An Efficient Method for Solving the Best Coverage Path Problem in Homogeneous Wireless Ad-Hoc Sensor Networks

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Abstract. Barrier coverage is a well-established model within the domain of Wireless Ad-hoc Sensor Networks (WASNs), which finds substantial utility in numerous military and security applications within the Internet of Things (IoT). It is particularly pertinent for monitoring and detecting objects in motion across the sensing field. This research paper delves into the central aspect of barrier coverage within WASNs, with a specific focus on the maximal exposure path (MaEP) problem, a problem proven to be NP-Hard. The MaEP problem entails the pursuit of an optimal coverage path that either conserves energy or minimizes energy consumption while maintaining a short traversal distance. Prior studies in this domain predominantly relied on problem formulations based solely on Euclidean distance metrics, often addressed through computational geometry methodologies. However, this approach encounters significant challenges in scenarios characterized by large-scale, intricate, and highly sophisticated WASNs. To surmount this limitation, our research first casts the MaEP problem within the framework of the integral of sensing field intensity. Subsequently, we introduce a modified particle-swarm-optimization-based algorithm denoted as MaEP-PSO, meticulously designed to efficiently address the MaEP problem. To gauge the efficacy of this proposed algorithm, we conduct an extensive series of experiments and present comprehensive experimental results.

Keywords: Wireless Ad-hoc Sensor Networks · barrier coverage · Best coverage path · Maximal exposure path

1 Introduction

Coverage within wireless Ad-hoc sensor networks (WASNs) or Wireless Sensor Networks (WSNs) represents a fundamental and integral aspect that characterizes the network's capability and effectiveness in monitoring its designated sensing field. Generally, coverage is widely regarded as a critical metric for assessing the quality of service provided by WSNs. The choice of specific coverage metrics may vary across different ad-hoc network scenarios, contingent upon the intended objectives of the network model. Within the realm of WSNs, barrier coverage (BC) holds a prominent position as a well-established model, primarily applied in the domains of surveillance and intrusion

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detection. The central goal of BC is to efficiently monitor and detect the movement of objects traversing through the WSN. This essentially necessitates that the WSN maintains a high quality of service, as indicated by the degree of coverage it provides.

Recently, the academic community has extensively explored various methodologies aimed at assessing the quality of coverage of WSNs. Among these metrics, exposure has emerged as a particularly efficient and effective measurement for evaluating the level of coverage or the overall quality of service provided by WSNs [2,5,9,10,13]. Exposure exhibits a direct proportionality to the degree of coverage, signifying that higher exposure corresponds to improved coverage. This metric, exposure, occupies a central role in the domain of WASNs [7,11,12]. This research specifically concentrates on the exploration of penetration paths, a significant subdomain within the broader context of barrier coverage. More precisely, it delves into the quest for an optimal coverage path known as the Best-Case Coverage Path (BCCP) within WSNs. The BCCP framework pertains to the analysis of coverage concerning the trajectories traversed by mobile agents, including entities such as robots or human operators. In the pursuit of collecting information as they traverse the defined area, these mobile agents possess the capability to interact with sensor nodes. This interaction serves various purposes, encompassing data transmission and the reception of new tasks. Consequently, it becomes highly desirable for these mobile agents to maintain close spatial proximity to the sensor nodes during their movement within the field. This strategic proximity optimization plays a pivotal role in enhancing operational efficiency, primarily by minimizing factors such as power consumption.

The BCCP can be formulated in various ways, such as through a Maximal Support Path (MSP) or a Maximal Exposure Path (MaEP) [6]. While an MSP was defined as a path that minimizes the maximum distance between any point on the path and the sensor nodes, the MaEP between a source position and a destination position was a path in the sensor connecting the two points such that the exposure received from traveling the path is maximal [14]. The work in [6] had proved that MaEP belongs to NP-Hard problem. We are the first defining a MaEP as the integral of an intensity function. Efficient resolution of the BCCP problem can yield substantial advantages, as it finds applicability in several intrinsic applications. These applications often address queries related to optimizing data harvesting and deriving maximum benefits from WSNs while traversing the sensing field. For instance, consider the scenario of a light-detecting network. In this context, imagine a solar-powered autonomous robot navigating the network with the goal of accumulating the most light within a specified time frame. By utilizing the BCCP of the light-detecting network, the solar-powered robot can maximize its light intake during the allotted time. Consequently, the BCCP holds considerable importance for a user aiming to maximize the benefits or detection capabilities of the network.

