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Optimization of wireless sensor network deployment based on desert golden mole optimization algorithm

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Abstract

The deployment of wireless sensor networks (WSNs) in extreme environments such as nuclear fusion devices and the aerospace industry is crucial for real-time monitoring of critical parameters. However, it faces many challenges. In this paper, we propose the desert golden mole optimization algorithm (DGMOA), a novel algorithm inspired by the survival strategy of the desert golden mole and combined with the Dingo optimization algorithm (DOA). DGMOA addresses these challenges through two core mechanisms: the sand swimming strategy enhances the global search capability, and the hiding strategy is used for fine-grained local optimization. Through simulation tests, DGMOA shows excellent performance. It can quickly explore a large range of solution space in the initial search phase and adjust the position of individuals to avoid local optimal traps, resulting in a more uniform sensor layout and higher coverage. In convergence speed, it outperforms existing algorithms with faster convergence. Regarding energy consumption, the reasonable node layout reduces unnecessary waste and prolongs the service life of the sensor network. The results show that DGMOA is a highly effective solution for sensor layout in complex and extreme environments, with significant improvements in performance and energy consumption over traditional methods.

Keywords: Desert golden mole optimization algorithm, wireless sensor networks, coverage optimization, Dingo optimization algorithm, heuristic algorithm

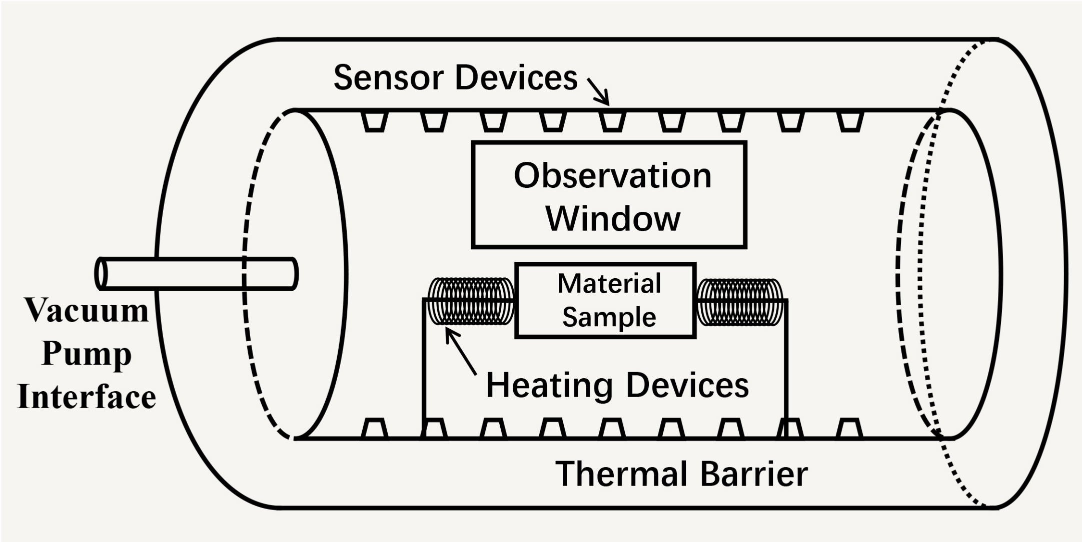

Figure 1. The simulated structure of the vacuum vessel.

1. INTRODUCTION

In high-tech equipment and experimental facilities, vacuum vessels, as a key component, are widely used in nuclear fusion devices, semiconductor manufacturing, and aerospace industry[1,2]. Since these vessels are required to operate in extreme environments, such as high temperatures, strong radiation, and complex pressure variations, real-time monitoring of their status is crucial[3]. Wireless sensor network (WSN) layout is one of the core means to achieve this goal, and by reasonably arranging multiple types of sensors, the temperature, pressure, stress, leakage, and other key parameters of the vacuum vessel can be comprehensively monitored to ensure its stability and safety.

The WSN layout should not only consider the geometry and operating environment of the vacuum vessel, but also need to incorporate its material properties and operating conditions. Complex geometries may lead to stress concentrations and localized hotspots, while weld points and seams in the vessel are often the key areas for monitoring[4]. Figure 1 shows the simulated structure of the vacuum vessel. In addition, the non-magnetic materials and high vacuum conditions of vacuum vessels present technical challenges for sensor selection and installation. Therefore, the type, number, location, and signal processing methods of the sensors must be carefully designed and optimized in order to minimize interference with the internal environment of the vacuum vessel while ensuring monitoring accuracy.

WSN is a network consisting of a large number of sensor nodes distributed in space that collaborate to collect, process and transmit environmental data through wireless communication[5]. Wireless sensors provide strong support for applications such as environmental monitoring, security, and smart agriculture[6–8]. In practical applications, the deployment of wireless sensors needs to address several key issues, including how to maximize coverage, ensure image resolution and quality, optimize energy consumption, and cope with changes in complex environments[9]. In WSNs, due to the wide distribution of nodes, limited resources, and uncertainty of network topology, it becomes a challenge to effectively solve the problems of node placement, routing, and energy management[10,11]. Optimization algorithms are widely used in WSNs as an effective solution, such as genetic algorithms[12], particle swarm optimization algorithms[13], ant colony algorithms[14], *etc.*, to improve the network coverage, energy utilization efficiency, and data transmission quality by optimizing the network topology and the node behaviors, so as to enhance the performance and reliability of WSNs.

In order to further improve the effectiveness of WSN deployment and coverage optimization, this paper proposes a new approach based on the desert golden mole optimization algorithm (DGMOA). DGMOA is a heuristic optimization algorithm inspired by the survival adaptations of the desert golden mole in extreme environments, which simulates its swimming and hiding behaviors in the sand and combines with the collaborative strategy of the Dingo optimization algorithm (DOA)[15] to search for the optimal solution. DGMOA is suitable for solving complex optimization problems due to its powerful global search capability and fast convergence. The following are the main contributions of this paper:

(1) Improved group synergy strategy: while retaining the group attack, chase, scavenger and survival rate strategies in DOA, DGMOA further enhances the inter-individual synergy, making the algorithm more efficient in global search and local optimization.

(2) Sand swimming strategy: the sand swimming behavior of desert golden mole rats shuttling in the desert is introduced, so that the algorithm can quickly explore a large range of solution space in the initial search phase to avoid falling into the local optimum too early. This strategy simulates the random search behavior of the golden mole when searching for food, which enhances the global search ability of the algorithm.

(3) Hiding strategy: this strategy simulates the hiding behavior of desert golden mole when encountering danger by adjusting the position of individuals to avoid dangerous regions or locally optimal traps in the search space. It improves the accuracy and adaptability of the algorithm in localized search and ensures that individuals are able to find more optimal solutions.

The remainder of this paper is organized as follows: Section 2 presents an overview of related work and the motivations behind our work. Section 3 describes the deployment model, sensor deployment and its steps based on the DGMOA algorithm. Section 4 details the experimental environment and discusses the experimental results. Finally, Section 5 concludes the paper.

