# Hybrid Particle Swarm Optimization-based Modeling of Wireless Sensor Network Coverage Optimization

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***Abstract*—To address the problem of insufficient coverage of WSN and poor network coverage in obstacle environments, the study proposes an improved particle swarm optimization (PSO) combined with a hybrid grey wolf algorithm. The speed and position of the PSO particle's search for superiority are enhanced through the guiding nature of the superior wolf in the grey wolf optimization (GWO), thus the convergence speed and search precision are improved. Based on this, the study applies the improved PSO to a wireless sensor networks (WSO) coverage optimization model and uses model comparison to test the effectiveness and superiority of the algorithm. According to the results, the node network coverage of PSO, genetic algorithm (GA), data envelopment analysis (DEA), GWO, and grey wolf particle swarm optimization (GWPSO) reach 85.97%, 87.24%, 88.76%, 89.31%, and 91.05% respectively in the trapezoidal obstacle environment. And the node network coverage of the research-designed GWPSO algorithm reaches the highest value of its kind. This shows that the research-designed GWPSO has superior performance in the optimization control of sensor coverage deployment compared with similar algorithms. The design provides a new path for optimizing wireless sensor node network coverage.**

***Keywords*—Particle swarm optimization; wireless sensor networks; network coverage; grey wolf optimization; grey wolf particle swarm optimization***

## I. INTRODUCTION

As a communication transmission technology under the development of modern network technology, wireless sensor networks (WSN) can freely connect and combine a large number of sensor nodes through wireless communication, forming a communication network. It integrates three information functions through information collection module, information transmission module, and information processing module to achieve coverage and integrated information processing [1-3]. So far, in order to improve the coverage effect of wireless sensor networks, a variety of different types of intelligent algorithms have been used as optimization tools. Among them, the particle swarm optimization algorithm, as an algorithm with strong practicability and robustness, has also received many adaptive improvements in application [4-5]. However, particle swarm optimization (PSO) itself has certain flaws. PSO has the problem of local optimal solutions, which is easily affected by initial values, resulting in inaccurate search; PSO is sensitive to parameter settings and requires multiple experiments to obtain suitable parameter combinations, making parameter tuning difficult; The current research is mostly limited to the improvement of PS itself, lacking research on the combination of PSO algorithm and other optimization algorithms. Therefore, it is necessary to introduce other algorithms to improve the PSO algorithm and enhance its practicality in WSN coverage optimization [6-8]. By introducing the grey wolf optimization (GWO) and combining it with the PSO for wireless sensor network coverage optimization, it can effectively avoid the local optimal solution problem of the PSO algorithm and improve the accuracy and stability of the search. The research will design and implement an adaptive algorithm for wireless sensor network coverage optimization based on GWO and PSO, effectively improving its optimization effect in practical application scenarios. At the same time, experimental verification will be conducted to further enhance its effectiveness and practicality.

## II. RELATED WORK

The hybrid PSO model, an improvement of the particle swarm algorithm, has been gaining ground in various fields in recent years. Şenel F A's team proposes a hybrid model that combines the PSO with GWO, which uses the particles of GWO to replace the relatively underperforming particles of PSO, and then applies the model to leather nested industrial technology problems. After evaluation by the researchers, this model has a performance advantage, being able to obtain the optimal solution faster with fewer iterations than its swarm and social spider counterparts [9]. Chen S's team proposes a new hybrid PSO algorithm model to predict pollutant concentration in air pollution detection. This model combines PSO with a support vector machine (SVM) and uses the pollutant influencing factors as the main model input variables. This hybrid PSO model has superior performance compared to similar models with the same variable elements [10]. Corazza M's team proposes a particle swarm hybrid heuristic algorithm for the portfolio decision problem, which uses a penalty function to redefine the portfolio problem as an unconstrained problem and uses adaptive updates in the optimization process of the unconstrained penalty parameters. This algorithm performs superior to PSO with constant penalty parameters and is more efficient overall [11]. In their study of lateral loading problems for pile-like structures, Khari M et al. proposed a hybrid PSO model that integrates artificial neural networks with particle swarm algorithms, which can effectively predict the lateral deflection of pile-like structures. The results of 183 simulations conducted by the researchers show that the model has higher accuracy in predicting the lateral deflection of pile-like structures compared to similar models, while the systematic error is smaller and it shows higher performance on both the training and test sets.[12] The Sohouli A N team combined the particle swarm algorithm with a genetic algorithm to form a new evolutionary hybrid PSO and applied the algorithm to the modeling of geological models. This algorithm is applied to the modeling of geological models and geological exploration. The method uses a particle swarm algorithm for magnetic data improvement and a genetic algorithm for model parameter estimation. The algorithm can offer valuable results for estimating model parameters under a 25% noise level [13].

