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Research Article

Optimization Method of RFID Reader Antenna Deployment in Obstacle Environment Based on Improved FA

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The aim of this study is to solve the problem of RFID reader antenna deployment when an obstacle in the environment or the material itself is an obstacle. The article establishes a new reader antenna constraint model based on the rectangular obstacle RFID antenna deployment optimization environment model and the reader antenna sensing model containing Gaussian distribution noise probability and applies the improved firefly algorithm to find the optimum with coverage rate, interference degree, and load balance function as multiobjective functions. First, to obtain a uniform traversal of the target space, and a cube mapping is applied for chaos initialization. Second, a weighting model is proposed to control the speed of firefly variation and combine the variable step strategy of elite individuals to expand the movement step of elite individuals and reduce the movement step of nonelite individuals to improve population diversity. Finally, to improve the algorithm's continuous optimality-seeking ability, a Gaussian variation operation strategy based on elite fireflies is introduced to ensure the algorithm's optimality-seeking throughout the process.

1. Introduction

Radio frequency identification (RFID) technology, as one of the important cores of the perception layer of the Internet of Things, not only promotes the rapid development of the Internet of Things, another revolution in the information industry after computers, the Internet of Things, and mobile communications, but also advances the application development of RFID technology, creating new industrial structures, new business models, new forms of service, and new lifestyles [1], and the technology is involved in manufacturing, warehouse management, logistics, smart meters, agriculture, military, medical, and other fields [2–4]. RFID technology is a noncontact automatic identification and tracking technology based on radio frequency (RF) communication [5], mainly, including the host system, RFID reader, and RFID tags, and other components, through the radio frequency signal in the reader and tag to transmit data between them. However, the radio frequency identification technology in the actual application, because the site environment is more complex, especially the existence of obstacles or the material itself is an obstacle situation, the RFID reader antenna deployment method (mainly, including the reader antenna quantity, deployment position, and direction) determines the reading rate of the given area label, its reading rate is one of the important factors in deciding the RFID system's performance.

Many valuable studies have been done by domestic and foreign scholars on RFID reader planning and deployment. Qiang et al. [6] for the complex propagation environment, in the two-dimensional plane using the signal threshold about the activation label and the threshold of the backscatter reader, received signal to judge the perception ability of the reader, established multiple objective functions based on reader coverage, reader cost, interfering degree between readers, uplink signal (label to reader signal), to simplify the operation process, introduce weighting coefficient to convert multiple objectives into a single objective, and apply a genetic algorithm to solve this complex optimization problem. Reference [7] proposed a coding scheme based on swarm intelligence optimization, using the swarm intelligence algorithms Flower Pollination Algorithm (FPA), Salp Swarm

Algorithm (SSA), and Sine Cosine Algorithm (SCA). Among them, FPA and SCA solve the deployment optimization problem of UAV with the highest efficiency and minimize the energy consumption of UAV operation, so as to minimize the energy consumption of information equipment transmission on the Internet of Things. Lin and Tsai [8] established a model about the reader coverage and cost model by applying omnidirectional reader reading distance to the restricted 3D reader network planning space of a large warehouse RFID system, fixed the location of readers, and proposed a microgenetic algorithm with spatial crossover and correction, whose algorithm is efficient and makes up for the disadvantage of the fast turnaround time of stored objects while ensuring a high tag coverage rate. Tang et al. [9] combined the actual situation of the mixed flow assembly line, summarized the requirements including fence coverage [10], full coverage, and distinguished coverage [11], and introduced fuzzy interference value [12] to measure the coverage capability of reader antenna and established a multiobjective nonlinear integer planning model in the two-dimensional plane to optimize the layout of the reader antenna with the objectives of cost and coverage performance. Most of the current research about RFID reader antenna deployment mainly simplifies the complex environment into a two-dimensional or three-dimensional environment without obstacles [13–15] and applies genetic algorithm (GA), such as particle swarm algorithms, and adaptive bacterial foraging algorithm, etc., to optimize the deployment of spatial RFID reader antennas.

However, RFID network optimization of the working environment often exists in metal and other environment where RFID is not easy to penetrate the object. That is, the obstacle. Currently, there are few problems in optimizing the deployment of reader antennas for obstacle environments. The current approach is to see the obstacle as a typical shape, such as a rectangle or square. Li Junjun et al. [16] for the logistics RF network with rectangular obstacles show that in the two-dimensional plane of the rectangular obstacles on the reader antenna recognition ability of the problem is reduced to the intersection of line segments and the diagonal of the rectangle, and the design "straddle test," using an ant colony algorithm to solve, improves the accuracy of the algorithm development because the actual obstacle is often rectangular. Zhang Rong et al. [17] although proposed to solve the three-dimensional space has rectangular obstacle RFID reader network planning problem, according to the antenna theory [18] established the reader antenna judgment recognition ability perception model, to coverage and reader interference degree as the optimization targets, apply a kind of firefly algorithm based on a simulated annealing mechanism to optimize the location and direction of the reader antenna, but only consider the obstacle is alone in RFID three-dimensional space, did not consider the tag exists between the obstacles or the material itself for the obstacle situation.

To be more in line with the RFID actual working situation, including the establishment of the RFID network working model as well as the location and direction of the reader to find the optimal. The key contributions in this paper can be summarized as follows:

(1) First, the RFID environment space is discretized and chaotic initialization is applied to the cube mapping to obtain uniform ergodicity of the target space.
(2) Second, we propose a weight model to improve the standard firefly algorithm to effectively control the speed of firefly variation and combine the variable step strategy of elite individuals to expand the movement step of elite individuals and reduce the movement step of nonelite individuals to increase the population diversity and improve the solution accuracy of the algorithm.
(3) Finally, to improve the algorithm's continuous optimality-seeking ability, a Gaussian variation operation strategy based on elite fireflies is introduced to ensure the algorithm's optimality-seeking throughout the process.

Effectively solve the problem of RFID reader antenna deployment when an obstacle in the environment or the material itself is an obstacle. The rest of this paper is organized as follows. Existing techniques are reviewed in Section 2. RFID reader antenna deployment optimization problem modeling is presented and formulated in Section 3. The solution method based on the improved FA is presented in Section 4. Simulation results of the proposed method on the case study in Section 5. Finally, the last section gives the conclusion of the whole study.

2. Literature Review

Metaheuristic algorithms have been the focus of academic research and are a class of algorithms distinguished from exact algorithms, which can provide approximate optimal solutions to some complex optimization problems [19]. Shokouhifar [20] introduced a population intelligence RFID network planning model with multiple antenna readers. A combined global-local metaheuristic algorithm based on the whale optimization algorithm and simulated annealing is proposed to enhance coverage in healthcare systems through RFID network planning while reducing total cost, interference, collisions, and power consumption. Fabian et al. [21] utilize an improved global search based on the firefly algorithm, followed by a local search improvement based on the simulated annealing to make a better exploration-exploitation balance during the search for the optimal solution. The presented method performs effectively better in reducing the time span using a different numbers of tasks and virtual machines. Reference [22] proposes a hybrid algorithm that integrates the K-means algorithm to produce a binary cuckoo search technique and a new local search operator to improve the utilization of the search space. Reference [23] evaluated a hybrid algorithm that improved the resource allocation results of the quantum cuckoo search algorithm using the k-nearest neighbor technique and applied it to the well-known multidimensional backpack problem. Reference [24] presents an improved ant colony optimization (ACOII) algorithm to solve dynamic facility layout problems for construction sites. The algorithm uses a construction method to construct layout solutions over time and uses discrete dynamic search with heuristic information based on relocation and mobility costs. Reference [25] proposed an enhanced version of the artificial bee colony nature-inspired metaheuristic algorithm to optimize the connection weights and hidden units of artificial neural networks. The quasi-reflection-based learning mechanism significantly improves the convergence speed of the original artificial bee colony algorithm and enhances the utilization together with the bounded-guided optimal solution, resulting in a significant increase in accuracy. In combination with a metaheuristic game theory-based strategy, reference [26] proposes an innovative hybrid game strategy and provides insights into domain decomposition schemes to improve computational efficiency and effectiveness in civil engineering structural design optimization. In reference [27], a parameter-free local search strategy was proposed to solve the graph coloring problem. None of the explicit or implicit parameters normally used in metaheuristics are used. Reference [28] utilizes fuzzy heuristic information from the current state of the problem to guide the metaheuristic algorithm, which results in better convergence speed. Heuristically fast speed and metaheuristically high solution quality can be achieved simultaneously.