2. RELATED WORKS

WSNs have been extensively studied due to their wide range of applications in areas such as environmental monitoring, security and smart agriculture. Deployment and optimization of sensor nodes in WSNs is crucial to maximize coverage, minimize energy consumption and ensure reliability of data transmission. Various optimization algorithms have been applied to address the challenges in WSN deployment. ZainEldin *et al.* proposed an improved dynamic deployment technique based on genetic algorithms (IDDT-GA), which aims to maximize the area coverage with a minimum number of sensor nodes, increasing the coverage and reducing the node overlapping area[16]. Deghbouch *et al.* proposed a hybrid bee colony algorithm and locust optimization algorithm (BAGOA) for optimizing node deployment in WSNs, which utilizes the advantages of each method and enhances the ability of local search, which improves the optimization accuracy and convergence speed[17]. Yao *et al.* proposed an optimization algorithm for node deployment in WSNs based on the improved moth flame optimization (MFO) algorithm, by introducing a variable spiral position update strategy and an adaptive inertia weighting strategy to enhance the global search capability of the algorithm, and combining with a virtual force interference strategy to optimize the deployment path of the nodes and improve the network coverage[18]. Wang *et al.* proposed an adaptive multi-strategy artificial bee colony algorithm (SaMABC) to optimize the coverage problem of WSNs[19]. The algorithm enhances the ability to jump out of local optimal solutions by designing a pool of policies and a fine-grained selection mechanism, combined with simulated annealing and dynamic search steps. Moreover, a hybrid approach combining multiple optimization techniques can achieve better results in WSN deployments. In terms of optimizing the performance of WSNs, Zhang *et al.* proposed a CERED active queue management method based on a priority scheduling policy to solve the congestion problem of WSN data packets[20]. Zhang *et al.* proposed adaptive N-strategy sleep scheduling for WSNs, which solves the high data packet delay problem of N-strategy sleep scheduling by introducing a wait state, while reducing energy consumption[21].

Heuristic algorithms have attracted significant attention due to their capacity to handle complex optimization challenges, and they have been widely applied in the context of WSN deployment. The DGMOA proposed in this paper is inspired by the survival adaptations of the desert golden mole. Similar nature-inspired algorithms, such as whale optimization algorithm (WOA)[22] and crayfish optimization algorithm (COA)[23], have shown remarkable success in diverse engineering optimization problems. They typically exhibit superior convergence speed and can often find high-quality solutions. For instance, the WOA models the unique hunting behavior of whales to search for optimal solutions effectively, while the COA emulates the behavior of crayfish in nature. However, these algorithms also have their limitations. They may not fully consider the specific characteristics and constraints of WSN deployment, such as the complex geometries and extreme operating conditions of the deployment environment, which could lead to suboptimal sensor placements. The DOA, proposed by Peraza-Vázquez *et al*., simulates the hunting and foraging behaviors of Dingoes[15]. It models strategies such as pack hunting, individual pursuit, and survival probability to solve optimization problems. While DOA has its strengths in certain scenarios, it may face challenges in adapting to the highly dynamic and constrained nature of WSNs. For example, in a WSN, the sensor nodes have limited resources and need to communicate wirelessly, which requires a more fine-grained optimization of node positions and energy consumption. In contrast, DGMOA is specifically designed to address the challenges in WSN deployment. It not only draws on the survival strategy of the desert golden mole but also integrates the collaborative strategies of DOA.

The desert golden mole lives under the sand dunes in the Namib Desert. To adapt to the extreme environment, it has evolved unique behavioral patterns. During the hot daytime, it digs holes under the sand dunes to avoid the high temperature, while at night, it needs to shuttle between the sand dunes in search of food and water. This movement behavior between the sand dunes inspired us to design the sand swimming strategy, which is incorporated into the DGMOA. Inspired by the desert golden mole's movement between sand dunes at night, in the initial search phase, this strategy allows the algorithm to quickly explore a large range of solution space. This is because it simulates the movement way of the desert golden mole between sand dunes, enabling the optimization algorithm to explore more flexibly in the search space and quickly traverse a large range of solution space, thus avoiding getting trapped in local optima too early and significantly enhancing the global search ability. When the desert golden mole encounters danger, it will use the surrounding environment to hide and choose the appropriate direction and position to avoid according to its relative position relationship with the danger source, the safe area and other individuals of the same kind. This hiding behavior is applied to the hiding strategy of DGMOA. This strategy adjusts the position of individuals to avoid dangerous regions or locally optimal traps in the search space, which improves the accuracy and adaptability of the algorithm in localized search and ensures that individuals can find more optimal solutions. By combining these unique strategies such as the sand swimming strategy and the hiding strategy, DGMOA is better able to meet the complex requirements of WSN deployment and optimize the coverage and energy consumption of the network more effectively than existing algorithms.

Effective sensor deployment strategies are essential to maximize coverage and ensure the reliability of WSNs. Various deployment models have been proposed, including deterministic, random, and hybrid approaches. Deterministic models place sensors at predetermined locations, while stochastic models randomly distribute sensors within the target area. Hybrid models combine the advantages of deterministic and random deployment to balance coverage and cost. The proposed DGMOA-based deployment strategy leverages the advantages of these models to maximize coverage by achieving optimal sensor placement through heuristic optimization.

3. METHODS

This section introduces the wireless sensor deployment model and the DGMOA, which combines the synergistic strategy of the DOA and simulates the sand swimming and hiding behaviors of the DGMOA to improve the convergence speed and coverage of the algorithm, and achieves a balance between global search and local optimization, and is applicable to the problem of optimizing the layout of a sensor network in a complex environment.

3.1. WSN deployment model

The WSN deployment problem can be converted into a constrained optimization problem, usually a nonlinear programming problem. Assuming that multiple wireless sensors are deployed in a two-dimensional planar area so that the area is well monitored, the deployment of sensors needs to be uniform and reasonable. The problem is expressed as follows:

$$\begin{aligned} &\text{Minimize } C(\alpha) = \left(F(\alpha_1,\alpha_2) \bigcup F(\alpha_3,\alpha_4) \bigcup \cdots \bigcup F(\alpha_{D-1},\alpha_D)\right) \bigcap MAP \\ &Subject\ to \quad \begin{array}{l} D = 2\times N \\ \alpha_k^{(l)} \le \alpha_k \le \alpha_k^{(u)}, k = 1,\ldots,D \end{array} \end{aligned} \tag{1}$$

Where α is a D-dimensional vector; N denotes the number of sensors to be deployed in the region; MAP indicates the set of two-dimensional planar area points; $F(\alpha_i,\alpha_{i+1})$ is the set of sensor sensing area points with (α_i,α_{i+1}) as the circle point; the radius will be different in the sensor model or type; $C(\alpha)$ denotes the coverage of the current sensor deployment.

Assume that the monitoring area is a two-dimensional plane and digitize it into $l \times u$ pixel points, each of equal size. N sensors are randomly thrown on this 2D plane, and the set of sensor nodes is $S = \{s_1, s_2, \cdots, s_N\}$, where the sensor sensing radius is r and the coordinates of node i are $s_i = \{x_i, y_i\}$. The distance between the i-th sensor and the pixel point $site(x,y)$ is calculated using Euclidean distance:

$$d_{i,site} = \sqrt{(x-x_i)^2 + (y-y_i)^2} \tag{2}$$

In this paper, we use a binary perception model where the sensor node i perceives the target pixel point $site$ as:

$$F(s_i) = \begin{cases} 1, & d_{i,site} \le r \\ 0, & d_{i,site} > r \end{cases} \tag{3}$$

The set of area points contained in the sensor s_i is recorded. The area coverage points for all sensor nodes are:

$$C(S) = \left(F(s_1) \bigcup F(s_2) \bigcup \cdots \bigcup F(s_N)\right) \bigcap MAP \tag{4}$$

The goal of WSN coverage optimization is to achieve maximum coverage area using a minimum number of sensors, which is expressed in the form of a coverage ratio in order to facilitate the comparison of the coverage area of the sensors:

$$C_{Rate} = \frac{C\left(S\right)}{l \times u} \tag{5}$$

Which is used as an objective function, and an optimization algorithm is employed to find a set of sensor node combinations to maximize the coverage.

The model uses an optimization algorithm to reasonably deploy sensor nodes in the two-dimensional plane and maximize the coverage area of the monitoring area by introducing a coverage objective function. Through mathematical modeling and formula derivation, it can effectively describe and solve the deployment problem of WSNs.

3.2. DGMOA

In this paper, based on the research of Fielden *et al.*, we deeply analyzed the behavioral patterns of the desert golden mole, proposed the sand swimming strategy and the hiding strategy, and implemented these strategies through code [24]. Meanwhile, combined with the DOA proposed by Peraza-Vázquez *et al.*, the DGMOA shows significant advantages in terms of performance and flexibility [15]. Combining the sand swimming strategy and the hiding strategy, the DGMOA performs well in WSN coverage deployment, and is able to improve the network coverage and optimize the distribution of nodes more efficiently, thus significantly improving the overall performance of the WSN.

