

Article

Coverage Optimization of Wireless Sensor Networks for Soil Temperature Monitoring Based on an Adaptive Chaotic Lévy Flight Prairie Dog Optimization Algorithm

Mingtian Tan ^{1,2,3}, Jinmei Kou ^{1,2,3,*}, Chenglong Ban ^{1,2,3} and Min Tian ^{1,2,3,*}

¹ College of Mechanical and Electrical Engineering, Shihezi University, Shihezi 832000, China; 20242009062@stu.shzu.edu.cn (M.T.); banchenglong@stu.shzu.edu.cn (C.B.)

² Xinjiang Production and Construction Corps Key Laboratory of Modern Agricultural Machinery, Shihezi 832000, China

³ Key Laboratory of Northwest Agricultural Equipment, Ministry of Agriculture and Rural Affairs, Shihezi 832000, China

* Correspondence: joujinmei@shzu.edu.cn (J.K.); tm_inf@shzu.edu.cn (M.T.); Tel.: +86-133-9993-1702 (J.K.); +86-13319937952 (M.T.)

Abstract

Soil temperature wireless sensor networks provide essential data for continuous soil temperature monitoring in cotton fields and support agricultural environmental regulation and crop growth management. However, conventional sensor node deployment methods often lead to coverage blind spots, redundant coverage, and insufficient utilization of sensing resources, which restrict network monitoring performance. To address these issues, this study proposes an Adaptive Chaotic Lévy Flight Prairie Dog Optimization algorithm, named ACLFPDO, for optimizing node deployment in soil temperature wireless sensor networks. The incremental novelty of ACLFPDO does not lie in the individual use of chaotic initialization, adaptive parameter adjustment, or Lévy-flight perturbation, which have been widely used in metaheuristic optimization, but in coupling these strategies with a stage-based Prairie Dog Optimization (PDO) position-updating framework and a coverage-oriented fitness design tailored to the STWSN area-coverage problem. An idealized two-dimensional simulation model was established, in which the cotton-field monitoring region was simplified as a regular square area and each sensor node was modeled using a fixed-radius circular binary sensing model. Coverage rate and node utilization efficiency were used as the main evaluation metrics. Comparative simulations were conducted against Prairie Dog Optimization, Snake Optimization (SO), and Whale Optimization algorithms (WO). Under a monitoring area side length of 50, sensing radius of 5, and 42 sensor nodes, ACLFPDO achieved a coverage rate of 98.49% and a node utilization efficiency of 74.65%. Compared with PDO, SO, and WO, the coverage rate increased by 16.88, 9.52, and 10.86 percentage points, respectively. The results indicate that ACLFPDO can improve coverage performance and sensing resource utilization under idealized simulation conditions. However, practical cotton-field deployment still requires further consideration of irregular boundaries, ridges, furrows, obstacles, burial-depth differences, communication connectivity, energy consumption, and soil spatial heterogeneity.

Keywords: soil temperature wireless sensor networks; sensor node deployment; coverage optimization; Prairie Dog Optimization; ACLFPDO; Lévy flight; chaotic initialization; node utilization efficiency; cotton field monitoring

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1. Introduction

Soil temperature is one of the critical environmental factors influencing crop root development, nutrient uptake, water transport, and yield formation. In the context of cotton production, soil temperature not only affects seed germination, root vitality, and nutrient absorption processes but is also closely linked to water and fertilizer management in cotton fields, the assessment of crop growth status, and the ultimate formation of yield. With the advancement of smart agriculture and precision agriculture, the Internet of Things (IoT) and wireless sensor networks (WSNs) have increasingly emerged as essential technological tools for the real-time perception of agricultural field environments [1,2]. Soil Temperature Wireless Sensor Networks (STWSNs) enable continuous and distributed monitoring of soil temperature within cotton fields, thereby providing data support for precision irrigation, fertilizer management, and the regulation of the agricultural environment. However, the monitoring efficacy of STWSNs depends significantly on the spatial deployment strategy of the sensor nodes. If node distribution is suboptimal—even with an ample number of sensors—issues such as coverage blind spots, redundant coverage, and the wasteful use of sensing resources may arise, thereby compromising the completeness and reliability of the acquired soil temperature data.

In practical agricultural monitoring applications, sensor nodes are typically deployed using empirical, regular, or random strategies. Regular deployment can establish a relatively uniform node structure within an ideal area; however, it struggles to adapt to complex terrains, irregular boundaries, and agricultural environments characterized by high spatial heterogeneity. Conversely, random deployment offers greater flexibility but frequently results in localized node clustering, coverage gaps, and redundant sensing zones. Existing studies have demonstrated that coverage and connectivity are pivotal factors influencing the monitoring performance of WSNs, and that a rational node deployment strategy can significantly enhance network coverage rates and the reliability of data acquisition [3,4]. For STWSNs in cotton fields, optimizing node deployment is critical not only for ensuring that the entire monitoring area is adequately sensed but also for guaranteeing the efficient utilization of sensor resources. Consequently, the key challenge in enhancing the deployment efficiency of agricultural sensor networks lies in minimizing node redundancy while simultaneously maintaining a high level of coverage.

To address the challenges associated with WSN node deployment, researchers have proposed various coverage optimization methods based on intelligent optimization algorithms. Particle Swarm Optimization (PSO)—along with its various improved variants—has been widely applied to the optimization of sensor node placement, owing to its simple structure and robust search capabilities. For instance, Bhargavi et al. proposed an enhanced Particle Swarm Optimization method designed to determine the optimal node positions within a specific region of interest and to improve overall network coverage [5]. Tong et al. further proposed an enhanced hybrid Particle Swarm Optimization method incorporating spatial position encoding, which simultaneously improves coverage while reducing the number of deployed nodes [6]. Siamantas and Kandris applied PSO to WSN node deployment under k -coverage and single-connectivity constraints, emphasizing the importance of the collaborative optimization of coverage and connectivity constraints [7]. Furthermore, Chen et al. investigated the trade-offs among deployment cost, sensing reliability, and network reliability in heterogeneous WSNs from a multi-objective optimization perspective [8]. These studies demonstrate that intelligent optimization algorithms can effectively improve the spatial distribution of nodes; however, within complex search spaces, issues such as premature convergence, entrapment in local optima, and uneven node distribution may still persist.

In recent years, swarm intelligence optimization algorithms—along with their improved variants—have found expanded application in WSN coverage optimization.

Zhang proposed a hybrid swarm intelligence algorithm for the deployment and coverage optimization of self-powered WSNs [9]; Yao et al. employed an Army Ant Search Optimization algorithm to enhance the coverage performance of wireless multimedia sensor networks [10]; Sun et al. combined a Genetic Algorithm with an improved Whale Optimization Algorithm to mitigate coverage redundancy and coverage holes during WSN deployment [11]; and Li et al. proposed a virtual-force-guided improved Sand Cat Swarm Optimization algorithm to enhance node coverage capabilities and alleviate the problem of coverage holes [12]. While these methods have improved WSN coverage performance from various angles, their optimization efficacy is typically influenced by factors such as the quality of the initial population, search step size, parameter update mechanisms, and local exploitation capabilities. When variables such as the number of nodes, the scale of the monitoring area, or the sensing radius change, some of these algorithms still struggle to consistently achieve deployment results characterized by high coverage rates and low redundancy.

To further enhance the search performance of meta-heuristic algorithms, researchers have begun to introduce improvement strategies such as chaotic mapping, adaptive factors, multi-strategy search, Lévy flight, and learning mechanisms. Shaikh et al. proposed an improved Chaotic Grey Wolf Optimization algorithm to enhance both WSN coverage and connectivity while simultaneously accounting for deployment constraints [13]. Wang and Li incorporated Tent mapping, a Golden Sine-guided mechanism, and a phase-adjustment strategy into an improved Marine Predator Algorithm to enhance the stability of the coverage optimization process [14]. Guo et al. incorporated path loss and false alarm probability into their node coverage model, thereby bringing the deployment optimization process closer to actual sensing conditions [15]. Yang et al. proposed an improved Cuckoo Search algorithm incorporating multiple strategies, demonstrating superior coverage optimization performance compared to various benchmark algorithms [16]. Furthermore, deep reinforcement learning and graph neural networks have been introduced into tasks involving dynamic WSN coverage optimization and node state prediction, aiming to enhance adaptive scheduling capabilities within complex environments [17,18]. However, learning-based approaches typically demand large-scale training data and substantial computational resources; for lightweight agricultural environment monitoring scenarios, the trade-offs regarding their deployment complexity and real-time applicability still require further evaluation. In contrast, improved swarm intelligence algorithms offer advantages such as simplicity of implementation, minimal reliance on training data, and ease of integration with coverage models, making them well-suited for node deployment optimization problems in agricultural WSNs.

Research on WSN coverage optimization tailored to agricultural scenarios has encompassed monitoring tasks related to soil elements, soil moisture, and other environmental parameters. Liu et al. proposed an adaptive chaotic Gaussian mutation Snake Optimization algorithm (SO) for WSN coverage optimization in soil element monitoring; this approach successfully enhanced network coverage while simultaneously reducing the number of required sensor nodes [19]. Liang et al. designed an adaptive Cauchy mutation Butterfly Optimization algorithm for WSN coverage optimization in soil moisture monitoring, thereby bolstering the algorithm's global search and local exploitation capabilities [20]. Wang et al. introduced an adaptive multi-strategy Artificial Bee Colony algorithm, which improved WSN coverage optimization performance through the integration of a strategy pool, adaptive selection mechanisms, simulated annealing, and dynamic search step sizes [21]. Taşdemir et al. investigated the application of variants of the Immune Plasma Algorithm in WSN coverage optimization, further validating the potential of bio-inspired optimization algorithms for enhancing coverage performance [22]. The aforementioned studies demonstrate that swarm intelligence-based optimization methods tailored to agricultural sensor networks can effectively improve coverage performance;

however, existing research tends to focus predominantly on maximizing coverage rates, while paying insufficient attention to node utilization efficiency, the control of coverage redundancy, and the ability to maintain coverage quality under conditions involving a reduced number of nodes. This is particularly pertinent in the context of soil temperature monitoring in cotton fields, where the challenge of simultaneously achieving high coverage rates and high perceptual resource utilization efficiency—given a limited number of nodes—remains an open problem requiring further investigation.

The Prairie Dog Optimization (PDO) algorithm is a recently proposed swarm intelligence optimization algorithm that simulates the foraging and anti-predation behaviors of prairie dogs [23]. Although PDO has potential global search capability, its direct application to STWSN coverage optimization is limited by uneven initial population distribution, insufficient dynamic search control, and susceptibility to local optima. Moreover, most existing improved metaheuristic deployment methods mainly emphasize coverage maximization, whereas the simultaneous consideration of coverage completeness, node utilization efficiency, overlap reduction, and deployment compactness remains insufficient for node-limited cotton-field monitoring scenarios.

Although chaotic initialization, adaptive parameter adjustment, and Lévy-flight perturbation have been widely used in metaheuristic optimization, this study does not claim these strategies as new standalone operators. The novelty of ACLFPDO lies in their problem-oriented coupling with the PDO search structure for STWSN area-coverage optimization. Specifically, each candidate solution is encoded as a complete two-dimensional sensor-node coordinate deployment scheme, and the original PDO updating process is reorganized into a stage-based adaptive framework that coordinates chaotic population initialization, adaptive search control, Lévy-flight perturbation, and stage-specific position updating. In addition, the fitness function incorporates coverage rate, a scenario-level node-scale compactness term, coverage overlap ratio, and a coverage-dependent distribution penalty. Under each fixed-node scenario, the node-scale term remains constant and is therefore used to reflect the compactness of the deployed node scale rather than to rank different coordinate layouts. The within-scenario search is mainly driven by coverage maximization, overlap reduction, and the coverage-dependent distribution penalty. Therefore, ACLFPDO should be regarded as an incremental but problem-specific deployment optimization framework for node-limited cotton-field STWSNs rather than a simple aggregation of existing improvement operators.

The main contributions of this paper are as follows:

- (1) A stage-based adaptive PDO deployment framework, named ACLFPDO, is proposed for STWSN coverage optimization. Rather than treating chaotic initialization, adaptive parameter adjustment, and Lévy-flight perturbation as independent methodological innovations, the framework couples them with node-coordinate encoding, stage-based position updating, and a coverage-oriented fitness function. This design transforms the original PDO into a problem-specific deployment optimizer for node-limited cotton-field STWSNs.
- (2) Addressing the problem of area coverage optimization in STWSNs, a node deployment optimization framework based on a binary sensing model is established. This framework encodes a set of sensor node coordinates into candidate deployment schemes and employs coverage rate, node utilization efficiency, and coverage overlap degree as evaluation criteria to facilitate a comprehensive assessment of the spatial distribution effectiveness of the nodes.
- (3) This paper focuses specifically on coverage optimization performance under varying conditions regarding the number of nodes. By configuring experiments with various node scales, the study analyzes ACLFPDO's ability to maintain coverage as the

number of nodes decreases, thereby validating the algorithm's potential for reducing node redundancy and enhancing node deployment efficiency.

- (4) Simulation experiments were designed across different monitoring area scales and node quantities to compare ACLFPDO against PDO, SO, and Whale Optimization algorithms (WO). The experimental results demonstrate that ACLFPDO exhibits superior performance in terms of coverage rate, node utilization efficiency, and convergence characteristics, yielding more uniform node deployment results and significantly fewer coverage blind spots.

