Journal of Computer Science and Cybernetics, V.41, N.2 (2025), 163-180
DOI: 10.15625/1813-9663/21945

SOLVING THE MAXIMAL EXPOSURE PATH PROBLEM IN HETEROGENEOUS DIRECTIONAL WIRELESS SENSOR NETWORKS USING AN IMPROVED GENETIC ALGORITHM

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Abstract. Barrier coverage is a well-known model within the Internet of Things Wireless Sensor Networks (WSNs) domain, playing a vital role in various military and security applications. It is particularly important for monitoring and detecting moving objects across a sensor field. This research paper examines the fundamental aspect of barrier coverage in WSNs, with a specific focus on the maximal exposure path (MaEP) problem, which is classified as NP-Hard. The MaEP problem involves identifying an optimal coverage path that either conserves energy or minimizes energy usage while maintaining a short traversal distance. Previous studies in this area primarily relied on problem formulations based on Euclidean distance metrics and were often addressed using computational geometry techniques. However, these methods encounter significant difficulties when applied to large-scale, complex, and highly sophisticated WSNs. To address this, our research reinterprets the MaEP problem through the lens of the integral of sensing field intensity. We then introduce an improved genetic algorithm, named MIGA, specifically tailored to efficiently solve the MaEP problem. The polynomial complexity and convergence of the proposed MIGA are mathematically obtained. Moreover, to evaluate the effectiveness of this algorithm, we conduct a comprehensive series of experiments and provide detailed experimental results.

Keywords. Wireless sensor networks, barrier coverage, maximal exposure path, improved genetic algorithm.

1. INTRODUCTION

Barrier coverage in wireless sensor networks (WSNs) has gained attention as a model that creates a virtual boundary using sensors to detect movement across designated areas, such as borders or restricted zones [1–4]. Unlike full area coverage, which monitors every point, barrier coverage forms a sensor line to detect intrusions, making it crucial for security, surveillance, and environmental monitoring. Its effectiveness depends on sensor placement, range, and energy use to maintain continuous detection while minimizing resource consumption [1, 5, 6]. Heterogeneous directional wireless sensor networks (HeDWSNs) efficiently

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monitor large areas using sensors with directional capabilities [7]. These sensors focus on specific regions, enhancing wide-area coverage and precision. However, their directional nature presents challenges in optimizing coverage and ensuring critical areas receive sufficient exposure [8]. A key barrier coverage issue in HeDWSNs is the Maximal Exposure Path (MaEP) problem, which identifies a path maximizing sensor exposure [1]. This is vital for applications such as surveillance, where optimal exposure enhances security by detecting intruders, and search-and-rescue, where it improves the chances of locating individuals in distress. In wildlife monitoring, maximizing exposure aids in tracking movements and studying migration, underscoring the need for efficient MaEP solutions. The MaEP problem in HeDWSNs is challenging due to sensor heterogeneity in coverage range, energy use, and orientation, creating a non-uniform coverage landscape. The directional nature of sensors further complicates optimization, as coverage is limited to specific orientations. These factors make it difficult to find a path that maximizes exposure while addressing coverage gaps. Additionally, the MaEP problem is NP-hard [9], making exhaustive search infeasible for large networks, while metaheuristic approaches offer near-optimal solutions. Particle Swarm Optimization (PSO) is a widely explored metaheuristic for solving MaEP [10], excelling in balancing exploration and exploitation in large search spaces. However, PSO tends to converge prematurely to local optima, especially in irregular search landscapes like HeDWSNs. This issue is worsened when coverage distribution is highly non-uniform or when multiple near-optimal solutions exist. Moreover, PSO's performance is sensitive to parameter tuning, requiring significant effort to optimize, reducing its robustness in critical applications.

This paper introduces an improved genetic algorithm, MIGA, to solve the MaEP problem in HeDWSNs. Genetic algorithms (GAs) are effective for complex optimization problems as they rely on the principles of evolution—selection, crossover, and mutation—to iteratively improve potential solutions. However, standard GAs may struggle with convergence speed and solution quality. To overcome these limitations, the proposed MIGA incorporates several enhancements, including: adaptive crossover and mutation to maintain population diversity and prevent premature convergence and local search integration to refine solutions further and ensure optimal path discovery. Extensive simulations in various HeDWSN scenarios demonstrate MIGA's superiority in solution quality, convergence speed, and scalability. Our improved GA-based approach not only addresses the limitations of traditional methods but also provides a practical and efficient solution for real-world applications. By optimizing the exposure path while considering the heterogeneous and directional nature of sensors, our method enhances the network's overall performance, ensuring reliable detection and efficient resource utilization. This approach represents a significant step forward in solving the MaEP problem and underscores the potential of advanced GA-based techniques in improving the effectiveness of HeDWSNs. To the end, our contributions are summarized as follows:

- We formulate the problem of finding the Maximal Exposure Path under the probabilistic sensing coverage model within HeDWSNs.
- We propose an efficient algorithm, referred to as MIGA, that draws inspiration from genetic algorithms with adaptive individual initialization, crossover and mutation operators, and an enhancing local search technique.
- The convergence of our proposed algorithm is mathematically obtained. Furthermore, numerical results demonstrate that the proposed method outperforms the existing literature in solution quality while requiring competitive computational resources.

The rest of this paper is organized as follows Section 2 presents a survey of related literature. Preliminaries and problem formulation for the maximal exposure path are discussed in Section 3. Section 4 introduces the proposed algorithm, while experimental results are described and analyzed in Section 5. Finally, Section 6 draws the conclusions of the paper.

2. RELATED WORKS

This section presents an overview of relevant research on the barrier coverage problem in WSNs, focusing on the MaEP with significant practical relevance and numerous applications. In general terms, barrier coverage issues in WSNs are generally divided into two main domains [1, 5]: constructing intrusion barriers and identifying penetration paths. For intrusion barriers, a sensor network may have to ensure k-barrier coverage across a belt-shaped region, meaning any crossing path must pass through at least k different sensors. A crossing path is a trajectory starting on one side of the sensor field and ending on the other. This topic has received extensive attention [3, 4, 11, 12]. Fan et al. [11] addressed the barrier construction problem in directional sensor networks with an efficient scheme utilizing adjustable sensing ranges and combined detection from neighboring nodes. This minimizes costs and extends network lifetime compared to mobile sensor-based systems. The studies in [3, 4, 12] examine strategies for building strong barriers. Ma et al. [12] propose an exact algorithm to verify barrier existence using feasible orientation ranges and an efficient selection method. Binh et al. [4] develop a genetic algorithm-based metaheuristic for constructing k-strong barriers, while [3] presents a polynomial-time exact method for k-strong coverage in HeWMSNs.