3. RFID Reader Antenna Deployment Optimization Problem Modeling

3.1. Rectangular Obstacle RFID Antenna Deployment Optimization Environment Model. The mathematical analysis part of RFID reader antenna deployment optimization is to convert the process of tag T being identified in the target monitoring area of reader antenna R into a mathematical model. The main objective of this paper is to establish an RFID network working model, construct the calculation formula for finding the reader antenna sensing distance containing Gaussian distribution noise and the reader antenna sensing model, and apply the improved firefly algorithm under the multiobjective constraints of tag coverage, interference degree, and load balance function to find an RFID reader antenna deployment scheme to meet the user quickly in the specified space range Design the RFID reader location, direction, and improve the recognition rate of the reader antenna to the tag. Let the RFID environment where tags exist between rectangular obstacles or where the material itself is an obstacle, simplify it by. The rectangular obstacle RFID antenna deployment optimization environment model is shown in Figure 1. The space formed by the label and the rectangular obstacle is length A, width B, and height C. The interval distance between the label and the rectangular obstacle is h. The reader antenna is deployed on the left, right, or upper side of the space of the whole formed by the label and the rectangular obstacle. The following are the perception models of RFID reader antenna, tag coverage function, reader interantenna interference degree function, and reader antenna load balance function, respectively.

3.2. Perception Model of RFID Reader Antenna. In an RFID system, the reader carries on the wireless communication with the tag through the antenna, and its reader antenna can be an independent part, and also, can be built into the reader. The reader antenna in this paper is a separate part. Because the antenna has direction, it is divided into directional and omnidirectional antennas. The directional antenna shows radiation in a certain angle range on the horizontal direction diagram, the radiation range is similar to an unshaped flip cone, the horizontal beam is narrow, the vertical beam is wide, and the communication distance is long. It can identify the stacked very high goods normally, avoiding the problem of misreading and string reading. The reader antenna studied in this paper is a directional antenna, which will be idealized. The RFID reader antenna three-dimensional perception model is shown in Figure 2.

The passive tag cannot actively transmit signals, needs to obtain energy in the magnetic field generated by the reader, and the communication with the reader antenna must satisfy the Friis Transmission Equation [29]:

$$P_R = P_T G_R^2 G_T^2 \left(\frac{\lambda}{4\pi d}\right)^4 T, \tag{1}$$

where P_R is the power received by the reader antenna, P_T is the power transmitted by the reader antenna, G_R is the antenna gain of the reader antenna, G_T is the antenna gain of the tag antenna, λ is the wavelength of the working environment, d is the distance between the reader antenna and the tag, T is the propagation loss of backscattering. In the actual RFID environment, the received signal is subject to environmental noise and noise from electronic components. To be more representative, the sensing model of the dome vertebrae in the article introduces noise that follows a Gaussian distribution to determine the recognition distance l_r. The process is as follows:

Calculate the size of the energy that can be received by the reader antenna:

$$P_R = P_T G_R^2 G_T^2 \left(\frac{\lambda}{4\pi l_r}\right)^4 T + \mathrm{G}_\sigma, \tag{2}$$

where $G_\sigma \sim \mathrm{P}_N(x)$ is a random variable with mean 0 and variance σ^2,Eq. $P_N(x)$ is

$$P_N(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{x^2}{2\sigma^2}\right). \tag{3}$$

Let the threshold for a reader antenna to be able to successfully identify a tag be ξ. When the signal received by the reader antenna is less than the threshold value ξ, then, the probability of the label being successfully identified is 0. If the reader receives a signal above the threshold value ξ, the probability that the label can be successfully identified is determined by

$$\begin{aligned} Pro\left(P_r\left(P_T, l_r\right) > \xi\right) &= Pro\left(G_\sigma > \xi - P_T G_R^2 G_T^2 \left(\frac{\lambda}{4\pi l_r}\right)^4 T\right) \\ &= F(x) > pv. \end{aligned} \tag{4}$$

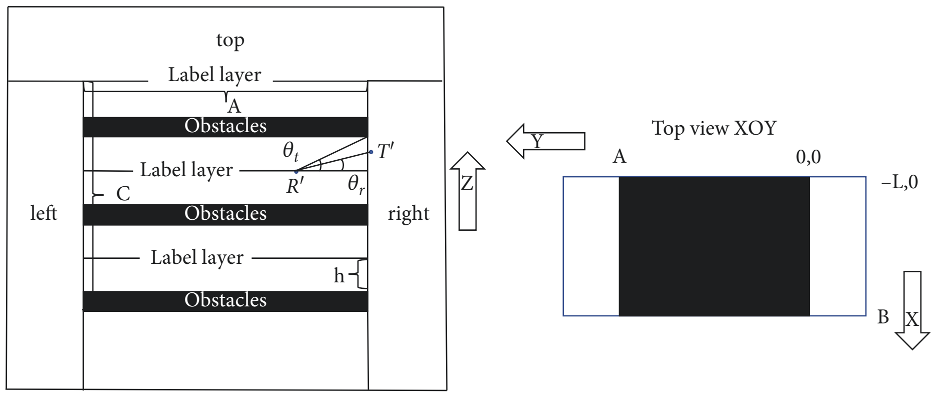

Figure 1: Rectangular obstacle RFID antenna deployment optimization environment model.

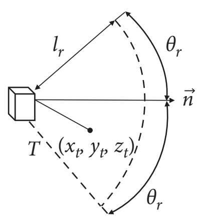

Figure 2: RFID reader antenna sensing model schematic.

Among them,

$$F(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \int_x^{+\infty} \exp\left(-\frac{u^2}{2\sigma^2}\right) du. \tag{5}$$

In the formula $x = \xi - P_T G_R^2 G_T^2 (\lambda/4\pi l_r)^4 T$, $P_r(P_T, l_r)$ is a function of the signal strength received by the reader antenna associated with P_T and l_r. Determined by equation (2). pv is a known predetermined value, while the known values of the transmitting power P_T, G_R , G_T are known. Then the recognition distance of the idealized perceptual model of the dome vertebra in this paper can be calculated according to equation (4), and then, l_r is calculated as follows:

$$l_r = \frac{\lambda}{4\pi} \left(\frac{P_T G_R^2 G_T^2 T}{\xi - x} \right)^{1/4}. \tag{6}$$

3.3. Constraint Model of the RFID Reader Antenna. In the actual environment, there are often rectangular obstacles or the material itself is an obstacle, only the introduction of Gaussian noise does not meet the requirements, so to better meet the actual environment, optimize the RFID reader antenna in the three-dimensional space deployment method, the RFID environment space for discrete processing, so that the RFID environment space into a finite unit cube t_{xyz} composed of x, y, z for the unit cube of the space coordinates, and the unit cube for the significant process. Specifically: $t_{xyz} = 0$ is the rectangular obstacle distribution area, $t_{xyz} = 1$ is the tag distribution area, and $t_{xyz} = 2$ is the RFID reader antenna deployment area.

