ECAH: A New Energy-Aware Coverage Method for Wireless Sensor Networks using Artificial Bee Colony and Harmony Search

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***Abstract*—Wireless Sensor Networks (WSNs) offer diverse applications in the research and commercial fields, such as military applications, medical science, waste management, home automation, habitat monitoring, and environmental observation. WSNs are generally composed of a large number of low-cost, low-power, and multifunctional sensor nodes that sense, process, and communicate data. These nodes are connected by a wireless medium, allowing them to collect and share data with each other. To achieve network coverage in a WSN, a few to thousands of tiny and low-power sensor nodes should be placed in an interconnected manner. Over the last decade, deploying sensor nodes in a WSN to cover a large area has received much attention. Coverage, regarded as an NP-hard problem, is an essential parameter for WSNs that determines how the deployed sensor nodes handle each point of interest. Various algorithms have been proposed to tackle this problem. However, they often come with a trade-off between energy efficiency and coverage rate. Moreover, the scalability of the algorithms needs to be considered for large-scale networks. This paper proposes a novel energy-aware method combining Artificial Bee Colony (ABC) and Harmony Search (HS) algorithms to address the coverage problem in WSN, called ECAH. The proposed ECAH algorithm has been tested with various network scenarios and compared with other existing algorithms. The results show that ECAH outperforms the existing methods in terms of network lifetime, coverage rate, and energy consumption. Additionally, the proposed algorithm is also more robust and efficient as it can adjust to dynamic network environment changes, making it suitable for various network scenarios.**

Keywords—Artificial bee colony; coverage; deployment; harmony search; wireless sensor network

I. Introduction

Recent years have seen a significant advancement in wireless and emerging technologies, particularly the Internet of Things (IoT) [1], Wireless Sensor Networks (WSNs) [2], artificial intelligence [3, 4], machine learning [5-7], smart grids [8], Blockchain [9, 10], 5G connectivity [11], and cloud computing have successfully brought many benefits to society.

WSNs are composed of economical, energy-efficient, and tiny sensor nodes which are widely employed in many applications [12-14]. For instance, in a military application, the WSN can be utilized for battlefield surveillance and asset monitoring [15]. Environmental monitoring, building monitoring, forest fire detection, and natural disaster prevention are examples of civil applications of WSNs [16]. The sensors have three prominent roles; sensing, computing, and wireless communication [14]. The sensors can shift separately after a random placement indicating the sensors' self–deploys. Some sensors have the self-repair ability where nodes can reposition themselves when another node fails [17]. Some environmental information, such as temperature, humidity, or other environmental data, is measured by each node periodically. This information should be sent to a central node named sink [18].

Coverage problems pose a major challenge to the development of effective sensor networks. In a sensor network, the coverage problem serves as an indicator of QoS [19]. The coverage is classified into three groups such as area, point, and barrier coverage. The WSNs aim to cover and manage an environment completely. There must be at least one sensor placed at each point in the area. In the area coverage, the best coverage occurs when the target area is fully covered by the lowest number of sensors [20]. The point coverage aims to cover the specific points of the environment. Sensors do not cover the whole area in this model; just some areas are covered. So, some particular points specify goals that need to be controlled. In barrier coverage, the sensors do not cover the entire area. At least one sensor controls the goals in barrier coverage, and all existing plans are controlled by that area. Maintaining connectivity and coverage requires finding the optimal number of active nodes [21].

Coverage in WSNs is an NP-hard problem, and many heuristic methods are proposed to increase the coverage rate in these networks. One of the developed metaheuristic algorithms is Harmony Search (HS). The HS algorithm has fewer mathematical requirements compared to other meta-heuristic algorithms. With the HS algorithm, efficient regions are found within a reasonable timeframe. However, it suffers from non-convergence to an optimal solution, low convergence accuracy, and more time to reach optimal response. It is possible to improve accuracy and convergence rates by combining HS with the Artificial Bee Colony (ABC) algorithm. The ABC algorithm performs better than other evolutionary algorithms and optimizes harmony memory with its variants. This paper presents an algorithm combining HS and ABC algorithms to resolve the coverage optimization problem in WSNs. Briefly, the paper makes the following contributions:

- Maximizing the coverage rate in WSN;

- Minimizing the energy consumption in the WSN;
- Increasing the lifetime of the WSN.

The paper is organized in the following manner. The related work is discussed in Section II. The proposed hybrid algorithm is presented in Section III. Section IV reports the experimental results. The conclusion is discussed in the last part.

II. Related Work

Many meta-heuristic algorithms have been adopted by researchers in recent years in order to improve the performance of WSNs, with various effects on the coverage area, network lifetime, the routing strategy, and node distribution. Each algorithm has its own advantages and drawbacks, and selecting the most suitable algorithm for a given application is an important step for successful deployment of WSNs. Therefore, it is important to understand the characteristics of each algorithm in order to make an informed decision. Additionally, many algorithms can be combined to further improve network performance. Finally, it is important to continuously evaluate and monitor the performance of a WSN to ensure optimal performance.

Ab Aziz, et al. [22] have utilized the PSO algorithm and Voronoi diagrams to optimize the coverage problem in the WSNs. In this work, the target area is a two-dimensional square environment, considered a convenient and practical model that can be used for different applications. The sensors are placed in the region of interest using the Voronoi diagram instead of the grid and PSO algorithm. In this work, the Voronoi diagram is produced initially on an unbounded area considering the position of sensors in a specific region of interest. This way, each boundary is covered with a set of randomly selected points. The proposed method performs well regardless of the number of sensors used or the size of the region of interest. On the other hand, there are some disadvantages to using the Voronoi diagram. One disadvantage is that it can be more difficult to generate the diagram for more complex shapes. Another disadvantage is that the diagram can be sensitive to changes in the position of the sensors, which can lead to inaccurate results.

Also, Panov and Koceski [23] have solved the area coverage problem in WSNs using the HS algorithm. The HS algorithm determines the location and number of the optimal sensor nodes in this study. Therefore, the network coverage and cost can be improved. To start the HS algorithm, harmony memory stores an initial population of solution vectors. Each vector represents a sensor node location denoted by its real number. Based on the obtained results, the HS algorithm requires more iterations than the PSO algorithm. Thus, HS achieves faster convergence and rapid evaluation than other heuristic methods. However, the HS algorithm also has some drawbacks. One such drawback is that the HS algorithm can be easily trapped in a local optimum. This is due to the fact that the HS algorithm relies on the harmony memory to generate new solutions. Thus, the HS algorithm is not as effective as other heuristic methods in terms of escaping local optima.

In addition, Fidanova and Marinov [24] developed an algorithm based on the ACO algorithms for addressing the coverage issue in WSNs, focusing on reducing nodes and increasing coverage. Pheromone trails are bound by a fixed upper and lower bound in the proposed method. Thus, part of the possible movements and repetition of the similar and identical solution will prevent the accumulation of high pheromones. Their method implementation utilizes two main features of the ACO algorithm, an in-depth exploration of space in search of the best solution and extensive research into the best solution. Compared to simulated annealing and cataclysmic mutation algorithms, the ACO optimization algorithm needs fewer evaluations to achieve good results. In addition, the ACO algorithm reaches similar or higher fitness values with 2000 times less effort than simulated annealing or cataclysmic mutation.

Maleki, et al. [25] have suggested a new hybrid method based on the differential evaluation (DE) and PSO algorithms for the distribution of the sensors for area coverage in WSNs. The hybrid method considers two factors, suitable distribution of the sensors and their energy consumption. In the hybrid method, the most optimized points for n sensors are searched according to the PSO algorithm for covering p-aimed points. Searching takes place based on the particles near the goal and can cover the ground suitably, and then the mutation and crossover operations on n sensors take place using the DE algorithm. The hybrid method increases the network's lifetime, reduces energy use and covers all points optimally. The authors have compared the proposed hybrid method with the PSO algorithm to demonstrate its efficiency. Results prove that the hybrid algorithm has a better coverage ratio and network lifetime than the PSO algorithm.

