

## Research Article

# Planning Optimization of the Distributed Antenna System in High-Speed Railway Communication Network Based on Improved Cuckoo Search

Zhaoyu Chen,<sup>1</sup> Yanheng Liu,<sup>1,2</sup> Geng Sun ,<sup>1,2,3</sup> Xu Zhou,<sup>4,5</sup> Boyu Li,<sup>1,2</sup> Shuang Liang,<sup>1,6</sup> and Qianyu Zhou<sup>1</sup>

<sup>1</sup>College of Computer Science and Technology, Jilin University, Changchun 130012, China

<sup>2</sup>Key Laboratory of Symbolic Computation and Knowledge Engineering of Ministry of Education, Jilin University, Changchun, China

<sup>3</sup>School of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, GA 30332, USA

<sup>4</sup>Center for Computer Fundamental Education, Jilin University, Changchun, Jilin 130012, China

<sup>5</sup>College of Communication Engineering, Jilin University, Changchun, Jilin 130012, China

<sup>6</sup>Department of Information Technology, Changchun Vocational Institute of Technology, Changchun 130033, China

Correspondence should be addressed to Geng Sun; [sungeng207@foxmail.com](mailto:sungeng207@foxmail.com)

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The network planning is a key factor that directly affects the performance of the wireless networks. Distributed antenna system (DAS) is an effective strategy for the network planning. This paper investigates the antenna deployment in a DAS for the high-speed railway communication networks and formulates an optimization problem which is NP-hard for achieving the optimal deployment of the antennas in the DAS. To solve this problem, a scheme based on an improved cuckoo search based on dimension cells (ICSDC) algorithm is proposed. ICSDC introduces the dimension cell mechanism to avoid the internal dimension interferences in order to improve the performance of the algorithm. Simulation results show that the proposed ICSDC-based scheme obtains a lower network cost compared with the uniform network planning method. Moreover, ICSDC algorithm has better performance in terms of the convergence rate and accuracy compared with the conventional cuckoo search algorithm, the particle swarm optimization, and the firefly algorithm.

## 1. Introduction

High-speed railways are gradually replacing the traditional railways with the advantages of high capacity, less time-consuming, safety, comfort, and high punctuality rate [1]. The communication demands in a high-speed railway network mainly include two aspects that are controlling and scheduling of the trains based on the mobile network and the mobile data communication for the passengers. However, the traditional mobile communication mode is not suitable for the high-speed railway because the application scenarios of these two railways are quite different [2]. For example, the Doppler shift is very serious in high-speed railway communications [3, 4]. Thus, it is important to design an appropriate communication mode for the high-speed railway mobile communications [5].

Distributed antenna system (DAS) is a discrete form of the leak feeder technology [6]. In a DAS, multiple antennas are geographically distributed in order to reduce the distance of accessing [7]. Moreover, there are not any complicated signal processing technologies on the antenna terminals, thereby reducing the cost of the system. DAS has many advantages such as small hand-off loss, low power consumption, and large system capacity, compared with the traditional collocated antenna systems, and it has been used in many kinds of specific communication systems [8]. Thus, DAS can be also applied in the high-speed railway communications to achieve better performance. However, the network structure of the DAS is different from the typical cellular network. Moreover, the network scale in high-speed railway communication networks is much huger [9]. Therefore,

how to effectively plan the distributed antennas in the DAS of the high-speed railway communication networks to achieve the optimal system performance becomes a key point.

The optimal network planning is to reduce both the costs of the whole networks and to ensure the communication quality of the network. Huang et al. [10] propose a novel algorithm for automatically placing the base stations (BS). Chen et al. [11] define a coverage problem of the network planning in the mobile multihop relay networks based on integer linear programming. Moreover, they propose a super graph tree algorithm to place the BS and the relay stations with the lowest cost. With the rapid development of computing intelligence technologies, more and more intelligent optimization algorithms with higher convergence rate and better accuracy appear. Moreover, evolutionary algorithm and swarm intelligent algorithm are effective methods for solving the nonlinear problems and have been successfully applied into the network planning, the high-speed railway networks, and the DAS problems.