The goal of penetration path identification is to find a crossing path where every point meets a predefined coverage requirement, differing from intrusion barrier construction, which ensures certain points on all paths satisfy coverage criteria. Coverage requirements fall into two categories: the best-case and worst-case coverage paths, also known as the maximal and minimal exposure paths (MEP), widely studied for evaluating network monitoring effectiveness [10, 13–15]. MEPs have been thoroughly investigated [9, 16, 17], with studies introducing efficient algorithms to complement maximal exposure solutions. The Maximal Breach Path problem, enhancing network robustness, was addressed in [18], while [19] transformed MEP into a high-dimensional optimization problem, proposing the HPSO-MMEP algorithm. Extending this research, the authors in [17] introduce the MEP in real-world settings with obstacles, proposing the Family System-based Evolutionary Algorithm to tackle challenges posed by irregular network landscapes. For the maximal exposure path problem, which respectively evaluates the network's capacity to detect intruders or maximize monitoring over a path [9, 10, 13]. The MaEP problem is proven as NP-Hard in [9], thus requiring heuristic/metaheuristic or approximation techniques for feasible solutions. This foundational study provided a benchmark for handling MaEP complexity, influencing subsequent research. The authors in [13] examine best-case and worst-case coverage issues for homogeneous camera sensor networks in complex areas, aiming to identify a maximal support path or breach path within these regions. Using a polygon sensing model, they developed an efficient algorithm with low time complexity for each problem, demonstrating that these algorithms yield optimal solutions when the complex region has a known convex partition. The work in [13] differs from that in [10], where Thien et al. define the best coverage path, or maximal exposure path, as the integral of the sensing coverage intensity function. The authors then propose the MaEP-PSO, inspired by the PSO. However, the solution quality achieved by MaEP-PSO could be further improved, as it tends to get trapped in local optima or suffer from premature convergence. Accordingly, it is imperative to develop a novel method to effectively address the MaEP problem in HeDWSNs. Although significant research has been conducted on WSN coverage and the MaEP problem, few solutions have been specifically developed for heterogeneous directional wireless sensor networks. This study addresses this gap by introducing MIGA, a novel optimization approach tailored to MaEP in HWSNs.

3. PRELIMINARIES AND PROBLEM FORMULATION

3.1. Preliminaries

3.1.1. The attenuated directional sensing model

The sensing model describes the ability of a sensor node to detect or cover points or objects. Various sensing models exist, and a shared characteristic among many is that the quality or strength of the sensor's detection decreases with increasing distance from the sensor node. A fundamental example of such a model is the Boolean disk sensing model, which assumes that a sensor, denoted as S, can detect an object, denoted as O, if the Euclidean distance $d(S,O)$ between the sensor's position and the object's location is within the sensor's sensing range r. However, this paper explores a more accurate and widely used sensing model known as the "attenuated directional sensing model". The mathematical formulation that defines the sensing function of sensor s for the attenuated direction model is as follows

$$f(s,O)=\begin{cases}\min\left\{1,\frac{C}{d(S,O)^{\mu}}\right\}, & \text{if } d(S,O)\le r \text{ and } \cos\alpha\le\frac{\overrightarrow{SO}\cdot\overrightarrow{Wd}}{d(S,O)}\\ 0, & \text{otherwise.}\end{cases} \tag{1}$$

where C is a constant that depends on the characteristics of the sensor, and μ is the attenuation exponent, which is influenced by both the sensor and the surrounding environment, α is half of the sensing angle of the sensor s, and $\overrightarrow{Wd}$ is the unit vector whose direction coincides with the bisector of the sensing angle. The condition $\cos\alpha\le\frac{\overrightarrow{SO}\cdot\overrightarrow{Wd}}{d(S,O)}$ means that α is greater than the angle between $\overrightarrow{SO}$ and $\overrightarrow{Wd}$, hence ensures that object O lies within the sensing angle of sensor. In summary, the sensing model of sensor s can be characterized by a 7-tuple of components

$$s:=\langle x,y,C,\mu,r,\alpha,\beta\rangle, \tag{2}$$

where (x,y) is of the coordinates of the sensor position, C,μ,α,r are previously explained, and $\beta=\angle(\overrightarrow{Wd},\overrightarrow{Sx})$ is the angle between $\overrightarrow{Wd}$ and the horizontal axis, also called the orientation angle of the sensor. An example of this sensing model is depicted in Figure 1.

We further explore the ability to simultaneously sense or cover multiple sensor nodes at a specific point within their sensing field, a concept commonly known as "the sensing intensity model". In a WSN, each sensor node is equipped with a maximum transmission power, allowing it to communicate with all nodes within its transmission range. Therefore, we consider a WSN consisting of a set of sensor nodes $\mathcal{S}=\{s_1,\dots,s_N\}$, the total exposure of an object within the sensing field, or at any specific point in the sensor field, can be defined

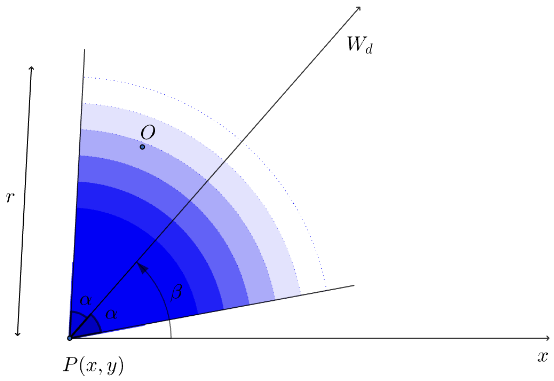


Figure 1: The attenuated directional sensing model

as the sum of all individual exposure values, as expressed by the following equation

$$\mathsf{E}(\mathcal{S}, O) = \sum_{i=1}^{N} f(s_i, O). \tag{3}$$

3.1.2. Exposure of a crossing path and the maximal exposure path

Exposure refers to the ability of the sensor network to detect an object as it moves through the sensing field. It can be described as the expected average capability to observe a target within the sensor field. Formally, exposure is the integral of a sensing function, which usually depends on the distance from the sensors along a path that starts at an initial point $B = (x_B, y_B)$ and ends at a destination point $D = (x_D, y_D)$. A path connecting these points is described as a continuous function, denoted as $\mathcal{P}(t) = (x(t), y(t))$, with boundary conditions $\mathcal{P}(0) = B$ and $\mathcal{P}(T) = D$. The exposure along it is defined in Definition 1.

Definition 1. (Exposure of a path) Let $\mathcal{P}(t) = (x(t), y(t))$ be a path connecting two points B and D within a HeWDSN. The exposure along this path is defined as the total exposure encountered by the sensor network as an object moves along this trajectory. This total exposure can be mathematically represented as follows

$$\mathsf{E}(\mathcal{S}, \mathcal{P}) = \int_{0}^{T} \mathsf{E}(\mathcal{S}, \mathcal{P}(t)) \sqrt{\left(\frac{dx}{dt}\right)^2 + \left(\frac{dy}{dt}\right)^2}\, dt \approx \sum_{k=0}^{\lfloor T/\Delta t \rfloor} \sum_{i=1}^{N} f\left(s_i, \mathcal{P}(k\Delta t)\right) \Delta t, \tag{4}$$

where $\mathsf{E}(\mathcal{S}, \mathcal{P}(t))$ represents the exposure by the sensor network $\mathcal{S}$ at point $\mathcal{P}(t) = (x(t), y(t))$, as computed through Equation (3) and Δt is a sufficiently small time interval.