3.2.1. DOA

Dingoes usually hunt small animals, chasing them relentlessly until they capture them alone. The persecution strategy is modeled below:

$$\overrightarrow{\alpha_k\left(x+1\right)} = \xi_1 e^{\xi_2}\left(\overrightarrow{\alpha_{t_1}\left(x\right)} - \overrightarrow{\alpha_k\left(x\right)}\right) + \overrightarrow{\alpha_B\left(x\right)} \tag{6}$$

Where $\overrightarrow{\alpha_k(x+1)}$ represents the new position of Dingoes k, ξ_1 is a random number generated uniformly in the interval $[-2, 2]$, ξ_2 is a random number generated uniformly in the interval $[-1, 1]$, t_1 is a random number generated in the interval from 1 to the maximum number of Dingoes searched for, $\overrightarrow{\alpha_{t_1}(x)}$ represents the position of the t_1-th Dingoes ($t_1 \neq k$), $\overrightarrow{\alpha_k(x)}$ represents the position of Dingoes k, and $\overrightarrow{\alpha_B(x)}$ is the last search iteration of the best position.

Dingoes usually hunt small prey, such as rabbits, alone, but when targeting larger animals such as kangaroos, they hunt in packs. Group Attack strategy is their most common hunting strategy where they surround their prey in a range and start chasing it until it tires. This strategy is modeled below:

$$\overrightarrow{\alpha_k\left(x+1\right)} = \frac{\xi_1}{\omega}\sum_{j=1}^{\omega}\left[\beta_j(x) - \overrightarrow{\alpha_k(x)}\right] - \overrightarrow{\alpha_B(x)} \tag{7}$$

Where $\overrightarrow{\alpha_k(x+1)}$ represents the new location of Dingoes k, ξ_1 is a uniformly generated random number in the interval $[-2, 2]$, ω is a random integer in the interval $[2, Q/2]$ (Q denotes the population size of the Dingoes), $\beta_j(x)$ is the subset of Dingoes that will be subject to pack hunting (the Dingoes that will be subject to pack hunting are randomly selected), $\overrightarrow{\alpha_k(x)}$ represents the location of Dingoes k, and $\overrightarrow{\alpha_B(x)}$ is the best location from the previous search iteration.

When Dingoes fail to find prey, they roam their habitat in search of carrion. The Scavenger strategy is modeled as follows:

$$\overrightarrow{\alpha_k\,(x+1)} = \frac{e^{\xi_2}\overrightarrow{\alpha_{t_1}\,(x)} - (-1)^{\mathfrak{M}}\overrightarrow{\alpha_k\,(x)}}{2} \tag{8}$$

Where $\overrightarrow{\alpha_k(x+1)}$ represents the new position of Dingoes k, ξ_2 is a random number generated uniformly in the interval $[-1,1]$, t_1 is a random number generated in the interval from 1 to the maximum number of dingoes searched, $\overrightarrow{\alpha_{t_1}(x)}$ represents the position of the t_1-th dingo $(t_1 \neq k)$, $\mathfrak{M}$ is randomly chosen to be either 0 or 1 and $\overrightarrow{\alpha_k(x)}$ represents the position of Dingoes k.

Australian Dingoes are at risk of extinction due to illegal hunting. Their probability of survival is modeled as follows:

$$LiveRate\,(k) = \frac{fun_u - fun\,(k)}{fun_u - fun_d} \tag{9}$$

Where fun_u denotes the value of the best fitness for this iteration, fun_d denotes the value of the worst fitness for this iteration, and $fun\,(k)$ denotes the value of the Dingoes k fitness, which is executed to update the Dingoes when their survival probability is below a certain value:

$$\overrightarrow{\alpha_k\,(x)} = \frac{\overrightarrow{\alpha_{t_1}\,(x)} - (-1)^{\mathfrak{M}}\overrightarrow{\alpha_{t_2}\,(x)}}{2} + \overrightarrow{\alpha_B(x)} \tag{10}$$

Where $\overrightarrow{\alpha_k\,(x)}$ denotes the current Dingoes with low probability of survival, t_1 and t_2 are random numbers generated from the interval from 1 to the maximum number of Dingoes searched $(t_1 \neq t_2)$, $\overrightarrow{\alpha_{t_1}\,(x)}$ represents the position of the t_1-th Dingoes, $\overrightarrow{\alpha_{t_2}\,(x)}$ represents the position of the t_2-th Dingoes, $\mathfrak{M}$ is randomly chosen to be either 0 or 1, and $\overrightarrow{\alpha_B\,(x)}$ is the optimal position from the previous search iteration.

3.2.2. Desert golden mole sand swimming strategy

In this paper, we introduce a sand swimming strategy for desert golden moles to optimize the search process by simulating the desert golden mole's behavior of shuttling between sand dunes at night. The desert golden mole is a small mammal living under sand dunes in the Namib Desert that survives in extreme environments with its unique behavior. During the hot days of the desert, they often shelter from the heat by digging holes under the dunes, but at night they need to travel between the dunes in search of food and water. Observing this behavior of desert golden mole inspired the design of an optimization strategy, the sand swimming strategy.

The sand swimming strategy is used to improve the global search capability of the optimization algorithm by simulating the way the desert golden mole moves between dunes at night. Assuming that $\overrightarrow{\alpha_k\,(x)}$ denotes the multi-dimensional coordinates of the desert golden mole's current position, υ denotes its moving velocity vector, and θ denotes the angle vector of the desert golden mole's moving direction in each dimension, the desert golden mole's dune movement at night can be written as:

$$\overrightarrow{\alpha_k\,(x{+}1)} = \overrightarrow{\alpha_k\,(x)} + \upsilon \odot \mathrm{w}\,(\theta{+}\sigma) \tag{11}$$

Where $\odot$ denotes the element-by-element product and σ is a unit vector of random deviations in the interval $[0, 1]$ used to increase the randomness of the moving direction. w is a function to map the angle vector to the unit vector so that the angle of the moving direction can be correctly applied to each dimension. The calculation makes the movement of the desert golden mole in multi-dimensional space more flexible and versatile, and can adapt to various complex terrain situations. In the desert, the desert golden mole needs to shuttle between sand dunes to search for food and water, especially at night. This behavior is simulated in the formula to improve the global search ability of the optimization algorithm. The position of the desert golden mole is represented by the multi-dimensional coordinate $\overrightarrow{\alpha_k\ (x)}$. The moving velocity vector υ and the angle vector θ of the moving direction in each dimension are introduced. The unit vector of random deviations σ in the interval $[0, 1]$ is added to increase the randomness of the moving direction. w is used to map the angle vector to the unit vector, so that the angle of the moving direction can be correctly applied to each dimension. Through these elements, the formula is constructed to simulate the flexible and adaptable movement of the desert golden mole in the multi-dimensional space, which enables the algorithm to search and optimize in complex environments.

In particle swarm optimization, the position update of particles mainly depends on their own historical optimal positions and the group's historical optimal positions. Consequently, the search direction is relatively concentrated around the known relatively good regions, and there is a high risk of getting trapped near the local optimal solution. In contrast, within the DGMOA's sand swimming strategy, the position update for the desert golden mole is expressed as $\overrightarrow{\alpha_k\ (x{+}1)} = \overrightarrow{\alpha_k\ (x)} + \upsilon \odot \mathrm{w}\ (\theta{+}\sigma)$. $\overrightarrow{\alpha_k\ (x)}$ represents the multi-dimensional coordinates of the desert golden mole's current position, υ is the movement velocity vector, θ is the angle vector of the movement direction, σ is a unit vector of random deviations within the interval $[0, 1]$ that serves to enhance the randomness of the movement direction, and w is a function that maps the angle vector to a unit vector. This design enables the desert golden mole to move more flexibly and diversely in the multi-dimensional space, thereby better adapting to various complex terrain situations. Specifically, it allows the algorithm to quickly traverse a larger range of solution space during the initial search phase, effectively avoiding premature convergence to local optimal solutions. The sand swimming strategy considers the movement of the desert golden mole in a multi-dimensional space. By leveraging multi-dimensional coordinates and angle vectors of the moving direction, it can adapt to diverse terrain conditions, including alterations in the height and inclination of sand dunes. This multi-dimensional adaptability renders the sand swimming strategy highly effective in complex environments.