In light of these considerations, this paper directs its attention to the MaEP problem in homogeneous wireless sensor networks known as MaEP-HWSN. Notably, the MaEP is a NP-Hard problem, and must incorporate a maximum length constraint or a delay constraint to specify the duration for which an object can remain within the sensor field. Without such constraints, an object could potentially perpetually travel without reaching its destination or indefinitely linger at a point with positive exposure, thereby accumulating infinite coverage. Therefore, we propose an efficient nature inspired meta-heuristic algorithm for solving the MaEP, called MaEP-PSO (MaEP- Particle Swarm Optimization). The nature inspired meta-heuristic algorithms can surmount a lot of optimization problems in various fields such as [1–5, 10, 13].

The main contributions of this paper are as follows:

– Formulate the maximal exposure path problem in homogenous wireless sensor networks under the Boolean sensing and the attenuated sensing model.
– Proffer an efficient strategy named MaEP-PSO for solving the considered problem.
– Conduct various experimental scenarios to examine the proposed algorithms and compare the proposed method to state-of-the-art. Analyze the results and give some insights into the performance obtained by the proposed algorithm.

The rest of the paper is organized as follows. Section 2 presents Related works. Preliminaries and formulation for the MaEP problem are discussed in Sect. 3. Section 4 introduces the proposed algorithms. Experimental results are given and analyzed in Sect. 5. Finally, the conclusions of the paper are presented in Sect. 6.

2 Related Works

This section provides a succinct overview of pertinent research concerning the barrier coverage problem in WSNs, with particular emphasis on the MaEP problem, which holds significant relevance in numerous practical applications. Barrier coverage problems within Wireless Ad-hoc Sensor Networks (WASN) can be broadly categorized into two distinct domains: constructing intrusion barriers and identifying penetration paths [15]. Notably, the exploration of penetration paths represents a highly dynamic and captivating research area within this field [1–3, 5, 8–10, 14].

Veltri et al. were the pioneers in introducing the MaEP concept in their work [14]. Notably, they established the NP-Hard nature of the MaEP problem. Subsequently, the authors proposed a localized approximation algorithm to address this challenge, leading to the generation of approximate solutions. In the study conducted by Megerian et al. [8], attention was directed towards both the worst and best-case coverage problems within sensor networks. In the context of the best-case coverage problem, the authors introduced the notion of a support concept to formalize the Best-Case Support-Based Coverage Problem. They then devised a computational approach, employing techniques from computational geometry and graph theory, particularly the Delaunay triangulation and graph search algorithms, to address this problem. Furthermore, in a separate study by Binh et al. [1], the focus was placed on the Maximal Breach Path, specifically catering to the safety considerations related to intruders attempting to penetrate the network, corresponding to the worst-case coverage scenario. In response to this challenge, the authors developed a heuristic algorithm aimed at effectively resolving the Maximal Breach Path problem.

The literature presented in [2, 3, 5, 9, 10] has extensively explored the domain of the worst-case coverage path, which is inherently associated with the concept of the Minimal Exposure Path (MEP). These studies have approached this problem from various angles, incorporating different sensing models, varying environmental assumptions, and other relevant factors. Subsequently, they have introduced efficient algorithms designed to address these challenges effectively. The authors in [10,13] specifically directed their attention toward the Minimal Exposure Path problem within wireless mobile sensor networks, denoted as MMEP. Initially, they formalized the MMEP problem, subsequently transforming it into a high-dimensional numerical-functional optimization problem characterized by non-differentiation and non-linearity. To contend with these inherent characteristics, the authors proposed the HPSO-MMEP algorithm. This algorithm draws inspiration from natural evolutionary processes, blending principles from genetic algorithms and particle swarm optimization techniques.