To obtain a specific coverage ratio, Qin and Chen [26] developed an area coverage algorithm based on differential evolution. WSNs are monitored to maximize their lifetime using the proposed algorithm. To realize the optimization process by WSNs, coverage of continuous areas is translated into coverage of discrete points. The main objective is to maintain coverage performance while consuming minimal energy. Binary differential evolution is redeveloped in the area coverage algorithm to find an improved node subset and satisfy coverage requirements. It has been demonstrated that the differential evolution area coverage algorithm provides 90% network coverage and is energy efficient and computation efficient.

He, et al. [27] have developed a model for optimizing WSN coverage using an improved marine predator algorithm. The algorithm improves its solution accuracy by introducing a dynamic inertia weight adjustment approach to the exploration and exploitation stages of the global exploration and local exploitation phases. A multiple random leading method is also employed in the improved algorithm to improve information exchange between population members and to jump out of local optimums. Wu, et al. [28] studied a sensor-based angle coverage judgment method. To monitor the planting region from k angles, using topological analysis, a multi-objective optimization function is developed based on the relationship between targets and sensors. In experiments, judgement was found to be more efficient than the other methods.

According to the above discussion, the majority of existing research focuses on reducing energy consumption or improving network coverage. In the proposed method, both enhancements to the lifetime of the networks and coverage issues are addressed in order to maintain a balance between the amount of energy consumed and the total area covered by the sensors in the sensing region. The proposed method optimizes the deployment of sensors in order to maximize the coverage while minimizing energy consumption. It also addresses the problem of network heterogeneity and scalability, making it an attractive choice for large-scale WSNs. In the first step, the optimal position of the sensors is calculated. The radius of the sensing region required for maximum coverage is then determined. In the next step, the hybrid algorithm is used to place the nodes in their optimal positions. The network lifetime is then improved by optimizing the transmission range of the nodes. Finally, the coverage and lifetime of the network are evaluated and the performance is compared with other algorithms.

III. Proposed Method

The sensor position has the main factor in the coverage problems. Sensors should be placed to ensure the total usage of the sensing ability, increasing the covered area. On the other hand, optimal coverage increases network lifetime and also reduces network power consumption.

A. *Network Model and Assumptions*

The problem is premised on the following assumptions:

- All sensors have a similar sensing radius;
- The nodes are mobile and homogeneous;
- The deployment strategy is a random type;
- The sensing model is a probabilistic model;
- All sensors cover an area of two dimensions.

According to the problem assumptions, the sensing area contains N randomly distributed nodes. The density of all nodes is homogeneous and uniform. All nodes are capable of performing sensing, receiving, and transmitting. For each sensor, three radius types of the same size are considered, sensing radius represented as R_s , communication radius defined as R_c , and uncertainty sensor detection radius illustrated asR_e. The network model of the suggested method is shown in Fig. 1.

B. *Coverage Problem Definition*

The optimum position of the network sensors in the area is considered the main challenge in WSN coverage [29]. After the sensors are positioned for the first time in the static version, they cannot move in the network, which is a limitation for this version of sensor deployment [30]. However, the sensors in dynamic networks can move along coordinates within the mission space. Sensors gather data around an area that falls under their detection ranges (like their location) and then share that information with their neighbors. The communication of sensors with each other and sharing of their information causes effective detection in a network [31]. Therefore, in the coverage problem, the positional flexibility of the mobile sensors is used to enhance the ratio of the covered area. Generally, the coverage ratio of the WSN is computed via Eq. 1 [31], in which t denotes the overall size of the area of interest, s signifies the set of the nodes, and c_i refers to the coverage of a sensor i.

$$CR = \frac{\cup c_i}{t} \,.\, i \in s \tag{1}$$

a) Sensing Models

Searching the adequate coverage and monitoring ability depends on the sensing model. Two kinds of sensing models, such as binary and probability sensing models, are mainly applied in the study of WSN [32].

Binary sensing model: An area with radius R_s is the coverage area of sensor nodes in a two-dimensional plane. This circular area is called the sensing disk. R_s is called the sensing radius, which is determined by the physical properties of the sensing unit. Consider the coordinates of the node S_i are $S(X_{si}\ , Y_{si})$ in the binary sensing model, for any point P at (x,y) on the plane, the probability of that node S_i can detect the events that occur on P calculated by Eq. 2. Where d $(S_i$, P) stands for the average Euclidean distance from the sensor node to the demand point in the plane, calculated by Eq. 3.

$$C_{xy}\ (S_i) = \begin{cases} 1 & x < 0 \\ 0 & otherwise \end{cases} \tag{2}$$

$$\mathrm{d}\ (S_i, \mathrm{P}) = \sqrt{(\ x_{si} - x)^2 + (y_{si} - y)^2} \tag{3}$$

Probability sensing model: The binary sensing model enables the detection of events. Nevertheless, the sensor node detection capability is unstable in virtual application environments due to interference from ambient noise and a decrease in signal strength. Implementing the probability sensing model in real-world environments is more practical since, instead of considering the sensor's radius and distance from the target, multiple dependent factors must be considered. Fig. 2 illustrates the probability sensing model. Probability is determined by Eq. 4 [32].

$$C_{xy}(S_i) = \begin{cases} 1 & \mathrm{d}\ (S_i.\mathrm{p})\ \le\ R_s\ -\ R_e \\ e^{-(\alpha_1\lambda_1\beta_1)/(\lambda_2\beta_2+\alpha_2))} & R_s\ -\ R_e\ <\ \mathrm{d}\ (S_i.\mathrm{p})\ <\ R_s\ +\ R_e \\ 0 & d(S_i, p) \ge\ R_s\ +\ R_e \end{cases} \tag{4}$$

In Eq. 4, $R_e(0 < R_e < R_s)$ refers to the uncertainty in the sensor detection radius. Sensor node characteristics are represented by $\alpha_1, \alpha_2, \beta_1, \beta_2, \lambda_1$, and λ_2, where λ_1 and λ_2 are expressed as Eq. 5 and Eq. 6.

$$\lambda_1 = R_e - R_s + d(s_i.\,i) \tag{5}$$

$$\lambda_2 = R_e + R_s + d(s_i.\,i) \tag{6}$$

Due to overlapping sensors of sensing areas, this type of sensing model compensates for low detection probability potential. Eq. 7 determines this joint sensing probability when a demand point i lies in the overlap area of a set of sensors (s_{ov}).

$$C_{xy}(k_{sov}) = 1 - \Pi_{s_i \epsilon s_{ov}}\ (1 - C_{xy}\ (s_i)) \tag{7}$$

In Eq. 7, if $C_{xy}(k_{sov}) > C_{th}$, demand point p is considered to be effectively covered, where C_{th} refers to the coverage threshold, and its value is application dependent. The proposed method uses a probabilistic sensor detection model that includes points of different probabilities in the area. In this model, the area coverage is determined using probabilistic terms, so the results are realistic.

b) Coverage Model

Eq. 8 calculates the area coverage rate of the node set, where, $R_{area}(k_{sov})$ stands for the total ratio of the coverage area and m×n is the size of the sensing area.

$$R_{area}(k_{sov}) = \frac{\sum_{x=1}^{m}\sum_{y=1}^{n} C_{xy}(k_{sov})}{m\times n} \tag{8}$$

c) Energy Consumption Model

Energy efficiency is a very important issue in WSNs due to the limitation of battery resources. We need mechanisms that keep the energy resources because these mechanisms affect the network lifetime. In general, there are two mechanisms for conserving energies in a WSN, reducing the sensing range and planning of the sensor node activity. In cases where setting the sensing range is permissible, active sensors should dynamically adjust their sensing ranges so as to meet the entire sensing objective [33]. Energy savings can be achieved by reducing the communication range when an option to adjust the range of sensor communication radius would exist. In the proposed method, the introduced energy model in [33] is used to calculate the energy. According to the model, the consumption energy of the sensors is calculated via Eq. 9-11, where l denotes the length of the data transmitted, d_0 signifies threshold transmission distance, d represents the distance between sensor nodes, $E_{T.x}$ refers to the consumed energy for transmission, $E_{R.x}$ stands for the consumed energy for reception, E_{elec} specifies the amount of dissipated energy per bit to run the transmitter or the receiver circuit, and E_{Fs} and E_{Tr} depend on the transmitter amplifier model. The value of E_{elec}, E_{Fs}, and E_{Tr} are $E_{elec} = 50nJ/bit$, $E_{Fs} = 10pJ \times bit^{-1} \times m^{-2}$, $E_{Tr} = 0.0013pJ \times bit^{-1} \times m^{-4}$, and d= transmission radius or communication range.