3.2.3. Desert golden mole hiding strategy

In this paper, we introduce the hiding strategy of the desert golden mole to optimize the search process by simulating the hiding behavior of the desert golden mole when encountering danger. In the optimization algorithm, the hiding strategy is used to adjust the exploration direction during the search process to avoid falling into unfavorable local optimal solutions or encountering dangerous regions in the search space as much as possible.

Suppose the position of the desert golden mole is a multi-dimensional vector $\overrightarrow{\alpha_k\,(x)} = (\eta_1, \eta_2, \ldots, \eta_{\mathrm{dim}})$, where each dimension η_i denotes the position of the desert golden mole in the i-th dimension. $\mathbf{d_w} = (d_{w1}, d_{w2}, \ldots, d_{wn})$ indicates the relative distance between the desert golden mole and the worst positioned mole; $\mathbf{d_s} = (d_{s1}, d_{s2}, \ldots, d_{sn})$ indicates the relative distance of the desert golden mole to the best-positioned mole; $\mathbf{c} = (c_1, c_2, \ldots, c_n)$ denotes a vector of safe locations, where each element indicates whether the desert golden mole is safe in the first dimension, and smaller means safer; $\mathbf{r} = (r_1, r_2, \ldots, r_n)$ denotes a vector of randomized hazard parameters, where each denotes the hazard level of the predator encountered in the first dimension. The hiding strategy is expressed as:

$$\overrightarrow{\alpha_k\ (x+1)} = \overrightarrow{\alpha_k\ (x)} + \mathbf{c} \odot \left(p\mathbf{d}_w + q\mathbf{d}_b\right) \odot \mathbf{r} \tag{12}$$

Where $\overrightarrow{\alpha_k\,(x)}$ denotes the current position vector of the desert golden mole and $\overrightarrow{\alpha_k\,(x+1)}$ indicates the updated position vector. p and q are coefficients used to adjust the degree of influence of the danger factor and safety factor on hiding movement. $\odot$ denotes the element-by-element multiplication operation. The desert golden mole moves to hide in the more dangerous dimension according to the hiding factor vector, and considers the danger level and relative distance of the encountered predators, so as to avoid the danger more effectively and find a suitable hiding place. When the desert golden mole senses danger, it will comprehensively consider its own position, the relative positions with other individuals of the same kind (including the worst and best positions), the safety degree of the surrounding environment, and the randomly emerging danger factors to determine the next moving direction and distance. The part $\mathbf{c} \odot \left(p\mathbf{d}_w + q\mathbf{d}_b\right) \odot \mathbf{r}$ calculates an adjustment vector based on the safe position vector $\mathbf{c}$, the relative distance vectors $\mathbf{d}_w$ and $\mathbf{d}_b$ between the desert golden mole and the worst and best-positioned individuals, and the coefficients p and q. This adjustment vector reflects the direction and magnitude of the position adjustment that the desert golden mole should make based on its own position, the positions of other individuals in the group, and safety factors. Multiplying by the random danger parameter vector $\mathbf{r}$ further introduces randomness to simulate the random hiding behavior of the desert golden mole when facing uncertain dangers, and finally obtains the new position of the desert golden mole at the $(x+1)$-th iteration.

The hiding strategy simulates the evasive behavior of the desert golden mole in the face of dangerous situations by using a multi-dimensional vector to represent the position of the desert golden mole and introducing a series of parameters to influence the evasive movement. By calculating the relative distances between the desert golden mole, the worst-positioned mole and the best-positioned mole, and considering the safe position and the random danger parameters, it realizes the intelligent adjustment of the exploration direction to avoid falling into the local optimal solution or encountering a dangerous area. The advantage of this strategy is that it can intelligently adjust the moving direction based on environmental conditions, enabling the algorithm to avoid dangers more effectively and find safer hiding places, thus improving the search efficiency and global search ability.

3.2.4. WSN coverage deployment with DGMOA

Firstly, the size of the sensor deployment area is set to $l \times u$, the number of sensors is S, the population size of the Desert Golden Mole is M, and the number of iterations of the algorithm is Max_iter, and the number of iterations of the algorithm is . The WSN deployment model is introduced, and the computation is conducted using the DGMOA [Figure 2], and the specific steps are as follows:

Step 1: Initialize the position vector of the desert golden mole. The position of each desert golden mole represents a possible sensor deployment scenario. Initialize a vector of relative distances between the worst position mole and the best position mole to represent the distance of each desert golden mole from the current worst and best positions. Initialize a vector of safe locations to represent the level of safety at each location. Initialize a vector of random hazard parameters for adding randomness to the exploration process.

Step 2: Based on the current position vector of the desert golden mole, the fitness of each desert golden mole, i.e., the value of the objective function, is calculated.

Step 3: The DGMOA is used to update the position of the desert golden mole, adjusting its exploration direction and step size.

Step 4: During each periodic nighttime sand swimming event, the position vector of the desert golden mole