2. Materials and Methods

2.1. STWSN Coverage Optimization Problem

The optimization of node deployment in STWSNs is, in essence, a problem of optimizing area coverage within wireless sensor networks. Its objective is to enhance the effective coverage rate of a target region—while simultaneously minimizing redundant coverage among nodes and the wasteful expenditure of sensing resources—by optimizing the spatial positioning of sensor nodes, given a specific monitoring area, a fixed number of nodes, and a defined sensor sensing radius. Currently, the prevalent coverage strategies employed in sensor networks primarily fall into three categories: area coverage, target coverage, and barrier coverage [24]. Among these, area coverage aims to ensure that every point within the entire monitoring region is covered by at least one sensor node; this approach is frequently utilized in scenarios such as environmental monitoring. Target coverage focuses on the surveillance of specific target points, making it suitable for applications such as target tracking. Conversely, barrier coverage emphasizes the establishment of a protective boundary, a strategy typically deployed in scenarios involving intrusion detection. Given that the subject of the present study is the continuous monitoring of soil temperature in cotton fields, area coverage has been adopted as the optimization objective for STWSN node deployment, with the specific aim of maximizing the coverage rate of the monitoring region through the optimization of node placement.

In this study, an idealized simulation model is adopted to evaluate the algorithmic performance of ACLFPDO. The soil temperature monitoring area in the cotton field is simplified as a two-dimensional regular square planar region, and the sensing range of each sensor node is represented by a fixed-radius circular area. This simplification is used to isolate and compare the coverage optimization capability of different algorithms under controlled conditions. Real cotton-field factors, such as ridges, furrows, irregular boundaries, obstacles, burial-depth differences, and soil spatial heterogeneity, are not explicitly modeled in the present simulation framework and are discussed as practical limitations in Section 4. Therefore, the experimental results in this study should be interpreted as controlled algorithm-comparison results for an idealized area-coverage optimization problem, rather than direct predictions of field deployment performance in real cotton-field environments. Let the monitoring region be denoted by A , with a side length of w and an area of $w \times w$. A total of N soil temperature sensor nodes are deployed in this region, and the node set is denoted as $S = \{s_1, s_2, \dots, s_N\}$. The position of the i -th sensor node is represented as $s_i = (x_i, y_i)$, where x_i and y_i denote the horizontal and vertical coordinates of the node in the two-dimensional plane, respectively. The coordinates of all nodes are constrained within the boundary of the monitoring region, namely $0 \leq x_i \leq w$ and $0 \leq y_i \leq w$.

In the area coverage model, the sensing range of each sensor node is simplified as a circular region centered at the node position, with a sensing radius of R . For any sampling point $p = (x_p, y_p)$ in the monitoring region, the point is considered to be covered by the network if its Euclidean distance to any sensor node is not greater than the sensing radius. This coverage relationship can be expressed as

$$d(s_i, p) = \sqrt{(x_i - x_p)^2 + (y_i - y_p)^2} \quad (1)$$

Sampling point p is covered by node s_i when the following conditions are met:

$$d(s_i, p) \leq R \quad (2)$$

The schematic diagram of the area coverage model is shown in Figure 1.

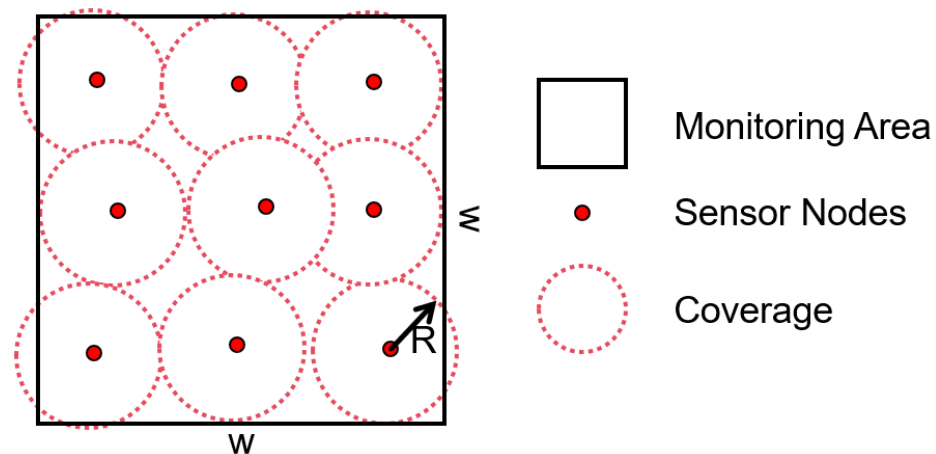


Figure 1. Regional coverage model of STWSNs.

If a point in the monitoring region is covered by at least one sensor node, it is regarded as an effectively covered point. The optimization objective of this study is to find an optimal set of node coordinate combinations under a given number of nodes N and sensing radius R . This objective aims to maximize the coverage rate of the monitoring region while reducing coverage redundancy among sensor nodes.

2.2. Sensor Sensing Model and Assumptions

The sensing model of sensor nodes is a key factor that affects network coverage performance. Considering the deployment requirements of soil temperature wireless sensor networks, this study adopts the Binary Sensing Model for sensor nodes. This model is widely used in coverage optimization studies of wireless sensor networks because it is computationally simple and has high practical applicability. In the Binary Sensing Model, the sensing range of each sensor node s_i is modeled as a circular region centered at the node position (x_i, y_i) , with a sensing radius of R . For any point $p(x, y)$ in region A , whether it is covered by sensor node s_i is determined according to Equation (3), and its coverage state can be expressed as

$$c_i(p) = \begin{cases} 1, & d(s_i, p) \leq R \\ 0, & d(s_i, p) > R \end{cases} \quad (3)$$

where $c_i(p) = 1$ indicates that the sampling point p is covered by node s_i and $c_i(p) = 0$ indicates that it is not covered by this node. If the sampling point p is covered by at least one sensor node, the network coverage state of this point can be expressed as

$$C(p) = \begin{cases} 1, & \sum_{i=1}^N c_i(p) \geq 1 \\ 0, & \sum_{i=1}^N c_i(p) = 0 \end{cases} \quad (4)$$

To facilitate the use of the sensor coverage model in the subsequent node optimization process, this study makes further simplifications. The target region is assumed to be

a two-dimensional plane, and sensor nodes are allowed to be placed at any location within the monitoring region.

- (1) When a node is placed in the target region, the node itself is treated as a point object.
- (2) The sensing distance of each node is R .

A schematic diagram of the Binary Sensing Model is shown in Figure 2.

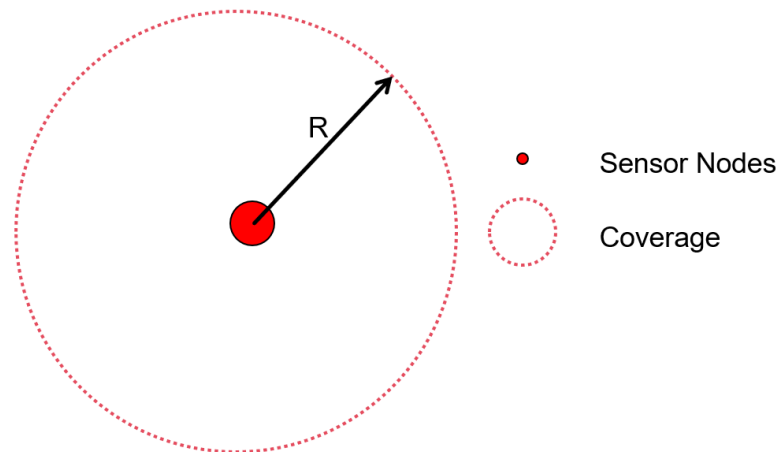


Figure 2. Binary sensing model.

2.3. Evaluation Metrics

To evaluate the coverage effectiveness and resource utilization of different node deployment schemes, this study selects the coverage rate and node utilization efficiency as the main evaluation metrics. The coverage rate is used to measure the extent to which the monitoring region is effectively covered by the sensor network. Node utilization efficiency is used to measure the extent to which the theoretical sensing resources of sensors are effectively used in practice.

The coverage rate (Coverage Rate, C) is used to characterize the degree to which the monitoring region is effectively covered by sensor nodes. Let the monitoring region be a two-dimensional discrete grid with a side length of w , and its area is $A = w^2$. For ease of calculation, this study discretizes the monitoring region into $w \times w$ grid sampling points with a unit step size. For numerical calculation, the monitoring region was discretized using a square grid with a sampling interval of Δ . In the main experiments, $\Delta = 1$ was used as the default unit step, and the sampling points were generated consistently within the monitoring boundary. A point was regarded as covered when its Euclidean distance to at least one sensor node was not greater than R . To evaluate the influence of grid discretization, a grid-resolution sensitivity analysis was further conducted using $\Delta = 1, 0.5$, and 0.25 . The coverage rate is defined as the ratio of the area covered by at least one node in monitoring region A to the total area, as shown in Equation (5):

$$C = \frac{\sum_{i=1}^w \sum_{j=1}^w C(x, y)}{w^2} \quad (5)$$

Equation (5) is used for the default unit-grid calculation, whereas the same point-counting principle is extended to finer grid intervals in the grid-resolution sensitivity analysis.

Node utilization efficiency (Node Utilization Efficiency, E) is used to characterize the extent to which the nominal theoretical sensing capacity of the deployed nodes contributes to effective coverage within the monitoring region. In this study, node utilization efficiency does not refer to the utilization rate of the number of nodes. Instead, it is defined as the ratio of the actual effective coverage area to the total nominal theoretical sensing area of all deployed nodes:

$$E = \frac{A_c}{N\pi R^2} \quad (6)$$

where A_c denotes the actual effective coverage area, and $N\pi R^2$ denotes the theoretical sensing area of all sensor nodes without considering overlap or boundary truncation. Since A_c can be approximated by Cw^2 in the discretized calculation, node utilization efficiency can be further expressed as

$$E = \frac{Cw^2}{N\pi R^2} \quad (7)$$

It should be noted that this metric is an approximate redundancy-oriented indicator based on the nominal sensing capacity of the deployed nodes. It does not correct the denominator by the truncated sensing area when a sensing circle extends beyond the monitoring boundary. Therefore, sensing areas outside the target region, as well as overlapping sensing areas among nodes, are treated as non-effective sensing resources because they do not contribute to additional target-region coverage. This definition is used to consistently compare the relative resource utilization and redundancy levels of different algorithms under the same idealized square-region simulation setting.

A higher node utilization efficiency indicates less redundant coverage among nodes and a higher effective utilization level of the sensing resources of each node. When the number of nodes is reduced, if the network can still maintain a high coverage rate and high node utilization efficiency, the deployment scheme has good node-saving capability.

2.4. Fitness Function Construction

During the STWSN node deployment optimization process, the coverage rate C is the core metric used to evaluate the quality of a deployment scheme. Therefore, this study uses it as the primary optimization term in the fitness function. However, maximizing coverage alone may lead to redundant coverage or local node aggregation, which reduces the utilization efficiency of node sensing resources. To address this issue, this study further introduces node-scale efficiency (η_N), the coverage overlap ratio, and a node distribution penalty term into the fitness function. These terms are used to constrain node redundancy and improve the spatial distribution of nodes.

First, a node-scale compactness factor η_N is defined to describe the relationship between the deployed number of nodes and an idealized area-ratio lower-bound estimate of the node number:

$$\eta_N = \min\left(\frac{N_{opt}}{N}, 1\right) \quad (8)$$

where N is the actual number of deployed nodes, and N_{opt} is an idealized area-ratio lower-bound estimate of the node number.

$$N_{opt} = \frac{w^2}{\pi R^2} \quad (9)$$

This metric reflects the utilization level of the current node scale relative to the theoretical coverage requirement. When the actual number of nodes is close to the theoretical minimum number of nodes, η_N has a higher value, indicating that the node deployment scale is more compact.

To reduce redundant coverage among nodes, the coverage overlap ratio (O) is defined to characterize the degree to which grid points are repeatedly covered. Let n_{ij} denote the number of times that grid point p_{ij} is covered by sensor nodes. The coverage overlap ratio is defined as

$$O = \frac{\sum_{i=1}^w \sum_{j=1}^w \max(n_{ij} - 1, 0)}{w^2} \quad (10)$$

When a grid point is covered by multiple nodes at the same time, all repeated coverage except the first effective coverage is counted as overlapping coverage. A lower coverage overlap ratio indicates a more reasonable node distribution and less waste of sensing resources.

Based on the above definitions, a comprehensive fitness function is constructed as follows:

$$F = w_1 C + w_2 \eta_N - w_3 O - w_4 U \quad (11)$$

where C is the coverage rate, η_N is the node-scale efficiency, O is the coverage overlap ratio, and U is the node distribution penalty term. w_1 , w_2 , w_3 , and w_4 are the weight coefficients of the corresponding terms, respectively. The coverage-dependent dispersion regularization term U is used to weakly constrain the coordinate distribution during the optimization process. It is not designed as the primary term for detecting local node aggregation; repeated sensing and local redundancy are mainly penalized by the overlap ratio O . Instead, U provides an auxiliary regularization effect by limiting excessive coordinate dispersion or unstable perturbations when the current coverage rate is still low. It is defined as

$$U = \frac{\text{std}(X, Y)}{w} (1 - C)^2 \quad (12)$$

where $\text{std}(X, Y)$ denotes the standard deviation of the node coordinate distribution, and w is the side length of the monitoring region. The factor $(1 - C)^2$ makes this regularization term coverage-dependent. When the coverage rate is low, the term has a stronger auxiliary effect on suppressing unstable coordinate updates. As the coverage rate increases, its effect gradually weakens, thereby avoiding excessive interference with local refinement in the later optimization stage.