Let the position coordinates of the reader antenna R be (x_r, y_r, z_r), The antenna plane normal vector $\vec{n}$ of the reader is (a, b, c), The coordinates of the position of a certain label T are (x_t, y_t, z_t), The constraints under which the tag can be sensed by this reader antenna are as follows:

$$\begin{cases} (x_r - x_t)^2 + (y_r - y_t)^2 + (z_r - z_t)^2 \le l_r^2, \\ \arccos\left([x_r - x_t, y_r - y_t, z_r - z_t], [a, b, c]\right) \le \theta_r, \\ \text{barrier} = 0, \end{cases} \tag{7}$$

where: l_r is the read-write antenna R according to equation (6) formula to calculate the reading distance, θ_r is the reading angle of the reader antenna R, barrier used to indicate whether the rectangular obstacle exists between the reader antenna R and the tag T to affect its communication. The space of the whole formed by the label and the rectangular obstacle is length A, width B, and height C. The label is arranged between the rectangular obstacle, and the interval distance between the label and the rectangular obstacle is h. The reader antenna is deployed on the left, right, or upper side of the space formed by the label and the rectangular obstacle.

The method to determine whether the rectangular obstacle exists between the reader antenna R and the label T is as follows:

(1) judgment reader antenna is located on the left, right, or upper side of the space of the whole formed by the label and the rectangular obstacle.

(2) Construct the label T and the reader antenna R three-dimensional space connection, if the reader antenna is located in the left or right side area, then, the label T and the reader antenna R three-dimensional space connection line is projected to the yoz side, and then, enter the step 3 judgment condition (i) and (ii); if located in the upper side, then, directly enter the step 3 judgment condition (iii).

(3) Judgment Conditions.

(i) If the reader antenna is located on the right side, the reader antenna projects to the yoz side. If the constraint of the following equation (8) is satisfied, then, barrier = 0, indicates that no rectangular obstacle exists between the tag T and the reader antenna R; if the equation is not satisfied, then, barrier = *1*.

$$\begin{cases} \theta_t' = \arccos\left(\left[A - x_t, z_t + h - z_t\right], \left[A - x_t, z_t - z_t\right]\right), \\ \theta_r' = \arccos\left(\left[x_r - x_t, z_r - z_t\right], \left[x_t - x_t, z_t - z_t\right]\right), \\ \theta_t' \geq \theta_r', \end{cases} \tag{8}$$

where θ_t' is the maximum angle between the label T and the rectangular obstacle boundary, θ_r' is the construction tag T and reader antenna R three-dimensional space connection in the *yoz* plane projection and *xoz* direction of the direction vector of the angle.

(ii) If the reader antenna is located on the left side, the reader antenna projects to the *yoz* side. If the constraint of the following equation (9) is satisfied, then, barrier = *0*, indicates that no rectangular obstacle exists between the tag T and the reader antenna R; If the equation is not satisfied, then, barrier = *1*.

$$\begin{cases} \theta_t' = \arccos\left(\left[0 - x_t, z_t + h - z_t\right], \left[0 - x_t, z_t - z_t\right]\right), \\ \theta_r' = \arccos\left(\left[x_r - x_t, z_r - z_t\right], \left[x_t - x_t, z_t - z_t\right]\right), \\ \theta_t' \geq \theta_r', \end{cases} \tag{9}$$

(iii) If the reader antenna is located on the upper side, only need to judge whether the reader antenna Z coordinate is greater than the overall height of the label and the rectangular obstacle C; if greater than C, then, barrier = *0*, indicates that no rectangular obstacle exists between the tag T and the reader antenna R; otherwise barrier = *1*.

3.4. Optimization of the Objective Function

3.4.1. Tag Coverage Function. Whether in wireless sensor networks, RFID networks, or other wireless networks, coverage is one of the important indicators of their performance. The tag coverage rate in this thesis is defined as the ratio of the total number of unit cubes in the monitoring area covered by all reader antennas to the total number of all unit cubes in the monitoring area, the higher the ratio, the better the coverage performance is indicated, and in the following formula indicates the coverage rate that:

$$f_1 = \sum_{t=1}^{Nt} \frac{X_t}{N_t}, \tag{10}$$

where N_t denotes the total number of unit cubes $t_{xyz} = 1$ that may appear labeled in the target space, X_t represents the communication of this unit cube with the reader antenna, $X_t = 1$ means that the unit cube can be sensed by at least one reader antenna, $X_t = 0$ then, indicates that the unit cube is not sensed by the reader antenna.

3.4.2. Interference Degree Function between Reader Antennas. The interference degree between the reader antennas is also one of the important indexes to measure the RFID network system performance as the RFID reader antenna distribution is compact, the reader antenna sensing range is easy to overlap situation, leading to mutual interference between the reader antennas, affecting the cross-coverage area within the tag is perceived by the reader. Interference degree f_2 between reader antennas is defined as

$$f_2 = -\sum_{t=1}^{N_t} \frac{\left(\sum_{r=1}^{N_r} p_{(t,r)} - 1\right) \cdot X_t}{N_t}. \tag{11}$$

Equation (11) N_r indicates the number of reader antennas deployed in the three-dimensional space of the RFID environment deployment. Where $p_{(t,r)}$ adopts 0-1 sensing probability model and indicates the probability that the tag T is read by the reader antenna R. When there is no rectangular obstacle between the tag T and the reader antenna R, and the reader antenna R and the tag T satisfy the constraint condition of the reader antenna perception model equation (8), $p_{(t,r)} = 1$, consider that the reader antenna R senses the tag T as 100%, otherwise $p_{(t,r)} = 0$. The greater the value of the formula (12), the smaller the space of the overlapping area of the read-write antenna sensing range and the lower the interference degree of the read-write antenna with each other.

3.4.3. Load Balancing Function of Reader Antenna. The load balance of the reader antenna refers to the RFID environment deployment of the three-dimensional space with the reader antenna to communicate the number of tags as equal as possible. Otherwise, a reader antenna while processing too much tag signal will increase the reader antenna and tag energy consumption increase, the interference between the signals and RFID system performance will decline. Then, the load reader antenna network load function is expressed as follows:

$$f_3 = \prod_{i=1}^{N_t} \frac{1}{k_i}, \tag{12}$$

where k_i indicates the number of reader antennas that can sense the i label. The larger the equation (12), the more balanced the number of tags sensed by each reader antenna and the more balanced the load distribution of the RFID network.

In comprehensive analysis, in the rectangular obstacle environment, RFID reader antenna deployment needs to meet the maximum tag coverage, the lowest interference between reader antennas, and the most balanced load of three goals to achieve the optimal deployment of reader antennas. Therefore, in this paper, the above three objectives are linearly combined and converted into a single-objective problem for optimization, so the optimization objective function for the optimal deployment of the RFID reader antenna in this paper is as follows:

$$f = w_1 f_1 + w_2 f_2 + w_3 f_3. \quad (13)$$

In the formula, $w_1 + w_2 + w_3 = 1$, w_1, w_2, w_3 are the weights of tag coverage, interference degree between reader antennas, and reader antenna network load balance, respectively. As in the actual deployment of RFID reader antennas, coverage is the primary solution, so w_1 should be greater than 0.5, and w_2, w_3 is based on the actual situation. The target function value, namely, the adaptation degree value f takes the biggest value, then, can guarantee the label coverage rate maximum premise, read-write antenna interferes with each other to the smallest degree, while read-write antenna load is the most balanced.