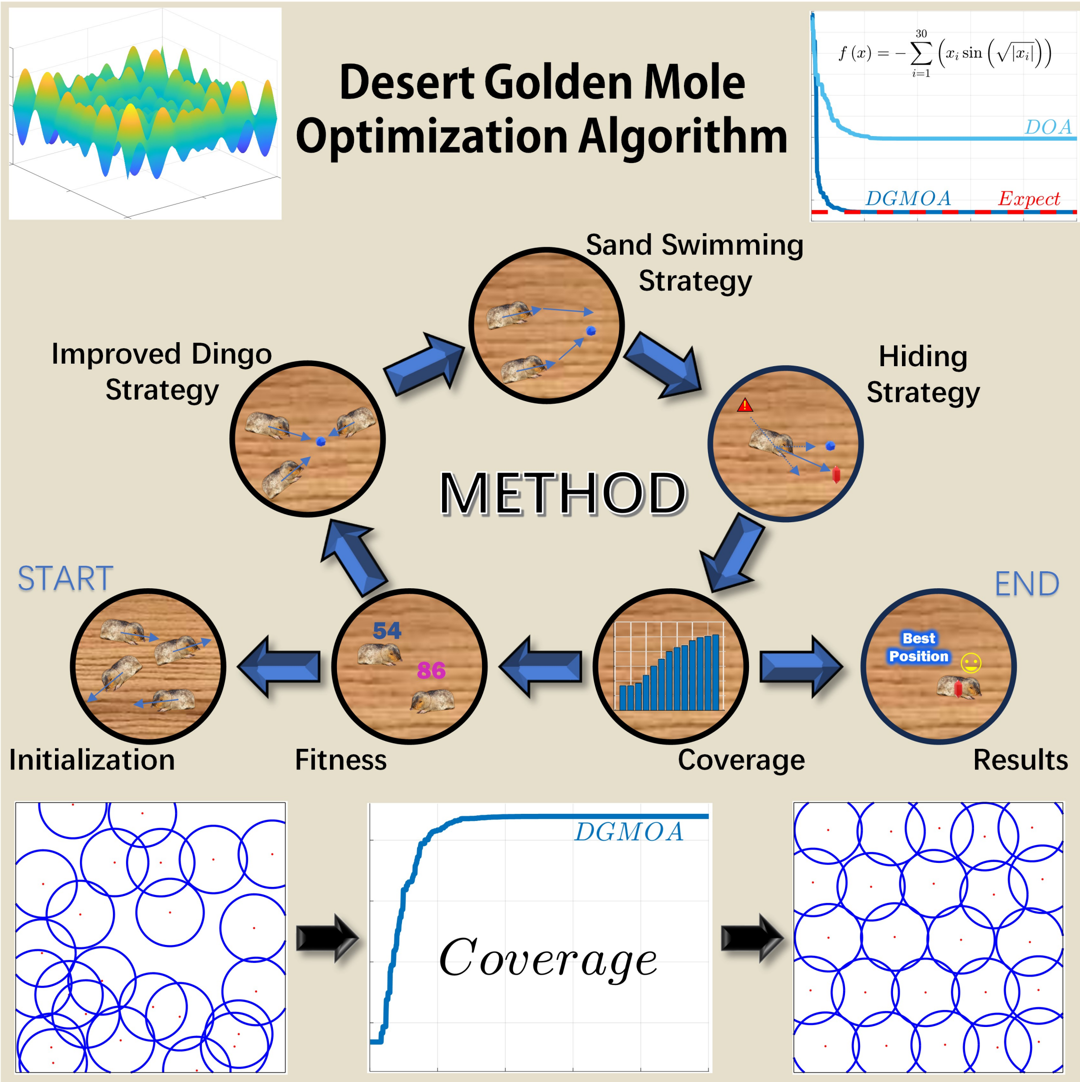

Figure 2. DGMOA application to WSN deployment modeling. DGMOA: Desert golden mole optimization algorithm; WSN: wireless sensor network.

is adjusted according to the mathematical model of the sand swimming strategy to simulate its movement through the desert. This strategy increases the randomness and exploration of movement directions by introducing velocity vectors and random deviations.

Step 5: With a probability of encountering a predator of L, the position vector of the desert golden mole is adjusted according to the mathematical model of the hiding strategy, allowing it to intelligently choose a hiding place to avoid detection. This strategy optimizes the moving position of each desert golden mole by calculating the relative distance and the safe position so that it avoids dangerous areas.

Step 6: Based on the WSN coverage deployment model, calculate the coverage ratio under the current desert golden mole location to assess the coverage effect of the sensor network. The coverage ratio indicates the proportion of the sensor deployment scenario that covers the entire area.

Step 7: Repeat steps 3 to 6 until a set number of iterations or convergence conditions are reached. In each iteration, the sensor deployment scheme is continuously optimized through the combination of position update, sand swimming strategy and hiding strategy to improve the coverage and deployment efficiency.

Step 8: Output the location vector of the optimal or near-optimal solution, along with the corresponding fitness value and coverage. The optimal solution represents the best deployment solution for the sensors that maximizes the coverage area and optimizes the energy consumption.

Through the above steps, the DGMOA is able to search the problem space intelligently, simulate the behavior of the desert golden mole in the natural environment by using the sand swimming strategy and the hiding strategy, so as to improve the algorithm's searching efficiency and global searching ability, and finally output the optimization results. The introduction of the shared optimal solution mechanism further enhances the optimization performance of the algorithm and makes it perform better in complex environments.

4. EXPERIMENTS

The experiments were conducted in a MATLAB R2023a environment on a standard PC equipped with a 3.20 GHz processor and 16 GB of memory. To test the performance of the proposed DGMOA for WSN deployment, we utilized simulated environments of 20 m × 20 m and 50 m × 50 m areas. We compared the latest optimization algorithms, including DOA, COA, salp swarm algorithm (SSA) [25], WOA, and MFO [26], in terms of coverage rate, convergence speed, and computational efficiency.

4.1. Ablation experiments

To evaluate the impact of the sand swimming strategy and the hiding strategy, we designed an ablation experiment. We compared the performance of the original DGMOA algorithm (with sand swimming strategy and hiding strategy), DGMOA with sand swimming strategy removed and DGMOA with hiding strategy removed. The experimental setups of the three algorithms are consistent in terms of simulated environment, sensor parameters and maximum number of iterations. The population size of the optimization algorithms is categorized as 500 and the maximum number of iterations is set to 1,000. The simulated environment used for the deployment of the WSN is a 20 m × 20 m area.

Under the same experimental setting, it can be seen from the convergence curve of the 20 m × 20 m area experimental results in Figure 3 that when the "sand swimming strategy" is removed from the DGMOA algorithm, the performance changes significantly. The algorithm that removes the "sand swimming strategy" requires more iterations to approach the coverage of the DGMOA algorithm. This shows that the sand swimming strategy plays an important role in improving the convergence speed of the algorithm, which can help the algorithm quickly explore a wider range of solution spaces in the early search period, thereby improving the overall performance. When the "hiding strategy" is removed from the DGMOA algorithm, although the convergence speed in the initial stage is similar to that of DGMOA, it is easy to fall into the local optimal solution during the iteration process. The specific performance is that after reaching a certain coverage, the coverage is improved slowly, and the final convergence result is lower than that of the DGMOA algorithm.

4.2. Datasets

We set up different scenarios for the comparison of the experiments, 20 m × 20 m and 50 m × 50 m areas for WSN deployment, respectively, and the population size of the optimization algorithm is set to 30, 50, 75, 125, 250, and 500, respectively, and the maximum number of iterations is set to 1,000. For the initialization of the population, we use a random initialization method to determine the initial position of the sensor nodes in the monitoring area. In the monitoring areas of 20 m × 20 m and 50 m × 50 m, the position coordinates of the sensor nodes are randomly generated within the corresponding area. For example, in the area, the abscissa x and the ordinate y of each sensor node are real numbers randomly selected within the interval $[0, 20]$. This random initialization method can provide diverse initial solutions for the algorithm and avoid the algorithm

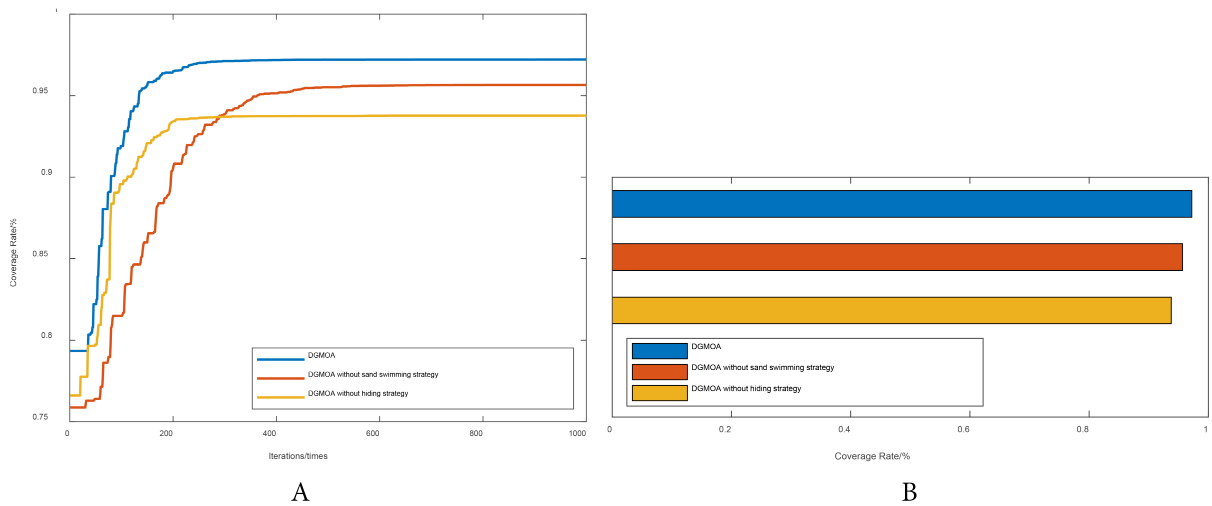

Figure 3. Graphical representation of the results of the ablation experiment under the same experimental setup. (A) Convergence curve of experimental results for 20 m × 20 m area; (B) final coverage statistics for the 20 m × 20 m area in the ablation experiment.