Khalaf O I applied the honeybee algorithm to wireless sensor coverage optimization and compared the results with those of a genetic algorithm. The results show that compared to the genetic algorithm, the honeybee-based wireless sensor coverage optimization has better optimal coverage and consumes fewer resources in the computing process [14]. Cao L et al. proposed a WSN coverage strategy based on the social spider optimization algorithm, which decomposes the combined optimization problem by building and WSN model. The insufficient search capability and convergence speed of the social spider algorithm are improved and finally combined to form an optimization model. The results show that the model is effective in preventing blind spots and redundant spots in the network coverage [15]. Hoffmann R's team proposes a meta-cellular automata approach that solves the optimal wireless sensor coverage problem with smaller sensor tiles to achieve a 2D spatial coverage, which in turn forms a sensor-centered pixel envelope. The results show that the model rules formed by this method can evolve to a more stable optimal coverage state and allow more time for model evolution after the optimal coverage is found.[16]. Li Q's team developed a mathematical model to improve the low overall coverage of wireless sensors and designed a mobile node scheme to improve the coverage optimization of the target area, which can effectively enhance the optimal coverage problem in the detection area. The results show that the strategy designed in the study can effectively enhance the network coverage and prolong the network service time [17]. ZainEldin H's team proposed a dynamic deployment technology based on a genetic algorithm and applied it to the optimization of WSN coverage, which is used to reduce the overlapping area between adjacent nodes by optimizing the minimum quantity of nodes, thus forming the coverage effect. The results of the study show that the designed method is compatible with the proposed method. The results of the study show that the method designed in the study has higher stability compared to other methods [18].

## III. WSN Coverage Optimization Model Construction Based on GWPSO Hybrid Algorithm

### A. *PSO Optimization based on the Standard GWO*

WSN is a distributed large-scale network, mainly composed of micro-nodes that can sense and process information and communication capabilities, and through a decentralized and self-organizing form of network, its network structure mainly consists of aggregation nodes, sensors, networks, etc. WSN on the target environment, such as temperature, humidity, and image information is collected and processed, and transmitted to the sensor terminal device, for the need of information. The WSN collects and processes information such as temperature, humidity, and images from the target environment and transmits it to the sensor terminals to serve the users who need the information. Multiple sensor nodes are placed in the target area, which collects temperature, humidity, and image information and sends it to the gateway or aggregation node via multi-hop routing. The WSN architecture is shown in Fig. 1.

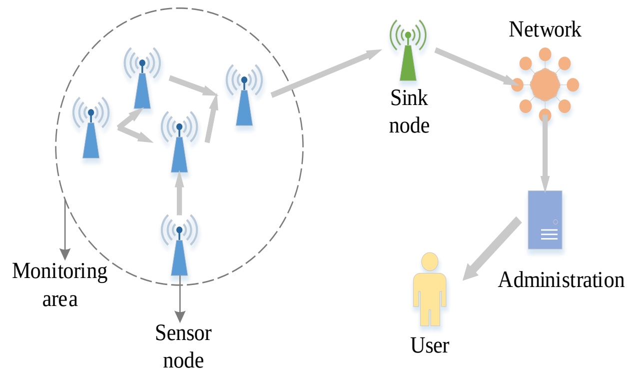



Fig. 1. WSN Structure.

Typically, a WSN node consists of a sensing unit, an energy unit, a processing unit, and a communication device, all of which work together to sense, collect and transmit target data. The sensing unit is responsible for converting the sensed analogue signal into a digital signal, which consists of sensors and A/D converters; the processing unit processes and compresses the collected data; the communication unit is responsible for data transmission and exchange of control information in the network; and the energy unit is responsible for providing energy to the other units, which are usually powered by micro batteries. The WSN node structure is shown in Fig. 2.

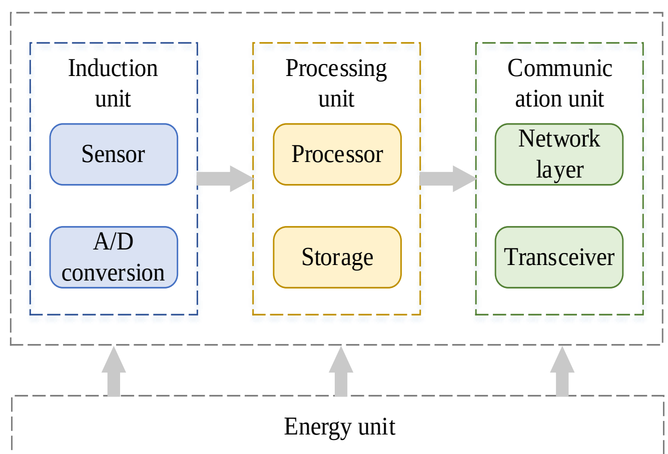



Fig. 2. WSN Node Structure.

Suppose there are $n$ sensor nodes in WSN, and the set is $S=\{s_1,s_2,\cdots,s_i,\cdots,s_n\}$, these nodes are identical and all have a radius of $r$, and the target detection area is a rectangle with an area of $Z$ m2. This grid monitoring area is transformed into $Z$ a small rectangular grid of equal size whose geometric centre represents the monitoring position of the wireless sensor node in the target area. A monitoring action is successful when the range between the target point and any node shall not be greater than the monitoring radius of the node. The set of monitoring target points is $M=\left\{m_1,m_2,\cdots m_j,\cdots,m_Z\right\}$, the two-dimensional spatial coordinates of $s_i$ in the set are $\left(x_i,y_i\right)$, the two-dimensional spatial coordinates of $m_j$ are $\left(x_j,y_j\right)$, and the Euclidean distance between two nodes is shown in equation (1).

$$d(s_i,m_j)=\sqrt{\left(x_i-x_j\right)^2+\left(y_i-y_j\right)^2} \quad (1)$$

The joint probability of all sensor nodes denoted as $s_{all}$, $s_{all}$ to the target monitoring node $m_j$ is shown in equation (2).