In this study, $w_1 = 0.90$, $w_2 = 0.08$, $w_3 = 0.02$, and $w_4 = 0.10$. Among these terms, the coverage rate C is the primary objective of STWSN node deployment optimization, so it is assigned the highest weight. The overlap ratio O directly penalizes repeated coverage and local redundancy, whereas the coverage-dependent dispersion regularization term U provides a weak auxiliary constraint on unstable coordinate dispersion. Node utilization efficiency E is used only as an evaluation metric for the final deployment result and is not directly equivalent to the auxiliary terms in the fitness function. The node-scale compactness factor η_N is retained in the composite objective as a scenario-level compactness term. Because N is fixed within each simulation scenario, η_N does not affect the ranking of candidate coordinate layouts in that scenario. Therefore, the coordinate search process is mainly governed by C , O , and U , while η_N reflects the compactness of the selected node scale when different node-number settings are compared.

It should be noted that the four coefficients in the fitness function are not designed as normalized weights in a convex linear combination. Instead, they are used as priority-control coefficients to guide the search process. The coverage rate is the dominant optimization objective in STWSN node deployment; therefore, w_1 is assigned the largest value to ensure that the algorithm primarily searches for deployment schemes with high coverage. The node-scale efficiency and overlap ratio are used as auxiliary terms to reduce node redundancy and repeated sensing, and thus w_2 and w_3 are assigned relatively small values. The coefficient w_4 controls the distribution penalty term, which is further modulated by the coverage-dependent factor $(1 - C)^2$. Therefore, this penalty is mainly active when the coverage rate is low and gradually weakens as the coverage performance improves. For this reason, the sum of the four coefficients is not constrained to be equal to

1.0. This setting allows the fitness function to emphasize coverage improvement while still providing auxiliary constraints on node redundancy and spatial distribution.

The coefficient vector $(w_1, w_2, w_3, w_4) = (0.90, 0.08, 0.02, 0.10)$ was selected according to a coverage-priority design and a local coefficient-combination sensitivity analysis. Since the primary objective of STWSN deployment optimization is to maximize the effective coverage of the monitoring region, w_1 was assigned the dominant value. The node-scale compactness factor, overlap ratio, and distribution regularization term were introduced as auxiliary terms to reduce repeated sensing and maintain deployment compactness and spatial distribution quality. Therefore, w_2 , w_3 , and w_4 were assigned relatively smaller values. These coefficients are not normalized weights in a convex multi-objective formulation, but priority-control coefficients used to guide the search process toward high-coverage solutions while maintaining auxiliary constraints on deployment compactness and spatial distribution quality.

2.5. ACLFPDO Algorithm

Prairie Dog Optimization is an emerging swarm intelligence algorithm. It performs optimization by simulating the foraging and evasive behaviors of prairie dogs. Its basic procedure includes three main steps: population initialization, position updating, and fitness evaluation [23]. However, when the original PDO algorithm is used for coverage optimization in soil temperature wireless sensor networks, which is a complex optimization problem, it may suffer from slow convergence, premature convergence to local optima, and insufficient coverage uniformity. To overcome these limitations, this study proposes an ACLFPDO algorithm. The original PDO algorithm is improved by introducing an adaptive operator, a chaotic operator, and a Lévy flight strategy, so as to improve the coverage rate of STWSNs. Following the workflow of PDO, this section describes the design and implementation of these improvements. These include the dynamic adjustment mechanism of the adaptive operator, the population initialization optimization based on the chaotic operator, and the enhanced position updating strategy based on Lévy flight. These improvements are used to enhance the coverage performance of STWSNs.

In this study, each candidate solution represents a complete STWSN node deployment scheme. Let the number of sensor nodes be N . The i -th candidate solution can be expressed as

$$X_i = [x_1, y_1, x_2, y_2, \dots, x_N, y_N] \quad (13)$$

Therefore, the search dimension of the optimization problem is $D = 2N$. Here, q denotes the population size of the algorithm, namely the number of candidate solutions; N denotes the number of sensor nodes; T denotes the maximum number of iterations; w denotes the side length of the monitoring region; and R denotes the sensing radius of each sensor node. The optimization objective is to find the optimal combination of node coordinates under the boundary constraints $0 \leq x_k \leq w$ and $0 \leq y_k \leq w$, so that the network coverage rate is maximized. During the optimization process, some updated coordinates may exceed the monitoring boundary after position updating. In this study, a coordinate clipping repair strategy was adopted rather than reflection or resampling. For each updated coordinate $x_{i,d}$, the repaired coordinate was calculated as

$$X_{i,d}^{repair} = \min(\max(x_{i,d}, LB_d), UB_d) \quad (14)$$

where LB_d and UB_d denote the lower and upper bounds of the d -th coordinate dimension, respectively. In the square monitoring region used in this study, $LB_d = 0$ and $UB_d = w$. Therefore, coordinates smaller than 0 were set to 0, and coordinates larger than w were set to w .

2.5.1. Introduction and Design of the Adaptive Operator

In the original PDO algorithm, the position updating process depends on fixed step sizes and perturbation factors. It lacks a dynamic response to the optimization process, which limits its convergence speed and global search capability. To address this problem, this study introduces an adaptive operator into ACLFPDO. The operator dynamically adjusts the step size and perturbation factor according to the current coverage rate and iteration progress, thereby optimizing the search strategy. Specifically, the adaptive operator includes the adaptive step-size factor DS and the adaptive perturbation factor PE , which are defined as follows:

$$DS = DS_{max} \cdot \left(1 - \frac{t}{T}\right) \cdot (-1)^{\text{mod}(t,2)} \quad (15)$$

$$PE = PE_{max} \cdot \exp\left(-\alpha \frac{t}{T}\right) \cdot (-1)^{\text{mod}(t,2)} \quad (16)$$

where DS_{max} and PE_{max} are the initial maximum step size and perturbation factor, which are set to 2.5 and 2.0, respectively. t is the current iteration number, and T is the maximum number of iterations. The decay coefficient α is set to 3 to control the exponential decay of the perturbation factor. The term $(-1)^{\text{mod}(t,2)}$ is used to introduce an oscillatory characteristic, which enhances search diversity. In the early stage of the algorithm, when t/T is small, DS and PE remain at relatively large values to promote global search. As the iteration proceeds and t/T approaches 1, both factors gradually decrease, which accelerates local convergence. This adaptive mechanism dynamically balances global exploration and local exploitation according to the optimization process, thereby improving the optimization efficiency of STWSN coverage.

2.5.2. Chaotic Initialization of STWSN Nodes

In the population initialization stage, the original PDO algorithm uses random generation. This approach may lead to an uneven initial node distribution and affect the coverage rate in subsequent optimization. To improve the diversity and uniformity of the initial population, this study introduces a chaotic operator into ACLFPDO. The randomness and ergodicity of chaotic sequences are used to optimize the population initialization process. The mathematical expression is as follows:

$$z_{k+1} = \mu \cdot z_k \cdot (1 - z_k) \quad (17)$$

where z_k is the chaotic value at the k -th iteration. The initial value z_0 is randomly selected from the interval $(0, 1)$. The control parameter μ was set to 3.7 in this study. This value was selected based on the parameter sensitivity analysis in Section 3.2, where $\mu = 3.7, 3.8, 3.9$, and 4.0 were compared under the representative simulation scenario. For a population with q candidate solutions in a D -dimensional search space, where $D = 2N$ includes both x - and y -coordinates of all sensor nodes, the chaotic sequence z_k is mapped to the boundary interval to generate the initial position:

$$X_{i,j} = LB_j + (UB_j - LB_j) \cdot z_{i,j} \quad (18)$$

where $X_{i,j}$ is the initial position of the i -th candidate solution in the j -th dimension. LB_j and UB_j are the lower and upper bounds of the j -th dimension, respectively. In this study, $LB_j = 0$ and $UB_j = w$ are set to facilitate subsequent algorithm optimization. Compared with random initialization, the chaotic operator can generate initial solutions with a more uniform distribution and better ergodicity. This helps avoid node concentration or uneven initial deployment, provides a better basis for subsequent optimization, and improves the coverage rate of STWSNs.

2.5.3. Integration and Optimization of the Lévy Flight Strategy

The position updating strategy of the original PDO algorithm lacks jump-based search capability. Therefore, it is prone to falling into local optima in complex search spaces. To enhance the global search capability of the algorithm, this study introduces the Lévy flight strategy into ACLFPDO. This strategy uses the long-tailed distribution of Lévy flight to perform large-scale jump-based position updates. The step length L of Lévy flight is generated as follows:

$$L = \frac{u}{|v|^{1/\beta}} \quad (19)$$

where u and v are normally distributed random numbers. u follows a normal distribution with a mean of 0 and a variance of σ_u^2 , while v follows a standard normal distribution with a mean of 0 and a variance of 1. The value $\beta = 1.5$ was selected because it lies within the commonly used interval (1, 2) for Lévy-flight-based search and provided stable and competitive performance in the parameter sensitivity analysis in Section 3.2, where β was tested from 1.1 to 1.9. The variance σ_u^2 is calculated as follows:

$$\sigma_u = \left(\frac{\Gamma(1 + \beta) \cdot \sin(\pi\beta/2)}{\Gamma((1 + \beta)/2) \cdot \beta \cdot 2^{(\beta-1)/2}} \right)^{1/\beta} \quad (20)$$

The main advantage of Lévy flight is that its step-length distribution has the characteristic of frequent short-distance movements and occasional long-distance jumps. This enables the algorithm to conduct large-scale jump-based search in the early optimization stage and explore a broader solution space. In the later stage, short step-length adjustments are used for fine local optimization. Therefore, in the proposed ACLFPDO framework, the Lévy-flight strategy is mainly used to provide supplementary jump-based exploration and to help maintain search diversity. According to the ablation results, its contribution under the current regular square-region simulation settings is auxiliary rather than dominant.

2.5.4. Stage-Based Position Updating Strategy

Different position updating strategies are adopted according to the iteration stage of the algorithm. This design enables ACLFPDO to emphasize different search behaviors at different phases of the optimization process, thereby achieving a balance between global exploration and local exploitation. In this study, the optimization process is divided into three equal stages, namely the early, middle, and late stages. The equal-division strategy is adopted as a deterministic and reproducible stage-control scheme, which assigns comparable iteration budgets to global exploration, transition search, and local refinement without introducing additional segmentation parameters. Although the stage boundaries are fixed at $T/3$ and $2T/3$, the search intensity within each stage is still dynamically adjusted by the adaptive step-size factor, the adaptive perturbation factor, the Lévy flight perturbation, and the coverage-dependent penalty term in the fitness function. Therefore, the stage boundaries mainly determine the dominant update mode, whereas the adaptive mechanisms provide fine-grained dynamic control during the optimization process. This design reduces parameter-tuning complexity while maintaining the ability of the algorithm to adjust its search behavior across iterations. The specific updating equations are given as follows:

If $t < T/3$, the algorithm is in the early search stage. At this stage, global exploration is strengthened to improve the ability of the population to cover the solution space.

$$X_{i,j}^{new} = w_t \cdot X_{i,j} + L_{i,j} \cdot chaos \cdot (UB_j - LB_j) \quad (21)$$

where w_t denotes the inertia weight at iteration t , and it is used only in the position-updating equation and should not be confused with the fitness-function coefficients w_1 ,

w_2 , w_3 , and w_4 or the side length w of the monitoring region. $L_{i,j}$ denotes the Lévy-flight step generated according to Equations (19) and (20) for the i -th candidate solution in the j -th dimension. $chaos$ denotes the Logistic chaotic factor generated from Equation (17), with its value mapped to the interval $[0, 1]$.

If $T/3 \leq t < 2T/3$, the algorithm is in the middle search stage. At this stage, global search and local search are balanced. Individuals are guided toward the global optimal position, while perturbations are introduced to maintain a certain level of exploration.

$$X_{i,j}^{new} = w_t \cdot X_{i,j} + DS \cdot (X_{best,j} - X_{i,j}) + PE \cdot randn \quad (22)$$

where DS is the adaptive step-size factor, PE is the adaptive perturbation factor, and $randn$ is a normally distributed random number.

If $t \geq 2T/3$, the algorithm is in the late search stage. At this stage, local search is strengthened. Fine adjustments are performed around the global optimal position, and the perturbation amplitude decreases with the iteration process. This ensures convergence accuracy and ultimately improves the coverage rate.

$$X_{i,j}^{new} = X_{best,j} + PE \cdot randn \cdot \exp\left(-\frac{t}{T}\right) \cdot \frac{UB_j - LB_j}{w} \quad (23)$$

In Equation (23), $X_{best,j}$ denotes the j -th dimensional coordinate of the current global best candidate solution. The late-stage update performs local refinement around the current best deployment scheme, while the adaptive perturbation amplitude decreases with the iteration process.