falling into the local optimal solution at the initial stage. At the same time, we clarify the value range of the population size and its impact on the experiment. In different experiments, the population size is set to 30, 50, 75, 125, 250 and 500, and the adaptability and stability of the DGMOA algorithm are comprehensively evaluated by comparing the performance of the algorithm under different population sizes. For the parameters in the sand swimming strategy, the initial value of the velocity vector υ is calculated and evaluated according to the current optimal effect, current worst effect and survival rate, so that the algorithm dynamically adapts to the convergence speed of the search space. The initial value of the angle vector θ is also randomly generated at each iteration, and its value range is between $[0, 2\pi)$, which ensures that the direction of movement of the desert golden mole in the multi-dimensional space is random, which helps the algorithm to explore the solution space widely in the initial search stage. Each element in the random deviation vector σ is randomly generated within the interval $[0, 1]$, which is used to introduce additional random factors to avoid premature convergence of the algorithm. Regarding hiding strategy-related parameters, the initialization of the safe position vector $\mathbf{c}$ is set according to the known safe area or relatively safe position information in the monitoring area. If there is no pre-defined safety zone information, the initial value of $\mathbf{c}$ is set to 1, indicating that the security of all positions is the same at the beginning. As the algorithm runs, the value of $\mathbf{c}$ will be dynamically updated according to the interaction between the individual and other individuals and the environment. The coefficients p and q are used to balance the influence of the risk and safety factors on the hidden movement. In the experiment, the initial values of p and q are set to 0.5. Through multiple experimental comparisons, it is found that this setting can make the algorithm achieve a good balance between avoiding danger and tending to safety in most cases. Each element of the random danger parameter vector $\mathbf{r}$ is randomly generated at each iteration, and its value range is between $[0, 1]$, which is used to simulate the uncertainty of the desert golden mole in encountering danger in the real environment.

4.3. Experimental results and analysis

In a 20 m $\times$ 20 m area, 24 wireless sensors were deployed, the sensing radius was set to r = 2.5 m, and the monitoring area was discretized into $2,000 \times 2,000$ pixel points. From the simulation experiment results in Figure 4, it can be seen that DGMOA shows high coverage in the initial stage. This is mainly because the sand swimming strategy of DGMOA simulates the behavior of desert golden moles shuttling between sand dunes at night, allowing it to quickly explore a large range of solution spaces in the initial search phase and avoid falling into the local optimum too early. In contrast, other algorithms may not be as comprehensive in the initial search, resulting in a slower increase in coverage. Especially when the population size is 500, the convergence

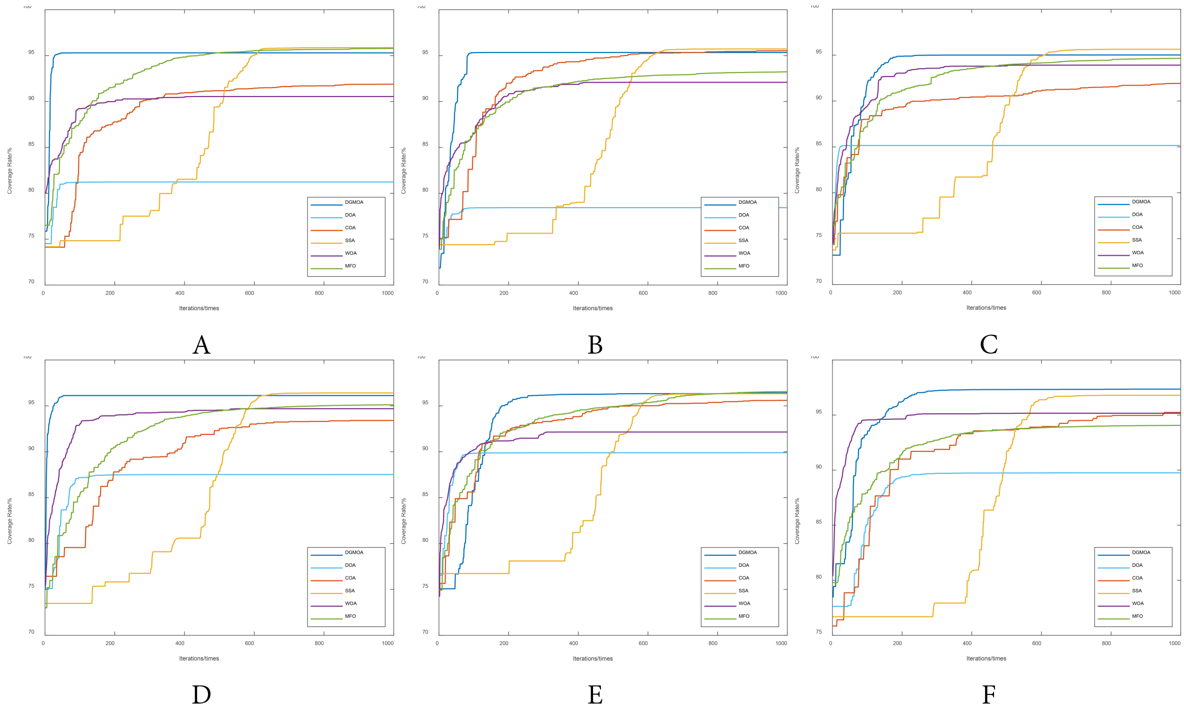

Figure 4. Coverage performance of the proposed DGMOA algorithm in a 20 m × 20 m area, based on different population sizes compared with five other algorithms. (A) Population size is the result of 30; (B) 50; (C) 75; (D) 125; (E) 250; (F) 500. DGMOA: Desert golden mole optimization algorithm.

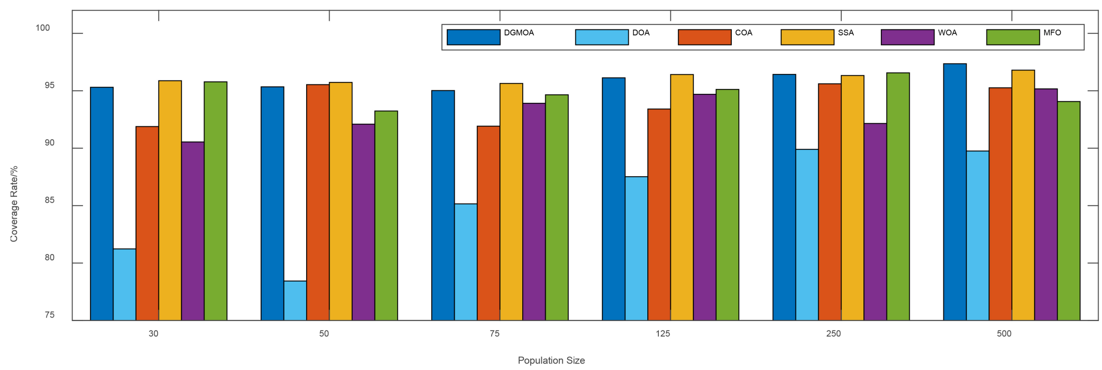

Figure 5. Statistical map of final coverage in a 20 m × 20 m area.

speed of DGMOA is significantly faster than other algorithms. As the population size increases, as shown in Figure 5, the performance of most algorithms improves. DGMOA performs particularly well in the case of large-scale populations. The reason is that the improved group synergy strategy of DGMOA further enhances the inter-individual synergy, enabling it to better balance global search and local optimization. In contrast, some other algorithms may experience poor coordination or reduced search efficiency when the population size increases. The effect of WSN coverage deployment in a 20 m × 20 m area is demonstrated in Figure 6. The sensor layout under the DGMOA algorithm is more uniform. This is because the hiding strategy of DGMOA adjusts the position of individuals to avoid dangerous regions or locally optimal traps in the search space, making the sensor nodes more reasonably distributed in space. Other algorithms may lack such an intelligent position adjustment mechanism, resulting in uneven node distribution or larger coverage overlaps and gaps.