$$C_p\left(s_{all},m_j\right)=1-\prod_{i=1}^{n}\left(1-p_{\mathrm{cov}}\left(s_i,m_j\right)\right) \quad (2)$$

In equation (2), $p_{\mathrm{cov}}$ represents the probability of a node sensing a target monitoring point $s_i$ $m_j$. Calculate the joint sensing probability of all target points, and the altogether joint sensing probability of target points is the coverage area, and the coverage rate $C_r$ is as in equation (3).

$$C_r=\frac{\sum_{j=1}^{Z}C_p\left(s_{all},m_j\right)}{Z} \quad (3)$$

A prerequisite for the self-organisation of sensor nodes to form a WSN is that the network remains connected. The nodes in the study have a sensing radius of $r$ and a maximum communication distance of $2r$. When the range between nodes $s_i$ and $s_j$ does not exceed the sensing length, the two nodes are adjacent and the edge between nodes is 1. When the range between $s_i$ and $s_j$ exceeds the sensing radius, the two nodes are not adjacent and the edge between nodes is 0. Accordingly, the nodes' corresponding adjacency matrix $AM$ is constructed and the connectivity of the network is judged using $AM$. The matrix $N$ is shown in equation (4).

$$N=AM+AM^2+\cdots+AM^{n-1} \quad (4)$$

In equation (4), $n$ represents the number of sensors, determining whether the elements in this matrix are all 1, if yes, the network is connected, otherwise the network is not connected.

The GWO imitates the hunting mechanism of grey wolves and has the advantage of being plain, flexible, and scalable, and uses fewer parameters in the algorithm. The mathematical model of the algorithm simulates a wolf pack divided into four classes $\alpha$, $\beta$, $\delta$ and $\omega$, with a structure similar to that of a pyramid, as shown in Fig. 3.

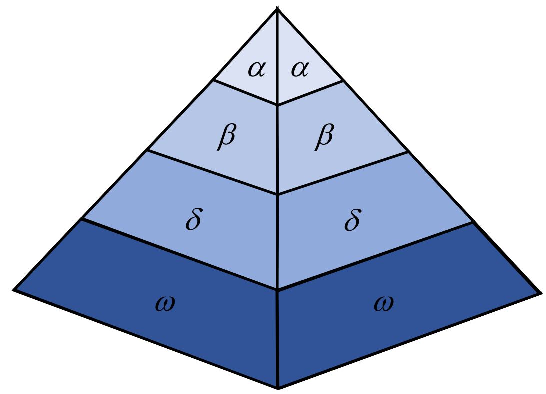



Fig. 3. Ranking Structure of Wolves.

The wolves are ranked according to the fitness value of individual grey wolves, and the top three grey wolves in the pack are ranked in the $\alpha$, $\beta$ and $\delta$ levels respectively. $\alpha$ has the highest rank and indicates the current optimal solution. $\omega$ The grey wolf individuals with the highest rank are the candidate in this group. $\omega$ In the iteration of the algorithm, the grey wolves in the first three levels are responsible for guiding the grey wolves in the $\omega$ level to search for prey, and the grey wolves in the $\omega$ level improve their fitness value by searching for prey. Assuming that the actual location of the prey is unknown to individual grey wolves during the hunting process, the wolves with the highest to lowest ranks of $\alpha$, $\beta$ and $\delta$ are closest to the prey, so the wolves in the $\omega$ layer can surround the prey according to the positions of the wolves in the $\alpha$, $\beta$ and $\delta$ layers, and keep approaching the prey and finally find the prey. $\omega$ The distances between the wolves in the, and $\alpha$ $\beta$ $\delta$ layers are shown in equation (5).

$$\begin{cases}D_\alpha=C_1*X_\alpha\left(t\right)-X_\omega\left(t\right)\\D_\beta=C_2*X_\beta\left(t\right)-X_\omega\left(t\right)\\D_\delta=C_3*X_\delta\left(t\right)-X_\omega\left(t\right)\end{cases} \quad (5)$$

$t$ In equation (5), $D_\alpha$, $D_\beta$ and $D_\delta$ represent the distances between $\alpha$, $\beta$ and $\delta$ and $\omega$ respectively, $X_\alpha\left(t\right)$, $X_\beta\left(t\right)$, $X_\delta\left(t\right)$ and $X_\omega\left(t\right)$ are the positions of $\alpha$, $\beta$, $\delta$ and respectively, and $\omega$ $C_1$, $C_2$ and $C_3$ represent the orientation variables of $\omega$ when the layer wolves move towards $\alpha$, $\beta$ and respectively. $\delta$ $\omega$ After calculating the distance between the layer wolves and the positions of the $\alpha$, $\beta$ and $\delta$ layer wolves during the hunt, the layer wolves kept approaching them in certain steps respectively and finally reached the predetermined position. The position of the $\omega$ wolf was updated as shown in equation (6).

$$\begin{cases} X_1 = X_\alpha - A_1 * D_\alpha \\ X_2 = X_\beta - A_2 * D_\beta \\ X_3 = X_\delta - A_3 * D_\delta \end{cases} \tag{6}$$