$$E_{T.x}(l.d) = l \times E_{elec} + l \times E_{Fs} \times d^2 \ .if\ d < d_0 \tag{9}$$

$$E_{T.x}(l.d) = l \times E_{elec} + l \times E_{Tr} \times d^4 \ .if\ d > d_0 \tag{10}$$

$$E_{R.x}(l.d) = l \times E_{elec} \tag{11}$$

d) Lifetime Model

The length of time between the initial deployment of the network and running out of the energy of the first relay node defines the network lifetime. In this work, lifetime is expressed according to the seconds, and for a single node, it can be estimated with Eq. 12 [33], where $e_{initial}$ is the initial energy of sensor nodes and e_{total} refers to the amount of consumed energy for data transmission and reception calculated by Eq. 13.

$$\text{Lifetime} = \frac{e_{initial}}{e_{total}} \tag{12}$$

$$e_{total} = E_{T.x}(l.d) + E_{R.x}(l.d) \tag{13}$$

e) Objective Function

Objective functions are one of the most vital factors in optimization algorithms. According to the energy and lifetime models, both of these models depend on the distance between the sensors. Also, according to the network coverage definition, the network becomes an optimal coverage when the distance between the sensors is less than their sensing radius. On the other hand, as the coverage rate increases, more sensors will be active, and reducing the number of active sensors will result in a lower coverage rate. The problem is mathematically described as follows: given a set of N potential sensors, $k = \{s_1.s_2.s_3.s_4 \dots .s_N\}$. In this regard, the optimization goal is calculated as follows.

$$z = \max(f_1.f_2) + \min(f_3) \tag{14}$$

In Eq. 14, f_1 , f_2, and f_3 stand for the coverage rate, network lifetime, energy consumption, respectively. The fitness function is calculated using Eq. 15, wherew_1,w_2 and w_3 are weight coefficients used to normalize coverage, energy, and network lifetime values.

$$Fitness = w_1\left(\frac{\sum_{x=1}^{m}\sum_{y=1}^{n} C_{xy}(k_{sov})}{m\times n}\right) + w_2\left(\frac{1}{(l\times E_{elec}+l\times E_{Fs}\times d^2)+(l\times E_{elec})}\right) + w_3\left(\frac{e_{initial}}{(l\times E_{elec}+l\times E_{Fs}\times d^2)+(l\times E_{elec})}\right) \tag{15}$$

C. Proposed Coverage Algorithm

Due to the NP-Hard nature of the area coverage problem in WSN, the optimal approximate solution could be suitable. The traditional greedy algorithm is inefficient in solving the coverage problem, and finding the best solution is impossible. In the previous methods, the optimal results are not included in the coverage rate, energy consumption, and network lifetime. In this work, a new hybrid method is suggested based on the ABC and HS algorithms for resolving the coverage problem of the WSNs. The HS algorithm is one of the latest and the easiest methods to optimize the issues inspired by music. This algorithm has premature and slow convergence problems, particularly over the multimodal fitness landscape. Also, convergence to the optimal solution occurs slower [34].

In the present work, the ABC algorithm is used to improve the accuracy and convergence of the HS algorithm and to optimize harmony memory. Honey bees' intelligent foraging behavior is crucial in generating an ABC algorithm as a new swarm intelligence method. Harmony memory can be improved using the ABC and its variants. A significant advantage of the ABC algorithm is its ability to seek global and local results throughout each iteration. This advantage is compared to GA, PSO, and other intelligent computing methods. Therefore, finding optimal solutions increases and is avoided in the stuck of local optimization. The hybrid method uses the HS algorithm as the primary global search technique. In contrast, the ABC algorithm is the subprocedure of the local search and optimizes the harmony memory.

The coverage problem of the WSNs is proportional to the behavior of honey bees to find the optimal position of food sources and how the musician plays music. The position of the food sources represents the coordinates of the sensors in the sensing area, the value of each food source indicates the network coverage rate, and the maximum value for the fitness function represents the highest coverage rate for each sensor. In terms of the parameters of the HS algorithm, each harmony vector represents an optimal position for the sensors. The harmony vector components also represent the decision variables, i.e., coverage rate, energy consumption, and sensor lifetime.

a) Preparing the Hybrid Method

This step consists of two sub-steps, the production of the initial population and the initialization of the harmony memory. In general, the HS algorithm has five main steps. Steps 1 and 2 are used in the first step of the proposed method, and steps 3, 4, and 5 are used to improve the newly generated solutions and update the harmony memory in the third step of the proposed method.

Generation of an initial population: This step generates the initial population (initial solutions) randomly. The initial population for the coverage problem is the coordinates of the sensors based on (x,y) in the sensing area. At this step, each sensor's coordinates (x,y) are generated, and the sensors are distributed under these coordinates in the sensing area. The size of the population should be equal to the size of the harmony memory.

Initialization of harmony memory: After generating the initial population of the sensors in steps 1-1 and distributing these sensors in the sensing area based on their x and y coordinates, a harmony vector is generated for each sensor. After generating the harmony vector for each sensor, the fitness function for each vector is calculated. Then the harmony memory is initialized with these vectors and their fitness values. Each harmony vector consists of three decision variables, coverage rate, energy consumption, and network lifetime. The harmony vector structure and harmony memory are described as follows.

- Harmony vector: Each solution in the HS algorithm is referred to as a harmony vector, representing the number of parameters of the optimization problem in a D-dimensional vector. Since the optimization parameters in the coverage problem are the coverage rate, energy consumption, and the sensors' lifetime, the harmony vector is considered a three-dimensional vector.

- Harmony memory: The HS algorithm uses a harmony memory to store possible solutions (harmony vectors) and their objective function values [35]. The number of initial populations determines harmony memory size. Eq. 16 represents harmony memory as a matrix.

$$\text{Harmony memory} = \begin{array}{c} \begin{array}{cc} \text{Decision variables} & \text{Fitness function} \end{array} \\ \left[\begin{array}{ccccc|c} x_1^1 & x_2^1 & x_3^1 & \dots & x_D^1 & f(x^1) \\ x_1^2 & x_2^2 & x_3^2 & \dots & x_D^2 & f(x^2) \\ x_1^{HMS} & x_2^{HMS} & x_3^{HMS} & \dots & x_D^{HMS} & f(x^{HMS}) \end{array}\right] \end{array} \tag{16}$$

- Improving the harmony memory using the ABC algorithm

In this step, harmony memory is improvised by the ABC algorithm. The solution to the optimization problem is represented by the position of food sources in the ABC algorithm. A food source's nectar amount corresponds to the associated solution's fitness (quality). The employed artificial bees are located in the artificial bee colony's first half, and the onlookers are placed in the second half. Also, each food source has only one employed bee. Conforming to the above description, in the coverage problem, the location of the sensor nodes in the sensing area identifies the food sources, and each food source's value is defined as the sensor nodes' coverage value. In this step, a bee is assigned to each position of sensors in the sensing area. These sensors perform a series of movements and change their current position in the worker and onlooker bee phases. Changing the sensor's position makes the sensors find their optimal position, increasing the network's coverage. Generally, the ABC algorithm has four main phases: initialization, employed bees, onlooker bees, and scout bees' phase. The initial population of ABC algorithms is the harmony vectors generated and evaluated in step 1.