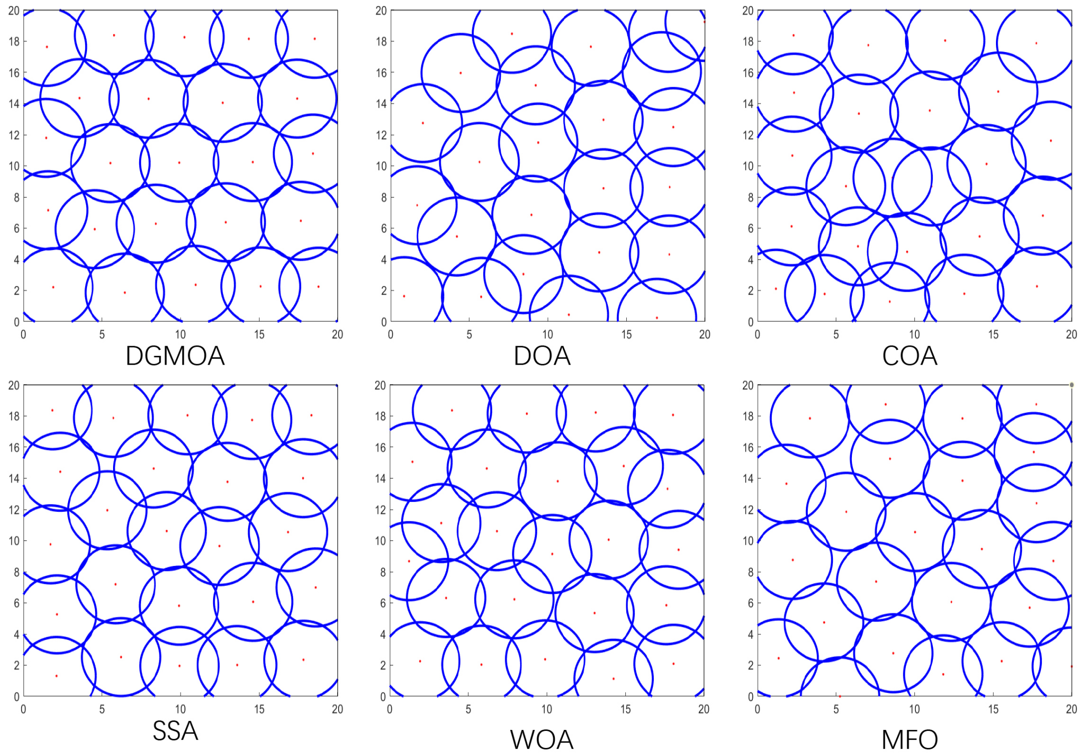

Figure 6. Deployment diagram of WSN coverage in a 20 m × 20 m area. WSN: Wireless sensor network.

The performance results under different population sizes in a 50 m × 50 m area show that DGMOA consistently outperforms other algorithms in terms of coverage and convergence speed. As can be seen in Figure 7, DGMOA is able to rapidly improve the coverage in the initial iterations and achieve nearly 95% coverage with fewer iterations. This is due to the combined effect of the sand swimming strategy and the hiding strategy of DGMOA, and the improved group synergy strategy. The sand swimming strategy enhances the global search ability, allowing it to quickly locate potential excellent solutions in a large and complex environment. The hiding strategy improves the accuracy and adaptability of local search and avoids falling into the local optimum. The improved group synergy strategy improves the overall search efficiency. In contrast, other algorithms may have deficiencies in one or more of these aspects, resulting in poorer performance in terms of coverage, convergence speed, and node distribution uniformity. In addition, Figure 8 shows the statistical analysis of the final coverage rates for different population sizes, and compared with other algorithms, DGMOA achieves higher coverage rates, especially when the population size is larger, and its advantage is more obvious. Figure 9 shows that the deployment of DGMOA-optimized WSNs results in a more even distribution of nodes and less overlap between coverage areas, further emphasizing the effectiveness of DGMOA in solving large-scale WSN coverage problems.

Through the results of the WSN coverage deployment simulation experiment, it can be seen that DGMOA shows significant excellence in sensor network deployment. The deployment of the sensor location is more uniform, the overlap and gap between the coverage area is less, achieving a higher coverage rate, and can effectively utilize the sensor resources to maximize the coverage area. Compared with other algorithms, DGMOA has significant advantages. It can quickly improve the coverage rate in a shorter time while maintaining the uniformity and efficiency of sensor deployment, proving that it outperforms the other compared algorithms in terms of global search, fast convergence, and final coverage effect. In summary, DGMOA has significant superiority in sensor network optimization and deployment and can quickly and efficiently achieve high coverage.

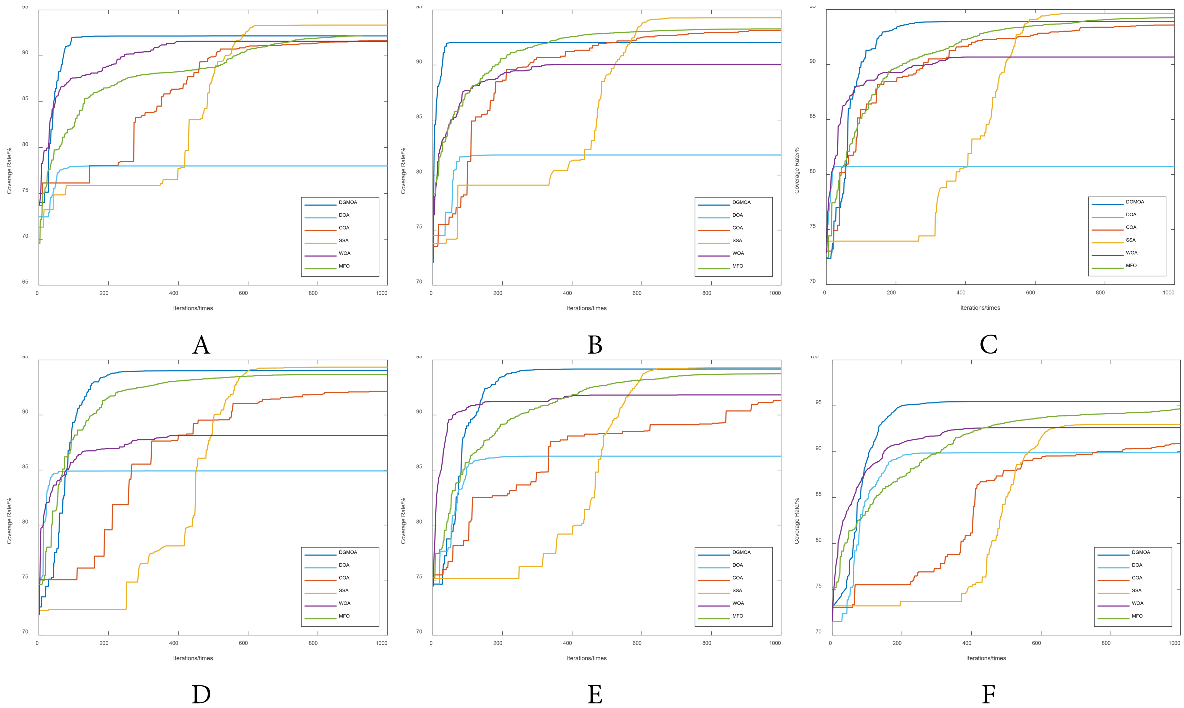

Figure 7. Coverage performance of the proposed DGMOA algorithm in a 50 m × 50 m area, based on different population sizes compared with five other algorithms. (A) population size is the result of 30; (B) 50; (C) 75; (D) 125; (E) 250; (F) 500. DGMOA: Desert golden mole optimization algorithm.