In equation (6), $X_1$, $X_2$ and $X_3$ indicate the position of the wolf in the $\omega$ layer when it is guided by the wolves in the $\alpha$, $\beta$ and $\delta$ layers, respectively, and $t$ indicates the current iterations. $A_1$, $A_2$, $A_3$ indicate the step length of the $\omega$ layer wolf as it approaches the prey under the guidance of the $\alpha$, $\beta$ and $\delta$ layers, respectively. When, $|A_1|<1$ $\omega$ wolves will conduct a fine search around the prey, and when $|A_1|>1$, $\omega$ wolves will expand their search around the prey. $A_1$ The formulae for $A_2$ and $A_3$ are shown in equation (7).

$$\begin{cases} A_1 = 2a * rand - a \\ A_2 = 2a * rand - a \\ A_3 = 2a * rand - a \end{cases} \tag{7}$$

In equation (7), $a$ is the convergence factor, which represents the iterative process of decreasing from 2 to 0. The convergence factor $a$ is calculated by equation (8).

$$a = 2 - 2\left(\frac{t}{t_{\max}}\right) \tag{8}$$

$t_{\max}$ The GWO algorithm generates the initial wolf pack, divides the pack into four classes: $\alpha$, $\beta$, $\delta$ and $\omega$, gauges the range between individual grey wolves and their prey, then updates their respective positions according to the measured lengths, with each individual grey wolf in the pack representing a solution that is continuously updated during the search process. The GWO process is shown in Fig. 4.

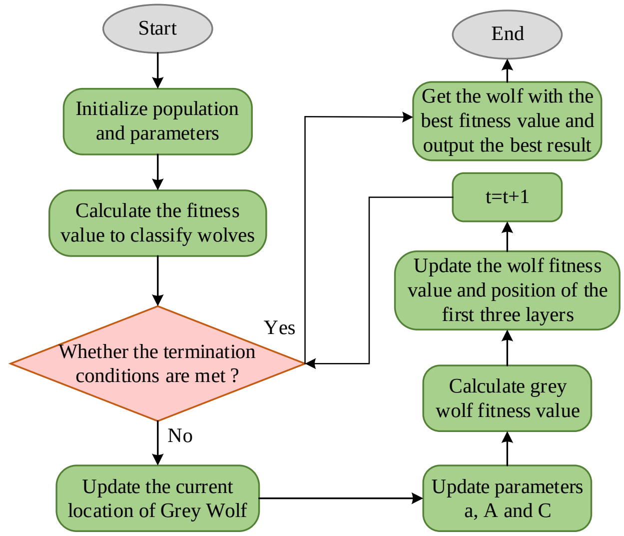



Fig. 4. Flow of GWO.

### B. WSN Coverage Optimization Model for the GWPSO Hybrid Optimization Algorithm

The PSO always moves in the direction of the optimal individual's position, so its convergence velocity is relatively fast but the ability to balance the global search is still deficient, which leads to the inability of the algorithm to precisely seek the global optimal solution when solving complex optimization problems; GWO does not learn from the experience of others when searching for the optimal solution, so it is easy to ripe untimely. To address the shortcomings of both algorithms, the DEA algorithm is incorporated into PSO, and at the beginning, the chaos multi-way learning strategy is used to improve the population variance, and the convergence factor is dynamically adjusted to consider the global and local optimization. The properties of chaotic mapping can be able to properly enrich the variety of the initial population so that the particles can find the optimal solution, and the study uses Tent mapping to create the initial population [19-20]. Multi-way learning strategy can generate corresponding solutions by evaluating upper and lower-bound solutions and original solutions; the optimal solution of fitness value is selected from these solutions. The improved differential evolution PSO uses a mixed multidirectional learning strategy, according to which a multidirectional population is generated, the individuals of the generated multidirectional chaotic population are compared with the individuals of the original chaotic population in terms of their fitness values, and the individuals with the best fitness values are set as the initial population. Assuming that the population size is $N$ and the spatial dimension of it is $D$, a chaotic sequence is generated in the space using the Tent chaos mapping $W = \{W_j, j = 1, 2, \cdots, D\}$ and $W_j = \{W_{i,j}, i = 1, 2, \cdots, N\}$. The Tent chaos mapping function is shown in equation (9).

$$W_{i+1,j} = \begin{cases} Z_{i,j} / 0.65, & Z_{i,j} < 0.65 \\ (1 - W_{i,j}) / 0.35, & Z_{i,j} \geq 0.65 \end{cases} \tag{9}$$

The chaotic sequence generated by the chaotic mapping is mapped to the solution space to obtain the population $Y_j = \{Y_i, i = 1, 2, \cdots, N\}$, $Y_i = \{Y_{i,j}, j = 1, 2, \cdots, D\}$, and the population individuals $Y_{i,j}$ denoted as shown in equation (10).

$$Y_{i,j} = Y_{\min,j} + Y_{i,j}(Y_{\max,j} - Y_{\min,j}) \tag{10}$$

In equation (10), $Y_{\min,j}$ and $Y_{\max,j}$ are the bounds on the particle finding solution, and $Y_{i,j}$ is the value of the $i$ th particle in the space corresponding to the $j$ th dimension. The multidirectional populations $OY_j$ and $OY_i$, $MY_j$ and $MY_i$ are calculated as shown in equation (11).

$$\begin{cases} OY_{i,j} = Y_{\min,j} + Y_{\max,j} - Y_{i,j} \\ MY_{i,j} = Y_{\max,j} - Y_{\min,j} + Y_{i,j} \end{cases} \tag{11}$$