In the research conducted by Binh et al. [2], the authors embarked upon the formulation of the MEP problem within the framework of the Probabilistic Coverage Model, incorporating noise considerations. In this context, they introduced a novel definition for the exposure measurement specific to this model. Subsequently, they transformed this problem into a numerical functional optimization challenge. To effectively address these characteristics, the authors devised two approximation methods tailored to solving the modified problem. In their work presented in [5], the research focus shifted towards a systematic and comprehensive investigation of the MEP problem under real-world network environments, taking into account the presence of obstacles. The authors introduced an algorithm designed to construct arbitrary-shaped obstacles within the deployment area of WSNs. They proposed an elite algorithm, namely the Family System-based Evolutionary Algorithm, which incorporates innovative concepts related to the Family System. This algorithm was specifically developed to efficiently tackle the challenges posed by their problem domain. Furthermore, they extended the capabilities of a custom-made simulation environment to incorporate a diverse range of network topologies and obstacle configurations.

After conducting an exhaustive review of references pertaining to the BCCP problem, it becomes evident that a significant portion of prior research has primarily concentrated on addressing the MSP problem. These approaches typically leverage computational geometry methodologies such as the Voronoi Diagram and Delaunay Triangulation to convert the continuous geometric search space of the problem into a discrete graph problem. Nevertheless, it is noteworthy that computational geometry-based algorithms tend to centralize their computations, whereas MSP problems inherently involve distributed elements. Moreover, it is imperative to recognize that the BCCP problem has been formally classified within the category of NP-Hard problems. Consequently, there exists an opportunity to enhance the quality of solutions generated through previous research endeavors. Consequently, the primary focus of this paper shifts towards addressing the MaEP within homogeneous WSNs.

3 Preliminaries and Problem Formulation

3.1 Preliminaries on the Sensing Model and Exposure of a Crossing Path

The Attenuated Disk Sensing Model.
The sensing model characterizes the sensing or coverage capability of a sensor node concerning points or objects. There exist several types of sensing models, and a common feature among most of them is that the sensing quality or intensity of a sensor diminishes as the distance from the sensor node increases. In such instances, it becomes

feasible to disregard the coverage measure and practical approximations can be derived by truncating the coverage measure for greater distances. One of the most elementary models introduced in this context is the Boolean disk sensing model, which defines its sensing function as follows:

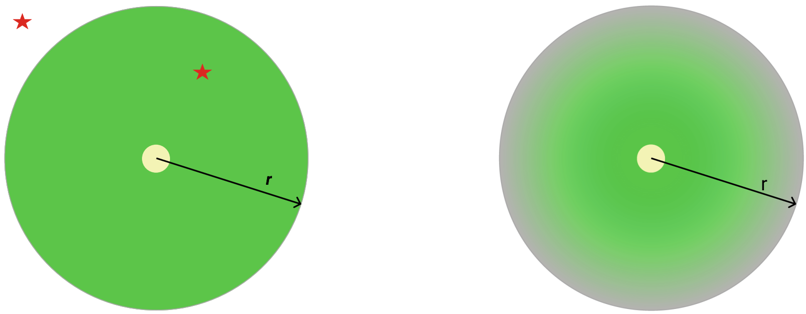
$$f(s_i, l) = \begin{cases} 1 & \text{if } d(s_i, l) \leq r \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where s_i represents the position of the sensor, l denotes the location under consideration, and $d(s_i, l)$ signifies the Euclidean distance between them. Additionally, r is used to denote the sensing range of the sensor. Figure 1a visually illustrates the Boolean disk coverage model.

This paper, however, delves into a more precise and extensively employed sensing model recognized as the "attenuated disk sensing model". The mathematical expression characterizing the sensing function $f(s_i, l)$ for the attenuated disk model is as follows:

$$f(s_i, l) = \min\left\{1, \frac{C}{d^{\lambda}(s_i, l)}\right\} \tag{2}$$

where C is a constant depending on the essence of a sensor, λ is the attenuation exponent, which depends both on the sensor and the environment. An illustration of this sensing model can be found in Fig. 1b.