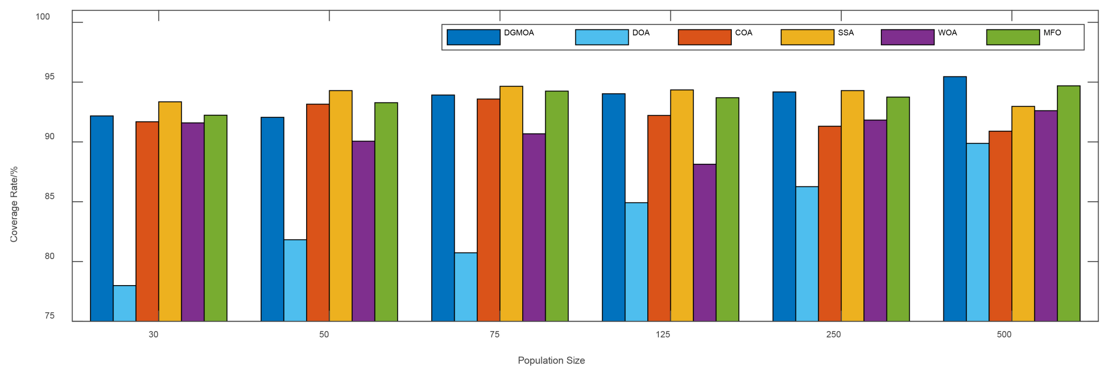

Figure 8. Statistical map of final coverage in a 50 m × 50 m area.

In terms of energy consumption, DGMOA deploys sensors to make the node layout more reasonable, reducing unnecessary energy waste, and thus improving the overall energy utilization efficiency. The unified sensor layout avoids the rapid energy consumption caused by too dense nodes, and also reduces the additional energy consumption that may be caused by coverage blind spots. Compared with other algorithms, DGMOA can maintain the effective operation of the network with lower energy consumption under the same monitoring tasks, prolonging the service life of the sensor network, especially suitable for complex and extreme environments with limited resources.

4.4. DGMOA algorithm analysis

In order to deeply explore the performance of the DGMOA algorithm, a systematic and multi-dimensional experiment and detailed analysis work was carried out. In the experimental planning, different scale simulation areas such as 20 m × 20 m and 50 m × 50 m were selected to build WSN deployment scenarios and simulate var-

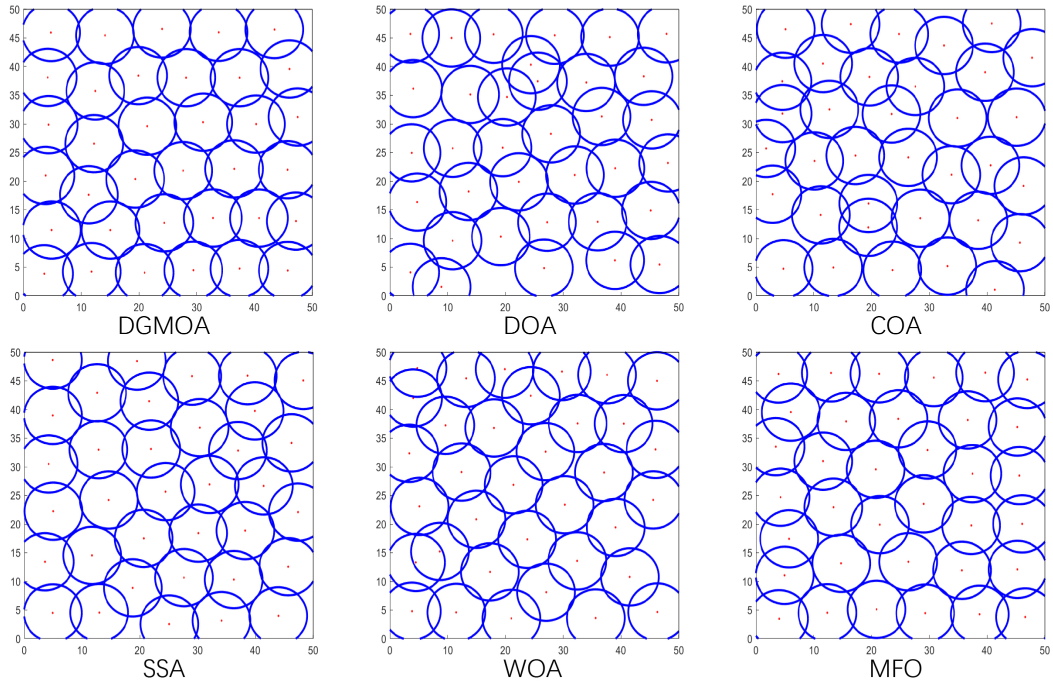

Figure 9. Deployment diagram of WSN coverage in a 50 m × 50 m area. WSN: Wireless sensor network.

ious actual environments. The performance analysis focuses on the core indicators of coverage performance, convergence speed and spatial distribution efficiency, so as to accurately measure the performance of the algorithm. Compared with DOA, COA, SSA, WOA, MFO and other algorithms, the DGMOA algorithm stands out and has significant advantages. In the 20 m × 20 m area, the initial coverage degree is high, and the 95% coverage target can be quickly achieved. When the population size reaches 500, the convergence speed far exceeds that of other methods; in the 50 m × 50 m area, the coverage effect is good and the convergence is fast. The node distribution is balanced and the coverage overlap is less.

Through the design of ablation experiments, the effectiveness of the two strategies of sand swimming and hiding is verified. As far as the sand swimming strategy is concerned, from the convergence curve of the experiment in the 20 m × 20 m area, it can be seen that after removing the strategy, the algorithm needs more iterations to approach the original coverage level, because it can efficiently explore the solution space in the early search stage, greatly reduce the calculation time, and effectively improve the time efficiency. The hiding strategy focuses on avoiding the local optimum and ensuring the convergence effect. After removing it, although the initial convergence speed is not much different, the subsequent iterations are prone to fall into the dilemma of local optimum, the coverage rate climbs slowly, and the final convergence result is not as good as the original algorithm, which shows its key role in guiding the algorithm to avoid unfavorable areas and optimize coverage.

Overall, the DGMOA algorithm has shown good performance in different scale regional experiments. The sand swimming and hiding strategies complement each other, and the combined efforts significantly enhance the comprehensive performance of the algorithm, which effectively confirms the important and effective position of the two algorithms in the algorithm system. This provides a solid theoretical and practical foundation for the algorithm to be deployed in complex WSNs.

5. CONCLUSIONS

This paper presents the DGMOA, which makes significant contributions. The sand swimming strategy, inspired by the desert golden mole's movement between sand dunes at night, allows the algorithm to quickly explore a large range of solution spaces in the initial search phase. This effectively avoids falling into local optima too early and greatly enhances the global search ability. The hiding strategy, simulating the desert golden mole's hiding behavior when encountering danger, adjusts the position of individuals to avoid dangerous regions or locally optimal traps in the search space. This improves the accuracy and adaptability of the algorithm in localized search and ensures more optimal solutions. These two strategies make DGMOA highly applicable in WSN deployment, optimizing the sensor layout and improving the network's performance and energy consumption.

Although DGMOA shows excellent performance, it still has some limitations. For example, in some extremely complex and dynamic environments, the algorithm may need to further adapt and optimize. Future research will focus on extending the algorithm to multi-objective optimization problems, considering multiple factors such as coverage, energy consumption, and latency simultaneously. Additionally, the application of DGMOA in real-world industrial scenarios will be explored, aiming to validate and improve its practical effectiveness and provide more valuable solutions for industrial applications.

DECLARATIONS

Authors' contributions

Made substantial contributions to conception and design of the study and performed data analysis and interpretation: Wang Z, Guo C
Performed data acquisition and provided administrative, technical, and material support: Sui J, Cui C

Availability of data and materials

The results of this study are obtained through machine-generated random data and algorithmic calculations. There is no applicable raw data to share. The details of the algorithms and the experimental process are described in the manuscript to ensure the reproducibility of the research.

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Conflicts of interest

All authors declared that there are no conflicts of interest.

Ethical approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

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