4. Improved FA Design Based on Reader Antenna Deployment Optimization

4.1. Firefly Algorithm Theory. The firefly algorithm is a biological heuristic swarm intelligence optimization algorithm [30]. The position of each individual of the firefly is a feasible solution to the problem sought, and all the individuals of its population are the space to the solution of the problem sought. The brightness of the firefly is positively correlated with the value of the objective function sought. The higher the brightness of the firefly, the better the solution to the objective functions. The direction of movement of fireflies is related to their brightness, i.e., fireflies with weaker brightness will be attracted to the direction of stronger firefly brightness. The distance that fireflies move is positively correlated with the brightness of individual fireflies and negatively correlated with the distance between fireflies. As long as the location of the population continues to change, most of the fireflies in the population will gather near the brighter fireflies, and the location of the brightest firefly represents the optimal value of the solution [31], so the problem of solving the optimal value can be viewed as a problem of finding the brightest firefly [32].

The formula for the relative brightness of fireflies:

$$I_{ij}\left(r_{ij}\right) = I_i \times e^{-\gamma . r_{ij}^2}. \quad (14)$$

In the formula: I_{ij} indicates the relative brightness of the individual, I_i denotes the absolute brightness of the individual, i.e., the objective function value of the location of the firefly. γ is the light absorption coefficient, indicates that there will be losses in the process of light propagation in media such as air. The size of its value affects the convergence speed of the algorithm, and the theoretical value of the range of $[0, \infty]$. r_{ij} is the Cartesian distance between fireflies i and j, which is denoted by

$$r_{ij} = \left\| x_i - x_j \right\| = \sqrt{\sum_{k=1}^{d} \left(x_{i,k} - x_{j,k}\right)^2}. \quad (15)$$

In the formula: x_i and x_j are the spatial locations of fireflies i and j, respectively. d is the dimension of the requested space, $x_{i,k}$ denotes the position information of the ith firefly in the kth dimensional direction in space, ditto for $x_{j,k}$.

The mutual attractiveness formula:

$$\beta_{ij}\left(r_{ij}\right) = \beta_0 \times e^{-\gamma . r_{ij}^2}, \quad (16)$$

where β_0 is the maximum attraction, that is, $r_{ij} = 0$ when the source of light firefly is located in their current position of attraction, generally taking the value of 1.

Location update formula:

$$x_i(t+1) = x_i(t) + \beta_0 e^{-\gamma r_{ij}^2}\left(x_j(t) - x_i(t)\right) + a \cdot \text{rand}, \quad (17)$$

where t is the number of iterations of the population, random iteration step of $a \in [0, 1]$ perturbation, rand is the random perturbation vector, standard normal distribution of general rand $= \text{rand}(-0.5, 0.5)$ or $U(0, 1)$.

4.2. Improved Implementation of Firefly Algorithm for Optimal Deployment of Reader Antennas

4.2.1. Encoding and Initialization Based on Chaotic Strategies. The RFID three-dimensional network planning problem in this paper refers to the reader antenna deployment problem, and its control variables are the location coordinates and angle of the reader antenna (i.e., expressed by the normal vector of the antenna), so the coding expression is as follows:

$$x_i = \left[x_i^1, y_i^1, z_i^1, a_i^1, \ldots, x_i^{N_r}, y_i^{N_r}, z_i^{N_r}, a_i^{N_r}, b_i^{N_r}, c_i^{N_r}\right], \quad (18)$$

where: $(x_i^j, y_i^j, z_i^j, a_i^j, b_i^j, c_i^j)$ represents the deployment position of the $j \in (1, N_r)$ reader antenna in space (i.e. the starting point of the antenna normal vector) and the location terminal position of the antenna normal vector, respectively, then the normal vector of the reader antenna is $\vec{n} = (x_i^j - a_i^j, y_i^j - b_i^j, z_i^j - c_i^j)$, N_r represents the number of reader antennas deployed in the three-dimensional space, $i \in [1, M]$, M indicates the population size.

(1) The RFID environment space is discretized so that the RFID environment space becomes composed of finite unit cubes t_{xyz}, x ,y , z are the spatial coordinates of the unit cube, and the unit cube is signified, specifically: $t_{xyz} = 0$ is the rectangular obstacle distribution area, $t_{xyz} = 1$ is the tag distribution area, and $t_{xyz} = 2$ is the RFID reader antenna deployment area.

(2) The literature [33] proved through rigorous mathematical reasoning that cubic chaos mapping has faster convergence and better traversal uniformity than Logistic mapping [34], and in this paper, the population is initialized by generating a chaotic sequence through the cubic chaos operator, and the chaotic sequence is mapped to the value space of the control variables through a linear transformation, as in equation.

$$y_{(i+1),d} = 4y_{i,d}^3 - 3y_{i,d} \quad i = 0, 1, \ldots M. \quad (19)$$

Among them, $y_{i,d} \in [-1, 1]$, d denotes the dth dimension of the $D = 6N_r$-dimensional target space.

Then, the specific steps of chaos optimization for the initial population of fireflies are as follows:

(1) Initialize chaotic variables for M fireflies x_i in the $D = 6N_r$-dimensional space, randomly generate $Y = (y_{1,1}, y_{1,2}, \ldots, y_{1,D})$, an D-dimensional vector of initialized variables as new individuals in the $y_{i,d} \in [-1, 1]$ interval according to the nature of cubic chaotic mapping.

(2) $M - 1$ iterations for each dimension of Y according to equation (19) yielded $D \cdot (M - 1)$ chaotic variables for the remaining individuals.

(3) The chaotic sequence generated above is mapped to the search space of control variables according to equation (20) to generate an initial population consisting of M firefly individuals:

$$x_{i,d} = lb_{i,d} + \left(1 + y_{i,d}\right) \cdot \left(\frac{ub_{i,d} - l_{i,d}}{2}\right), \tag{20}$$

where $x_{i,d}$ denotes the coordinates of the position of the ith firefly in the dth dimension of the target space, $ub_{i,d}$ and $l_{i,d}$ denote the upper and lower bounds of the dth dimension of the control variable space region, respectively. $y_{i,d}$ denotes the chaotic variable of dimension d corresponding to the ith firefly generated according to equation (19). Due to a large number of unit individuals, to make the firefly more effective, the target space is divided into multiple regions, and there are differences in the range of spatial coordinates taken by different readers, so the region variable is introduced to determine the range of spatial coordinates for the deployment of the reader antenna according to different regions.

When region%3 = 0 represents the reader antenna is located on the upper side of the space of the whole formed by the label and the rectangular obstacle, region%3 = 1 represents the reader antenna is located on the left side of the space of the whole formed by the label and the rectangular obstacle, and region%3 = 2 represents the reader antenna is located on the right side of the space of the whole formed by the label and the rectangular obstacle.

4.2.2. Location Update Calculation Model. According to the location update formula of the standard firefly algorithm equation (17), it is prone to cause individuals with strong firefly brightness in the firefly evolution process to quickly attract other firefly individuals to gather around them, resulting in a very low probability of individual variation, a decrease in the searchability of the algorithm or even stagnation, premature convergence, and difficulty in improving the search accuracy. Therefore, inertia weight w and variable step size strategy a_i for elite individuals are introduced, and the traction effect of the best individual P_{ibest} in the historical population on other individuals in the population is increased. Then, the position update calculation model is changed to:

$$\begin{aligned} x_i(t+1) &= w_i(t) \cdot x_i(t) + \beta \cdot \left(x_j - x_i\right) + \alpha_i(rand - 0.5) \\ &\quad + w_i(t) r_i \left(P_{ibest}(t) - x_i(t)\right), \end{aligned} \tag{21}$$

In the equation, the first term $w_i(t) \cdot x_i(t)$ on the right side represents the influence of the spatial position of the previous generation of firefly individuals on the position of the current generation of fireflies, and the fourth term $w_i(t) r_i (P_{ibest}(t) - x_i(t))$ represents the traction of the best individuals of the population in the historical iteration on the individuals of the current iteration of the population, which is used to control the degree of influence of the best individuals of the current history on the current generation of individuals and improve the "self-perception" of the current generation of individuals. Where r_i is a random number between [0, 1]; P_{ibest} denotes the optimal position experienced in the historical firefly.