The fitness values of the primitive population and the multi-way population individuals are further calculated, and the particles with more favourable positions are selected from the population individuals based on the fitness values. The value of the coefficient $A$ changes with the distance control parameter $a$ during the iterative process, so setting the distance control parameter $a$ to a reasonable value can effectively provide a solution to the balance between the speed of particle population search and the accuracy of particle local search. In the particle search process, the distance control parameter $a$ needs to be set to a larger value in the first stage to expand the search range, which is beneficial to the particle search. In the later stage, the distance control parameter $a$ needs to be set to a smaller value to concentrate the particle population around the optimal solution for fine searching. The linearly decreasing distance control parameter $a$ cannot be adapted to the actual solving situation. To address this drawback, a cosine convergence factor strategy incorporating state coefficients is proposed to effectively take into account the overall optimization efficiency of the algorithm. Under this strategy, the distance control parameter $a$ is non-linearly decreasing and its value is dynamically adjusted according to the properties of the random variables. With this strategy, the algorithm will search more vigorously at the initial stage of the iteration, and at the final stage of the iteration the particles will focus on the fine search around the optimal value, increasing the probability of finding the global optimum. The dynamic adjustment strategy for the convergence factor is shown in equation (12).

$$a = -2 * \frac{\delta^2}{\delta_{\max}^2} \cos\left(\frac{\pi t}{2 t_{\max}}\right) \tag{12}$$

In equation (12), $\delta$ denotes the particle state coefficient, $t$ is the current iteration and $t_{\max}$ is the maximum iteration. The study combines the convergence factor adjustment strategy of state coefficients and cosine transform, which effectively improves the speed of global particle search. The smaller change in the convergence factor at the end of the iteration is beneficial to the local fine search of the particle, thus improving the accuracy of the optimal solution. The GWO algorithm mainly adjusts its own position by combining the obtained position of individual grey wolves with the relationship between the first three levels of optimal solutions in the pack, enabling the exchange of information between the two. By introducing the idea of updating the position information in the GWO algorithm, the PSO's search capability is optimized so that the particles in space can expand the search space and enhance the search effort, thus finding the optimal solution more efficiently and accurately [21]. The updated formula for the particles $V_{ij}$ and $X_{ij}$ after the introduction of the GWO idea is shown in equation (13).

$$\begin{cases} V_{ij}(t+1) = \omega V_{ij}(t) + c_1 r_1 \left(\omega_1 X_1(t) + \omega_2 X_2(t) + \omega_3 X_3(t)\right) \\ \qquad + c_2 r_2 \left(p_{best}(t) - X_{ij}(t)\right) \\ X_{ij}(t+1) = X_{ij}(t) + V_{ij}(t+1) \end{cases} \tag{13}$$

In equation (13), $c_1$ represents the cognitive learning factor, which describes how much the finding of an optimal solution by an individual particle affects the finding of an optimal solution by all particles in the space; $c_2$ represents the social learning factor, which describes how much the finding of an optimal solution by a population of particles affects the algorithm. $c_1$ Larger values indicate that particles are more likely to concentrate locally, and larger values of $c_2$ indicate that particles are more likely to find a locally optimal solution early and converge on that solution. $r_1$ and $r_2$ are random numbers in the range [0,1]. $\omega_1$, $\omega_2$ and $\omega_3$ denote the inertia weight coefficients of the grey wolf. To take into account the global and local optimality finding capacity of the particles, the grey wolf inertia coefficients are improved as in equation (14).

$$\begin{cases} \omega_1 = \dfrac{|X_1|}{|X_1 + X_2 + X_3|} \\ \omega_2 = \dfrac{|X_2|}{|X_1 + X_2 + X_3|} \\ \omega_3 = \dfrac{|X_3|}{|X_1 + X_2 + X_3|} \end{cases} \tag{14}$$

When searching for the optimal value, the particle will learn from the current global optimum. When the difference between the current value and the global optimum is large, the learning of the particle will lead to an error and the particle will sink into the local optimum. If the global historical optimal solution approaches the current optimal solution, using the perturbation strategy will increase the range between the particle and the optimal solution, so the perturbation strategy should be used for particles that fall into the local optimum or perform poorly. As the 'early' particles are located closer to the optimal solution in some dimensions of space, external forces are applied to these particles to move them from their current position and proceed with the search. To address the problem of large fluctuations in the particle population, the perturbation strategy is used to limit the perturbation operation to a distance of no more than 20%. The formula for updating the position of a particle after the perturbation is shown in equation (15).

$$X_{ij}(t+1) = r_1 V_{ij}(t+1) + (1 - 0.2 r_2) X_{ij}(t) \tag{15}$$

In equation (15) $r_1$ and $r_2$ are random numbers in the range [-1,1]. Applying GWPSO hybrid optimization algorithm to the optimal deployment of node coverage in WSN, by using the coverage function as the fitness value of the algorithm. The beginning of the algorithm introduces a chaotic multi-way learning strategy to initialize the population and combines the state coefficients to improve the convergence factor using the cosine variation principle, thus enabling the algorithm to gain an improvement in its optimization-seeking capability. The inertia weight coefficients of the grey wolf are improved to update the position and speed of the particles, and finally, the speed and position of them are perturbed to improve the population diversity and thus the search accuracy of the particles, which effectively improves its search capability. The optimal fitness value at the end of the algorithm iteration is the global optimal solution. The flow of the algorithm is shown in Fig. 5.