Definition 2. (The maximal exposure path) The maximal exposure path in a sensor network is the path with the highest coverage, formally defined as the path connecting two predetermined points in the sensor field that maximizes exposure. i.e. maximizes the function $\mathsf{E}(\mathcal{S}, \mathcal{P})$ described in (4), subject to a predefined length constraint.

3.2. The maximal exposure path optimization problem

Consider a region of interest $\mathbf{\Omega}$ with width W and height H, where N heterogeneous multimedia sensors are randomly deployed, denoted as $\mathcal{S} = \{s_1, s_2, \ldots, s_N\}$, and governed by an exposure model. An intruder moves along a trajectory within this monitored region, starting from the point $B(x_B, y_B = 0)$ and ending at the point $D(x_D, y_D = H)$, traveling at a constant velocity V_I. The concept of the "maximal exposure path" refers to a specific route within the sensor network that connects the starting point B to the ending point D, chosen to maximize the exposure experienced by the target as it moves along the path. The problem of identifying this path is referred to as the MaEP problem in HWDSNs and is mathematically formulated as follows.

Input:

- W, H: the width and the length of the sensing field $\mathbf{\Omega}$; N: the number of sensors.
- $\mathcal{S} = \{s_i = \langle x_i, y_i, C_i, \mu_i, \alpha_i, \beta_i\rangle\}_{i=1}^{N}$: the set of sensors in the field.
- V_I: the speed of intruder; y_B, y_D: the coordinates of the source B and destination D.
- ℓ: the maximum length of the crossing path ($\ell > BD$).

Output: A path $\mathcal{P}$ in region $\mathbf{\Omega}$ connecting B and D, which is discretized as

$$\mathcal{P} = \big\{P_k = (x_k, y_k)\big\}_{k=0}^{\tau}, \tag{5}$$

where the travel time duration is divided into τ interval, and $P_k = (x_k, y_k)$ is the location of time step k.

Objective: The exposure of path $\mathcal{P}$ is maximized, which means

$$\underset{\mathcal{P} = \{(x_k, y_k)\}_{k=0}^{\tau}}{\text{maximize}} \quad \mathsf{E}(\mathcal{S}, \mathcal{P}) = \sum_{k=0}^{\tau}\sum_{i=1}^{N} \min\left\{1, \frac{C}{d^{\mu}(s_i, (x_k, y_k))}\right\} \cdot \frac{T}{\tau}, \tag{6a}$$

subject to

$$d\big(P_k, P_{k-1}\big) = d\big(P_k, P_{k+1}\big) \;\forall k \in \{1, 2, \ldots, \tau\}, \tag{6b}$$

$$\sum_{k=0}^{\tau-1} d\big(P_k, P_{k+1}\big) \le \ell, \tag{6c}$$

$$P_0 = B, P_\tau = D, \tag{6d}$$

where the constraint (6b) is because of the unchanging speed, (6c) is the length constraint, and (6d) represents the beginning and ending point of the crossing path.

4. IMPROVED GENETIC ALGORITHM FOR MAXIMAL EXPOSURE PATH OPTIMIZATION

Evolutionary algorithms are a class of optimization algorithms inspired by the process of natural selection, which can surmount many optimization problems in various areas. Leveraging the discoveries and superiority of evolutionary algorithms in tackling complex problems within modern communication networks as discussed in [20] and references therein, we propose the MIGA algorithm, which evolves a population of candidate solutions through processes such as mutation, crossover, local search and selection to solve the considered MaEP problem. The flowchart of MIGA is illustrated in Figure 2, while the pseudo-code is described in Algorithm 1.

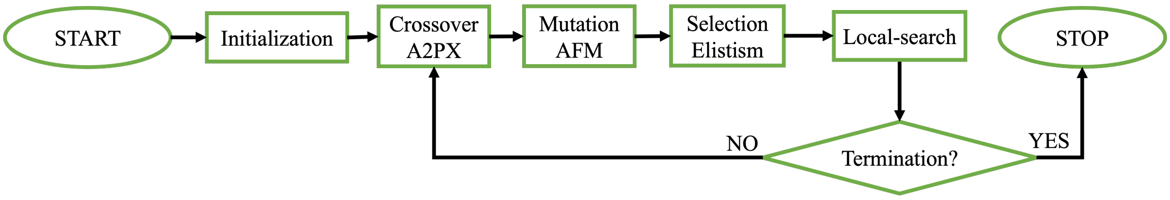


Figure 2: The flowchart of the proposed MIGA

4.1. Solution representation and population initialization

4.1.1. Solution representation

In MIGA, an individual represents a feasible solution and is described as an ordered sequence of points, starting at B and ending at D. These points are commonly referred to as the genes of the individual. The number of genes within an individual in MIGA is predetermined and set by a parameter denoted as m. Figure 3 illustrates the path derived from an individual with a sequence of $m = 6$ points, namely $P_1, \dots, P_6$, connected in the specified order. Additionally, the individual must satisfy the constraint of the maximum length of the problem.

Remark 1. It is noted that the points P_i in an individual are not identical to the discretized points used in the problem solution as shown in (5). To calculate the fitness of an individual, MIGA does not consider the genes within the individual. Instead, it directly divides the trajectory that connects these genes into τ equal segments and calculates according to (6).

4.1.2. Solution repairing

It is inevitable that individuals represented as described in Section 4.1.1 may violate the constraint that the path length must be less than or equal to ℓ. Therefore, in MIGA, we propose a repairing technique to make individuals valid if they violate the maximum length constraint. The idea behind this technique is to first sort the points of the individual in increasing order of their x-coordinates. After that, if the individual is still invalid, we adjust the path connecting the genes to be closer to the straight-line segment BD. In particular, whenever the individual is not valid, we find the genes $P_{k_{\max}} = (x_{k_{\max}}, y_{k_{\max}})$ whose the largest distance to the line BD and perform the substitution

$$(x_{k_{\max}}, y_{k_{\max}}) \leftarrow \left(x_{k_{\max}}, \frac{y_{k_{\max}} + y_{BD,P_{k_{\max}}}}{2} \right), \tag{7}$$

where $y_{BD,P_{k_{\max}}}$ is the y-coordinate of the point on the line BD that shares the same x-coordinate with $P_{k_{\max}}$ computed as $y_{BD,P_{k_{\max}}} = (y_D - y_B)x_{k_{\max}}/H + y_B$. An illustration of

Algorithm 1: Maximal exposure path - improved genetic-based algorithm (MIGA)