The introduction of inertia weight w can better balance the global and local search ability of the algorithm in the optimization search process; when w is larger, the algorithm has stronger search ability globally; when w is smaller, the algorithm has stronger search ability locally. In this paper, we propose nonlinear dynamic inertia weights w to make the algorithm search for the global optimal solution, which is calculated as follows:

$$\begin{aligned} w_i(t) &= w_{\min} + (w_{\max} - w_{\min}) \\ &\quad \left(1 - \frac{(w_{\max}/w_{\min})^{a(t/T)} - (w_{\max}/w_{\min})^{-a(t/T)}}{(w_{\max}/w_{\min})^{a(t/T)} + (w_{\max}/w_{\min})^{-a(t/T)}}\right), \end{aligned} \tag{22}$$

where: t is the number of current iterations; T is the maximum number of iterations; $w_{\max}$, and $w_{\min}$ are the maximum and minimum values of w.

The image of the noninertial weight function w for different values of a is shown in Figure 3. From this figure, it can be seen that the parameter a controls the speed of weight transformation, and the larger the value of a, the greater the speed of slope transformation before $t/T = 0.5$, i.e., the better the global search ability when before the number of iterations reaches half of the maximum number of iterations, so $a = 4$ is chosen as the nonlinear dynamic inertia weight function w.

4.2.3. Variable Step -Size Strategy Based on Elite Individuals. The third term on the right side of equation (21) uses a dynamic variable step size strategy based on elite individual division. The expression is as follows:

$$a_i(t+1) = \begin{cases} a_i(t) + a_0 \cdot \dfrac{a}{T}, & f_i > \theta \cdot P_{\text{ibest}}(t), a_i(t) \le 1, \\ a_0, & f_i > \theta \cdot P_{\text{ibest}}(t), a_i(t) > 1, \\ a_i(t) - a_0/T, & \text{others}, \end{cases} \tag{23}$$

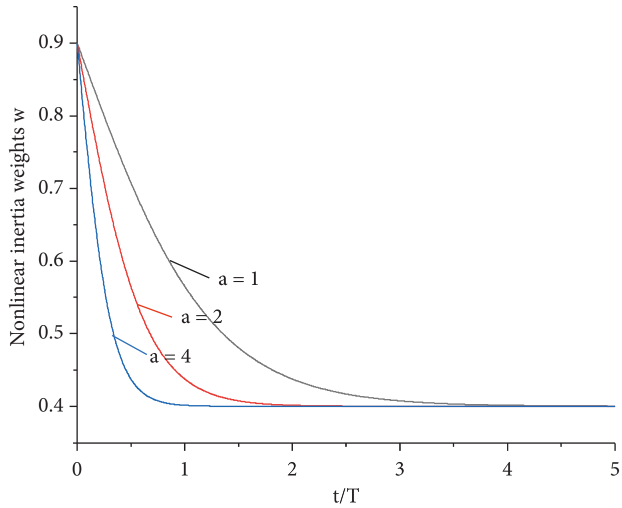

FIGURE 3: Images of the noninertial weight function w for different values of a.

where $a_i(t+1)$ represents the iteration step size of the ith individual firefly at the $t+1$th iteration of the algorithm; a_0 denotes the initial given step size; $a = randint[1, T/2]$ represents a random integer in the range $[1, T/2]$ of values of a, a is the stochastic acceleration of step length variation, which tends to diversify the selection of firefly step length and promotes the change of population diversity; f_i denotes the fitness value of the objective function, i.e., the fluorescence brightness of firefly i; A is a constant value used to classify elite individuals, i.e., when the brightness of firefly B is higher than C times the brightness of the best historical firefly, it is classified as an elite individual. Increasing the step size of such fireflies ensures that they move in the global field of view and search for larger areas to improve the diversity of the population and avoid early local convergence of the population. If the moving step size E after the mobilization of firefly D has been greater than 1, it is reset to the initial given step size. $\theta \in [0.85, 0.95]$ is a constant value used to classify elite individuals, i.e., when the brightness of firefly i is higher than θ times the brightness of the best historical firefly, it is classified as an elite individual. Increasing the step size of such fireflies ensures that they move in the global field of view and search for larger areas to improve the diversity of the population and avoid early local convergence of the population. If the moving step size $a_i(t)$ after the mobilization of firefly i has been greater than 1, it is reset to the initial given step size. If the brightness of firefly i is less than θ times the brightness of the best historical firefly, then, the step size of a_0/T is reduced and the local elite search is performed to induce the population to converge gradually and improve the solution accuracy of the algorithm.

4.2.4. Gaussian Variant Manipulation Based on Elite Individuals. The firefly algorithm falls into a local optimum characterized by stagnation in the firefly evolution process after several successive iterations of the population's historical optimal value that has not changed. Therefore, by using multiple trials with the count, it is found that for 10 consecutive times, i.e. count ≥10, the historical optimal value of the iterative population does not change, and then, the algorithm is determined to be trapped in a local optimum, Therefore, to break away from the local optimal value of the firefly population. In this paper, Gaussian variation is used to perform various operations on the elite individuals of each objective function while realizing the local search within a small range of the optimal elite individuals, the specific implementation process of which is as follows:

$$\begin{cases} population[0, 0.1M] = \\ population[0.9M, M] \cdot (1 + gs(0,1)) \\ population[0.1M, 0.2M] = \\ population\_f_1[0.9M, M] \cdot (1 + gs(0,1)) \\ population[0.2M, 0.3M] = \\ population\_f_2[0.9M, M] \cdot (1 + gs(0,1)) \\ population[0.3M, 0.4M] = \\ population\_f_3[0.9M, M] \cdot (1 + gs(0,1)) \\ population[0.4M, 0.5M] = \\ population[0.9M, M] \cdot (1 + rand(-1,1)). \end{cases} \tag{24}$$

All firefly individuals are sorted in ascending order according to the magnitude of the combined fitness value f and the three individual objective function values $f1, f2$ and $f3$ and assigned to population, population_f_1, population_f_2, and population_f_3, respectively. The fireflies of the last $[0, 0.4M]$ in the ranking of the combined fitness value are replaced by the state and updated with Gaussian state variants using each of the $[0.9M, M]$ elite fireflies with the best ranking mentioned above, respectively, to jump out of the local optimum. Where $gs(0,1)$ is a random vector obeying a Gaussian distribution with expectation 0 and variance 1. At the same time, the last ranked $[0.4M, 0.5M]$ is replaced with the best $[0.9M, M]$ elite fireflies of the integrated fitness value, and a random search is performed in the (−1, 1) range around the state value of the best $[0.9M, M]$ elite fireflies to find the optimal value in a small local area.

4.3. Improved Firefly Algorithm Optimizes the Implementation Process of Deploying Reader Antennas. The flow chart of the optimization method of reader antenna deployment with improved firefly algorithm is shown in Figure 4.

Step 1: Input the total number of reader antennas N_r, the power emitted by the reader antennas P_T, the antenna gain of the reader antennas G_R, the antenna gain of the tag antennas G_T , and the reading angle θ_r, the propagation loss of backscatter T, and the RFID three-dimensional space information, the RFID environment space is discretized, so that the RFID environment space becomes composed of a finite unit cube t_{xyz}, and the unit cube is signified.