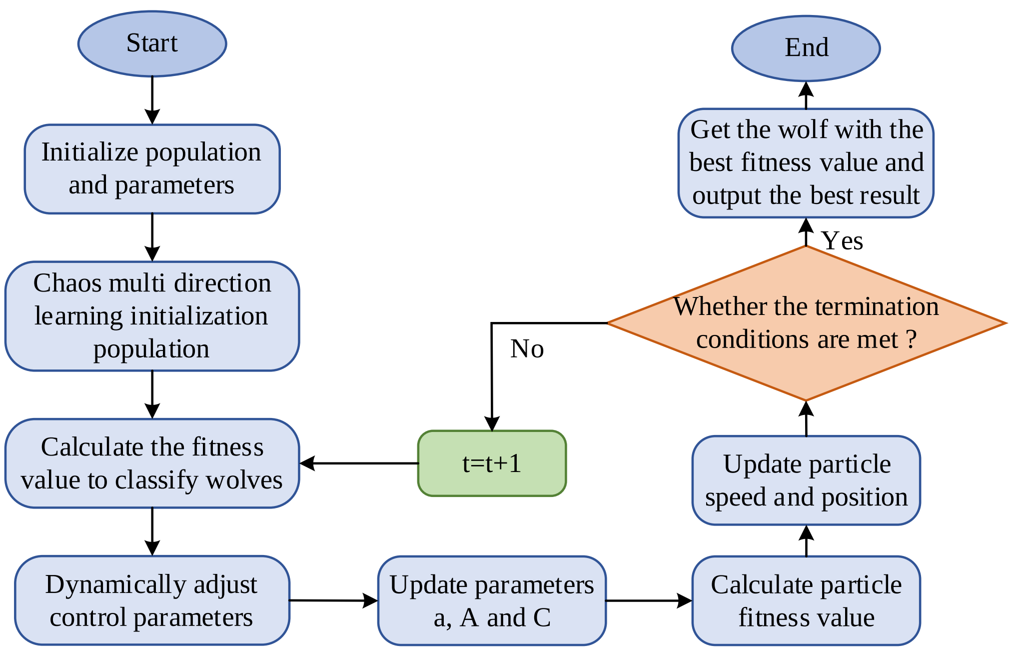



Fig. 5. Flow of GWPSO.

## IV. Analysis of WSN Coverage Optimization Results based on the GWPSO Hybrid Optimization Algorithm

The superiority of the GWPSO algorithm was demonstrated through simulation experiments in the MATLAB R2016a environment. Three different unimodal benchmark test functions and three different multimodal benchmark test functions were selected to test the convergence of the five algorithms. The population size in the test was 30, with 500 iterations. Any test function was independently run 50 times to record its average value. The study demonstrates the performance of the GWPSO hybrid optimization algorithm and its advantages through simulation experiments. Six functions are used to test the convergence function of the algorithm and to compare the performance with PSO, GA, DEA, and GWO algorithms. The four algorithms are used to optimise the deployment of WSN node coverage in an obstacle-free environment and a trapezoidal obstacle environment respectively, and finally, the results obtained are analysed. There are three single-peak-based test functions and three multi-peak-based test functions among the six selected test functions, and the optimal values in the GWPSO test theory are all 0. The test functions are shown in Table I.

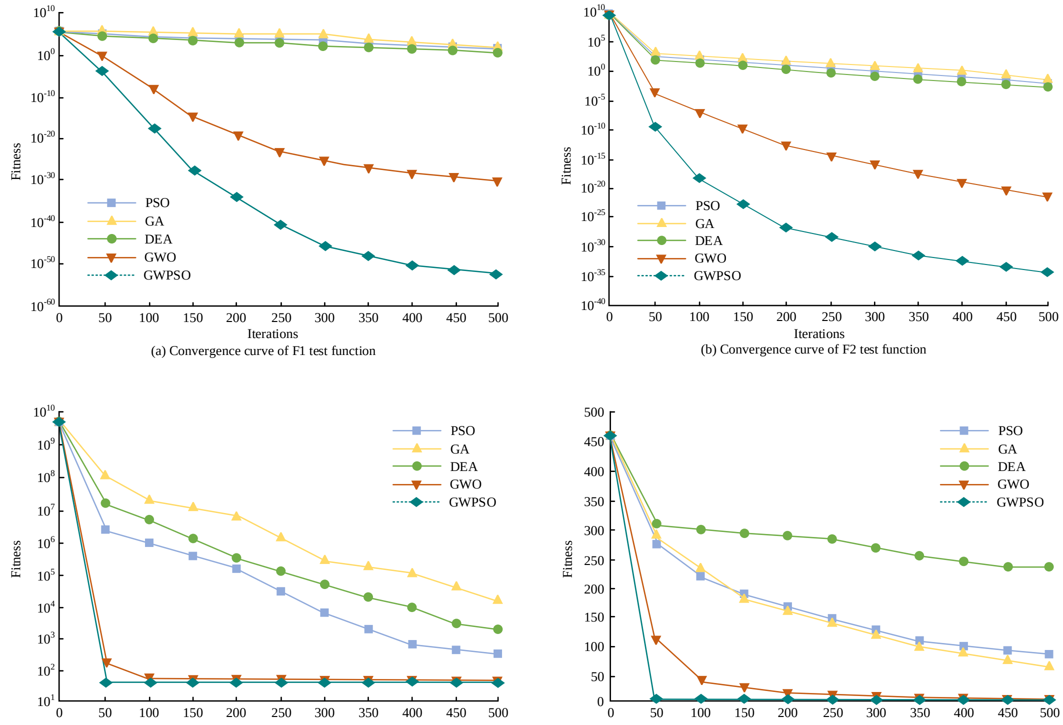
The study compares the convergence of the PSO, GA, DEA, and GWO algorithms and the study's proposed GWPSO hybrid optimization algorithm under the test functions, and the algorithm's convergence under F1, F2, F3 and F4 is compared as shown in Fig. 6.