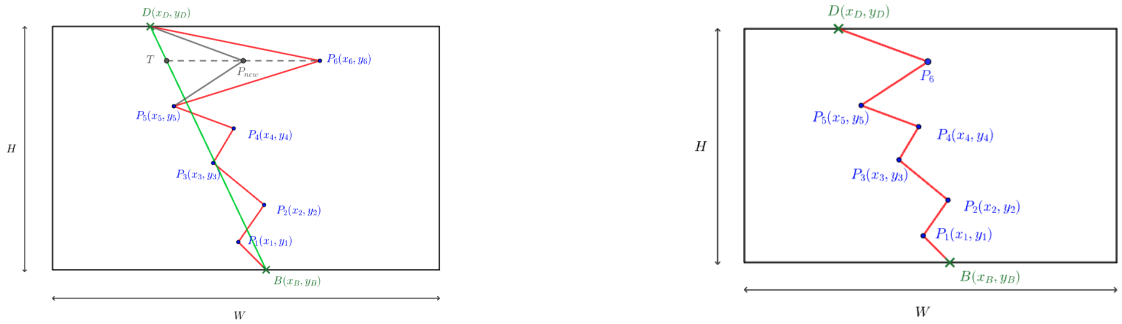
Input: The list of sensors $\mathcal{S}$, the beginning and ending points B and D.
Parameters: Population size $\mathsf{Pop}_{\mathsf{size}}$, crossover and mutation rates p_c, p_m, maximum number of generations $G_{\max}$, local search rate γ.
Output: The sub-optimal solution for the MaEP problem.

begin
    Initialization: Generate a population with $\mathsf{Pop}_{\mathsf{size}}$ random individuals
    Main loop:
    while *terminate condition not met* **do**
        Crossover and Mutation:
        foreach *individual* indi *in the population* **do**
            if $\mathcal{U}(0,1) < \mathsf{p}_{\text{cr}}$ **then**
                $\mathsf{indi}' \leftarrow$ a random individual in the population
                Add A2PX$(\mathsf{indi}, \mathsf{indi}')$ to the population.
            end
            if $\mathcal{U}(0,1) < \mathsf{p}_{\text{mu}}$ **then**
                Add AFM(indi) to the population.
            end
        end
        Evaluate and select individuals.
        Local search:
        for $i \leftarrow 0$ **to** $\Gamma = \lfloor \gamma \cdot \mathsf{Pop}_{\mathsf{size}} \rfloor$ **do**
            $\mathsf{indi} \leftarrow$ a random individual in the population.
            $\mathsf{indi}' \leftarrow \mathsf{indi} + \boldsymbol{\nu}$
            if $f(\mathsf{indi}) < f(\mathsf{indi}')$ **then**
                Add indi' to the population and eliminate indi
            end
        end
    end
    return the best individual of the population.
end

this method is described in Figure 3, where P_6 is replaced by the midpoint P_{new}. We observe that if this technique is applied repeatedly, the individual will converge to the straight line BD as the number of iterations approaches infinity. Since the input requirement is $\ell > BD$, the mechanism is guaranteed to terminate.

4.1.3. Population initialization

It is important to note that MaEP is a problem with constraints that make traditional GA or other population-based algorithms impossible to apply directly. Hence, in this study, we propose a method to initialize the individuals for the population of MIGA. To start, the field is first divided into m equal segments, each with a height of H/m. Next, $m-1$ points $P_1, P_2, \ldots, P_{m-1}$ are randomly generated, where each point P_i has an x-coordinate of $i \times H/m$ and a y-coordinate that is a random real number within the range $y_{P_{i-1}} \pm Wm/H$. An individual is then formed by connecting the points $(0, y_B), P_1, P_2, \ldots, P_{m-1}, (H, y_D)$ with the lines $x = j\Delta x$, where j ranges from 0 to n. The number of individuals in the population is limited by the population size, denoted as $\mathsf{Pop}_{\mathsf{size}}$.



(a) The individual before repairing. (b) The individual after repairing

Figure 3: Illustration of the repairing technique applied to an individual with $m = 6$

4.2. Evolutionary operators: crossover and mutation

The crossover and mutation operators in GAs are fundamental mechanisms that greatly enhance not only the quality but also the diversity within the population. These operators introduce variability by combining and altering the genetic material of individuals, leading to new offspring. This diversity is essential for the evolutionary process, as it helps prevent premature convergence to suboptimal solutions and enables the algorithm to explore a broader search space, thereby increasing the chances of finding optimal or near-optimal solutions. In GAs, crossover operators combine two distinct individuals, called parents, to produce one or more new individuals. Research on GAs has proposed and demonstrated the effectiveness of several evolutionary operators with real number representation, such as simulated binary crossover (SBX). However, for the MaEP problem, although the genotype of individuals is equivalent to an array of real numbers, their phenotype represents a path from B to D. Furthermore, this operator must satisfy the heritability property [21], meaning that offspring should inherit highly-contribute-to-fitness segments from their parents. Based on this, in this study, we propose a new crossover operator named the Adjusted 2-Point Crossover (A2PX). The core concept of A2PX involves copying the initial and terminal genes of the parents while exchanging the genetic information in the middle segments of the parents' chromosomes. Specifically, for two parent individuals, $\mathsf{pr}_1 = \{P_1, P_2, ..., P_m\}$ and $\mathsf{pr}_2 = \{Q_1, Q_2, ..., Q_m\}$, the first offspring $\mathsf{ofs}_1 = \{C_1, C_2, ..., C_m\}$ inherits the segment from P_1 to P_{point_1} and from P_{point_2} to P_m of pr_1, where $point_1$ and $point_2$ are randomly generated from $\{1, \ldots, m\}$ with uniform distribution. The remaining genes of ofs_1 are determined by recombining the earlier genes with the information from pr_2. This mean that we apply $C_i \leftarrow P_i$ for $i \in \{1, \ldots, point_1, point_2 + 1, \ldots, m\}$, and $C_i \leftarrow$ midpoint of segment $C_{i-1}Q_i$ for $i \in \{point_1 + 1, \ldots, point_2\}$. The second offspring ofs_2 is created in a similar manner by reversing the roles of the two parents. The new individuals are repaired before other steps of MIGA. The probability of parents to crossover is determined by the crossover rate p_{cr}.

For the MaEP problem, we introduce a novel mutation operator called the Attractive Force Mutation (AFM). The key idea behind the AFM is to enhance the exposure of each gene within an individual by drawing it closer to the sensor with the highest exposure. Specifically, the attractive force by a sensor s at $S(x, y)$ on a point P is calculated by

$$\overrightarrow{F}_{\text{AFM}}(s, P) = \alpha_{\text{AFM}} \cdot \overrightarrow{PS}. \tag{8}$$

This force is scaled by a parameter α_{AFM}, after which it is added to the original point if it results in an increase in exposure, i.e., when the exposure value is less than 1. The scaling parameter α_{AFM} is set to 0.5, balancing both the pulling efficiency and the potential increase in the gene length of the individual. In AFM, for each gene P_i, we find the sensor s_j^* with the largest exposure to P_i as $s_j^* \leftarrow \arg\max_{j=\overline{1,N}}\{f(s_j, P_i)\}$. The key idea of AFM is that if $f(s_j^*, P_i) < 1$, we can alter P_i to be nearer to s_j^* to improve the solution quality as $P_i \leftarrow P_i + F_{\text{AFM}}(s_j^*, P_i)$, otherwise, P_i stays the same. The number of individuals to mutation is limited by the rate p_{mu} and they are repaired before adding into MIGA's population.