Step 2: Initialize the firefly population size M, the maximum number of population iterations $MaxG$, the maximum attraction between fireflies β_0, and the light absorption coefficient γ, given the constant value α_0.

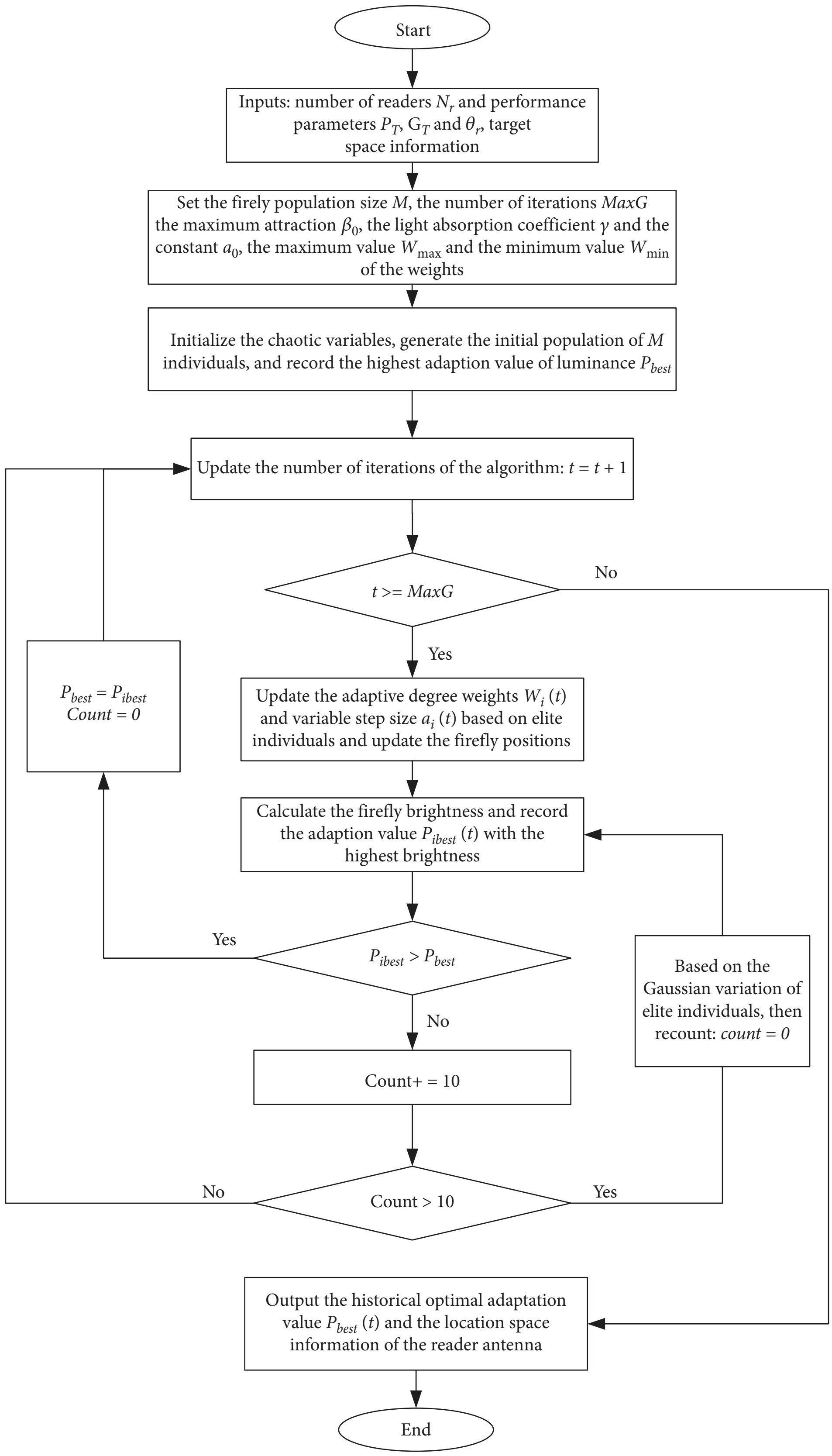

Figure 4: Flow chart of the optimization method of reader antenna deployment with improved FA.

Step 3: Initialize the population state values according to equation (20), substitute the reading distance l_r of the perceptual model of the dome vertebrae calculated by equations (4) and (6) into equations (10)–(13), calculate the objective function values $f1, f2, f3$, and the fitness value f for the first generation of fireflies, and record the maximum fitness value $P_{best}(t)$ and the minimum fitness value P_{imin}.

Step 4: Update the number of iterations of the algorithm so that $t = t + 1$, calculate the nonlinear inertia weight $w_i(t)$, elite individual variable step $a_i(t)$ based on equations (22) and (23), and set $w_{\max}$, $w_{\min}$ as 0.9, 0.4 respectively.

Step 5: The location update calculation model equation (21) updates the firefly location, calculates the objective function values $f1, f2, f3$ and the fitness value f for the first generation of fireflies according to the objective function equations (10)–(13), and records the contemporary maximum fitness value $P_{ibest}(t)$.

Step 6: judge the size of $P_{best}(t)$ and $P_{ibest}(t)$, and decide whether to assign $P_{ibest}(t)$ to $P_{best}(t)$. At the same time, record the value of the historical optimal value $P_{best}(t)$ without any consecutive changes count, if count >10, then, execute the Gaussian variation operation based on elite individuals, and return to step 5, otherwise execute sequentially.

Step 7: If $t > \text{Max } G$, output the historical optimal adaptation value $P_{best}(t)$ and the location direction information of the reader antenna. Otherwise, repeat steps IV~VII for iterative calculation of the population.

5. Simulation Experimental Design and Comparative Analysis of Results

5.1. Simulation Experimental Program Design. All calculations in this article were done under the PyCharm platform of the Windows 7 operating system, the computer's CPU model is Core i7, with 16 GB RAM.

The larger the target space, the more difficult it is to solve the 3D RFID reader antenna deployment problem, and in some mega spaces, it can be seen as composed of multiple subtarget spaces to solve the reader antenna planning scheme. In real life, we conduct research on factory-packaged aisle machines (similar to the security inspection machines for aircraft and high-speed railways entering the station). When entering the warehouse, through the passage machine, all the items in the package will be counted. For example, there are N water meters in a packaged box. When passing through the channel machine, the corresponding number of labels will be recognized. If the information of less than $N - 1$ labels is read only, it will be judged as a case of less packaging. Therefore, the position of the reader and the direction of the antenna have a great impact on the recognition rate of the tag. In this paper, the actual antenna deployment situation shown in Figure 5 is used for modeling and experimental simulation. In the experimental scheme, choose a $9.0\,\text{m} \times 5.1\,\text{m} \times 9.0\,\text{m}$ target space to carry on the reader network planning, first

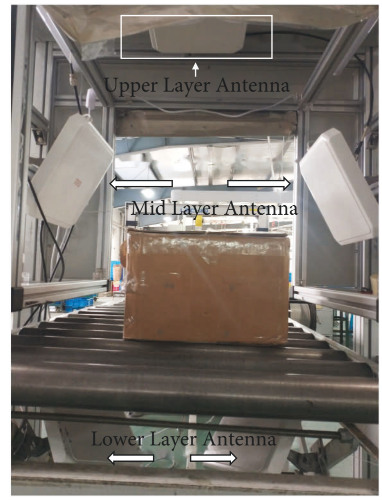

Figure 5: RFID reader actual antenna deployment.

according to the label distribution area, the obstacle distribution area, and the reader distribution area to carry on the line division, then, according to the $0.1\,\text{m} \times 0.1\,\text{m} \times 0.1\,\text{m}$ dispersion degree to discrete the target 413100 unit body. The material in this target space is itself an obstacle and can be seen as continuous individuals, the number is 3 and their sizes are all $5.1\,\text{m} \times 5.1\,\text{m} \times 0.1\,\text{m}$. According to the actual demand, the general material height is $0.2\,\text{m}$~$5.1\,\text{m}$, so set the monitoring area is $5.1\,\text{m} \times 5.1\,\text{m} \times 5.1\,\text{m}$, the target space information of the antenna deployment environment is shown in Figure 6. Establish a three-dimensional spatial coordinate system $Oxyz$, the x-axis is the length direction of the target surveillance space, the y-axis is the width direction of the target surveillance space, the z-axis is the height direction of the target surveillance space, and the distribution area of the label and the distribution area of the obstacle are part of the coordinates that have been marked, unit: decimeter.