Employed bee phase: The particular group of bees is called employed bees that use the available food sources. Each of the employed bees keeps the profitability of the associated food source and then returns to the hive and performs the waggle dance. Worker bees dance in different parts of the hive area to communicate with other bees. Generally, there are three types of dances: round, waggle, and tremble. In this phase, the new solution's fitness value (nectar amount) is essential in modifying the current solution by employing bees. When the fitness value of the new food source is higher than the old food source, the bee updates her position with the new one and rejects the old one. A position update equation for the j^{th} dimension of each i^{th} candidate in this phase is shown in Eq. 17 [34].

$$V_{ij} = X_{ij} + \varphi_{ij}\left(X_{ij} - X_{Kj}\right) \tag{17}$$

In Eq. 17, $\varphi_{ij}\left(X_{ij} - X_{Kj}\right)$ is called step size. Although k is determined randomly (k≠i). φ_{ij} is a random number between [−1, 1]. In the coverage problem, these working bees display the sensors. In this phase, these sensors change their current coordinates by Eq. 17. In the new position, the fitness function (objective function) is calculated, and a greedy selection is applied to the existing coordinates and old coordinates of the sensors.

Onlooker bee phase: Following the employed bee stage, the onlooker bee stage begins. In this stage, the employed bees share their fitness and position information with the onlookers in the hive [43]. Analyzing the available information, the onlooker bees choose (roulette wheel selection method can be used) a solution with a probability P_i, related to its fitness. The probability P_i is calculated using Eq. 18 [34], where fit_i refers to the fitness value of the i^{th} solution.

$$P_i = \frac{fit_i}{\sum_{i=1}^{HMs} fit_i} \tag{18}$$

Like the employed bees, the onlooker bees change the position of their memory and check the fitness of the candidate source. Like an employed bee, the bee also memorizes the new position and forgets the old one when the new one has a higher fitness value. In the coverage problem, after the sensors have changed their current positions in the worker's bee phase and calculated the fitness value for each of their new positions, in this phase, for each of these sensors, a probability value based on Eq. 18 and the fitness value of each of the sensors is calculated. Then, using a roulette wheel selection method, a random position is selected, the sensors are positioned in the chosen position, and then the same as in the employed bee phase, by Eq. 17, the current position of sensors is changed. Then the new position is compared with the current position, and choose a better position by selecting a greedy selection.

Scout bee phase: The scout bees are generally responsible for finding new food sources around the hive. Food sources are expected to be abandoned after a specified amount of time (called "limit") if their position has not been updated [36]. These bees choose new food sources based on Eq. 19, where lb and ub are lower and higher bounds of the decision variables, respectively.

$$X_{ij} = lb_j + rand(0.1)(ub_j - lb_j) \tag{19}$$

According to the above principle, an indicator is defined as a trial index for each network sensor in the coverage problem. In the worker and onlooker bees phase, if the new position of sensors has a higher value for coverage rate, these sensors memorize the new position and forget its current position; otherwise, these sensors keep their current position, and one unit adds to the trial index of these sensors. In this phase, these trial indexes will be examined for all sensors; if the trial index value for each sensor is higher than the specified limit, it means this position does not have a good value for the coverage, and then this position should be abandoned. The sensors should create a new position based on Eq. 19.

b) Improving New Harmony Vectors and Updating Harmony Memory

At this step, a new solution (new harmony vector) generated by the three phases of the ABC algorithm was developed and stored in harmony memory. Three sub-steps are included in this step.

Improvisation of new harmony vectors: Three rules, including a Harmony Memory Consideration Rate (HMCR), a Pitch Adjustment Rate (PAR), and random numbers (r_1 and r_2), are used to improve a new harmony vector X^{new} according to the HS algorithm, in which random numbers r_1 and r_2 ranging from 0-1 are generated. Memory consideration generates the decision variable $X^{new}(k)$ if r_1 is less than HMCR; otherwise, random selection achieves $X^{new}(k)$. If r_1 is greater than HMCR, the decision variable $X^{new}(k)$ is generated randomly using Eq. 19. A slight adjustment can be made by perturbing once x_i (k) and selecting one of the stored good values, with a probability of PAR. Lastly, fret width (FW or BW) determines the maximum pitch variation allowed. The new harmony vector is described in Eq. 20 [34].

$$x_i^{new} = \begin{cases} x_i\,(\mathrm{k}) \in \{\, x_i\,(1)\,, x_i\,(2)\,, \ldots\, x_i\,(\mathrm{k})\} & r_1 > \mathrm{HMCR} \\ x_i\,(\mathrm{k}) \in \{\, x_i^1\,, x_i^2\,, \ldots\,, x_i^{HMS}\,\} & r_1 <= \mathrm{HMCR} \\ x_i\,(\mathrm{k}) + r_2 \times \mathrm{BW} & r_1 <= \mathrm{PAR} \end{cases} \tag{20}$$

Evaluation and updating of harmony memory: Comparing the new candidate harmony and the worst harmony vector in the harmony memory leads to updating the harmony memory. New candidate vectors replace the worst harmony vectors if they are improved.

HS algorithm termination check: The termination condition in the HS algorithm depends on the number of decision variables, namely, sensor coverage, sensor energy consumption and sensor lifetime. In other words, the repetition loop for optimizing the new harmony vector with PAR probability is repeated three times. The first repetition is for the first component, the second repetition is for the second component, and finally, the third repetition is for the third component of the new harmony vector.

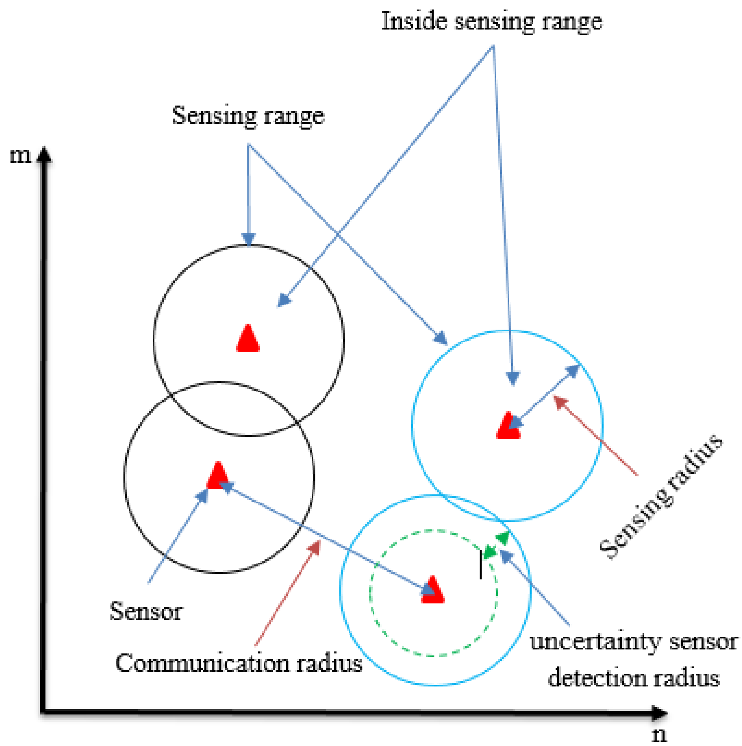

Fig. 1. Network model.

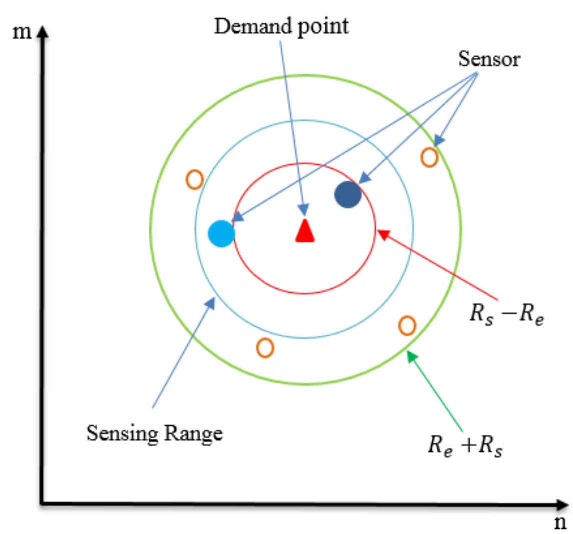

Fig. 2. An illustration of the probability-sensing model.