4.3. Selection, local search and termination condition

After applying the crossover and mutation operators, each individual indi is evaluated and assigned a fitness value, denoted as $f(\mathsf{indi})$, which is calculated using the objective function as explained in (6) in the previous section. The population is then sorted in ascending order according to these fitness values. The top $\mathsf{Pop_{size}}$ individuals, those with the largest fitness values, are selected to continue evolving in the subsequent generations. This selection process ensures that the fittest individuals are retained for further optimization.

We also observe that population-based optimization methods like GA, particle swarm optimization (PSO), and differential evolution (DE) may cause their population to fall into the local optimum. Hence, in this paper, after the selection process, MIGA chooses a number of random individuals, denoted as Γ, to perform a local search. To move the individual indi to a neighboring location, we generate a Gaussian vector $\boldsymbol{\nu} \sim \mathcal{N}(\mathbf{0}, \tilde{\sigma}^2\mathbf{I}_m)$, where $\tilde{\sigma}^2$ is a small variance, enabling effective exploration of the neighborhood. For an individual indi, the neighboring individual is generated as $\mathsf{indi}' = \mathsf{indi} + \boldsymbol{\nu}$. In this scenario, indi serves as a potential solution, and its fitness value is subsequently computed. If the fitness value of indi' is superior to that of indi, then indi' is selected and takes the position of indi in the population; otherwise, indi is retained.

MIGA will be terminated if one of the following two criteria is satisfied: (i) The number of generations reaches the specified maximum $G_{\max}$, (ii) the objective function remains unchanged over a predetermined number of generations.

4.4. Complexity and convergence analysis

The complexity of the solution repairing is in the order of $\mathcal{O}(m)$. For each individual, the initialization process also needs $\mathcal{O}(m)$, and therefore, the complexity of MIGA's population initialization in the order of $\mathcal{O}(m\mathsf{Pop_{size}})$. The crossover and local-search operators' complexity are both in the order of $\mathcal{O}(m)$, while the crossover operators' complexity is $\mathcal{O}(mN)$. Hence, in summary, the complexity of MIGA is $\mathcal{O}\left(m\mathsf{Pop_{size}}G_{\max}(\mathsf{p}_{\text{cr}} + \mathsf{p}_{\text{mu}}N + \gamma)\right)$.

We proceed to analyze the convergence of MIGA using probabilistic methods. Over successive generations, the population gradually converges towards an individual with acceptable quality. To begin, for small $\varepsilon > 0$, we define the ε-optimal set for (6) as.

Definition 3. (The ε-optimal set for problem (6)) The ε-optimal set for problem (6), denoted as $\mathbf{S}_\varepsilon^*$, is defined as follows

$$\mathbf{S}_\varepsilon^* = \Big\{\mathcal{P} = \big\{(x_k, y_k)\big\}_{k=0}^{\tau} \in \mathbf{S} \;\Big|\; \mathsf{E}(\mathcal{S}, \mathcal{P}) - \mathsf{E}(\mathcal{S}, \mathcal{P}^*) \leq \varepsilon\Big\}, \tag{9}$$

where $\mathsf{E}(\cdot,\cdot)$ and $\mathbf{S}$ is respectively the objective function and the feasible set of problem (6), $\mathcal{P}^* \in \mathbf{S}$ denotes the global optimum solution and ε is a small positive value.

Following a similar methodology as in [22], for a population $\mathbf{P}$ with $\mathsf{Pop}_{\mathsf{size}}$ individuals, the probability of the population converging to an individual in $\mathbf{S}^*_\varepsilon$ by exploiting MIGA is

$$\mathsf{Pr}\left(\mathbf{P} \cap \mathbf{S}^*_\varepsilon \neq \varnothing\right) \geq 1 - \left(1 - \mu_1 \mathsf{p}_{\mathrm{mu}}\right)^{\mathsf{Pop}_{\mathsf{size}}} \left(1 - \mu_2 \mathsf{p}_{\mathrm{cr}}\right)^{\mathsf{Pop}_{\mathsf{size}}} \left(1 - \mu_3 \left(\frac{1}{\tilde{\sigma}\sqrt{2\pi}}\right)^m e^{\frac{-2m}{\tilde{\sigma}^2}}\right)^\Gamma, \quad (10)$$

where $\mathsf{p}_{\mathrm{mu}}, \mathsf{p}_{\mathrm{cr}} \in [0,1]$ are respectively the mutation probability and the crossover probability of each individual defined in the previous section, μ_1, μ_2, and μ_3 are the measures to the space $\mathbf{S}^*_\varepsilon$ regarding the mutation, the crossover and the local search, respectively, m is the gene length, and Γ as the number of individuals perform local search step in this generation.

This result reveals that MIGA with local search exhibits a higher convergence probability compared to the standard GA. Specifically, it shows that the local search enhances the lower bound of the convergence probability. The probability that none of the individuals in the G-th population after performing reproduction and local search (let $\mathbf{Q}^{(G)}$ denote this population), belong to $\mathbf{S}^*_\varepsilon$ can be expressed as $\mathsf{Pr}\left(\mathbf{Q}^{(G)} \cap \mathbf{S}^*_\varepsilon = \varnothing\right) \leq 1 - \kappa^{(G)}$, where $\kappa^{(G)}$ is defined for the G-th population as

$$\kappa^{(G)} = 1 - \left(1 - \mu_1 \mathsf{p}_{\mathrm{mu}}\right)^{\mathsf{Pop}_{\mathsf{size}}} \left(1 - \mu_2 \mathsf{p}_{\mathrm{cr}}\right)^{\mathsf{Pop}_{\mathsf{size}}} \left(1 - \mu_3 \left(\frac{1}{\tilde{\sigma}\sqrt{2\pi}}\right)^m e^{\frac{-2m}{\tilde{\sigma}^2}}\right)^\Gamma. \quad (11)$$

Given that MIGA utilizes an elitist selection mechanism, the best individual is guaranteed to remain across generations. Consequently, the probability that the population $\mathbf{P}^{(G)}$ does not contain the ε-optimal solution to problem (6) is expressed as

$$\mathsf{Pr}\left(\mathbf{P}^{(G)} \cap \mathcal{S}^*_\varepsilon = \varnothing\right) = \prod_{i=1}^{G-1} \mathsf{Pr}\left(\mathbf{Q}^{(i)} \cap \mathcal{S}^*_\varepsilon = \varnothing\right) \leq \prod_{i=1}^{G-1}\left(1 - \kappa^{(i)}\right). \quad (12)$$