In this target space under the deployment of $N_r = 6$ directional antenna of the UHF RFID reader, the reader antenna transmits the power $P_T = 30\,\text{dB m} = 1W$. The antenna gain $G_R = 8\,\text{dB i}$ of the reader antenna is equivalent to the unitless value of 6.3. The antenna gain $G_T = 3.7\,\text{dB i}$ of the tag antenna is equivalent to the unitless value of 2.3. Read the angle of clamping $\theta_r = 50°$, the propagation loss of backscattering $T = -5\text{dB}$, and then, the equivalent unitless value of 0.32. The frequency of the working environment is $f = 915\text{MHz}$, that is, the working wavelength is $\lambda = 0.328\text{m}$. The threshold at which the reader antenna can successfully identify the tag is $\xi = -80\,\text{dB m}$, the parameter $\sigma = 5\,\text{dB}$ of the Gaussian model, and the predetermined value $pv = 0.9$. After several comparative tests of the improved firefly algorithm, the values of the parameters related to the algorithm were set as follows: firefly population capacity $M = 30$, maximum number of iterations of the population $\text{Max}\,G = 500$, maximum attraction between fireflies $\beta_0 = 1$, light absorption coefficient $\gamma = 1 \times 10^{-7}$, given constant values $\alpha_0 = 0.5$. According to the test analysis and the three objective functions important to the tag coverage of the weight set to $w_1 = 0.85$, the reader

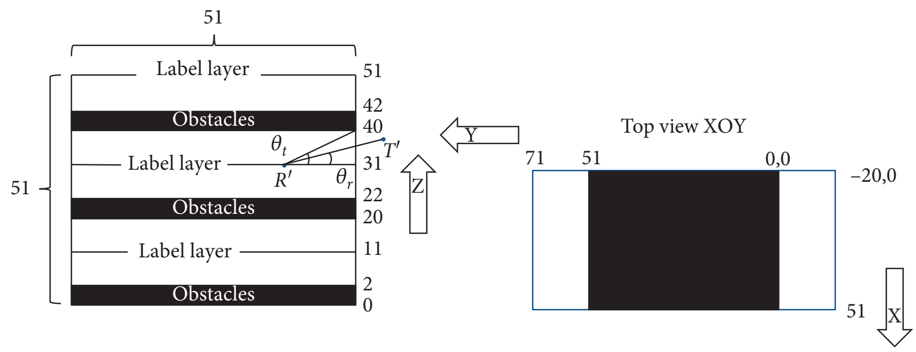

FIGURE 6: Target space information of RFID reader antenna deployment environment.

antenna interference degree of the weight set to $w_2 = 0.08$, and the reader antenna network load balance weight set to $w_3 = 0.07$.

5.2. Comparative Analysis of Different Results. In this paper, to verify the effectiveness and superiority of the improved firefly algorithm in solving the RFID reader antenna deployment problem in an environment with rectangular obstacles, the improved firefly algorithm FA_VA in this paper is compared and analyzed with the standard firefly algorithm FA, the firefly algorithm FA_WC based on chaotic initialization of weight position update, and the firefly algorithm that adds elite individual variable step FA_SA based on chaotic initialization of weight position update. Keeping the population size, the maximum number of iterations, maximum attraction, light absorption coefficient, and the given constant values the same, conduct 30 experiments and record the optimal results of the experiments. Where the improved firefly algorithm FA_VA used in this paper is compared with the standard firefly algorithm FA for nonparametric test statistical analysis. Using the Wilcoxon signed-rank test [35] method, the data from 30 experiments were analyzed using statistical software to analyze whether the effect of the improved firefly algorithm was significant. At the significance level of $\alpha = 0.05$, it shows that the effect of the improved firefly algorithm is significant. When the number of iterations is different and other conditions are the same, the optimal value of the firefly algorithm for function optimization is compared with the average value. The experimental results of different improved firefly algorithms are shown in Table 1. A comparison of the change curves of the integrated fitness values for different improved firefly algorithms is shown in Figure 7. The comparison between the optimal value and the average value of the firefly algorithm optimized by the function is shown in Figure 8. The left picture Figure 8(a) is the case of ($G = 50$, $S = 20$, $T = 300$ $f = 0.84667$, $D = 50$, $R = 6$), the right Figure 8(b) is the case of ($G = 200$, $S = 20$, $T = 300$ $f = 0.84667$, $D = 50$, $R = 6$).

From Table 1, we can see that the algorithm FA_VA in this paper gets the highest label coverage of 99.3%, close to 100%, and the highest fitness value, while the standard firefly algorithm gets the lowest optimal fitness value. From Figure 7, we can see that the standard firefly FA falls into a local optimum at the beginning, and the optimal fitness value stops changing in the early stage. Applying chaos initialization based on standard firefly FA as well as FA_WC with inertia weights, it is obvious that the initial optimal adaptation value of FA_WC is much larger than the initial value of the standard firefly algorithm, indicating that the population of fireflies are more evenly distributed, and the search time increases significantly after adding inertia weights, and the time to fall into local optimum is pushed back. FA_SA is a variable step length strategy based on elite individuals added to FA_WC, which increases the search range and also increases the local range of

TABLE 1: Comparison of experimental results of different improved firefly algorithms.

Experimental results	Algorithm name			
	FA_VA	FA	FA_WC	FA_SA
Population capacity	30	30	30	30
Maximum number of iterations	500	500	500	500
Given a constant value α_0	0.5	0.5	0.5	0.5
Optimal fitness value	0.830	0.558	0.6783	0.749
Coverage	0.993	0.901	0.95	0.920
Interference degree	0.290	0.256	0.37	0.41
Load balancing	0.085			

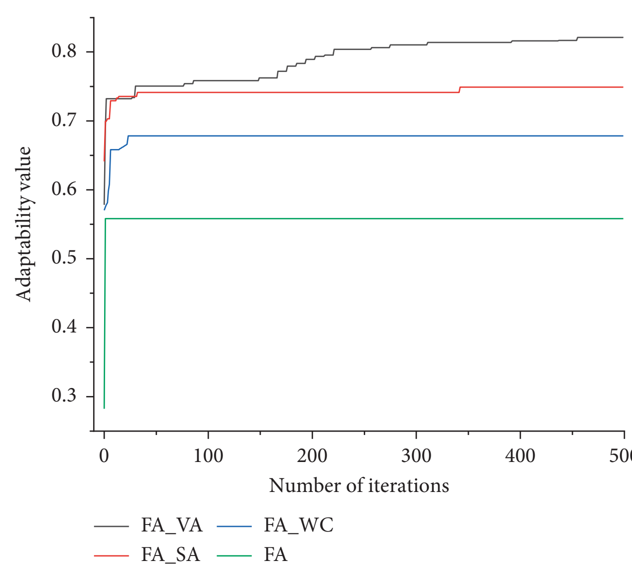

FIGURE 7: Comparison of optimal adaptation values.