(a) The Boolean disk sensing model.

(b) The attenuated disk sensing model.

Fig. 1. Illustration of sensing models

We will now examine the capability to concurrently sense or cover multiple sensor nodes at a specific point within their sensing field, a concept commonly referred to as "the sensing intensity model". Within a WASN, each sensor node is endowed with a maximum transmission power, enabling it to communicate with all nodes residing within its transmission range. Consequently, in a WASN comprising a set of sensor nodes $S = \{s_1, \ldots, s_N\}$, the cumulative exposure of an object within the sensing field, or at any given point within the sensor field, can be defined as the summation of all individual exposure values, expressed as follows:

$$I(S,l) = \sum_{i=1}^{N} f(d(s_i,l)) \tag{3}$$

Exposure of a Crossing Path and the Maximal Exposure Path
Exposure refers to the sensor network's capability to detect an object as it traverses the sensing field. It can be informally described as the anticipated, mean capability to observe a target within the sensor field. To provide a more formal definition, exposure can be expressed as the integral of a sensing function, typically contingent on the distance from sensors along a path originating from a beginning point denoted as B and extending to a destination point designated as D.

Consider two points, denoted as $B = (x_B, y_B)$ and $D = (x_D, y_D)$, situated within a two-dimensional sensor field. A path connecting these points is conceptualized as a continuous function, represented as $P(t) = (x(t), y(t))$, subject to the boundary conditions $x(0) = x_B$, $x(T) = x_D$, $y(0) = y_B$, and $y(T) = y_D$. The exposure along this path can be defined as the cumulative exposure experienced by the sensor network as an object traverses this path. This cumulative exposure can be expressed as follows:

$$E(f(S,(x(t),y(t)))) = \int_{0}^{T} I(S,(x(t),y(t)))\sqrt{\left(\frac{dx(t)}{dt}\right)^2 + \left(\frac{dy(t)}{dt}\right)^2}\,dt \tag{4}$$

$$\approx \sum_{k=0}^{\lfloor T/\Delta t \rfloor} \sum_{i=1}^{N} f\left(s_i, P(k\cdot\Delta t)\right)\Delta t \tag{5}$$

where $I(S,(x(t),y(t)))$ represents the exposure incurred by the sensor network S at the point $(x(t),y(t))$, as computed through Eq. (3) and Δt is sufficiently small.

The maximal exposure path is formally defined within a sensor network as a path connecting two predetermined points within the sensor field, distinguished by exhibiting the greatest exposure, as specified in Eq. (4). It is worth noting that, with increasing path length, there is a higher likelihood of achieving a greater exposure value. Consequently, in the context of maximal exposure paths, there exists a length constraint, wherein the length of these paths must not surpass a predefined acceptable threshold.

3.2 Problem Formulation

In the context of a WASN comprising N homogeneous sensors deployed randomly, denoted as $S = s_1, s_2, ..., s_N$, situated within a region of interest Ω with dimensions $W \times H$ and governed by an exposure model, we consider an intruder's trajectory within this monitored region. The intruder commences its journey at a starting point $B(x_B = 0, y_B)$ and concludes it at an ending point $D(x_D = H, y_D)$, characterized by a constant velocity V_I. The concept of the "maximal exposure path" between the starting location B and the ending location D refers to a specific path within the sensor network that connects these two points. Importantly, this path is selected to maximize the exposure

received as the target traverses it. This problem of finding the above-mentioned path is named MaEP (Maximal Exposure Path in Homogeneous Wireless Ad-hoc Sensor Networks). More precisely, this problem is formulated as follows.
Input

- W, H: the width and the length of the sensing field Ω.
- N: the number of homogeneous sensors
- $S = \{s_i = \langle(x_i, y_i)\rangle\}_{i=1}^{N}$: the set of sensors in the field.
- V_I: the speed of intruder.
- $(x_B, y_B); (x_D, y_D)$: the coordinates of the source point B and destination point D.
- ℓ: the maximum length of the crossing path.

