ability to find the best possible solutions. The overall trends show that as the active time slots increase, all algorithms yield better network lifetimes; however, the Genetic algorithm exhibits the steepest improvement, highlighting its ability to capitalize on increased scheduling flexibility. These findings underscore the GA's robustness and efficiency, suggesting that it is well-suited for maximizing network lifetime in complex scheduling problems.

Fig. 4 presents the results of the second experiment, which used 5 to 50 sensors, each with a 10 time slot. The results show that the Genetic Algorithm consistently outperforms the other two algorithms, achieving the longest network lifetimes at every sensor count. Interestingly, as the number of sensors increases, the network's lifetime also experiences a proportional increase. This observation indicates that having more sensors in the network allows for more effective coverage of target areas, leading to a prolonged network lifetime. This is likely due to the GA's ability to effectively explore a broad solution space and leverage evolutionary strategies such as selection, crossover, and mutation to generate high-quality solutions. By optimizing sensor schedules through these mechanisms, the GA successfully extends the network lifetime more effectively than the other algorithms.

On the other hand, the Greedy algorithm consistently delivers the lowest network lifetime, indicating its limitations when solving a complex problem. The pattern search algorithm performs better than the Greedy algorithm, but still worse than the Genetic algorithm (GA). Although the pattern search algorithm is able to navigate the solution space without information about the gradient, it proves to be more susceptible to local optima, which limits its efficiency in finding the best possible programs. The distance that increases between the GA and the other algorithms as the number of sensors increases underlines the greater adaptability and robustness of the GA, making it a more suitable approach for optimizing the lifetime of sensor networks. This comparison supports the conclusion that the genetic algorithm offers significant advantages in scenarios where it is critical to maximize the network lifetime.

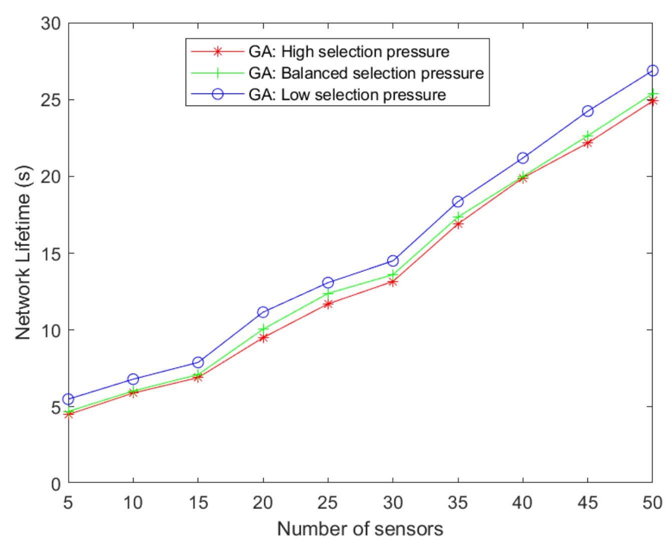

Fig. 5. The Impact of selections operation on GA's performance.

In the selection operation of the genetic algorithm (GA), the number of individuals randomly selected for reproduction, namely the selection pressure, can affect its performance. The selection pressure determines the number of individuals from the present generation selected to serve as parents for the subsequent generation. Fig. 5 illustrates a comparison of different selection pressure types High, Low, and Balanced selection pressure. The experiment involved 5 to 50 sensors, each with a 10 time slot, utilizing the single-point as crossover operation and single-gene as mutation types.

The results indicate that Low selection pressure outperforms High and Balanced selection pressure strategies due to their distinct operational processes. Due to high selection pressure, only the most elite individuals with the best reproductive fitness are retained, narrowing the gene pool considerably. On the other hand, Low selection pressure casts a wider net, including many more individuals, even those with lower fitness levels. In contrast, the concept of Balanced selection pressure seeks equilibrium, striving to balance exploration and exploitation by maintaining some diversity while also giving preference to individuals with higher fitness values.

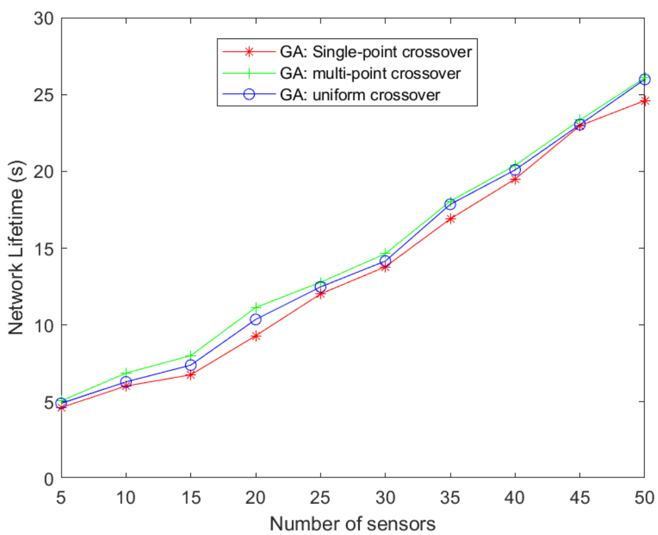

Fig. 6. The Impact of crossover operation on GA's performance.