IV. Experiments

This section presents the results of the applied experiments that were conducted to evaluate the performance of the proposed method. Subsection IVA provides an overview of the simulation environment and its adopted parameters. Section IVB discusses the dataset, and Section IVC presents the simulation outcomes.

A. Simulation Environment and Adopted Parameters

MATLAB simulator is used due to its capability of handling a large amount of data efficiently, focusing on coverage, network consumption, and the lifetime of WSNs. As an example of data processing platforms, MATLAB has been commonly used in WSNs because of its high ability to calculate mathematically and visualize results. The simulation parameters and ECAH variables are summarized in Table I.

TABLE I. VARIABLES IN SIMULATION

Parameters	Definition	Value
A (m×n)	Terrain of experiment	20×20(m) - 500×500(m)
N	Number of sensor nodes	20 -210
D	Transmission radius (nodes distance)	Changeable for variant scenarios
E_{total}	Total energy for data transmission	Changeable for variant scenarios
MaxIT	Maximum iteration	Changeable for variant scenarios
HMS	Harmony memory size	Changeable for variant scenarios
R_s	Sensing radius	Changeable for variant scenarios
L	Data generated by each node	100 bit
HMCR	Harmony memory consideration rate	0.96
PAR	Pitch adjustment rate	0.68
Limit	Abandonment criteria	100
R_e	Uncertainty radius for sensor detection	$R_s/2$
$E_{initial}$	Initial energy	2 J
E_{elec}	Energy consumed by radio electronics	$50nJ/bit$
E_{Fs}	Energy consumed by the power amplifier	$10pJ \times bit^{-1} \times m^{-2}$
E_{Tr}	Energy consumed by the power amplifier	$0.0013pJ \times bit^{-1} \times m^{-4}$
V_{ij}	New position for sensors	-
X_{ij}	Current position for sensors	-
P_i	Roulette wheel selection probability	-
fit_i	New position fitness	-
r1 and r2	Random numbers between 0 and 1	-

TABLE II. FIRST SCENARIO PARAMETERS

Simulation parameters							
Sensing radius						*Number of sensors*	*Network size*
1.5	2	2.5	3	4	5	20	20×20
Harmony search parameters							
HMCR=0.9	PAR=0.4	FW=0.2	α_1=1	α_2=0	β_1=1	β_2=0.5	

B. Dataset

The performance of the proposed method is compared with the performance of the HS [23], PSO [22], ACO [24], multi-objective GA [37], ABC [31], and hybrid PSO with DE [25] algorithms. Therefore, we considered the datasets and parameters used in these studies.

C. Obtained Results

This section compares our method with previous methods in six scenarios and shows its performance. In each scenario, the results are compared with those of previous methods. Lastly, the final scenario presents the effect of the number of sensors and the sensing radius on the network's coverage rate, energy, and lifetime.

In the first scenario, we used the parameters that are listed in Table II. Table III shows the results of applying our method and HS algorithm in area coverage for the different radii. The near-optimal solution for our approach is provided in fewer iteration than for the HS algorithm, as shown in Table III. The network environment for ECAH and HS algorithms with radius=2 m are shown in Fig. 3 and 4, respectively. The results demonstrate that our proposed approach can provide an optimal or near-optimal solution with faster convergence in terms of time and number of iterations. Furthermore, our proposed method can achieve a better coverage rate in a shorter time compared to the HS algorithm.

TABLE III. RESULTS FROM APPLYING THE PROPOSED METHOD AND HS FOR AREA COVERAGE WITH DIFFERENT RADIUSES

Radius (m)	Iteration (HS)	Iteration (ECAH)	Coverage rate (HS)	Coverage rate (ECAH)
1.5	7000	100	24.66%	53.71%
2	7000	100	45.97%	55.39%
2.5	7000	850	85.25%	77.66%
3	7000	1000	93.16%	93.34%
4	7000	100	99.50%	100%
5	7000	150	100%	100%

TABLE IV. SECOND SCENARIO PARAMETERS

Simulation parameters		
Sensing radius	Number of sensors	Network size
5	45	50×50

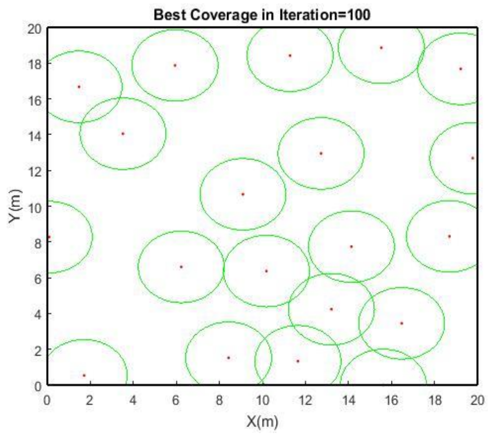

Fig. 3. The network environment in ECAH.

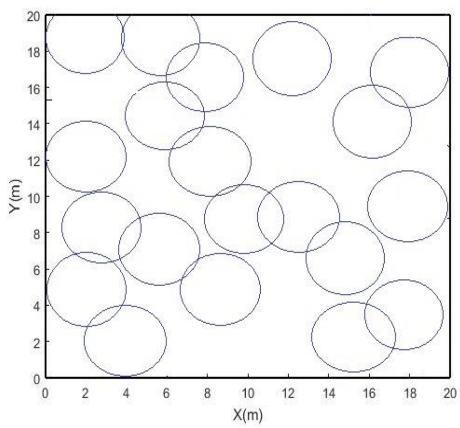

Fig. 4. The network environment in HS.

Table IV shows the parameters used in the second scenario. Our method and PSO algorithm were applied to the coverage of an area with a radius of 5 meters, as shown in Table V. The network environment for the proposed algorithm and the PSO algorithm with radius=5 m is shown in Fig. 5 and 6, respectively. PSO algorithm found the best coverage after the 100th iteration, whereas our method found it after 46 iterations. This shows that our method is significantly more efficient and accurate in finding the best coverage in a given area. It is able to find the best coverage in fewer iterations, indicating that it is more precise in its calculations and requires less time and resources to achieve the desired results.

TABLE V. RESULTS FROM APPLYING THE PROPOSED METHOD AND PSO FOR AREA COVERAGE WITH RADIUS=5

Radius (m)	Iteration (PSO)	Iteration (ECAH)	Coverage rate (PSO)	Coverage rate (ECAH)
5	300	100	80.08%	94.82%

TABLE VI. THIRD SCENARIO PARAMETERS

Simulation parameters		
Sensing radius	*Number of sensors*	*Network size*
22	100	278×278

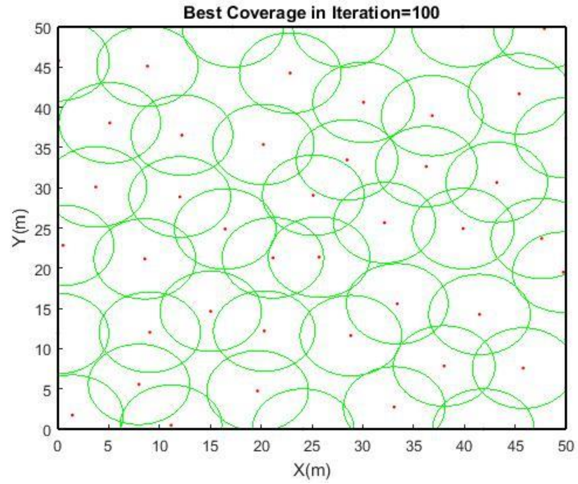

Fig. 5. The network environment in ECAH.