In Fig. 6, the five algorithms converge gradually with an increasing number of iterations on the four functions, with the PSO, DEA, and GA algorithms showing poor convergence performance and the GWPSO algorithm showing the best convergence on the four functions. The convergence of the algorithms on F5 and F6 is shown in Fig. 7.

The advantageous convergence function of the GWPSO owing to the chaotic multidirectional learning strategy that improves the initial population space dynamically adjusts the control parameters, and uses the optimization-seeking property of the GWO algorithm to expand the particle's global search range in the pre-optimization phase. The use of the perturbation strategy effectively prevents the particles from sinking into the local optimum and significantly enhances the search precision of the particles, thus effectively improving the particle search capability. Thirty-five WSN nodes were deployed in a 50m x 50m square region with a sensing radius of 5m and a communication radius of 10m, $N$ = 50 and $t$ = 30. After the initial locations of the nodes were deployed, the nodes were unequally spread, and there was a large amount of coverage redundancy as the initial locations were randomly selected. Five algorithms were used to optimise the node coverage deployment and the coverage results are shown in Fig. 8.

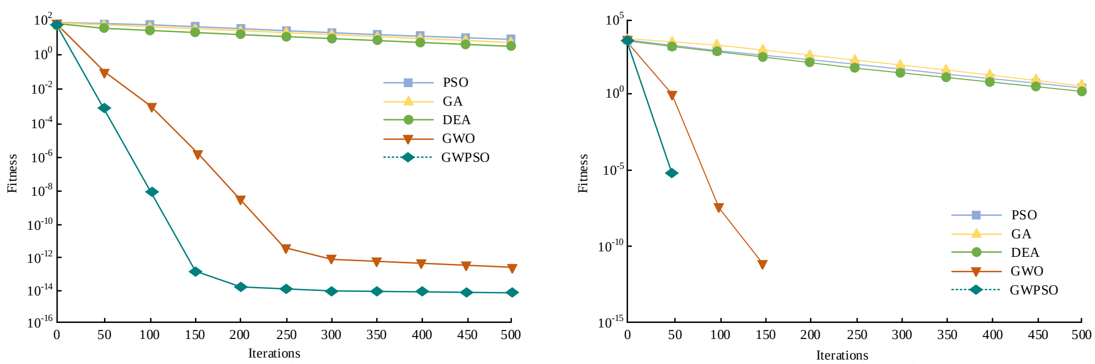
TABLE I. TEST FUNCTION

| ID | Function | Expression | Type |
|---|---|---|---|
| F1 | Sphere | $f(x)=\sum_{i=1}^{D} x_i^2$ | Unimodal |
| F2 | Schwefel2.22 | $f(x)=\sum_{i=1}^{D}\lvert x_i\rvert+\prod_{i=1}^{D}\lvert x_i\rvert$ | Unimodal |
| F3 | Rosenbrock | $f(x)=\sum_{i=1}^{n-1}\left(100\left(x_{i+1}-x_i^2\right)^2+\left(x_i-1\right)^2\right)$ | Unimodal |
| F4 | Rastrigin | $f(x)=\sum_{i=1}^{D}\left[x_i^2-10\cos\left(2\pi x_i\right)+10\right]$ | Multimodal |
| F5 | Griewank | $f(x)=\frac{1}{4000}\sum_{i=1}^{D}x_i^2-\prod_{i=1}^{D}\cos\left(\frac{x_i}{\sqrt{i}}\right)+1$ | Multimodal |
| F6 | Ackley | $f(x)=-20\exp\left(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D}x_i^2}\right)-\exp\left(\frac{1}{D}\sum_{i=1}^{D}\cos\left(2\pi x_i\right)\right)+20+e$ | Multimodal |




(a) Convergence curve of F1 test function
(b) Convergence curve of F2 test function
(c) Convergence curve of F3 test function
(d) Convergence curve of F4 test function

Fig. 6. CONVERGENCE CURVE OF F1, F2, F3 AND F4 TEST FUNCTIONS.




(a) Convergence curve of F5 test function
(b) Convergence curve of F6 test function

Fig. 7. CONVERGENCE CURVE OF F5 AND F6 TEST FUNCTIONS.

In Fig. 8, the network coverage was all improved after the node coverage deployment was optimized by the algorithms. The node network coverage after optimization by the PSO, GA, DEA, GWO, and GWPSO algorithms reached 86.75%, 88.24%, 89.54%, 90.48%, and 94.62% respectively. The node network coverage after optimization by the GWPSO algorithm was the highest among all algorithms and its optimization of node network coverage was the best, resulting in a significant coverage improvement. To further validate its availability, the study placed a trapezoidal obstacle in a 50m x 50m square monitoring area, which has an area of 500m2. A population size of 50 was set and 25 sensing nodes were deployed, of which 2 were fixed nodes and the rest were mobile nodes. The maximum sensing radius of the mobile nodes is 5m and the maximum communication range is 10m, while the maximum sensing radius of the fixed nodes is 7.5m and the maximum communication range is 15m. Five algorithms were used to optimize the coverage of the sensing nodes in the region, and the results are shown in Fig. 9.