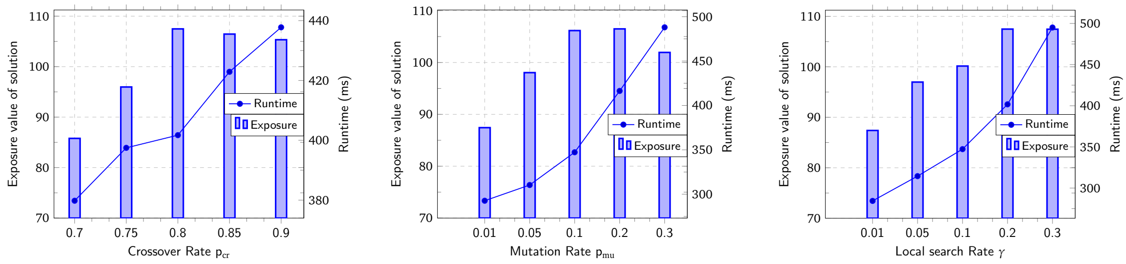
We further observe that $\sum_{G=1}^{\infty} \kappa^{(G)}$ diverges as $G \to \infty$, therefore, we get the following $\lim_{G\to\infty} \prod_{i=1}^{G-1}\left(1 - \kappa^{(i)}\right) = 0$. Consequently, we obtain the following results

$$\lim_{G\to\infty} \mathsf{Pr}\left(\mathbf{P}^{(G)} \cap \mathbf{S}^*_\varepsilon \neq \varnothing\right) = 1 - \lim_{G\to\infty} \mathsf{Pr}\left(\mathbf{P}^{(G)} \cap \mathbf{S}^*_\varepsilon = \varnothing\right) \geq 1 - \lim_{G\to\infty} \prod_{i=1}^{G-1}\left(1 - \kappa^{(i)}\right) = 1. \quad (13)$$

The evaluation in (13) validates MIGA's convergence probability to $\mathbf{S}^*_\varepsilon$ from an initial.

5. NUMERICAL RESULTS

To assess the efficiency and accuracy of the proposed algorithms, a series of experiments were carried out across various experimental scenarios for comparative purposes [23]. These experiments were subjected to thorough evaluations and analyses to derive detailed insights from the resulting data. The numerical computations were performed using Java on a computing system powered by an Intel® Xeon® CPU E5-2660 2.20GHz processor, which includes 16 logical cores (8 physical cores), and 16 GB of RAM. The experiments were conducted within an Ubuntu 18.04.5 LTS operating environment.



(a) (b) (c)

Figure 4: Demonstration of the examination of the optimal crossover rate, mutation rate, and local search rate for MIGA.

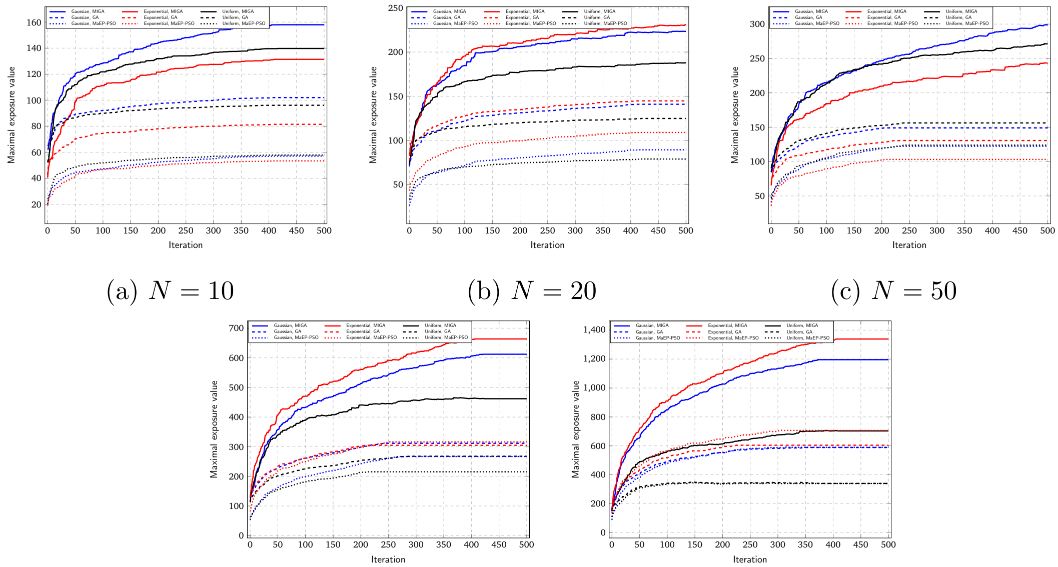
5.1. Experimental settings

We conducted simulations across five distinct network scales, each corresponding to a different number of sensor nodes within the target region. These simulations were organized into five separate datasets. For each network scale, we considered three sensor distributions: uniform, Gaussian, and exponential. For each distribution, ten random instances were generated, labeled as S_n_i, where S represents one of the distributions (UNI for uniform, GAU for Gaussian, EXP for exponential), n indicates the number of sensors in that instance ($n \in \{10, 20, 50, 100, 200\}$), and i denotes the instance index ($i \in \overline{1, 10}$). The sensor field dimensions were specified as $W = 500$ and $H = 100$. The source point, $B(0, y_B)$, and the destination point, $D(100, y_D)$, were defined with y_B and y_D values drawn from $\mathcal{U}(0, W)$, meaning they were uniformly sampled from the interval $[0, W]$. The maximum feasible path length was drawn from $\mathcal{U}(d(B, D), 2d(B, D))$. The intruder's velocity, V_I, was set at 5, and the time step Δt, used to approximate the exposure of the solution path, was set to 0.1.

5.2. Evaluating the best parameters for the proposed algorithm

To identify and fine-tune the best parameters for the proposed algorithm, MIGA, inspired by evolutionary algorithms, extensive experiments were conducted. Observations in Figure 4 highlight that MIGA is particularly sensitive to certain hyperparameters, such as the crossover and mutation rates. To determine the optimal parameters, we evaluated MIGA's performance on networks covered by 50 sensors. With a population size of 200 individuals evolving over 500 generations and a gene length of $m = 1000$, we tested crossover rates in $\{0.7, 0.75, 0.8, 0.85, 0.9\}$ and both mutation and local search rates in $\{0.01, 0.05, 0.1, 0.2, 0.3\}$. Each parameter directly impacts the exposure value of the solution, which reflects its quality, as well as the runtime, indicating the computational effort required.