2.5.5. ACLFPDO Procedure

Step 1: Algorithm initialization. Set the population size q , the maximum number of iterations T , the number of sensor nodes N , the search dimension $D = 2N$, the sensing radius R , the side length of the monitoring region w , and the lower and upper bounds of node coordinates, LB and UB .

Step 2: Chaotic initialization of population positions. According to Equations (17) and (18), the initial candidate solutions are generated using the Logistic chaotic map, so that each candidate solution represents a complete sensor node deployment scheme.

Step 3: Adaptive parameter calculation. According to Equations (15) and (16), the step-size factor and perturbation factor are calculated. According to Equations (19) and (20), the step-length matrix is generated and integrated into the position updating strategy to optimize the current search mode.

Step 4: Stage-based position updating. According to Equations (21)–(23), different position updating strategies are adopted based on the iteration stage, and the node deployment positions are updated.

Step 5: Boundary repair and optimal solution update. The updated node positions are repaired using the coordinate clipping strategy defined above. Coordinates smaller than the lower bound are set to the lower bound, and coordinates larger than the upper bound are set to the upper bound. The fitness value is then recalculated, and the individual best and global best solutions are updated.

Step 6: Iteration termination judgment. The current iteration number is checked. If it is smaller than the total number of iterations T , the algorithm returns to Step 4. Otherwise, the final coverage strategy is output.

The flowchart of ACLFPDO is shown in Figure 3.

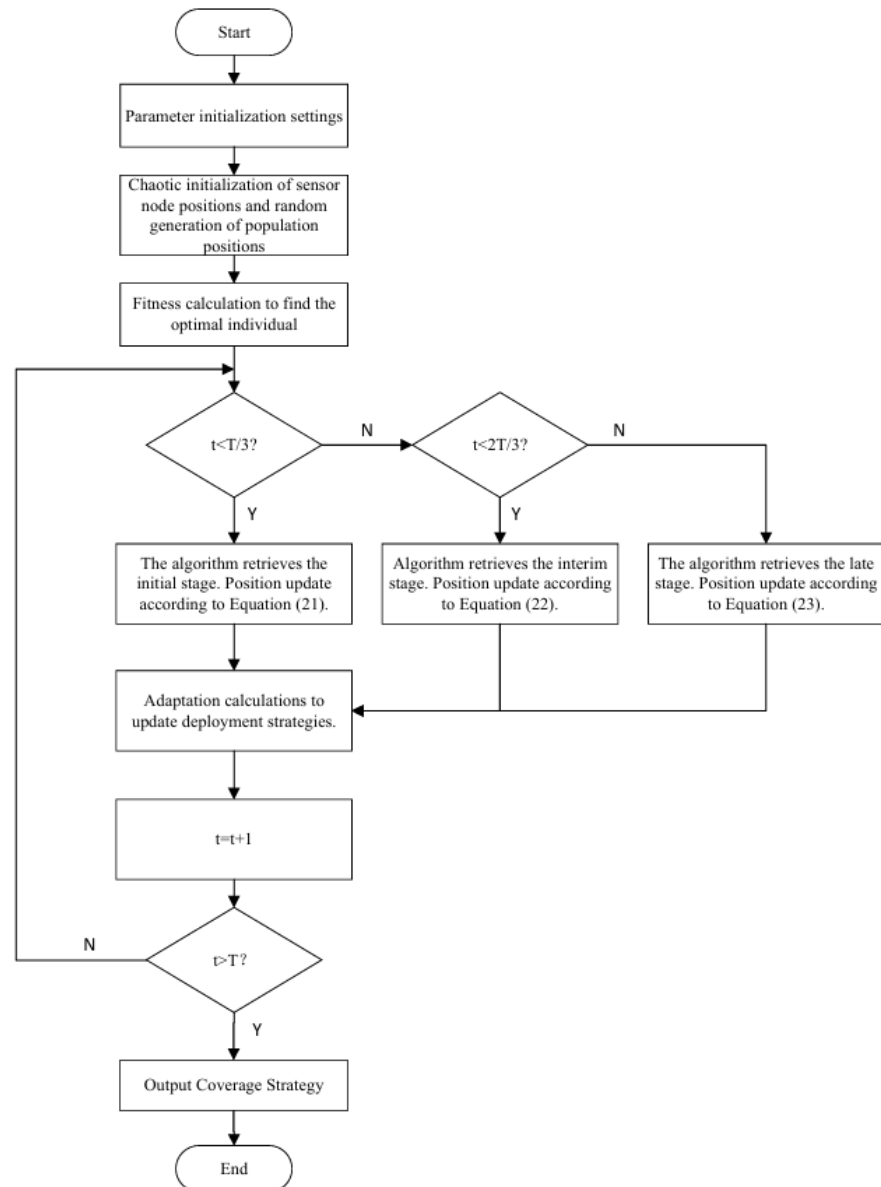


Figure 3. Flowchart of ACLFPDO in STWSNs.

2.6. Computational Environment

All algorithms and simulation experiments were implemented using custom scripts in MATLAB R2024b (The MathWorks, Inc., Natick, MA, USA). The simulations were performed on a desktop computer equipped with a 13th Gen Intel(R) Core(TM) i5-13490F processor (Intel Corporation, Santa Clara, CA, USA), 32 GB of RAM, and an NVIDIA GeForce RTX 5060 graphics processing unit with 8 GB of dedicated graphics memory (NVIDIA Corporation, Santa Clara, CA, USA), running the Windows 10 operating system (Microsoft Corporation, Redmond, WA, USA). All algorithms were executed under the same hardware and software environment to ensure a fair comparison.

3. Results

3.1. Simulation Experiment Setup

To verify the effectiveness of the proposed ACLFPDO algorithm for STWSN coverage optimization, simulation experiments were conducted. The results obtained by ACLFPDO were compared with those obtained by the prairie dog optimization algorithm (PDO), snake optimizer (SO), and whale optimization algorithm (WO). The simulation

results reported in this study include the network coverage rate and node utilization efficiency. Unless otherwise stated, the main comparison and ablation results were obtained from 100 independent runs and are reported as the mean $\pm$ standard deviation. All simulations were performed on the same device, and the fitness function used in the algorithms was defined according to Equation (11).

To ensure a fair comparison of different algorithms in the STWSN coverage optimization process, the population size q of all algorithms was set to 30, and the maximum number of iterations T was set to 1000. The detailed parameter settings of the four algorithms are shown in Table 1. The parameter settings of ACLFPDO were determined based on the parameter sensitivity analysis described in Section 3.2.

Table 1. Algorithm detailed parameter settings.

Algorithm Name	Basic Parameters of the Algorithm
ACLFPDO	$q = 30, T = 1000, w_1 = 0.9, w_2 = 0.08, w_3 = 0.02, w_4 = 0.10,$ $\alpha = 3, \beta = 1.5, \mu = 3.7, DS_{max} = 2.5, PE_{max} = 2.0$
PDO	$q = 30, T = 1000$
SO	$q = 30, T = 1000, c_1 = 0.5, c_2 = 0.5, c_3 = 2$
WO	$q = 30, T = 1000, b = 1, A = 2$

To facilitate the optimization of node deployment positions, the sensor nodes of the STWSN were assumed to be deployed in a square monitoring region with a side length of w and an area of $w \times w$. When w was set to 50, the sensing radius R was set to 5. When w was set to 40, the sensing radius R was set to 4. The number of sensor nodes deployed in the region was denoted by N . Experiments were conducted under different region sizes and node numbers. The values of N used in the four simulation groups were 42, 37, 32, and 31.

To further provide an additional validation under an enlarged idealized monitoring region and a broader node-number configuration, a supplementary experiment was conducted under $w = 60$ and $R = 6$, with $N = 52, 47$, and 42. The same four algorithms, namely ACLFPDO, PDO, SO, and WO, were compared under these additional scenarios. Each algorithm–scenario combination was independently executed 100 times, and the coverage rate and node utilization efficiency were reported as the mean $\pm$ standard deviation.

All comparison results were obtained from 100 independent runs and are reported as the mean $\pm$ standard deviation. The main comparison tables were generated from the same set of repeated simulations for ACLFPDO, PDO, SO, and WO to ensure consistency among the compared algorithms. In addition, an ablation study was conducted independently to evaluate the contribution of each improvement strategy in ACLFPDO. Because the ablation study and the main comparison study were performed as independent repeated experiments, minor numerical differences may appear for the overlapping PDO and ACLFPDO variants. The repeated runs were paired by the same random-seed index for each algorithm–scenario comparison. To further validate the ablation results, pairwise Wilcoxon signed-rank tests were conducted using the coverage rate and final objective value as the test variables. The significance level was set to $\alpha = 0.05$, and $p < 0.05$ was considered statistically significant.

3.2. Sensitivity Analysis

3.2.1. Parameter Sensitivity Analysis

To clarify the basis of the parameter settings and improve the reproducibility of ACLFPDO, a parameter sensitivity analysis was conducted under the representative condition $w = 50, R = 5$, and $N = 42$. This condition was selected because it corresponds to the main experimental scenario used to evaluate the coverage optimization performance of the proposed algorithm. In this analysis, one parameter was varied at a time while the

remaining parameters were fixed at their default values. Each parameter configuration was independently executed 30 times, and the mean and standard deviation of the coverage rate and node utilization efficiency were recorded.

The tested parameters included the maximum adaptive step-size factor DS_{max} , the maximum adaptive perturbation factor PE_{max} , the exponential decay coefficient α , the Lévy flight parameter β , the Logistic chaotic map parameter μ , and the coefficient combinations in the fitness function. The results are summarized in Table 2. For the Logistic chaotic map parameter, $\mu = 3.7, 3.8, 3.9$, and 4.0 were compared. The coverage-rate range under these settings was 98.35–98.58%, indicating that ACLFPDO was not highly sensitive to the Logistic parameter within the tested chaotic interval. Therefore, $\mu = 3.7$ was adopted as a stable and competitive setting in the subsequent experiments. Overall, ACLFPDO maintained stable coverage performance within the tested parameter ranges. Although slight differences were observed among different parameter settings, the variations in coverage rate and node utilization efficiency were relatively small. The selected setting, namely $DS_{max} = 2.5$, $PE_{max} = 2.0$, $\alpha = 3$, $\beta = 1.5$, $\mu = 3.7$, $w_1 = 0.90$, $w_2 = 0.08$, $w_3 = 0.02$, and $w_4 = 0.10$, provided stable and competitive performance while maintaining consistency with the main comparison experiments. Therefore, these parameters were adopted in the subsequent simulation experiments.

Table 2. Parameter sensitivity analysis of ACLFPDO under $w = 50$, $R = 5$, and $N = 42$.

Parameter Group	Tested Range	Selected Value	Coverage-Rate Range (%)	Coverage at Selected Value (%)	Node Utilization at Selected Value (%)
DS_{max}	1.5–3.5	2.5	98.32–98.56	98.45 ± 0.53	74.61 ± 0.40
PE_{max}	1.0–3.0	2.0	98.21–98.54	98.51 ± 0.70	74.66 ± 0.53
α	1–5	3	98.35–98.59	98.51 ± 0.65	74.66 ± 0.49
β	1.1–1.9	1.5	98.31–98.63	98.31 ± 0.69	74.51 ± 0.53
μ	3.6–4.0	3.7	98.35–98.58	98.35 ± 0.58	74.53 ± 0.44
Fitness function coefficient vector (w_1, w_2, w_3, w_4)	5 coefficient combinations	(0.9, 0.08, 0.02, 0.1)	98.28–98.66	98.45 ± 0.55	74.61 ± 0.42

Note: For the fitness-function coefficient vector $w = (w_1, w_2, w_3, w_4)$, five coefficient combinations were tested: (0.90, 0.08, 0.02, 0.10), (0.95, 0.03, 0.02, 0.05), (0.85, 0.10, 0.05, 0.10), (0.88, 0.06, 0.06, 0.10), and (0.90, 0.08, 0.02, 0.05). The first combination was used as the selected setting in the subsequent comparison experiments.

For the fitness-function coefficient vector, five coverage-dominant coefficient combinations were evaluated as a local grid-search sensitivity test. The tested combinations were designed around the selected setting by increasing or decreasing the relative emphasis on coverage rate, node-scale efficiency, overlap reduction, and distribution penalty. The coverage-rate range obtained under these five combinations was 98.28–98.66%, and the selected setting achieved $98.45 \pm 0.55\%$ coverage and $74.61 \pm 0.42\%$ node utilization efficiency. These results indicate that ACLFPDO was not highly sensitive to small changes in the coefficient vector. In addition, under the representative scenario $w = 50$, $R = 5$, and $N = 42$, the lowest coverage rate obtained by ACLFPDO among the tested coefficient combinations was still higher than the corresponding results of PDO, SO, and WO in the main comparison experiments. Therefore, the algorithm ranking remained stable under the tested coefficient settings.

3.2.2. Grid-Resolution Sensitivity Analysis

To evaluate whether the calculated coverage rate was affected by grid discretization, a grid-resolution sensitivity analysis was conducted using three sampling intervals, namely $\Delta = 1, 0.5$, and 0.25 . The final node deployment schemes obtained under the same experimental settings were re-evaluated using different grid intervals without re-

optimizing the node positions. This setting was used to isolate the influence of grid resolution from the stochastic search process of the algorithms.