Different crossover operations in a Genetic Algorithm (GA) can yield varied impacts on the algorithm's overall performance. The crossover procedure combines two parent people to produce one or more child individuals. Fig. 6 provides a comparison of crossover operators (such as single-point, multi-point, and uniform). The experiment encompassed scenarios with 5 to 50 sensors, each allocated a 10 time slot, employing the random selection operation with two individuals selected, and single-gene mutation types.

According to the results, the choice of crossover operator has a considerable impact on GA performance. In particular, multi-point crossover emerged as the most efficient option compared with single-point and uniform crossover. Single-point crossover divides the parental chromosomes at a single, randomly chosen point and exchanges the resulting segments. Although this type of crossing combines the genetic material of both parents, it does not always succeed in generating significant diversity, which slows down convergence in complex landscapes. In contrast, multi-point crossover divides chromosomes at random points and exchanges segments between parents. This type of crossover explores a wider solution space and is more likely to escape local optima than the single-point crossover. In addition, uniform crossover selects genes from both parents at a particular frequency, resulting in children with random genetic inheritance. This reduces convergence due to the likely loss of beneficial genetic information.

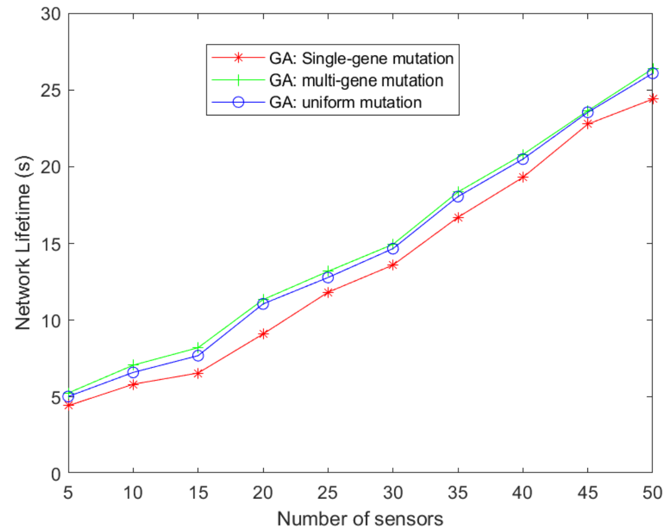

Fig. 7. The Impact of mutation operation on GA's performance.

Fig. 7 illustrates the results depicting the influence of the mutation operator (such as single-gene mutation, multi-gene, and uniform) on the algorithm's performance. The experiment involved 5 to 50 sensors, each a 10-time slot, employing the random selection operation with two individuals selected and single-point crossover types.

The results suggest that multi-gene and uniform mutations have the closest outcomes, with a notable advantage over the single-gene mutation. Single-gene mutation brings minor, localized adjustments by modifying a single gene in a chromosome, encouraging slow progress towards global optima. In contrast, multi-gene mutation brings more significant perturbations by modifying multiple genes, encouraging more expansive solution space exploration, and yielding improved overall solutions. Uniform mutation adds diversity by randomly altering gene values, which encourages exploration as it disrupts genes independently, potentially contributing to the discovery of improved solutions.

V. Conclusion

In this paper, we focus on the Maximum Coverage Set Scheduling (MCSS) problem, which is inherently hard and classified as NP-hard. To solve this problem, we use advanced mathematical techniques, namely genetic algorithms (GA) and integer linear programming (ILP), to find optimal coverage and scheduling solutions for wireless sensor networks (WSNs) with adjustable coverage areas. The genetic algorithm plays a crucial role in our approach, iteratively refining possible solutions until the most efficient scheduling, which maximizes network lifetime, is achieved. This iterative process, which involves the strategic use of selection, crossover, and mutation operations, results in more efficient network operation by extending the lifetime of the WSNs, making it particularly suited for applications requiring sustained and reliable monitoring.

The findings from our study are particularly relevant for specialized WSNs designed for critical applications in fields such as medicine and environmental monitoring. These networks are highly adaptable and can be customized to meet the specific needs of diverse scenarios, ensuring robust and reliable data collection. The results underscore the GA's ability to outperform traditional methods, like the Greedy and Pattern Search algorithms, in optimizing network lifetime. Looking forward, future work will aim to build on these findings by exploring additional parameters, such as sensor and target mobility, and their impact on WSN performance. Additionally, we intend to explore the application of machine learning techniques to further optimize network lifetime, exploring hybrid optimization methods, and examining the effects of sensor mobility on energy efficiency and performance in WSNs.

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