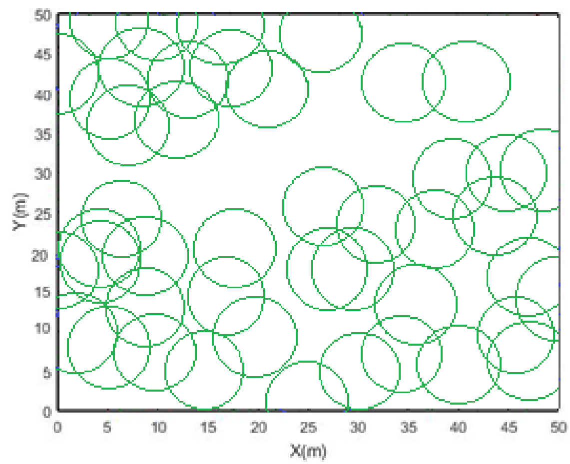

Fig. 6. The network environment in PSO.

In the third scenario, the parameters of [24] are used, shown in Table VI. Table VII gives the results of applying ECAH and ACO algorithms to area coverage for radius=22 m. The network environment for ECAH and ACO algorithms with radius=22 m is shown in Fig. 7 and 8, respectively. The ECAH has found the best coverage in the 85th iteration, while the best coverage of the ACO algorithm is achieved in the 100th iteration. The results show that the ECAH algorithm was able to achieve the best coverage in fewer iterations than the ACO algorithm, indicating that it is more effective and efficient at finding the best coverage in this network environment.

Table VIII shows the parameters adopted from reference [37] for the fourth scenario. Several sensors and iterations are used to conduct the experiment, which shows the detailed results in Table IX. The ECAH has found the best coverage in the 85th iteration, while the best coverage of the GA algorithm is achieved in the 100th iteration. According to the obtained results, the GA with 39 sensors and 100 iterations has reached the optimal coverage, but the proposed method has been optimized with 30 sensors and 100 repeats. The network environment for ECAH and GA algorithms with radius=13 m and N=40 are shown in Fig. 9 and 10, respectively.

TABLE VII. RESULTS FROM APPLYING ECAH AND ACO FOR AREA COVERAGE WITH RADIUS=22

Radius (m)	Iteration (ACO)	Iteration (ECAH)	Coverage rate (ACO)	Coverage rate (ECAH)
22	**100**	**100**	**87.08%**	**99.82%**

TABLE VIII. FOURTH SCENARIO PARAMETERS

Simulation parameters		
Sensing radius	**Number of sensors**	**Network size**
13	**100**	**100×100**

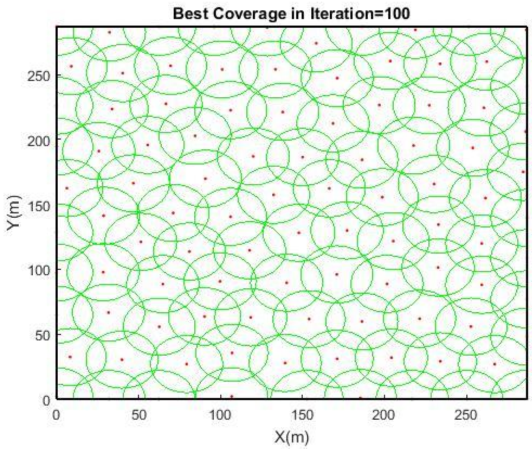

Fig. 7. The network environment in ECAH.

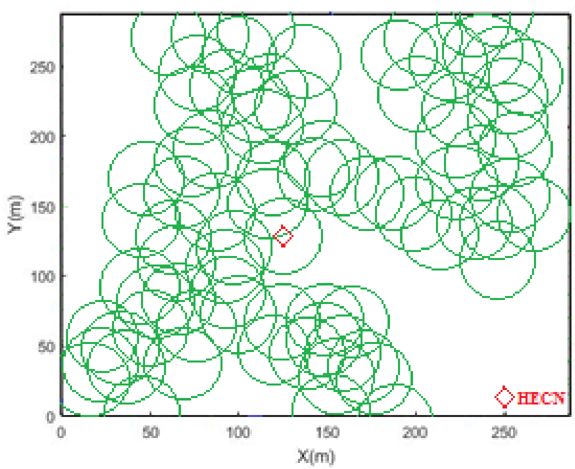

Fig. 8. The network environment in ACO.

TABLE IX. RESULTS FROM APPLYING ECAH AND GA FOR AREA COVERAGE WITH DIFFERENT RADIUS

Number of nodes	Best iteration for optimal coverage in GA		Best iteration for optimal coverage in ECAH	
	Iteration	*Coverage rate*	*Iteration*	*Coverage rate*
N=39	60	93.92%	60	99.92%
	120	95.6%	120	99.95%
N=40	80	94.40%	49	100%
N=37	120	95.6%	102	99.92%

TABLE X. FIFTH SCENARIO PARAMETERS

Simulation parameters				
Sensing radius		*Number of sensors*		*Network size*
7		100		100×100
Artificial bee colony parameters				
λ1 = 1	λ2 = 0	β1 = 1	β2 = 0.5	“limit”=100

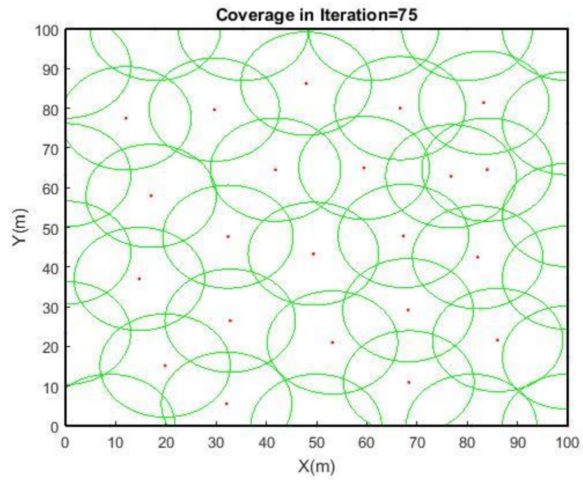

Fig. 9. The network environment in ECAH.

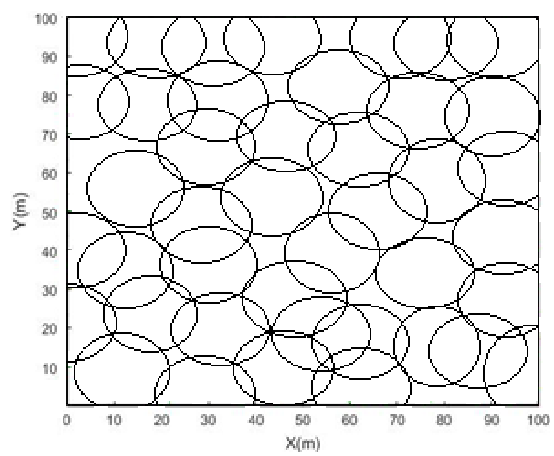

Fig. 10. The network environment in GA.

In the fifth scenario, we used the parameters of [31], which are shown in Table X. Table XI gives the results from applying ECAH and ABC algorithms for area coverage with radius=7 (m). According to the obtained results, ABC has found the best coverage in the 703rd iteration, while the optimal coverage of the ECAH algorithm is achieved in the 652nd iteration. The network environment for ECAH and ABC algorithms with radius=13 m and N=40 are shown in Fig. 11 and 12, respectively.

In the sixth scenario, we used the parameters of [25]. These parameters are shown in Table XII. Table XIII gives the results of applying ECAH and hybrid DEPSO algorithms for area coverage with radius=40 m. The network environments for ECAH and hybrid DE and PSO algorithms with radius=40 m and N=40 is shown in Fig. 13 and 14, respectively. Fig. 15 shows an overview of the coverage rate of the existing methods. As shown in Table XIV, the proposed method requires fewer iterations for convergence to optimal coverage than existing methods, which the proposed method has inferior runtime and higher run speed compared to existing methods.