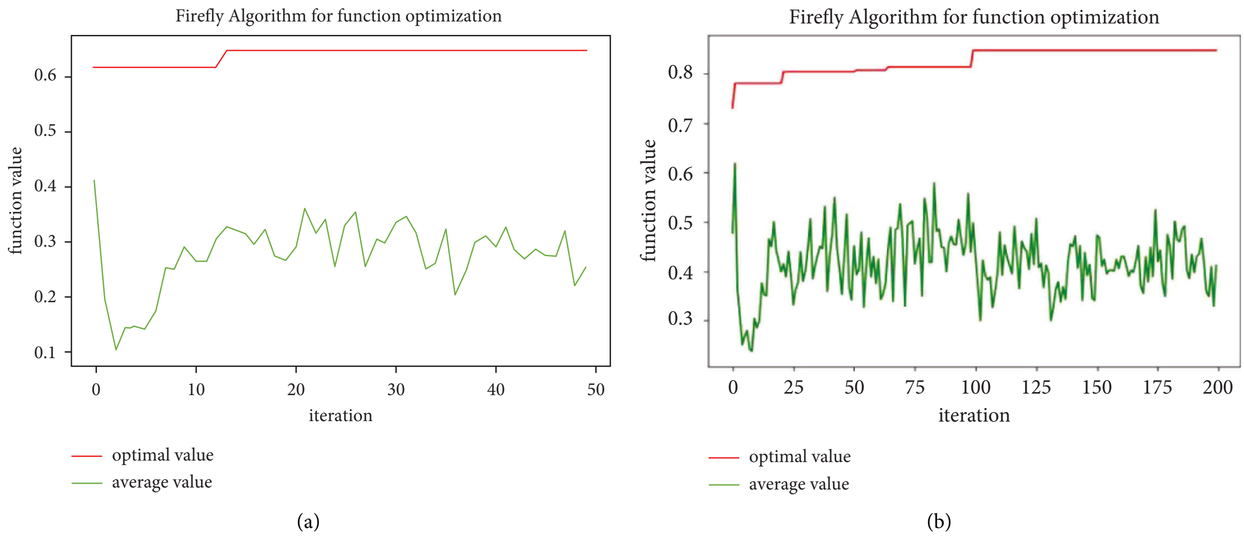

Figure 8: Comparison of optimal and average values of firefly algorithm for function optimization. (a) $G = 50$. (b) $G = 200$.

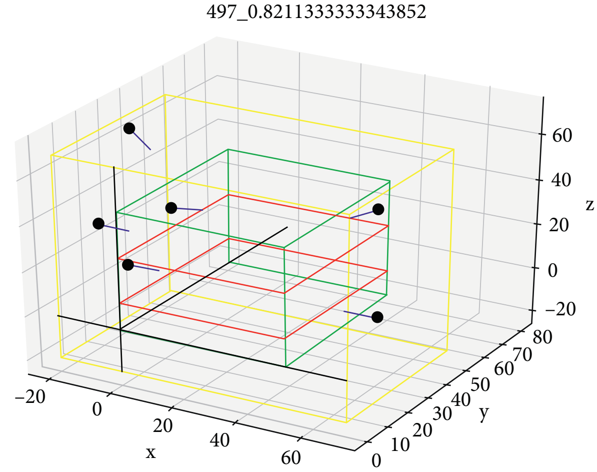

Figure 9: Reader antenna deployment solution.

search; and the time to fall into the local optimum is pushed back compared to FA_WC; and the change of the optimum value still occurs in the middle and late stages of the iteration; and a longer time is spent on effective search. In this paper, the algorithm FA_VA adds Gaussian variation operation based on elite individuals and local small-scale searches of elite individuals to FA_SA. As can be seen from Figure 6, FA_VA inherits the advantages of FA_WC and FA_SA while strengthening the search of the global field of view and the search of a small local area of elite fireflies, ensuring the continuous optimization of the optimal firefly in the whole process, which has a greater advantage in the search for the best. It is shown that the improved firefly algorithm FA_VA proposed in this paper can effectively solve the optimal deployment of RFID reader antennas in an environment with rectangular obstacles.

In addition, the FA_VA algorithm in this paper is compared and analyzed with the existing RFID coverage enhancement technology algorithms in recent years. The hybrid method based on artificial neural network and redundant antenna elimination algorithm RAE was proposed in the literature [36], for more than 50 independent runs of C30, the method has an average of 2.12 antennas with an average interference equal to −0.0477 and an average coverage of 99.83%, for C50, the method reaches an average of 4.2 antennas with an average coverage of 99.96% and an average interference of −0.0058, which allows the use of a minimum number of nonredundant antennas to achieve full coverage and zero interference. A multiobjective mayfly optimization algorithm (DSV-MOMA) based on dimensional exchange variation proposed in the literature [37] achieves an average coverage of 93.65% in 50 experiments, keeping interference above a moderate level and obtaining satisfactory load balance and power while ensuring higher coverage.

Therefore, the improved FA_VA algorithm proposed in this paper is used to solve the optimal deployment scheme of RFID reader antennas in a rectangular obstacle environment. The deployment distribution of the reader antenna in the target space is shown in Figure 9. The deployment values of each reader antenna are shown in Table 2. Its tag coverage

Table 2: Deployment value of reader antenna.

Number	Center coordinates of reader antenna (decimeter)			Coordinates of the direction of the normal vector of the reader antenna (decimeter)		
	x	y	z	a	b	c
1	−6	33	33	4	33	35
2	−12	8	38	−2	7	39
3	66	22	12	56	22	21
4	−16	29	67	−9	29	60
5	−19	31	5	−9	30	5
6	66	20	60	58	20	54

reaches 99.3%, the interference degree between reader antennas is 0.290, the load balance function value of reader antennas is 0.085, and the optimization target value is 0.830.

6. Conclusions

This paper takes the deployment problem of the reader directional antenna under the environment with a rectangular obstacle as the research object and constructs the calculation formula containing Gaussian distribution noise to find the reader antenna reading distance and the reader sensing model under the environment with the rectangular obstacle. And the optimal deployment model of reader antenna is established with the relationship between maximizing tag coverage and balancing the interference degree between reader antennas and load balance as the objective function, and a weight model and Gaussian variation operation theory based on elite firefly are proposed, which combines the cube mapping for initialization and the firefly algorithm based on the variable step length strategy of elite individuals for the optimal deployment scheme of reader antenna The design improves the algorithm's optimal search function in the global field of view and the search in the local range of elite individuals so that the firefly algorithm gets rid of the deadlock of local optimal.

In this paper, a target space is used as the research object, and simulation experiments are conducted on the PyCharm platform of the Windows 7 operating system. The experiment proves that the FA_VA algorithm can get nearly 100% tag coverage in the solution of RFID antenna deployment in an environment with rectangular obstacles and better balance the relationship between the interference degree problem and load balance among the reader antennas. To further prove the superiority of the FA_VA algorithm, it is compared with the standard firefly algorithm FA, the firefly algorithm FA_WC based on chaos initialized weight position update, and the firefly algorithm with elite individual variable step FA_SA based on chaos initialized weight position update, and the results show that the FA_VA algorithm has obvious advantages in convergence speed and optimization accuracy. It can effectively realize the reasonable deployment of RFID antennas in an environment with rectangular obstacles.

Data Availability

The data used to support the results of this study are available from the corresponding authors upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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