For the crossover rate ($\mathsf{p}_{\rm cr}$), Figure 4a shows that higher values generally improve exposure by enhancing genetic material exchange, promoting convergence. However, increased $\mathsf{p}_{\rm cr}$ raises runtime due to the computational cost of evaluating complex offspring. The optimal rate, $\mathsf{p}_{\rm cr} = 0.8$, balances high exposure and manageable runtime. Figure 4b illustrates that the mutation rate ($\mathsf{p}_{\rm mu}$) affects solution quality and runtime. While mutation prevents premature convergence by introducing diversity, excessive values cause stochastic behavior and inefficiency. The optimal rate, $\mathsf{p}_{\rm mu} = 0.1$, ensures exploration while maintaining effi-



(a) $N = 10$ (b) $N = 20$ (c) $N = 50$

(d) $N = 100$ (e) $N = 200$

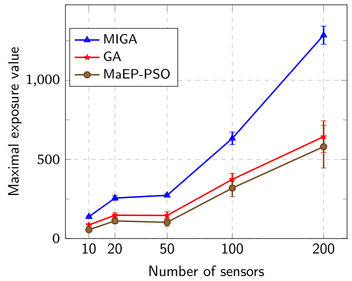
Figure 5: Demonstration of the convergence of MIEA, the standard GA for real variables [24] and MaEP [10] across different instances with varying sensor counts and distributions.

ciency. The local search rate (γ) refines solutions, improving exposure at the cost of higher runtime, as shown in Figure 4c. The optimal value, $\gamma = 0.2$, achieves a trade-off between performance and computational cost. The selected parameters, $\mathsf{p}_{\text{cr}} = 0.8$, $\mathsf{p}_{\text{mu}} = 0.1$, and $\gamma = 0.2$, ensure MIGA efficiently balances exploration and exploitation. These values enable a careful balance between exploration (via crossover and mutation) and exploitation (via local search and mutation), allowing the algorithm to navigate the solution space effectively.

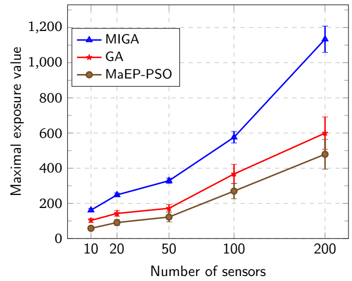
5.3. Performance of MIGA through various network topologies

5.3.1. Comparison of the convergence of MIGA with previous algorithms

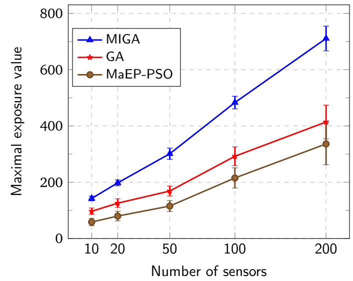
Many parameters affect the convergence speed for the MaEP problem, such as the sensor count, distributed sensors, generations/iterations, and so on. Based on observations from Figure 5, we can explain the obtained results regarding convergence speed, solution quality, and stability. As the sensor count increases from 10 to 100, convergence speed generally decreases due to the growing complexity of the problem space. When there are 10 sensors, all algorithms converge quickly, with MIGA variants achieving the highest exposure. At 20 and 50 sensors, convergence slows compared to 10 sensors, but MIGA variants still outperform other algorithms. At 100 and 200 sensors, convergence becomes significantly slower, and while MIGA variants continue to outperform, the performance gap narrows. Sensor position distributions also affect performance. A uniform distribution allows broader exploration, helping GA achieve optimal solutions faster. The exponential distribution, while less varied, still enables relatively fast convergence. In contrast, the Gaussian distribution, where values are concentrated around the mean, may limit the GA's ability to explore the solution space effectively, leading to slower convergence. The results indicate that sensor value distribution



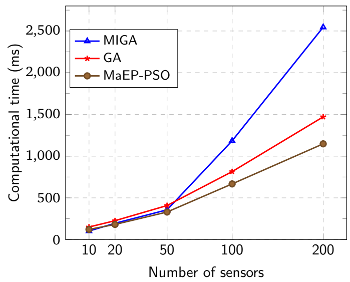
(a) Exposure, EXP distribution



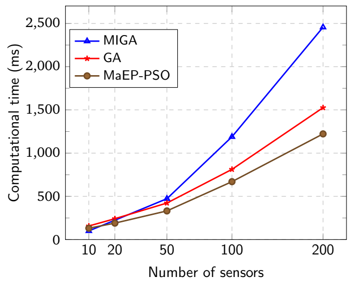
(b) Exposure, GAU distribution



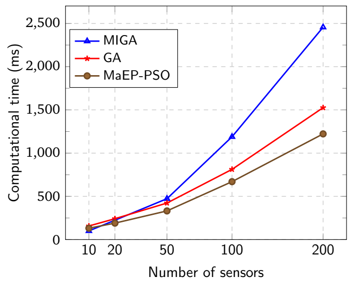
(c) Exposure, UNI distribution



(d) Runtime, EXP distribution



(e) Runtime, GAU distribution



(f) Runtime, UNI distribution

Figure 6: Illustration of the results obtained by MIGA, GA, MaEP-PSO under different distribution network topologies.

significantly impacts both convergence speed and maximum exposure. Uniform distributions generally lead to faster convergence than Gaussian and exponential distributions, as their broader range facilitates better exploration. However, they also tend to produce lower maximum exposure values. Overall, the results shown in Figure 5 demonstrate that the MIGA generally outperforms the standard GA [24] and MaEP-PSO [10] variants regarding convergence speed and maximum exposure value. This is likely due to MIGA's ability to explore the solution space more efficiently by utilizing sophisticated evolution operators.

5.3.2. The solution quality and stability of MIGA against prior algorithms

In terms of solution quality or the achieved maximum exposure value, the number of sensors is a key factor that impacts the solution. Moreover, computational time serves as an important metric for assessing the performance of algorithms.

From observation, Figure 6a shows the solution quality and stability of MIGA, GA, MaEP-PSO. Regarding solution quality, MIGA shows the highest maximal exposure value among the four algorithms across different numbers of sensors. This indicates that MIGA consistently provides the best solution in terms of maximizing exposure. While not as high as MIGA, GA still demonstrates relatively good performance. It is consistently better than MaEP-PSO, especially when the number of sensors is low. MaEP-PSO exhibits a lower maximal exposure value compared to MIGA and GA, particularly for larger numbers of sensors. Regarding stability 6a, the error bars for MIGA are generally smaller than those of other algorithms, indicating that it produces more consistent results across multiple runs.

This suggests that MIGA is more stable. GA shows moderate stability. The error bars are larger than those of MIGA but smaller than those of MaEP-PSO, suggesting that it has a reasonable level of stability. MaEP-PSO has larger error bars than MIGA and GA, indicating that it produces less consistent results. This suggests that MaEP-PSO is less stable. Figure 6d illustrates the computational time for MIGA, GA, and MaEP-PSO. Among the three algorithms, MIGA consistently takes the longest computational time, making it the most resource-intensive. GA exhibits a moderate computational time, generally lower than MIGA but higher than MaEP-PSO, particularly as the number of sensors increases. In contrast, MaEP-PSO consistently shows the shortest computational time, making it the most computationally efficient. In general, as shown in Figure 6d, MaEP-PSO is the most efficient algorithm, requiring the least time across different sensor configurations. MIGA, however, proves to be the least efficient, taking considerably more time than both GA and MaEP-PSO. In conclusion, if computational efficiency is the primary concern, MaEP-PSO is the preferred choice. However, if solution quality is the most important factor, the additional computational time of MIGA may be justified by its superior performance.