TABLE XI. RESULTS FROM APPLYING ECAH AND ABC FOR AREA COVERAGE WITH RADIUS=7

Radius (m)	Iteration (ABC)	Iteration (ECAH)	Coverage rate (ABC)	Coverage rate (ECAH)
7	1000	1000	97.52%	98.59%

TABLE XII. SIXTH SCENARIO PARAMETERS

Simulation parameters						
Sensing radius	Number of sensors					Network size
40	20	25	30	35	40	450×450

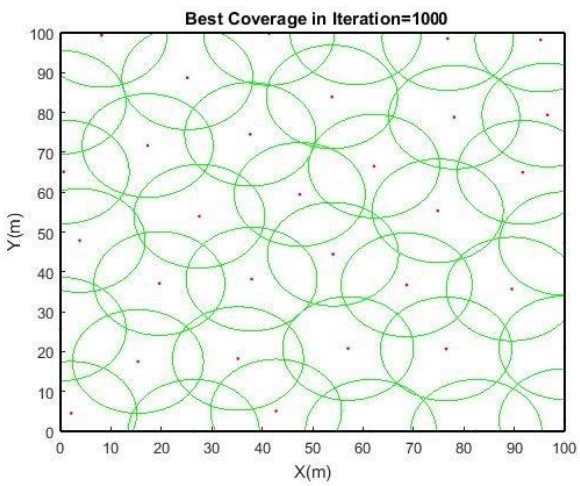

Fig. 11. The network environment in ECAH.

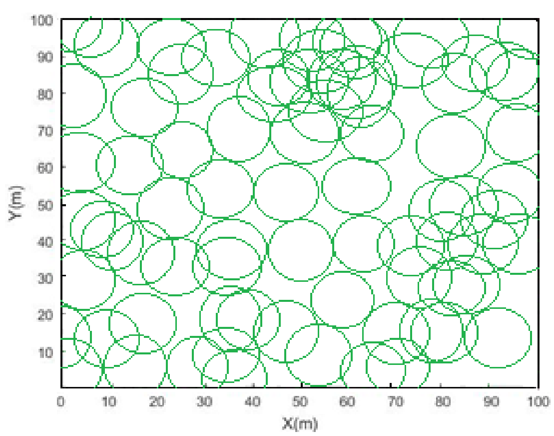

Fig. 12. The network environment in ABC.

TABLE XIII. RESULTS FROM APPLYING ECAH AND HYBRID DE AND PSO FOR AREA COVERAGE WITH RADIUS=40

Number of nodes	Best iteration for optimal coverage in hybrid DE and PSO		Best iteration for optimal coverage in ECAH	
N=20	Iteration	Coverage rate	Iteration	Coverage rate
	100	27%	54	49.25%
N=25	100	32%	99	61.15%
N=30	100	37%	98	70.92%
N=35	100	42%	48	78.56%
N=40	100	47%	31	84.44%

TABLE XIV. THE NUMBER OF ITERATIONS OF THE PROPOSED METHOD AND EXISTING METHODS IN DIFFERENT SCENARIOS

Scenario	Methods reviewed	Iteration	Scenario	Methods reviewed	Iteration
First scenario	ECAH	900	Forth scenario	ECAH	49
	HS	7000		GA	120
Second scenario	ECAH	100	Fifth scenario	ECAH	1000
	PSO	300		ABC	1000
Third scenario	ECAH	100	Sixth scenario	ECAH	31
	ACO	100		DE and PSO	100

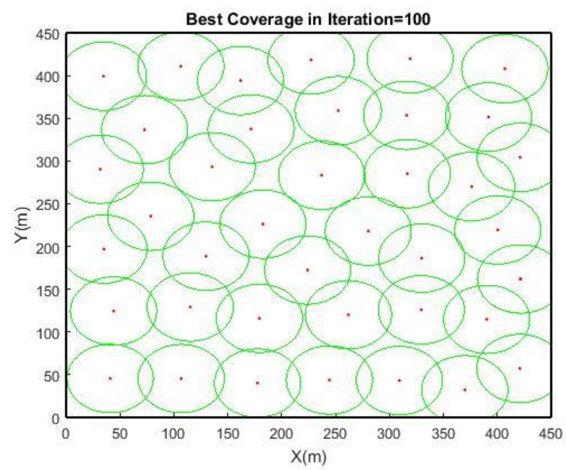

Fig. 13. The network environment in ECAH.

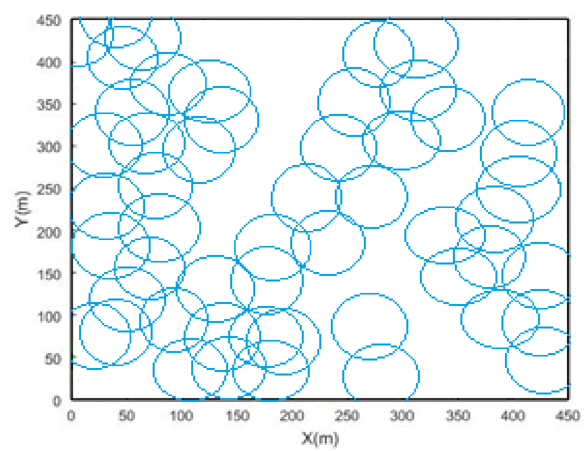

Fig. 14. The network environment in DEPSO.

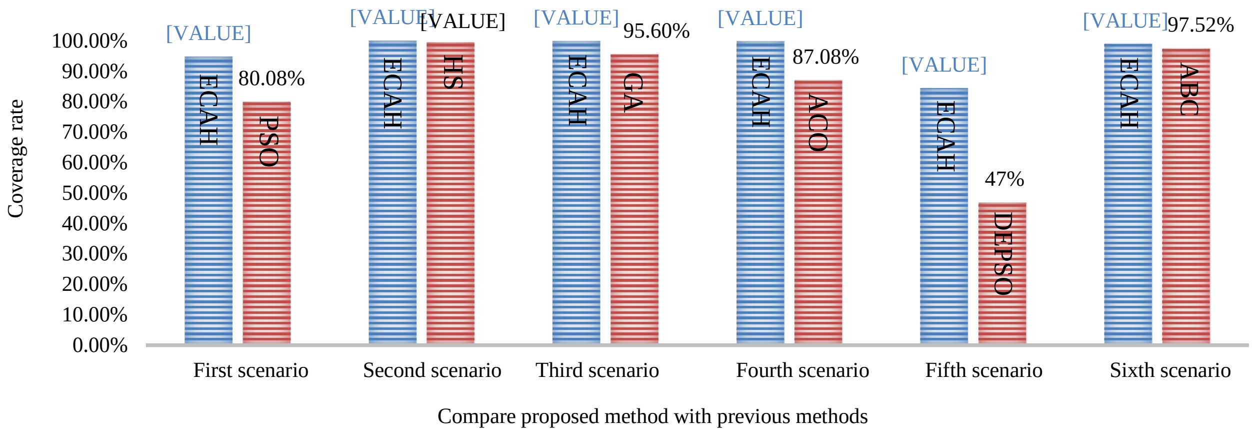

Fig. 15. Overview of the coverage rate of the existing methods.

V. Conclusion

Coverage problem is one of the most critical research fields for WSNs. The network's lifetime is increased by creating optimized coverage in WSNs. In addition, the optimal coverage causes the optimal consumption of the network energy. This paper combined the HS and ABC algorithms to increase the area coverage and the lifetime of the WSNs. The efficiency of the hybrid method is demonstrated by comparing it with HS, ABC, ACO, GA, hybrid DE, and PSO algorithms. Our method outperforms previous methods according to the simulation results. We hope that we will be able to find better and more optimized methods using other meta-heuristic algorithms for WSNs coverage problems. This algorithm will be improved in the future and applied to WSN coverage optimization in more complex environments. Additionally, the algorithm will be extended to a wide range of IoT optimization problems.

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References

[1] A. Mehbodniya et al., "Energy-Aware Routing Protocol with Fuzzy Logic in Industrial Internet of Things with Blockchain Technology," Wireless Communications and Mobile Computing, vol. 2022, 2022.

[2] F. Zhu and W. Wang, "A Distributed Unequal Clustering Routing Protocol Based on the Improved Sine Cosine Algorithm for WSN," Journal of Sensors, vol. 2022, 2022.