Two representative scenarios were selected for this analysis. The first scenario, $w = 50$, $R = 5$, and $N = 42$, corresponds to the main dense-node simulation condition. The second scenario, $w = 40$, $R = 4$ and $N = 31$, represents a node-limited condition. As shown in Table 3, the coverage rate decreased slightly as the grid interval became finer. This is because a finer grid can identify small uncovered areas that may not be sampled under the unit-step grid. Nevertheless, the changes in coverage rate were moderate. The maximum absolute difference among the three grid intervals was 2.33 percentage points, which occurred for ACLFPDO under the node-limited scenario.

Table 3. Grid-resolution sensitivity analysis under representative scenarios.

Scenario	Algorithm	$\Delta = 1$	$\Delta = 0.5$	$\Delta = 0.25$	Maximum Absolute Difference
$w = 50, R = 5, N = 42$	ACLFPDO	98.52 ± 0.58	97.57 ± 0.64	97.40 ± 0.64	1.12
$w = 50, R = 5, N = 42$	PDO	81.61 ± 1.94	81.33 ± 1.94	81.22 ± 1.96	0.38
$w = 50, R = 5, N = 42$	SO	88.80 ± 2.08	88.04 ± 2.03	87.86 ± 2.03	0.94
$w = 50, R = 5, N = 42$	WO	87.41 ± 1.92	86.78 ± 1.93	86.65 ± 1.93	0.76
$w = 40, R = 4, N = 31$	ACLFPDO	89.30 ± 1.00	87.38 ± 0.93	86.97 ± 0.91	2.33
$w = 40, R = 4, N = 31$	PDO	70.84 ± 1.92	70.33 ± 1.90	70.20 ± 1.91	0.64
$w = 40, R = 4, N = 31$	SO	78.74 ± 2.17	77.42 ± 2.09	77.13 ± 2.08	1.61
$w = 40, R = 4, N = 31$	WO	76.46 ± 1.87	75.49 ± 1.84	75.30 ± 1.82	1.15

Note: Values are reported as the mean $\pm$ standard deviation over 100 independent runs. The final node deployment schemes obtained under the same experimental settings were re-evaluated using different grid intervals without re-optimizing the node positions. The maximum absolute difference denotes the largest difference among the mean coverage rates obtained under $\Delta = 1, 0.5$, and 0.25 .

More importantly, the ranking of the compared algorithms remained unchanged under all three grid resolutions in both representative scenarios. ACLFPDO consistently achieved the highest coverage rate, followed by SO, WO, and PDO. These results indicate that the unit-step grid used in the main experiments provides a stable approximation for comparing the relative coverage optimization performance of different algorithms.

3.3. Ablation Study of ACLFPDO Components

To further evaluate the contribution of the main improvement strategies in ACLFPDO, an ablation study was conducted under all eight simulation scenarios used in the main comparison experiments. These scenarios included two monitoring-region settings, namely $w = 50, R = 5$ and $w = 40, R = 4$, and four node-number settings, namely $N = 42, N = 37, N = 32$, and $N = 31$. Therefore, a total of 48 variant–scenario combinations were tested, including six algorithmic variants under eight experimental scenarios. Each combination was independently executed 100 times, and the coverage rate, node utilization efficiency, coverage overlap ratio, and objective value were recorded.

To ensure a controlled ablation comparison, all variants used the same population size, maximum number of iterations, fitness function, boundary repair strategy, and number of independent runs. The tested variants were defined as follows: PDO denotes the strict original PDO baseline; PDO + Chaos denotes PDO using only Logistic chaotic initialization; PDO + Adaptive denotes PDO incorporating only the adaptive DS/PE mechanism; PDO + Chaos + Adaptive denotes PDO with both chaotic initialization and adaptive DS/PE but without the final stage-based ACLFPDO updating framework; ACLFPDO-NoLevy denotes the final stage-based ACLFPDO framework with the additional Lévy-flight perturbation removed; and ACLFPDO denotes the complete proposed framework.

To avoid an excessively large table in the main text, two representative scenarios are reported in Table 4. The first scenario, $w = 50$, $R = 5$, $N = 42$, corresponds to the main high-node-density condition used in the comparison experiments. The second scenario, $w = 40$, $R = 4$, $N = 31$, represents a node-limited condition and is used to further examine the robustness of the proposed framework when the number of available sensor nodes is reduced.

Table 4. Ablation study of ACLFPDO components under representative dense-node and node-limited scenarios.

Scenario	Variant	Coverage Rate (%)	Node Utilization Efficiency (%)	Overlap Ratio (%)	Objective Value
$w = 50$ $R = 5$ $N = 42$	PDO	81.61 ± 1.94	61.85 ± 1.47	44.17 ± 2.76	0.7856 ± 0.0181
	PDO + Chaos	70.77 ± 3.60	53.63 ± 2.73	59.21 ± 4.05	0.6838 ± 0.0337
	PDO + Adaptive	81.82 ± 1.94	62.01 ± 1.47	43.89 ± 2.82	0.7876 ± 0.0180
	PDO + Chaos + Adaptive	70.85 ± 3.45	53.70 ± 2.61	58.84 ± 4.21	0.6847 ± 0.0323
	ACLFPDO-NoLevy	98.48 ± 0.65	74.63 ± 0.49	20.84 ± 1.39	0.9431 ± 0.0059
	ACLFPDO	98.49 ± 0.62	74.64 ± 0.47	20.83 ± 1.58	0.9432 ± 0.0055
$w = 40$ $R = 4$ $N = 31$	PDO	71.01 ± 2.02	72.91 ± 2.08	23.12 ± 2.39	0.7122 ± 0.0189
	PDO + Chaos	62.66 ± 3.33	64.34 ± 3.42	33.60 ± 3.52	0.6336 ± 0.0312
	PDO + Adaptive	71.14 ± 1.99	73.05 ± 2.05	23.13 ± 2.56	0.7134 ± 0.0186
	PDO + Chaos + Adaptive	62.49 ± 3.40	64.16 ± 3.50	33.79 ± 3.54	0.6320 ± 0.0319
	ACLFPDO-NoLevy	89.35 ± 0.96	91.75 ± 0.98	5.70 ± 0.74	0.8827 ± 0.0087
	ACLFPDO	89.37 ± 1.00	91.77 ± 1.03	5.91 ± 0.84	0.8828 ± 0.0091

Note: Values are reported as the mean $\pm$ standard deviation over 100 independent runs. “ACLFPDO-NoLevy” denotes the final ACLFPDO framework after removing the additional Lévy-flight perturbation introduced in this study.

As shown in Table 4, the complete ACLFPDO framework achieved substantially better coverage performance than the strict original PDO baseline in both representative scenarios. Under $w = 50$, $R = 5$, $N = 42$, ACLFPDO increased the coverage rate from 81.61% to 98.49% and improved the node utilization efficiency from 61.85% to 74.64%. The overlap ratio was reduced from 44.17% to 20.83%. Under the node-limited scenario of $w = 40$, $R = 4$, $N = 31$, ACLFPDO improved the coverage rate from 71.01% to 89.37% and increased the node utilization efficiency from 72.91% to 91.77%, while reducing the overlap ratio from 23.12% to 5.91%.

The full ablation results across all eight scenarios showed a consistent trend. When averaged over the eight scenarios, the strict PDO baseline achieved an average coverage rate of 75.48% and an average node utilization efficiency of 68.21%, whereas ACLFPDO achieved 93.58% and 84.75%, respectively. The average overlap ratio was also reduced from 31.72% for PDO to 11.56% for ACLFPDO. These results demonstrate that the complete ACLFPDO framework can substantially improve the spatial distribution quality of sensor nodes and reduce redundant sensing.

The ablation results indicate that the effects of the proposed strategies are not simply additive when they are directly inserted into the original PDO framework. The adaptive DS/PE mechanism produced only a slight improvement over the strict PDO baseline, whereas chaotic initialization alone did not improve the original PDO under the tested scenarios. This result suggests that chaotic initialization and adaptive control are not effective as isolated plug-in operators in the original PDO updating structure. Instead, their effectiveness depends on being coupled with the stage-based adaptive position-updating framework. The large performance gap between PDO + Chaos + Adaptive and ACLFPDO-

No Levy indicates that the stage-based ACLFPDO search framework is the dominant source of improvement. In addition, the very small difference between ACLFPDO-No Levy and the complete ACLFPDO suggests that the additional Lévy-flight perturbation mainly provides supplementary jump-based exploration capability rather than serving as the primary contributor under the current regular square-region simulation settings.

Pairwise Wilcoxon signed-rank tests were further conducted to statistically validate the ablation results. As shown in Table 5, ACLFPDO significantly outperformed PDO, PDO + Chaos, PDO + Adaptive, and PDO + Chaos + Adaptive in all eight simulation scenarios in terms of both coverage rate and final objective value. For these comparisons, all p -values were far below 0.001, indicating that the performance improvement of ACLFPDO was statistically significant rather than being caused by random fluctuations in repeated stochastic runs. In contrast, no statistically significant difference was observed between ACLFPDO and ACLFPDO-NoLevy in any of the eight scenarios, with p -values ranging from 0.0916 to 0.9684 for coverage rate and from 0.0996 to 0.9698 for the final objective value. This result indicates that the stage-based adaptive ACLFPDO framework is the dominant source of performance improvement, whereas the additional Lévy-flight perturbation mainly provides supplementary exploration capability under the current regular square-region simulation settings.

Table 5. Statistical significance summary of the ablation study across all eight simulation scenarios.

Reference Variant	Compared Variant	p -Value Range for Coverage Rate	p -Value Range for Final Objective Value	Significant Scenarios	Interpretation
ACLFPDO	PDO	3.88×10^{-18} – 3.89×10^{-18}	3.90×10^{-18}	8/8	Significant
ACLFPDO	PDO + Chaos	3.89×10^{-18} – 3.89×10^{-18}	3.90×10^{-18}	8/8	Significant
ACLFPDO	PDO + Adaptive	3.88×10^{-18} – 3.89×10^{-18}	3.90×10^{-18}	8/8	Significant
ACLFPDO	PDO + Chaos + Adaptive	3.89×10^{-18} – 3.89×10^{-18}	3.90×10^{-18}	8/8	Significant
ACLFPDO	ACLFPDO-NoLevy	0.0916–0.9684	0.0996–0.9698	0/8	Not significant

Note: The p -value ranges were obtained from Wilcoxon signed-rank tests across the eight simulation scenarios. Coverage rate and final objective value were used as the test variables. A significance level of $\alpha = 0.05$ was adopted, and $p < 0.05$ was considered statistically significant.

3.4. Coverage Optimization Results Under Different Region Scales

Table 6 presents the comparative results of the coverage rate and node utilization efficiency of the four algorithms when the side length of the monitoring region was $w = 50$ and the sensing radius was $R = 5$. The results show that ACLFPDO achieved the highest network coverage rate and node utilization efficiency under all node-number conditions.

Table 6. Comparison of optimization results of algorithms with different number of nodes for $w = 50$ and $R = 5$.

Algorithm Name	Evaluation Metric	$N = 42$	$N = 37$	$N = 32$	$N = 31$
ACLFPDO	coverage rate (%)	98.49 ± 0.57	95.66 ± 0.79	90.55 ± 0.85	89.12 ± 1.00
	node utilization efficiency (%)	74.65 ± 0.44	82.30 ± 0.68	90.07 ± 0.84	91.51 ± 1.03
	coverage rate (%)	81.61 ± 1.94	77.39 ± 1.78	71.76 ± 1.96	70.71 ± 2.01
PDO	node utilization efficiency (%)	61.85 ± 1.47	66.58 ± 1.53	71.38 ± 1.95	72.61 ± 2.07
	coverage rate (%)	88.97 ± 1.68	85.10 ± 2.23	80.18 ± 1.83	78.79 ± 2.07
	node utilization efficiency (%)	67.43 ± 1.27	73.21 ± 1.91	79.76 ± 1.82	80.90 ± 2.12
SO	coverage rate (%)	87.63 ± 1.68	84.23 ± 1.71	78.05 ± 1.97	77.52 ± 2.07
	node utilization efficiency (%)	66.41 ± 1.27	72.46 ± 1.47	77.64 ± 1.96	79.60 ± 2.12
	coverage rate (%)				
WO	node utilization efficiency (%)				
	coverage rate (%)				
	node utilization efficiency (%)				

Note: Values are reported as the mean $\pm$ standard deviation over 100 independent runs. Node utilization efficiency is calculated using the nominal theoretical sensing area $N\pi R^2$ as the denominator and is therefore interpreted as an approximate redundancy-oriented indicator rather than a boundary-truncation-corrected effective-area metric.

When $N = 42$, ACLFPDO achieved a coverage rate of $98.49 \pm 0.57\%$ and a node utilization efficiency of $74.65 \pm 0.44\%$. Compared with PDO, SO, and WO, the coverage rate was improved by 16.88, 9.52, and 10.86 percentage points, respectively, and the node utilization efficiency was improved by 12.80, 7.22, and 8.24 percentage points, respectively. When the number of nodes was reduced to $N = 31$, ACLFPDO still achieved a coverage rate of $89.12 \pm 1.00\%$ and a node utilization efficiency of $91.51 \pm 1.03\%$, both of which were higher than those of PDO, SO, and WO.