Output: A path $\mathcal{P} : [0, T] \to [0, H] \times [0, W]$ in region Ω connecting B and D.
Objective: The exposure of path $\mathcal{P}$ is maximized, which means:

$$\sum_{k=0}^{\lfloor T/\Delta t \rfloor - 1} \sum_{i=1}^{N} \min\left\{1, \frac{C}{d^{\lambda}(s_i, \mathcal{P}(k \cdot \Delta t))}\right\} \Delta t \to \max \tag{6}$$

Constrains: There is a maximum length ℓ constraint on the maximal exposure path so the object cannot keep on moving in the sensor field to accumulate infinite exposure.

4 Proposed Algorithm

PSO Algorithm is an intelligent way of solving tricky problems by mimicking how creatures work together. This section describes an efficient particle-swarm-optimization-based algorithm named MaEP-PSO to solve the considered MaEP problem with a flowchart demonstrated in Fig. 2. In MaEP-PSO, a particle (individual) represents a feasible solution for the MaEP problem and can be depicted as an ordered sequence of contiguous points, commencing at the source point denoted as B and concluding at the destination point denoted as D. These points are commonly referred to as the genes of the individual. The number of genes within an individual in MaEP-PSO is predetermined and set by a parameter denoted as m. Figure 3 illustrates the path derived from an individual, which includes a sequence of six points, namely $P_1, \ldots, P_6$, connected in the specified order. According to the problem, the individual must also satisfy the constraint of maximum length.

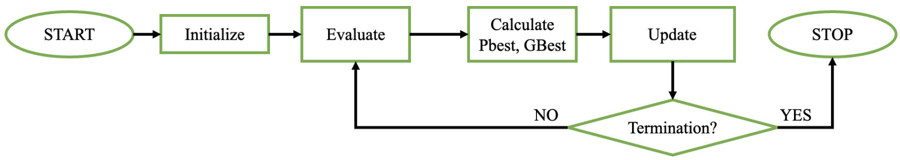


Fig. 2. The flowchart of the proposed algorithm MaEP-PSO.

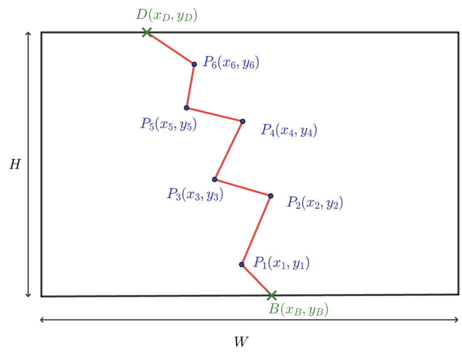


Fig. 3. Illustration of individual.

To initialize individuals in MaEP-PSO, first, the field is partitioned equally into m segments, each having a height of H/m. Then, $m-1$ points $P_1, P_2, .., P_{m-1}$ is randomly generated where the point P_i has its x-coordinate is $i * H/m$ and its y-coordinate is a random real number in range $[0, W]$. An individual is created with each of its genes are the intersecting points of the line $(0, y_B), P_1, P_2, .., P_{m-1}, (0, y_D)$ and the line $x = j\Delta x$ where $j = 0...n$. The number of individuals in the population is limited by the population size $\mathsf{P_s}$. The pseudo-code of the above initialization method is described in Algorithm 1.

The update of velocity and location vectors, which have m dimensions corresponding to m points, in MaEP-PSO are described as follows:
The velocity of the i-th particle at the time $t+1$ is calculated by:

$$v_i(t+1) = \omega v_i(t) + c_1 r_1 (Pbest(t) - u_i(t)) + c_2 r_2 (Gbest(t) - u_i(t)) \tag{7}$$

where, $v_i(t)$ is the velocity vector of the i-th individual at the time i; $u_i(t)$ is the location vector of the i-th particle in the search space at the time i; $Pbest_i(t)$ is the best position that the particle had achieved until the time i; $Gbest(t)$ is the best position that the particle in the swarm system that had achieved until the time i; r_1, r_2 are random numbers between $(0, 1)$ and generated at each iteration randomly for each particle; ω, c_1, c_2 are constants, in which ω is consider as inertial, and c_1, c_2 called acceleration coefficient.