[3] S. A. Saeidi, F. Fallah, S. Barmaki, and H. Farbeh, "A novel neuromorphic processors realization of spiking deep reinforcement learning for portfolio management," in 2022 Design, Automation & Test in Europe Conference & Exhibition (DATE), 2022: IEEE, pp. 68-71.

[4] F. Vahedifard, S. Hassani, A. Afrasiabi, and A. M. Esfe, "Artificial intelligence for radiomics; diagnostic biomarkers for neuro-oncology," World Journal of Advanced Research and Reviews, vol. 14, no. 3, pp. 304-310, 2022.

[5] R. N. Jacob, "Non-performing Asset Analysis Using Machine Learning," in ICT Systems and Sustainability: Proceedings of ICT4SD 2020, Volume 1, 2021: Springer, pp. 11-18.

[6] J. Akhavan, J. Lyu, and S. Manoochehri, "A deep learning solution for real-time quality assessment and control in additive manufacturing using point cloud data," Journal of Intelligent Manufacturing, pp. 1-18, 2023.

[7] S. R. Abdul Samad et al., "Analysis of the Performance Impact of Fine-Tuned Machine Learning Model for Phishing URL Detection," Electronics, vol. 12, no. 7, p. 1642, 2023.

[8] S. H. Haghshenas, M. A. Hasnat, and M. Naeini, "A Temporal Graph Neural Network for Cyber Attack Detection and Localization in Smart Grids," arXiv preprint arXiv:2212.03390, 2022.

[9] S. Meisami, M. Beheshti-Atashgah, and M. R. Aref, "Using Blockchain to Achieve Decentralized Privacy In IoT Healthcare," arXiv preprint arXiv:2109.14812, 2021.

[10] A. Morteza, M. Ilbeigi, and J. Schwed, "A blockchain information management framework for construction safety," in Computing in Civil Engineering 2021, 2021, pp. 342-349.

[11] S. Vairachilai, A. Bostani, A. Mehbodniya, J. L. Webber, O. Hemakesavulu, and P. Vijayakumar, "Body Sensor 5 G Networks Utilising Deep Learning Architectures for Emotion Detection Based On EEG Signal Processing," Optik, p. 170469, 2022.

[12] C. Lersteau, A. Rossi, and M. Sevaux, "Minimum energy target tracking with coverage guarantee in wireless sensor networks," European Journal of Operational Research, 2017.

[13] A. J. Al-Mousawi and H. K. Al-Hassani, "A survey in wireless sensor network for explosives detection," Computers & Electrical Engineering, 2017/12/01/ 2017, doi: https://doi.org/10.1016/j.compeleceng.2017.11.013.

[14] V. Markevicius et al., "Two thermocouples low power wireless sensors network," AEU - International Journal of Electronics and Communications, vol. 84, pp. 242-250, 2018/02/01/ 2018, doi: https://doi.org/10.1016/j.aeue.2017.11.032.

[15] A. Oracevic, S. Akbas, and S. Ozdemir, "Secure and reliable object tracking in wireless sensor networks," Computers & Security, vol. 70, pp. 307-318, 2017.

[16] P. B. Rasband, "Wireless sensor network," ed: Google Patents, 2017.

[17] S.-C. Wang, H. C. Hsiao, C.-C. Lin, and H.-H. Chin, "Multi-objective wireless sensor network deployment problem with cooperative distance-based sensing coverage," Mobile Networks and Applications, pp. 1-12, 2022.

[18] W. Osamy, A. M. Khedr, A. Salim, A. I. Al Ali, and A. A. El-Sawy, "Coverage, deployment and localization challenges in wireless sensor networks based on artificial intelligence techniques: a review," IEEE Access, 2022.

[19] S. J. Bhat and S. KV, "A localization and deployment model for wireless sensor networks using arithmetic optimization algorithm," Peer-to-Peer Networking and Applications, vol. 15, no. 3, pp. 1473-1485, 2022.

[20] P. Tirandazi, A. Rahiminasab, and M. Ebadi, "An efficient coverage and connectivity algorithm based on mobile robots for wireless sensor networks," Journal of Ambient Intelligence and Humanized Computing, pp. 1-23, 2022.

[21] Q. Li and N. Liu, "Coverage optimization algorithm based on control nodes position in wireless sensor networks," International Journal of Communication Systems, vol. 35, no. 5, p. e4599, 2022.

[22] N. A. B. Ab Aziz, A. W. Mohemmed, and B. D. Sagar, "Particle swarm optimization and Voronoi diagram for wireless sensor networks coverage optimization," in Intelligent and Advanced Systems, 2007. ICIAS 2007. International Conference on, 2007: IEEE, pp. 961-965.

[23] S. Panov and S. Koceski, "Area coverage in wireless sensor network by using harmony search algorithm," in Embedded Computing (MECO), 2014 3rd Mediterranean Conference on, 2014: IEEE, pp. 210-213.

[24] S. Fidanova and P. Marinov, "Optimal wireless sensor network coverage with Ant Colony Optimization," in International conference on swarm intelligence, 2011.

[25] I. Maleki, S. R. Khaze, M. M. Tabrizi, and A. Bagherinia, "A new approach for area coverage problem in Wireless Sensor Networks with hybrid particle swarm optimization and differential evolution algorithms," International Journal of Mobile Network Communications and Telematics (IJMNCT), vol. 3, no. 6, pp. 61-76, 2013.

[26] N.-n. Qin and J.-l. Chen, "An area coverage algorithm for wireless sensor networks based on differential evolution," International Journal of Distributed Sensor Networks, vol. 14, no. 8, p. 1550147718796734, 2018.

[27] Q. He, Z. Lan, D. Zhang, L. Yang, and S. Luo, "Improved Marine Predator Algorithm for Wireless Sensor Network Coverage Optimization Problem," Sustainability, vol. 14, no. 16, p. 9944, 2022.

[28] H. Wu, H. Zhu, and X. Han, "An improved k-angle coverage algorithm for multimedia wireless sensor networks based on two-layer tabu search," Peer-to-Peer Networking and Applications, vol. 15, no. 1, pp. 28-44, 2022.

[29] A. Zrelli and T. Ezzedine, "A new approach of WSN deployment, K-coverage and connectivity in border area," Wireless Personal Communications, vol. 121, no. 4, pp. 3365-3381, 2021.

[30] S. Sumitha Pandit and B. Kalpana, "Coverage Using Swarm Intelligence Family in Wireless Sensor Networks," in Soft Computing for Security Applications: Springer, 2022, pp. 351-363.

[31] C. Ozturk, D. Karaboga, and B. Gorkemli, "Probabilistic dynamic deployment of wireless sensor networks by artificial bee colony algorithm," Sensors, vol. 11, no. 6, pp. 6056-6065, 2011.

[32] Z. Fan and W. Zhao, "Network Coverage Optimization Strategy in Wireless Sensor Networks Based on Particle Swarm Optimization," 2011.

[33] M. N. Rahman and M. Matin, "Efficient algorithm for prolonging network lifetime of wireless sensor networks," Tsinghua Science & Technology, vol. 16, no. 6, pp. 561-568, 2011.

[34] B. Wu, C. Qian, W. Ni, and S. Fan, "Hybrid harmony search and artificial bee colony algorithm for global optimization problems," Computers & Mathematics with Applications, vol. 64, no. 8, pp. 2621-2634, 2012.

[35] K. S. Lee and Z. W. Geem, "A new structural optimization method based on the harmony search algorithm," Computers & structures, vol. 82, no. 9, pp. 781-798, 2004.

[36] J. C. Bansal, H. Sharma, and S. S. Jadon, "Artificial bee colony algorithm: a survey," International Journal of Advanced Intelligence Paradigms, vol. 5, no. 1-2, pp. 123-159, 2013.

[37] J. Jia, J. Chen, G. Chang, and Z. Tan, "Energy efficient coverage control in wireless sensor networks based on multi-objective genetic algorithm," Computers & Mathematics with Applications, vol. 57, no. 11, pp. 1756-1766, 2009.