Figure 6b shows the maximal exposure values for different sensor counts in Gaussian-distributed networks. MIGA consistently achieves the highest exposure values, demonstrating its superiority in solution quality. GA performs well, surpassing MaEP-PSO, especially with fewer sensors. MaEP-PSO shows the lowest maximal exposure values, particularly for larger sensor networks. In terms of stability, MIGA has the smallest error bars, indicating consistent performance across multiple runs. GA exhibits moderate stability, with error bars larger than MIGA but smaller than MaEP-PSO. MaEP-PSO is the least stable, with the largest error bars, reflecting higher variability in results. Overall, MIGA proves to be the most reliable and robust algorithm. Figure 6e presents the computational time analysis. MIGA requires the longest runtime, making it the most computationally expensive algorithm. GA has moderate runtime, lower than MIGA but higher than MaEP-PSO, especially for larger sensor counts. MaEP-PSO is the most efficient, consistently requiring the least computational time. In summary, for optimal solution quality, MIGA's additional computational cost is justified by its superior exposure values and stability.

Figure 6c illustrates that MIGA consistently achieves the highest maximum exposure values across different sensor counts in uniformly distributed networks. This confirms that MIGA is the most effective algorithm for maximizing exposure in this distribution. Compared to other methods, MIGA not only provides superior coverage but also demonstrates remarkable consistency. The error bars for MIGA remain consistently small, indicating that it produces highly stable results across multiple runs. This stability suggests that MIGA is less susceptible to variations in sensor placements, making it a robust choice for uniform distributions. In contrast, the computational time analysis in Figure 6f reveals that MIGA is the most resource-intensive among the evaluated algorithms. Despite this, the trade-off between computational time and solution quality is well justified, as MIGA consistently outperforms alternative methods in achieving the highest exposure values while maintaining reliability. Overall, MIGA emerges as the most effective approach in uniform sensor distributions. It not only maximizes exposure but also ensures stable and reliable performance across different scenarios. While its computational cost is higher, the significant improvement in coverage quality makes it the preferred choice for applications prioritizing robust intrusion detection and monitoring.

Table 1: The maximal exposure value, the standard deviation, and the average running time for 30 independent runs of MIGA, standard GA and MaEP-PSO (PSO).

Topology	**Best exposure value**			**Std. dev. (%)**			**Running time (ms)**		
	MIGA	GA	PSO	MIGA	GA	PSO	MIGA	GA	PSO
GAU10	**161.45**	103.16	58.19	**5.75**	10.46	16.64	**100.41**	157.10	131.57
GAU20	**248.24**	142.84	90.99	**4.45**	11.60	18.61	224.00	241.31	**190.27**
GAU50	**328.83**	172.03	122.38	**4.48**	12.48	22.46	472.80	422.64	**331.52**
GAU100	**576.02**	367.28	269.75	**5.66**	14.83	16.22	1189.17	812.12	**669.90**
GAU200	**1133.74**	599.47	479.25	**6.57**	15.30	17.67	2456.26	1525.74	**1222.36**
UNI10	**142.38**	96.99	58.70	**5.91**	12.14	22.30	**83.44**	161.70	127.44
UNI20	**197.84**	125.80	79.84	**5.30**	12.35	21.35	**149.73**	224.82	185.57
UNI50	**301.41**	168.93	115.43	**6.63**	10.44	16.79	452.50	412.12	**328.66**
UNI100	**483.21**	292.47	215.28	**4.66**	11.44	16.66	1013.53	795.57	**631.88**
UNI200	**710.89**	414.23	336.15	**6.19**	14.45	21.92	2249.59	1416.60	**1121.49**
EXP10	**137.90**	85.65	55.51	**4.02**	10.87	17.62	**102.41**	150.42	121.59
EXP20	**255.83**	147.36	111.44	**5.76**	10.28	15.22	195.44	226.43	**181.53**
EXP50	**273.20**	145.93	102.37	**4.28**	16.13	24.15	356.67	407.94	**330.39**
EXP100	**633.12**	373.87	318.91	**6.28**	10.30	17.19	1183.63	814.39	**667.20**
EXP200	**1285.33**	643.76	580.27	**4.46**	15.53	23.18	2545.15	1470.82	**1147.50**

Table 1 compares the performance of three algorithms—MIGA, standard GA and MaEP-PSO across various network topologies (GAU, UNI, EXP) of increasing size (10 to 200 sensor nodes). The results highlight MIGA's superior ability to maintain diversity during the search process, as evidenced by its consistently lower standard deviations across various network topologies and sizes. A low standard deviation indicates that MIGA consistently finds solutions close to the best solution across multiple runs, demonstrating robust exploration of the search space and reduced susceptibility to getting stuck in local optima. In contrast, standard GA and MaEP-PSO exhibit significantly higher standard deviations, indicating reduced diversity, less consistent performance, and a higher likelihood of premature convergence. Although the standard deviations increase with larger problem sizes across all algorithms, MIGA maintains a clear advantage, reflecting its ability to handle the increasing complexity of larger search spaces effectively. The diversity of MIGA, as implicitly captured through convergence behavior and stability across 30 runs, is a key factor behind its ability to achieve better and more reliable solutions compared to GA and PSO.

6. CONCLUSIONS

In conclusion, this paper has presented a highly efficient method called MIGA to solve the challenging MaEP problem in HeDWSNs, specifically focusing on finding the best coverage path. The quest for an optimal coverage path in sensor networks is crucial for a wide range of applications, including environmental monitoring, surveillance, and more. By leveraging the inherent strengths of GAs, we achieved a balance between exploration and exploitation, allowing our algorithm to efficiently search for near-optimal paths while enhancing both network performance and energy efficiency—two critical factors in the context of sensor networks. Through extensive experimentation and evaluation, we demonstrated the superiority of our improved GA-based approach in delivering high-quality solutions for the MaEP problem. While MIGA shows promising results, several limitations remain. The algorithm may face scalability issues in large networks due to increased computational costs.

Additionally, MIGA assumes a static and secure network topology, so incorporating adaptability would improve its robustness. Lastly, although the local search operator has the potential to enhance the probability of escaping local optimum traps, the risk of convergence to local optima is still a challenge in GA-based approaches. Addressing these limitations would further improve the algorithm's effectiveness and scalability in real-world sensor network applications and represent a potential direction for future research to meet evolving requirements in emerging applications.

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Received on November 13, 2024
Accepted on February 24, 2025