In terms of average performance, ACLFPDO achieved an average coverage rate of 93.46% under the four node-number conditions when $w = 50$ and $R = 5$. This value was 18.09, 10.20, and 11.60 percentage points higher than those of PDO, SO, and WO, respectively. Its average node utilization efficiency was 84.63%, which was 16.53, 9.31, and 10.60 percentage points higher than those of PDO, SO, and WO, respectively. These results indicate that, under the tested idealized square-region simulation settings, ACLFPDO can obtain a better spatial distribution of sensor nodes and maintain good coverage performance when the number of nodes is reduced.

Table 7 presents the coverage optimization results of the four algorithms when the side length of the monitoring region was $w = 40$ and the sensing radius was $R = 4$. Overall, ACLFPDO still achieved a high coverage rate and node utilization efficiency under different node-number conditions.

Table 7. Comparison of optimization results of algorithms with different number of nodes for $w = 40$ and $R = 4$.

Algorithm Name	Evaluation Metric	$N = 42$	$N = 37$	$N = 32$	$N = 31$
ACLFPDO	coverage rate (%)	98.45 ± 0.70	96.01 ± 0.99	90.73 ± 0.96	89.42 ± 0.89
	node utilization efficiency (%)	74.61 ± 0.53	82.60 ± 0.85	90.25 ± 0.95	91.82 ± 0.91
PDO	coverage rate (%)	81.85 ± 1.77	77.30 ± 1.79	72.19 ± 1.91	71.01 ± 2.02
	node utilization efficiency (%)	62.03 ± 1.34	66.50 ± 1.54	71.81 ± 1.90	72.91 ± 2.08
SO	coverage rate (%)	88.61 ± 2.14	85.01 ± 2.17	79.82 ± 2.14	79.06 ± 2.01
	node utilization efficiency (%)	67.16 ± 1.62	73.13 ± 1.87	79.40 ± 2.13	81.18 ± 2.07
WO	coverage rate (%)	86.72 ± 2.11	82.19 ± 2.22	77.22 ± 2.19	76.49 ± 2.01
	node utilization efficiency (%)	65.73 ± 1.60	70.70 ± 1.91	76.81 ± 2.18	78.54 ± 2.06

Note: Values are reported as the mean $\pm$ standard deviation over 100 independent runs.

When $N = 42$, ACLFPDO achieved a mean coverage rate of $98.45 \pm 0.70\%$ and a mean node utilization efficiency of $74.61 \pm 0.53\%$, both of which were higher than those of the other three algorithms. When the number of nodes was reduced to $N = 37$, the mean coverage rate of ACLFPDO still reached $96.01 \pm 0.99\%$, and its mean node utilization efficiency reached $82.60 \pm 0.85\%$. Under the conditions of $N = 32$ and $N = 31$, ACLFPDO maintained coverage rates of $90.73 \pm 0.96\%$ and $89.42 \pm 0.89\%$, respectively, and node utilization efficiencies of $90.25 \pm 0.95\%$ and $91.82 \pm 0.91\%$, respectively.

In terms of average performance, ACLFPDO achieved an average coverage rate of 93.65% under the four node-number conditions when $w = 40$ and $R = 4$. This value was 18.07, 10.53, and 13.00 percentage points higher than those of PDO, SO, and WO, respectively. Its average node utilization efficiency was 84.82%, which was 16.51, 9.60, and 11.87 percentage points higher than those of PDO, SO, and WO, respectively. These results indicate that ACLFPDO showed good coverage optimization stability under the tested idealized region sizes and node-number configurations.

To further address the limitation of relatively limited experimental scenarios, an additional validation experiment was conducted under a larger monitoring region. In this supplementary experiment, the side length of the monitoring region was set to $w = 60$, the sensing radius was set to $R = 6$, and three node-number settings, namely $N = 52, 47$, and 42 , were tested. The same four algorithms, namely ACLFPDO, PDO, SO, and WO, were compared. The results are shown in Table 8.

Table 8. Comparison of optimization results of algorithms with different numbers of nodes for $w = 60$ and $R = 6$.

Algorithm Name	Evaluation Metric	$N = 52$	$N = 47$	$N = 42$
ACLFPDO	coverage rate (%)	99.86 ± 0.19	99.54 ± 0.36	98.43 ± 0.62
	node utilization efficiency (%)	61.13 ± 0.12	67.41 ± 0.24	74.60 ± 0.47
PDO	coverage rate (%)	87.99 ± 1.63	85.09 ± 1.91	81.43 ± 1.90
	node utilization efficiency (%)	53.86 ± 1.00	57.63 ± 1.29	61.72 ± 1.44
SO	coverage rate (%)	93.51 ± 1.88	91.49 ± 1.68	89.38 ± 1.66
	node utilization efficiency (%)	57.24 ± 1.15	61.96 ± 1.14	67.74 ± 1.26
WO	coverage rate (%)	93.62 ± 1.28	91.00 ± 1.61	87.97 ± 1.43
	node utilization efficiency (%)	57.31 ± 0.78	61.63 ± 1.09	66.67 ± 1.08

Note: Values are reported as the mean $\pm$ standard deviation over 100 independent runs.

As shown in Table 8, ACLFPDO still achieved the highest coverage rate and node utilization efficiency under all three additional node-number settings. When $N = 52$, ACLFPDO obtained a coverage rate of 99.86% and a node utilization efficiency of 61.13%, which were higher than those of PDO, SO, and WO. When the number of nodes was reduced to $N = 42$, ACLFPDO still maintained a coverage rate of 98.43% and a node utilization efficiency of 74.60%, whereas the corresponding coverage rates of PDO, SO, and WO were 81.43%, 89.38%, and 87.97%, respectively.

In terms of average performance over the three additional node-number settings, ACLFPDO achieved an average coverage rate of 99.27%, which was 14.44, 7.81, and 8.41 percentage points higher than those of PDO, SO, and WO, respectively. Its average node utilization efficiency reached 67.71%, which was 9.98, 5.40, and 5.84 percentage points higher than those of PDO, SO, and WO, respectively. These results indicate that ACLFPDO can maintain superior coverage optimization performance under a larger idealized monitoring region with a proportionally increased sensing radius and expanded node-number configurations.

3.5. Convergence Performance and Running-Time Analysis

Figure 4 shows the convergence curves of the coverage optimization objective function under different node numbers when $w = 50$. As shown in Figure 4, ACLFPDO obtained higher final fitness values under all node-number settings and showed a faster convergence speed. Compared with PDO and WO, ACLFPDO increased the objective function value more rapidly in the early iterations. This result indicates that ACLFPDO has

stronger global search ability. Compared with SO, ACLFPDO still obtained higher final fitness values under most node-number settings.

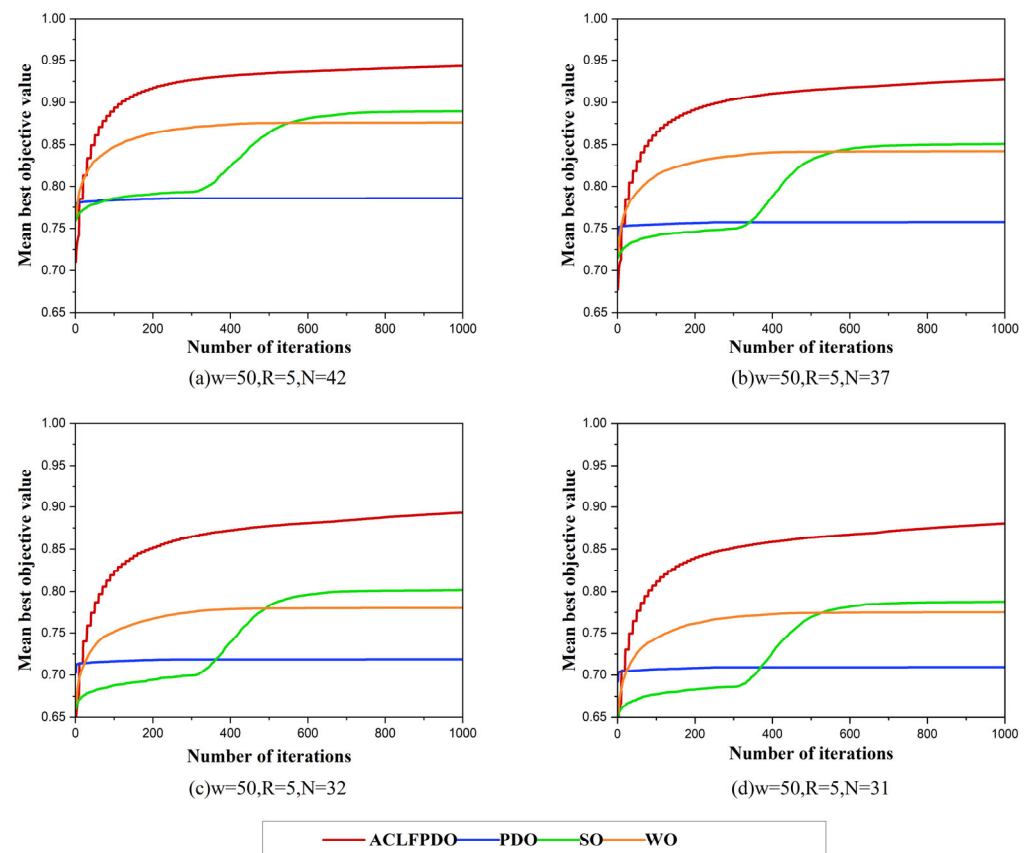


Figure 4. Mean convergence curves of the objective value under $w = 50$ and $R = 5$. (a) The convergence curves of the coverage optimization objective function under different node numbers when $w = 50$, $R = 5$, $N = 42$. (b) The convergence curves of the coverage optimization objective function under different node numbers when $w = 50$, $R = 5$, $N = 37$. (c) The convergence curves of the coverage optimization objective function under different node numbers when $w = 50$, $R = 5$, $N = 32$. (d) The convergence curves of the coverage optimization objective function under different node numbers when $w = 50$, $R = 5$, $N = 31$.

Figure 5 shows the convergence curves of the coverage optimization objective function under different node numbers when $w = 40$. The results show that ACLFPDO had good convergence stability and final optimization performance under most node-number settings. In particular, the advantages of ACLFPDO were more evident when $N = 42$ and $N = 37$. When the number of nodes was further reduced to $N = 32$ and $N = 31$, the gap in the final fitness value between ACLFPDO and SO became smaller. However, ACLFPDO still maintained better coverage optimization results.

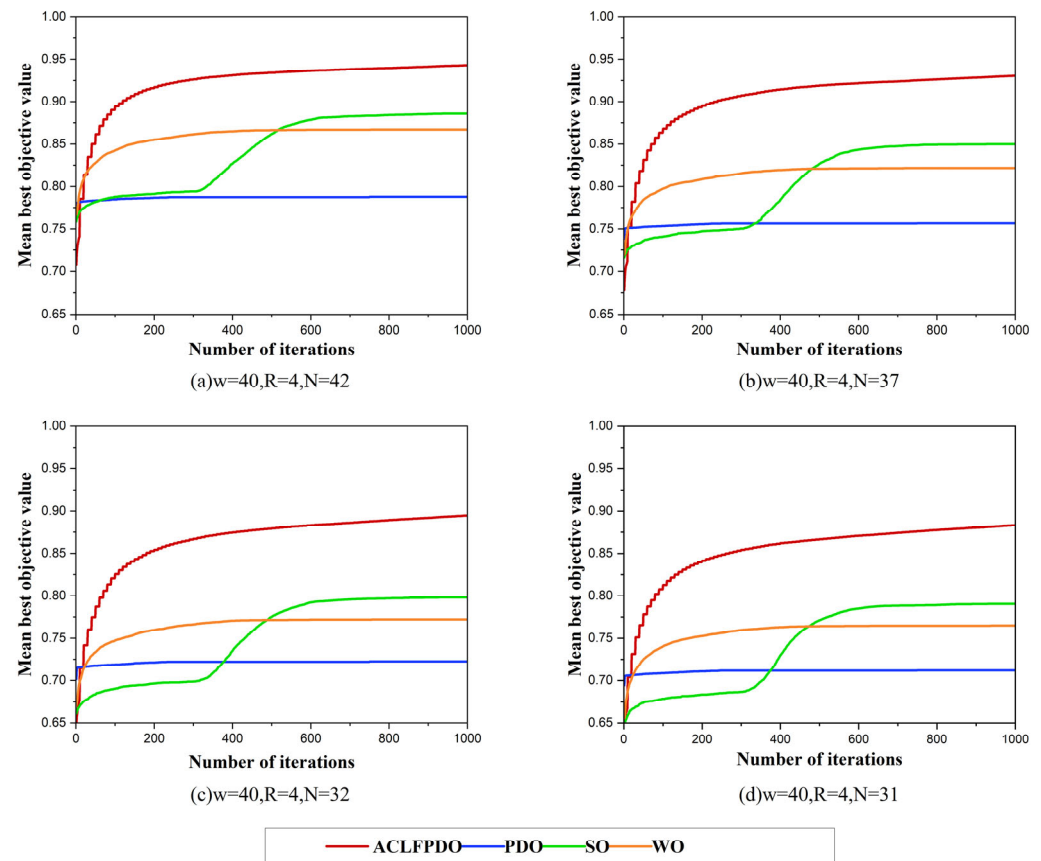


Figure 5. Mean convergence curves of the objective value under $w = 40$ and $R = 4$. (a) The convergence curves of the coverage optimization objective function under different node numbers when $w = 50$, $R = 5$, $N = 42$. (b) The convergence curves of the coverage optimization objective function under different node numbers when $w = 50$, $R = 5$, $N = 37$. (c) The convergence curves of the coverage optimization objective function under different node numbers when $w = 50$, $R = 5$, $N = 32$. (d) The convergence curves of the coverage optimization objective function under different node numbers when $w = 50$, $R = 5$, $N = 31$.