Tsiflikiotis and Goudos [12] use the cat swarm optimization (CSO) to solve the optimal power allocation problem for decentralized detection in the wireless sensor networks. Seguel et al. [13] solve the resource allocation optimization problem of indoor optical wireless communications by using genetic algorithm (GA) and cuckoo search (CS). Kumar and Murthy [14] formulate a multiobjective optimization problem to minimize the cost and the number of handovers of the mobile networks and use cuckoo optimizing algorithm to solve this problem. Safa and Ahmad [15] propose to use a tabu search-based method to design the tracking areas in the LTE networks. Parija et al. [16] adopt two optimization algorithms that are GA and binary particle swarm optimization (BPSO) to reduce the cost in cellular networks. In [17], BPSO is used for optimal reporting the cell planning technique with the objective of reducing the location management cost of a cellular network. Esposito et al. [18] use the software agent technology in conjunction with the GA and parallel computing to optimize the 3G networks. Tsoulos et al. [19] adopt the multiobjective GA to optimize the coverage and capacity optimization problem in the 4G systems. Liang et al. [20] build a new BS planning optimization problem of the 4G heterogeneous networks and use the multiobjective optimization algorithm to solve the problem. Sachan et al. [21] also use a GA-based approach to solve the network planning optimization problem in 5G. Moreover, Lin et al. [22] propose a hybrid algorithm of GA and differential evolution (DE) to solve the electromagnetic pollution and power consumption joint optimization problem in green 5G networks. Reference [23] gives a comparative analysis of the optimization methods such as GA and PSO for solving the radio network parameter optimization problems in the next-generation wireless mobile communications. Al-Naima and Hussein [24] propose a novel radio frequency identification network planning method based on particle swarm optimization (PSO). Liu et al. [25] propose a hybrid algorithm combined by genetic algorithm and quasi PSO to optimize the indoor wireless network planning problem. Wang et al. [26] investigate the network planning problem under the high-speed railway communication scenarios,

and a PSO-based network planning strategy is proposed to tackle it. However, the network planning algorithm proposed by Wang is not entirely based on PSO algorithm, which leads to the deficient in solving speed and solving precision. In addition to this, PSO algorithm is not the best choice for solving this problem because of the limited optimization ability.

CS is a swarm intelligence optimization algorithm, and the main idea comes from the breeding behavior of some genera cuckoos. CS can be widely used to various optimization problems [27–31]. With the deepening of the study of CS, the disadvantages of this algorithm gradually expose. For example, the traditional CS is easy to fall into local optima for some optimization problems. However, the antenna deployment of DAS for the high-speed railway is a complex nonlinear optimization problem. Thus, we should find a more effective way to improve the performance of the conventional CS for solving this problem.

The main contributions of this paper are summarized as follows:

- (1) We formulate a nonlinear optimization problem for achieving the optimal deployment of the antennas in the DAS for the high-speed railway communication networks. Moreover, the formulated optimization problem is proved as NP-hard.
- (2) We propose an improved cuckoo search algorithm based on dimension cells (ICSDC) to solve the proposed optimization problem. ICSDC introduces the dimension cell mechanism to avoid the internal dimension interferences in order to improve the performance of the algorithm.
- (3) We do several simulations to evaluate the performance of the proposed ICSDC. The results show that the ICSDC algorithm can obtain a lower network cost compared with the uniform antenna deployed method, and it can achieve better performance compared with the other benchmark algorithms.

The rest of this paper is as follows: Section 2 shows the system models. Section 3 formulates the optimization problem. Section 4 introduces the proposed ICSDC algorithm and the schemes for solving the optimization problem. Section 5 shows the simulation results, and Section 6 concludes the overall paper.

## 2. System Model

The structure of a DAS for the high-speed railway communication network is shown in Figure 1(a). It can be seen that a DAS mainly consists of several antenna units, passive optical splitters, and an optical line terminal. These three devices are connected via the optical fiber, and the detailed functions of these devices are presented in [7].