Algorithm 1: MaEP-PSO individual initialization

Input:

- The size of Ω: W, H, the beginning and destination point B, D
- The scale unit: Δx
- The number of segments: m

Output:
An individual $indi = (y_B, y_1, ..., y_{m-1}, y_E)$,

```
begin
    y ← y_B ; k ← (H/m) ;
    for i := 1 to m − 1 do
        ys ← random(0, W); yi ← (ys − y)/k;
        for j := 1 to k − 1 do
            indi ← indi ∪ y ;
            y ← y + yi ;
        end
    end
    indi ← indi ∪ y_E
end
```

The pseudo-code for MaEP-PSO is described as follows:

Algorithm 2: MaEP Evolutionary Operations

Input:

- Population Pop
- Personal best and velocity of each individual

Output: Next generation's population Pop'

```
begin
    gBest = findBestIndividual(Pop);
    foreach p ∈ Pop do
        Calculate the acceleration c_i^t;
        Generate random r_1, r_2 ;
        Update the velocity and location of the individuals;
    end
end
```

5 Numerical Results

In order to validate the efficiency and precision of the proposed algorithms, a series of experiments were conducted, encompassing diverse experimental scenarios, for the purpose of comparison. These experiments underwent comprehensive evaluations and analyses to provide thorough insights into the resulting data. The numerical computations were executed using Java on a computing system equipped with an Intel®

Xeon® CPU E5-2660 2.20GHz processor, featuring 16 logical cores (comprising 8 physical cores), and 16 GB of RAM. The operating environment for these experiments was Ubuntu 18.04.5 LTS.

5.1 Parameters Settings

We conducted simulations encompassing a total of five distinct topologies, each aligned with varying numbers of sensor nodes within the region of interest. These simulations were organized into five separate datasets.

For each topology, we generate ten random instances denoted as S_n_i, where n signifies the number of sensors in that particular instance ($n \in \{10, 20, 50, 100, 200\}$), and i denotes the instance index ($i \in \overline{1, 10}$). The sensor nodes within these datasets are uniformly and randomly deployed across the sensor field denoted as Ω. The dimensions of the sensor field are specified as $W = 500$ and $H = 100$. The source point is defined as $B(0, y_B)$, and the destination point is labeled as $D(100, y_D)$. The values of y_B and y_D are drawn from $\mathcal{U}(0, W)$, signifying that they are sampled uniformly from the interval $[0, W]$. The maximum length of a feasible path is drawn from $\mathcal{U}(d(B, D), 2d(B, D))$. The intruder's velocity, denoted as V_I, is assigned a value of 5. The value of Δt to approximately compute the exposure of the solution path is set as 0.1.

Table 1. The parameters for MaEP-PSO.

Parameter	Value
Number of generations	200
The population size	5000
Parameters c_1, c_2, ω	$c_1 = 0.5$, $c_2 = 2$, $\omega = 0.3$
Parameter m	50000

5.2 Experimental Result

In order to establish the accuracy and reliability of both our proposed model and algorithm, a comprehensive series of experiments has been conducted. Table 1 succinctly presents the optimal parameters meticulously determined for our MaEP-PSO algorithm, as ascertained through a rigorous array of experimental trials. Given the inherent non-deterministic nature of our proposed algorithm MaEP-PSO, it was executed 30 times on each instance, and the results are reported based on the calculated averages.

As discussed in the literature review, the BCCP problem has been the subject of investigation in prior research, often framed as the Maximal Support Path and typically addressed using Delaunay triangulation methodologies. To ensure an equitable and unbiased evaluation, adjustments were made to facilitate direct comparison between our proposed algorithm and the Adjusted Best-Point Heuristic (ABPH) methods, as outlined in [14]. Additionally, comparisons were drawn with the Minimum Spanning Trees (MST) algorithm, as delineated in [6].