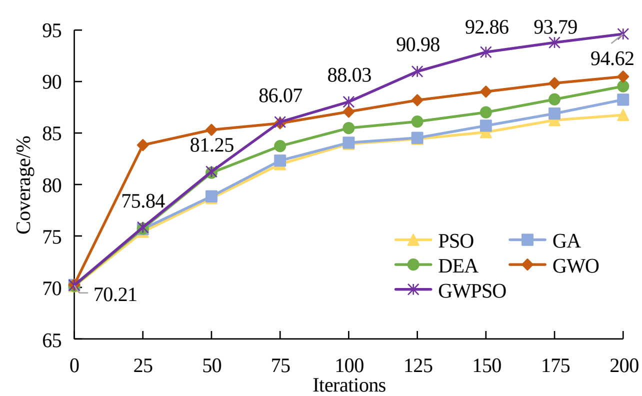



Fig. 8. COVERAGE RESULTS IN BARRIER-FREE ENVIRONMENT.

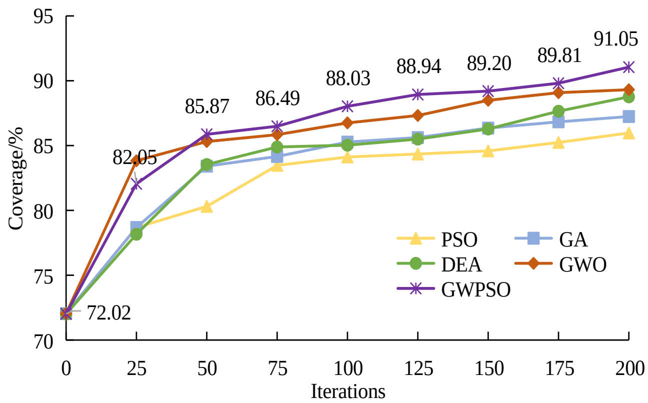



Fig. 9. Coverage Results in a Trapezoidal Obstacle Environment.

In Fig. 9, the network coverage in the trapezoidal obstacle environment was all improved after the algorithm was optimized for node coverage deployment. The node network coverage in the trapezoidal obstacle environment reached 85.97%, 87.24%, 88.76%, 89.31%, and 91.05% after optimization by the PSO, GA, DEA, GWO, and GWPSO algorithms respectively. The node network coverage after optimization by the GWPSO algorithm was the highest among all algorithms and its optimization of node network coverage was the best, resulting in marked upgradation in coverage. Because the number of sensor nodes in the trapezoidal obstacle environment was 10 less than the number of sensors in the barrier-free environment, the overall node network coverage after algorithm optimization was worse than that in the barrier-free environment, and the algorithm's optimization of node network coverage was also worse than that in the barrier-free environment. The results demonstrate that the GWPSO algorithm has the most significant optimization effect among all algorithms in both the obstacle-free and trapezoidal obstacle environments, fully verifying that the algorithm has superior performance in the optimal control of sensor coverage deployment, and providing an effective path for the optimization of WSN node network coverage.

## V. Discussion

The research aims to solve the problem of insufficient coverage of wireless sensor networks and poor coverage effect in obstacle environments. By combining the Grey Wolf algorithm and PSO algorithm, this study designed a GWPSO wireless sensor network coverage optimization algorithm and applied it to the sensor network coverage optimization model. The research results show that the GWPSO algorithm has the best convergence performance on all functions, and it achieves the best results in optimizing node network coverage, and also has the best coverage effect in obstacle environments. This shows that the GWPSO algorithm has better search accuracy and convergence speed, and has a significant application effect in the coverage optimization model of wireless sensor networks, with higher practicability. This research result provides effective algorithm support for the deployment and optimization of future wireless sensor networks, and can better adapt to complex real application scenarios. Future research based on this algorithm can further optimize its performance and enhance its applicability in application fields.

## VI. Conclusion

To solve the problems of insufficient coverage of WSN and poor coverage in obstacle environments, the study combines the GWO with the PSO algorithm, which in turn forms an optimization search algorithm with higher search accuracy and faster convergence. The study adopts the algorithm in an applicative design, applies it to a wireless sensor network coverage optimization model, and finally analyses the application of the model by way of model comparison and application validation. Five experimental models have been used for the optimization of WSN. The results demonstrate that the five algorithms tested converge gradually with an increasing number of iterations on six functions, and the GWPSO algorithm converges best on all functions. In the comparison of network coverage optimization results, the PSO, GA, DEA, GWO, and GWPSO algorithms achieved 86.75%, 88.24%, 89.54%, 90.48%, and 94.62% of node network coverage after optimization, respectively. The GWPSO algorithm had the highest optimized network coverage. In the obstacle environment, the node network coverage of PSO, GA, DEA, GWO, and GWPSO algorithms reached 85.97%, 87.24%, 88.76%, 89.31%, and 91.05% respectively. The optimized network coverage of the GWPSO algorithm was also the highest. This shows that the GWPSO network coverage optimization algorithm designed in the study has a superior performance and is more practical for the optimal control of sensor coverage deployment.

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