To further quantify the convergence behavior shown in Figures 4 and 5, the convergence generation T_{99} and the running time of each algorithm were statistically analyzed over 100 independent runs. The specific results are shown in Table 9. The results show that ACLFPDO achieved the highest final coverage rate and node utilization efficiency under all tested conditions. Although PDO and WO reached 99% of their final convergence values in fewer iterations in some cases, their final coverage performance was substantially lower, indicating that a smaller T_{99} does not necessarily correspond to better optimization quality. In contrast, ACLFPDO maintained superior final optimization performance while requiring an acceptable computational cost.

Table 9. Quantitative convergence and running-time comparison of different algorithms.

w	R	N	Algorithm	T_{99}	Runtime (s)
50	5	42	ACLFPDO	460.11 ± 113.09	3.7139 ± 0.1101
50	5	42	PDO	19.45 ± 43.19	6.0484 ± 0.0250
50	5	42	SO	574.95 ± 80.57	6.2180 ± 0.0419
50	5	42	WO	229.61 ± 100.21	2.5515 ± 0.5573
50	5	37	ACLFPDO	590.76 ± 117.33	3.3217 ± 0.0316
50	5	37	PDO	27.80 ± 54.05	5.3587 ± 0.0235
50	5	37	SO	567.00 ± 102.20	5.9369 ± 0.0431
50	5	37	WO	223.82 ± 99.12	2.2228 ± 0.1025

50	5	32	ACLFPDO	676.40 ± 109.73	3.1031 ± 0.0620
50	5	32	PDO	21.57 ± 44.57	4.6707 ± 0.0242
50	5	32	SO	561.29 ± 105.48	5.6245 ± 0.0447
50	5	32	WO	218.28 ± 99.69	1.9680 ± 0.0697
50	5	31	ACLFPDO	692.45 ± 102.48	2.9437 ± 0.0461
50	5	31	PDO	28.52 ± 54.62	4.5138 ± 0.0272
50	5	31	SO	550.55 ± 87.42	5.5723 ± 0.0402
50	5	31	WO	241.00 ± 102.66	1.8510 ± 0.0227
40	4	42	ACLFPDO	469.17 ± 124.10	2.7895 ± 0.0237
40	4	42	PDO	28.77 ± 51.93	4.4336 ± 0.0272
40	4	42	SO	570.30 ± 102.33	4.0821 ± 0.0326
40	4	42	WO	209.81 ± 106.73	1.6153 ± 0.0269
40	4	37	ACLFPDO	572.57 ± 112.07	2.5849 ± 0.0132
40	4	37	PDO	27.85 ± 54.19	3.9242 ± 0.0210
40	4	37	SO	562.58 ± 98.24	3.8936 ± 0.0340
40	4	37	WO	216.23 ± 121.30	1.4862 ± 0.0498
40	4	32	ACLFPDO	651.14 ± 133.35	2.3650 ± 0.0178
40	4	32	PDO	39.02 ± 61.59	3.4120 ± 0.0256
40	4	32	SO	561.50 ± 86.57	3.7273 ± 0.1027
40	4	32	WO	208.50 ± 109.32	1.3078 ± 0.0345
40	4	31	ACLFPDO	683.01 ± 105.63	2.3168 ± 0.0201
40	4	31	PDO	38.46 ± 59.99	3.3121 ± 0.0214
40	4	31	SO	561.78 ± 98.72	3.6559 ± 0.0310
40	4	31	WO	222.86 ± 105.59	1.2583 ± 0.0173

Note: Values are reported as the mean ± standard deviation over 100 independent runs. T_{99} denotes the first iteration at which the best recorded convergence value reached 99% of its final value. Runtime refers only to the optimization process and excludes plotting and file-export operations.

For $w = 50$ and $R = 5$, the average coverage rate of ACLFPDO over the four node-number settings was 93.46%, which was 18.09, 10.20, and 11.60 percentage points higher than those of PDO, SO, and WO, respectively. Its average node utilization efficiency was 84.63%, which was 16.53, 9.31, and 10.60 percentage points higher than those of PDO, SO, and WO, respectively. For $w = 40$ and $R = 4$, ACLFPDO achieved an average coverage rate of 93.65% and an average node utilization efficiency of 84.82%, again outperforming all baseline algorithms. These results demonstrate that ACLFPDO provides more stable and effective coverage optimization while maintaining a reasonable running time.

3.6. Node Deployment Results and Node Utilization Efficiency

Figures 6 and 7 show the optimized node deployment results of different algorithms when $N = 42$ and $N = 32$, respectively, under the condition of $w = 50$. As shown in Figure 6, when the number of nodes was relatively large, the nodes optimized by ACLFPDO were distributed more uniformly. The coverage holes were fewer, and the overlapping coverage areas were relatively smaller. Compared with PDO, SO, and WO, ACLFPDO formed a more continuous coverage structure in the target region.

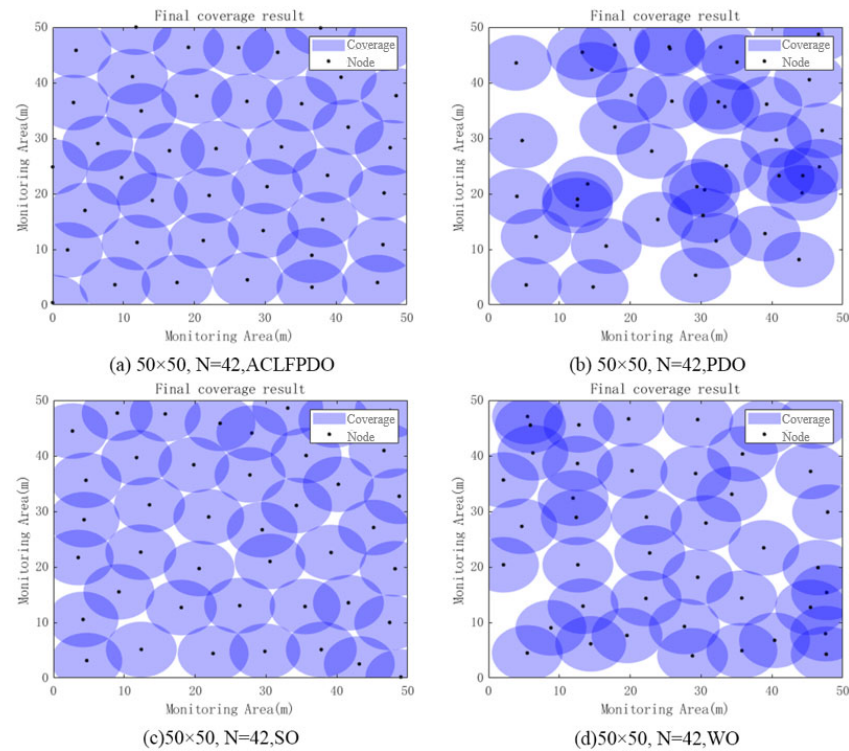


Figure 6. Comparison of coverage results for different optimization algorithms at $N = 42$.

When the number of nodes was reduced to $N = 32$, the coverage holes of all algorithms increased, as shown in Figure 7. However, ACLFPDO still maintained a relatively uniform node distribution. In contrast, PDO and WO were more likely to cause local node aggregation, which led to insufficient coverage in some regions. The deployment result of SO was relatively good, but its coverage completeness and node utilization efficiency were still lower than those of ACLFPDO.

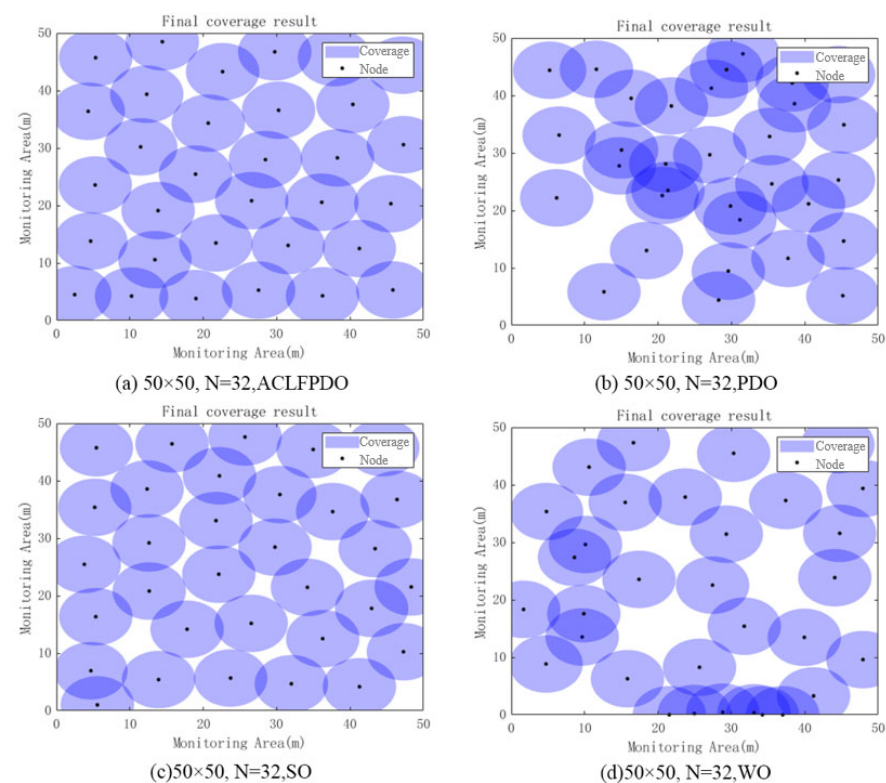


Figure 7. Comparison of coverage results for different optimization algorithms at $N = 32$.

Figure 8 shows the changes in node utilization efficiency under different node numbers when $w = 50$. The results show that the node utilization efficiency of the four algorithms generally increased as the number of nodes decreased. ACLFPDO achieved the highest node utilization efficiency under all node-number settings. This result indicates that ACLFPDO can reduce overlapping coverage while improving the effective utilization of the sensing resources of each sensor node.

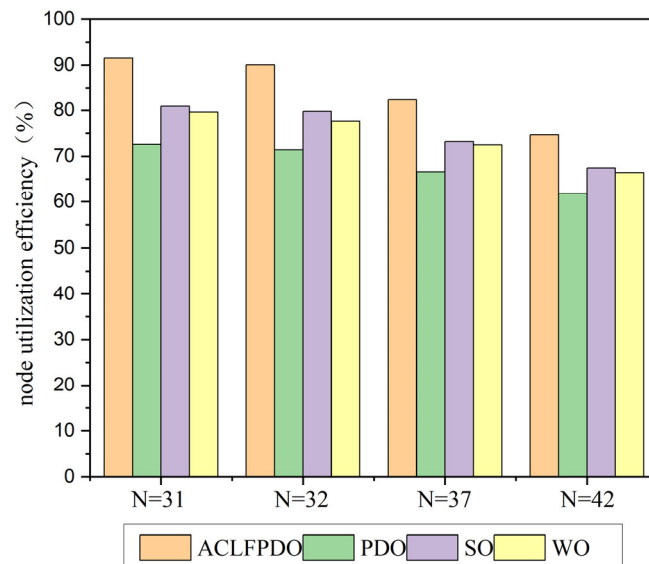


Figure 8. Node utilization efficiency under varying numbers of sensor nodes (N) for a $50 \text{ m} \times 50 \text{ m}$ monitoring area and a sensing radius of 5 m. ACLFPDO, Adaptive Chaotic Lévy Flight Prairie Dog Optimization algorithm; PDO, Prairie Dog Optimization algorithm; SO, Snake Optimizer; WO, Whale Optimization algorithm.

4. Discussion

4.1. Analysis of the Reasons for the Performance Improvement of ACLFPDO

The experimental and ablation results show that ACLFPDO outperformed PDO, SO, and WO in terms of coverage rate, node utilization efficiency, convergence performance, and coverage overlap reduction. The ablation study further indicates that the improvement of ACLFPDO is mainly derived from the coordinated effect of the final staged adaptive optimization framework rather than from a simple additive contribution of each individual operator. In particular, the adaptive DS/PE mechanism produced only a slight improvement over the strict PDO baseline, whereas chaotic initialization alone did not improve the original PDO framework under the tested scenarios. However, when chaotic initialization, adaptive search control, staged position updating, and the final ACLFPDO search structure were integrated, the algorithm achieved substantially higher coverage rates, higher node utilization efficiencies, and lower coverage overlap ratios. Therefore, the proposed mechanisms should be understood as coupled components within the complete ACLFPDO framework.