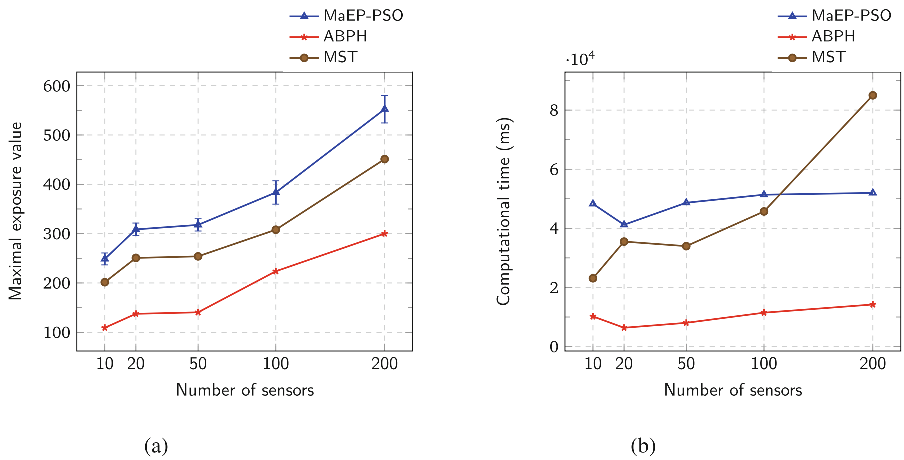


Fig. 4. Comparison between our proposed MaEP-PSO with the previous literature's approaches, i.e. ABPH [14] and MST [6]: (a) with respect to exposure value; (b) with respect to computational time (ms). The results are reported on average.

The results from the experiment depicted in Fig. 4 reveal the following findings:

- Regarding the quality of the solutions, Fig. 4a illustrates the maximal exposure values acquired by three algorithms while varying the number of sensors from 10 to 200. An observation of the results indicates that MaEP-PSO consistently outperforms both ABPH and MST in terms of maximal exposure values. This observation strongly suggests that our proposed algorithm is superior in terms of solution quality. This outcome aligns with expectations as the MaEP-PSO algorithm employs a diverse and intricate set of operators, contributing to its enhanced performance.
- Concerning computational time, Fig. 4b presents a graphical representation of the computation times for each algorithm. Evidently, the ABPH algorithm exhibits the shortest running times across all instances. However, it is notable that MaEP-PSO necessitates more time for computation than MST in the case of small-scale

instances, where the number of sensors varies from 10 to 100. Conversely, for large-scale instances, where the number of sensors exceeds 100, MST requires a longer computation time compared to MaEP-PSO.

Table 2 provides a comprehensive overview of essential metrics, including the best maximal exposure values, the average maximal exposure value, standard deviation, and running time, derived from 30 iterations of our proposed MaEP algorithm. Upon careful examination, it becomes apparent that there exists a proportional relationship between the number of deployed sensors in the region of interest and both the average maximal exposure value and the running time, as well as the best maximal exposure value. This observation signifies that an increased number of sensors in the deployment area yields larger maximal exposure values. Such results align with theoretical expectations, as a higher exposure value corresponds to a more efficient sensor network deployment, indicative of enhanced coverage quality. Furthermore, the data presented in Table 2, along with the graphical representation in Fig. 4a, unequivocally indicate that the standard deviation associated with the MaEP algorithm is exceptionally low, approaching zero. Figure 5 reveals that the algorithm converges to a solution consistently after approximately 130 to 150 generations across all data instances. These empirical findings provide substantial and persuasive evidence substantiating the stability and convergence attributes of our proposed algorithm.

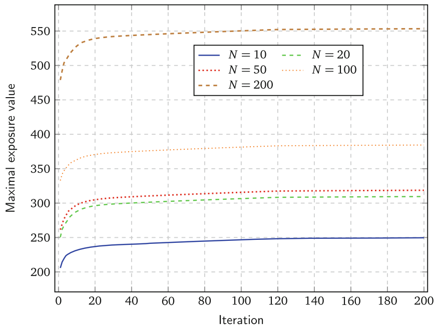


Fig. 5. The convergence of the MaEP-PSO algorithm is evident across experimental data topologies. The results are reported on average.

Table 2. The maximal exposure value, The average exposure, The standard deviation, and the average running time on datasets in each dataset for 30 running Time.

Instance	Best exposure value	Average exposure value	Standard deviation (%)	Average running time
S_10_1	316.39	300.86	4.66	46568
S_10_2	305.24	298.99	5.57	43209
S_10_3	384.50	359.22	5.32	46852
S_10_4	285.46	272.79	4.76	44364
S_10_5	201.26	192.82	4.59	47374
S_10_6	295.86	284.62	5.05	46130
S_10_7	203.79	193.26	4.64	43501
S_10_8	196.45	187.78	3.79	49264
S_10_9	209.95	200.59	5.12	43737
S_10_10	191.79	186.90	3.42	46585
S_20_1	366.11	349.07	4.92	46146
S_20_2	304.20	291.24	4.00	43701
S_20_3	378.90	355.10	3.13	43260
S_20_4	369.59	353.54	4.45	47111
S_20_5	387.41	363.33	4.79	43477
S_20_6	212.13	197.54	5.95	53313
S_20_7	306.63	292.31	5.25	49915
S_20_8	289.69	279.44	4.81	50524
S_20_9	404.93	378.83	4.19	41125
S_20_10	289.87	277.08	4.16	45879
S_50_1	379.22	357.57	4.81	48658
S_50_2	368.45	354.56	4.55	48102
S_50_3	293.13	282.55	4.58	48565
S_50_4	289.05	279.77	3.70	49716
S_50_5	343.41	323.09	3.96	49115
S_50_6	298.68	288.63	3.79	44396
S_50_7	277.62	262.76	5.89	52338
S_50_8	287.34	272.10	4.94	44960
S_50_9	385.50	368.61	5.72	46907
S_50_10	292.04	278.34	5.64	42423
S_100_1	362.71	341.43	5.46	47426
S_100_2	493.31	470.93	4.92	45690
S_100_3	376.08	352.15	5.01	49400
S_100_4	298.55	283.18	4.53	53878
S_100_5	391.20	367.89	5.39	51399
S_100_6	475.09	458.63	4.99	52734
S_100_7	502.40	480.59	2.54	46403
S_100_8	385.09	370.62	5.46	51011
S_100_9	330.54	310.68	5.51	50197
S_100_10	379.24	361.00	4.53	51696
S_200_1	592.80	572.61	3.47	44462
S_200_2	495.87	476.68	3.35	52430
S_200_3	611.08	574.93	5.23	50527
S_200_4	678.30	636.89	5.63	47632
S_200_5	469.88	446.41	4.50	50312
S_200_6	564.80	526.66	6.64	47886
S_200_7	501.13	476.31	5.06	49094
S_200_8	670.14	635.80	5.20	52754
S_200_9	585.64	565.25	4.98	49187
S_200_10	584.55	553.87	4.69	47305

6 Conclusions

In conclusion, this paper has presented a highly efficient method called MaEP-PSO to address the challenging maximal exposure path problem of finding the best coverage path in WASNs. The quest for an optimal coverage path in sensor networks is a crucial endeavor with wide-ranging applications, from environmental monitoring to surveillance and beyond. By leveraging the inherent characteristics of PSO, we have achieved a balance between exploration and exploitation, allowing our algorithm to efficiently search for near-optimal coverage paths. Through extensive experimentation and evaluation, we have showcased the superiority of our PSO-based method in delivering high-quality solutions for the best coverage path problem. It not only enhances network performance but also contributes to energy efficiency, a critical factor in the context of wireless sensor networks. As the demand for robust and energy-efficient sensor networks continues to grow, the presented approach offers a promising avenue for researchers and practitioners to address real-world challenges effectively. In summary, our work underscores the potential of PSO as a valuable tool in the toolkit of optimization techniques for improving the operational efficiency and effectiveness of homogeneous WASNs. Future research can further refine and extend these principles to accommodate the evolving requirements of emerging applications in the field.

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