First, when incorporated into the complete stage-based ACLFPDO framework, the chaotic initialization strategy can enhance the diversity and ergodicity of the initial population and reduce the probability of excessive node aggregation or local imbalance in the initial node distribution. For the STWSN coverage optimization problem, the quality of the initial node distribution directly affects the subsequent search process. A more uniform initial population provides a better search basis for the algorithm and reduces ineffective search in the early iterations.

Second, the adaptive parameter adjustment mechanism enables the algorithm to dynamically adjust the search step size and disturbance intensity according to the iteration process. In the early stage of optimization, a larger search step size helps the algorithm explore a wider solution space. In the later stage, a gradually reduced disturbance intensity helps improve the accuracy of local search. This mechanism effectively alleviates the limitations of traditional PDO, which uses a fixed search strategy and has insufficient dynamic adjustment ability.

Third, the additional Lévy-flight perturbation introduces jump-based search behavior with a long-tailed distribution. In the ablation study, the ACLFPDO-NoLevy variant achieved performance very close to that of the complete ACLFPDO across the representative scenarios and the overall cross-scenario results. This indicates that the additional Lévy-flight perturbation was not the dominant source of performance improvement under the current regular-region simulation settings. Nevertheless, Lévy flight provides supplementary exploration capability and may help maintain search diversity in more complex or irregular deployment scenarios.

Finally, the staged position update strategy enables the algorithm to use different search modes at different iteration stages. The early stage strengthens global exploration. The middle stage balances global search and local exploitation. The later stage performs fine adjustment around the global optimal solution. This staged search mechanism helps improve the convergence speed and final coverage quality of the algorithm.

The boundary clipping repair strategy may increase the probability that some updated coordinates are located exactly on the monitoring boundary when large search steps move individuals outside the feasible region. This effect is different from reflection-based repair, which redirects the search trajectory back into the feasible space, and from resampling-based repair, which introduces additional randomness. In the present study, clipping was adopted because the deployment region was modeled as a simple box-constrained square area, and the same boundary repair strategy was applied to all compared algorithms to ensure fairness. Although clipping may lead to local boundary accumulation in some iterations, the coverage-oriented fitness function and overlap constraint help reduce persistent redundant coverage, while the coverage-dependent dispersion regularization term weakly suppresses unstable coordinate dispersion during low-coverage stages. The final deployment results shown in Figures 6 and 7 also indicate that ACLFPDO maintained relatively uniform node distributions without obvious excessive boundary clustering under the tested simulation scenarios.

4.2. Effects of Node Number Variation on Coverage Performance

As shown in Tables 6 and 7, the coverage rates of all algorithms decreased to varying degrees when the number of nodes was reduced from 42 to 31. This is because a decrease in the number of sensor nodes directly reduces the theoretical coverage capacity of the network. As a result, coverage holes are more likely to appear in the target region. However, ACLFPDO still maintained a high coverage rate when the number of nodes was reduced. This indicates that it can adjust the spatial positions of nodes more effectively and use a limited number of nodes to cover the monitoring region as much as possible.

At the same time, node utilization efficiency generally increased as the number of nodes decreased. This indicates that after the number of nodes was reduced, the theoretical sensing area of the network decreased, whereas the effective coverage area did not decrease at the same rate. Therefore, the utilization degree of sensing resources per node increased. For agricultural environmental monitoring, this result has practical significance. When the basic coverage requirement is satisfied, a reasonable reduction in the number of nodes can help reduce deployment cost and maintenance complexity.

It should be noted that the performance gap between ACLFPDO and SO became smaller when the number of nodes was low, especially under the conditions of $w = 40$, $N = 32$, and $N = 31$. This indicates that when the number of nodes approaches the lower limit required for target-region coverage, the optimization space is restricted by the node scale. As a result, the performance differences among different algorithms gradually decrease. Therefore, in practical deployment, a reasonable number of nodes should be selected according to the coverage requirement, cost budget, and node maintenance conditions.

The additional validation experiment under $w = 60$, $R = 6$, and $N = 52, 47$, and 42 further confirmed this trend. ACLFPDO maintained the highest coverage rate and node utilization efficiency in the larger monitoring region, indicating that the proposed framework was not only effective under the original $w = 40$ and $w = 50$ settings but also showed stable performance under an expanded simulation scale.

4.3. Simulation-Based Implications for Cotton-Field STWSN Deployment

Cotton-field soil temperature monitoring requires good spatial coverage completeness and sensing-resource utilization. If sensor nodes are deployed improperly, local coverage holes may lead to incomplete soil-temperature information, while excessive node overlap may waste sensing resources. The simulation results in this study show that ACLFPDO achieved higher coverage rates and node utilization efficiencies than PDO, SO, and WO under the tested idealized square-region settings. Therefore, the proposed method can provide a simulation-based reference for coverage-oriented node deployment in cotton-field STWSNs.

From an application perspective, ACLFPDO can provide a simulation-based optimization method for agricultural sensor network deployment. Before practical deployment, the algorithm can be used to obtain a better node position distribution scheme according to the cotton-field area, sensor sensing radius, and available number of nodes. This can help reduce coverage insufficiency and resource waste caused by blind deployment.

However, these results should not be interpreted as a complete field-deployment solution. The current evaluation focuses on the area-coverage optimization capability of different algorithms under controlled assumptions, including a regular two-dimensional square monitoring region, homogeneous sensor nodes, and a fixed-radius binary sensing model. In practical cotton fields, actual deployment decisions should further consider field-boundary geometry, ridges and furrows, drainage ditches, agricultural machinery paths, burial-depth differences, soil spatial heterogeneity, communication connectivity, gateway location, routing requirements, and node energy consumption. Therefore, ACLFPDO can be regarded as a preliminary coverage-oriented optimization tool, and further field-oriented constraints need to be incorporated before direct practical deployment.

4.4. Practical Challenges in Real Cotton-Field Deployment

Although the proposed ACLFPDO algorithm achieved good performance in the simulation experiments, several practical challenges should be considered before applying it to real cotton-field STWSN deployment.

First, real cotton fields are not always regular square regions. Field boundaries may be irregular due to planting layout, field roads, ridges, irrigation channels, and management zones. In the current simulation model, the monitoring region is simplified as a two-dimensional regular square area, and all sensor nodes are constrained within this ideal boundary. However, in practical deployment, the feasible deployment region should be represented by an actual field boundary map or a polygonal constraint region. Otherwise, some optimized node positions may fall outside the cultivable area or in locations that are inconvenient for installation and maintenance.

Second, real cotton fields may contain temporary or permanent obstacles, such as agricultural machinery operation paths, drainage ditches, irrigation facilities, field ridges, and maintenance passages. These obstacles can reduce the available deployment area and may also affect node accessibility, installation safety, and data transmission stability. Therefore, obstacle regions should be treated as forbidden deployment areas in future optimization models. The algorithm should be extended from simple boundary constraints to obstacle-aware constrained optimization, in which sensor nodes are prevented from being placed in inaccessible or high-risk regions.

Third, soil spatial heterogeneity may cause nonlinear changes in the effective sensing range of soil temperature sensor nodes. In this study, the sensing range of each node is simplified as a circular region with a fixed radius under the binary sensing model. However, in real cotton fields, soil texture, soil moisture, salinity, bulk density, irrigation conditions, crop growth status, and micro-topography may affect the spatial correlation of soil temperature. As a result, the effective representativeness range of a sensor node may be anisotropic, spatially variable, and time-varying rather than a fixed circular area. Therefore, the sensing radius used in this study should be interpreted as an abstract effective coverage radius under simplified simulation conditions, rather than a constant physical sensing boundary in real soil environments.

To improve the practical applicability of ACLFPDO, future research should integrate real field boundary data, obstacle maps, and soil spatial heterogeneity information into the deployment optimization framework. For example, geographic information, UAV-based field maps, or measured soil temperature spatial distribution data can be used to construct irregular deployment regions and forbidden zones. In addition, probabilistic sensing models, anisotropic sensing models, or spatial correlation models can be introduced to replace the fixed-radius binary sensing model. These improvements would make the optimized deployment scheme more consistent with real cotton-field monitoring requirements.

4.5. Research Limitations and Future Work

Although ACLFPDO showed good coverage optimization performance in the simulation experiments, this study still has some limitations. First, this study used a two-dimensional regular square region as the monitoring region. It did not consider irregular boundaries, ridges, obstacles, and terrain differences that may exist in real cotton fields. Second, this study used homogeneous sensor nodes and a binary sensing model. It did not consider the effects of sensor sensing errors, soil spatial heterogeneity, and environmental noise on sensing quality. Third, the current optimization framework is mainly coverage-oriented. Coverage rate is used as the dominant optimization objective, while node utilization efficiency, coverage overlap, and node distribution are used to evaluate or constrain the spatial deployment quality. However, communication connectivity constraints and node energy consumption limitations were not incorporated into the optimization model. Recent studies also indicate that energy-aware communication and adaptive chaotic optimization are important for resource-constrained intelligent systems. For example, Zhu et al. proposed an energy-aware deep-reinforcement-learning-based dual-perception fountain coding framework for resource-constrained underwater acoustic sensor networks, highlighting the importance of jointly considering transmission reliability and energy consumption in sensor-network operation [25]. In addition, Wang et al. used an adaptive chaotic grey wolf optimization algorithm for SOFC dynamic-parameter exploration, showing that adaptive chaotic metaheuristic mechanisms can improve parameter-search performance in complex nonlinear systems [26]. These studies further support the need to extend the present coverage-oriented ACLFPDO framework toward energy-aware communication modeling and more robust parameter-adaptive optimization in future work. In practical WSN deployment, high area coverage does not necessarily

guarantee that all sensor nodes can reliably transmit data to the sink node or gateway. Similarly, a deployment scheme with good coverage may still lead to unbalanced energy consumption, excessive relay burden, or a shortened network lifetime. Therefore, the results of this study should be interpreted as a coverage-oriented node deployment reference rather than a complete deployment solution for real STWSN operation. This limitation may affect the direct practical applicability of the proposed framework in real cotton-field monitoring scenarios.

Future work will further verify the proposed method in real cotton-field scenarios. Irregular field boundaries, obstacle-constrained deployment regions, heterogeneous soil conditions, communication connectivity, energy consumption, and heterogeneous sensor models will be incorporated into the STWSN deployment optimization framework. In addition, field experiments will be conducted to evaluate whether the optimized deployment schemes can maintain stable coverage performance under practical agricultural monitoring conditions.

5. Conclusions

This study proposed an Adaptive Chaotic Lévy Flight Prairie Dog Optimization algorithm (ACLFPDO) to address coverage holes, node overlap, and insufficient sensing resource utilization in the node deployment of soil temperature wireless sensor networks. Based on the original PDO algorithm, ACLFPDO introduces Logistic chaotic initialization to improve initial population diversity, adaptive parameter adjustment to balance global exploration and local exploitation, Lévy-flight perturbation to enhance jump-based exploration, and a stage-based position updating mechanism to improve coverage optimization performance.

Based on an idealized two-dimensional area coverage simulation model, experiments were conducted under different monitoring region sizes and node-number conditions. In this model, the cotton-field monitoring region was simplified as a regular square area, and each sensor node was represented by a fixed-radius circular binary sensing model. ACLFPDO was compared with PDO, SO, and WO. Under the conditions of $w = 50$, $R = 5$, and $N = 42$, ACLFPDO achieved a coverage rate of 98.49% and a node utilization efficiency of 74.65%. Compared with PDO, SO, and WO, the coverage rate increased by 16.88, 9.52, and 10.86 percentage points, respectively, and the node utilization efficiency increased by 12.80, 7.22, and 8.24 percentage points, respectively. When the number of nodes was reduced, ACLFPDO still maintained relatively high coverage rate and node utilization efficiency, indicating its potential for reducing redundant sensing resources under idealized simulation conditions.

It should be emphasized that the present results should be interpreted as coverage-oriented simulation evidence rather than a complete field-deployment solution for real cotton-field STWSNs. The current model does not fully consider practical factors such as irregular field boundaries, ridges, furrows, drainage ditches, agricultural machinery operation paths, burial-depth differences, communication connectivity, node energy consumption, sensor heterogeneity, and nonlinear variations in the effective sensing range caused by soil spatial heterogeneity. These factors may affect the actual feasible deployment positions, sensing representativeness, data transmission reliability, and network lifetime in real agricultural environments. The additional validation under the enlarged idealized region further supports the robustness of ACLFPDO within the tested proportionally scaled simulation settings, but it does not eliminate the need for field-oriented modeling and experimental validation.

Future work will further extend the proposed framework from idealized square-region simulations to field-oriented deployment optimization. Real cotton-field boundary data, obstacle maps, soil spatial heterogeneity information, gateway or sink-node locations, communication connectivity constraints, routing requirements, energy

consumption constraints, and heterogeneous sensing models will be incorporated into the STWSN deployment optimization framework. Field experiments will also be conducted to evaluate whether the optimized deployment schemes can maintain stable coverage and communication performance under practical cotton-field monitoring conditions.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ACLFPDO	Adaptive Chaotic Lévy Flight Prairie Dog Optimization algorithm
IoT	Internet of Things
WSNs	wireless sensor networks
STWSNs	Soil Temperature Wireless Sensor Networks
PSO	Particle Swarm Optimization
PDO	Prairie Dog Optimization
C	Coverage Rate
E	Node Utilization Efficiency
SO	Snake Optimizer
WO	Whale Optimization Algorithm

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