Figure 1(b) shows the logical cells consist of several distributed antennas of the high-speed railway communication networks. For simplification and without loss of generality, each logical cell has fixed number of antenna units [32]. These antenna units transmit data with the same frequency, and the

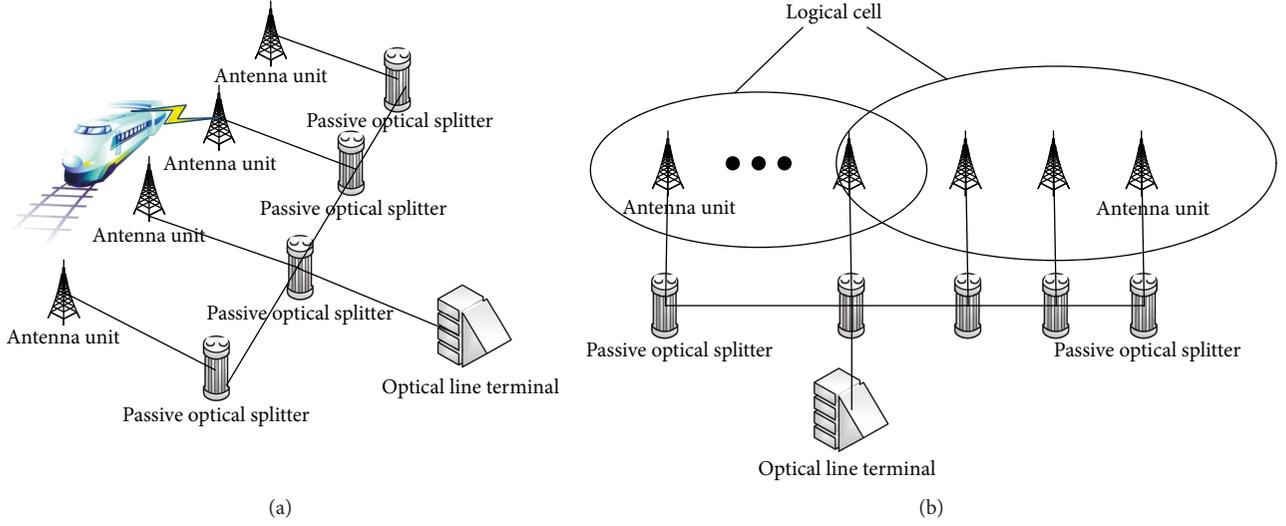


FIGURE 1: DAS used for mobile communication of the high-speed railway: (a) DAS of the high-speed railway and (b) logical cells of the DAS.

mobile terminals do not need to hand over in the same logical cell. When the mobile terminals cross over different logical cells, the handover operation will carry out. Thus, the less number of logical cells can not only reduce the number of handovers, but also can improve the handover success rate.

Table 1 shows the parameters of used in this section. The coordinate system of the railway can be set up in a way so that the start point of high-speed train station is defined as the origin. Moreover, we define the train driving direction along the  $x$ -axis and assume that the length of the whole railway is  $L$ . Thus, the start and finish coordinates are  $(0, 0)$  and  $(L, 0)$ , respectively. The current location of high-speed train is set as  $(l, 0)$ , where  $l \in [0, L]$ . Moreover, the logical cells are numbered from the start point to the end point of the railway, and the total number of the logical cells is  $I$ . Using  $i$  to represent the sequence number of logical cell,  $i \in 1, 2, \dots, I$ .  $M_i$  is the number of the antennas in the  $i$ th logical cell. Thus, the total number of the antennas in a DAS is as follows:

$$N = \sum_{i=1}^I M_i, \quad M_i \in N^+, \quad (1)$$

where  $N^+$  is a positive integer. For simplifying the problem, only the downlink conditions are considered. According to the Shannon theory, the maximum transmission rate of the train located in  $(l, 0)$  is as follows:

$$T_r(l, M_i, X_i, Y_i) = B \log_2 [1 + \rho \overline{\text{SNR}}(l, M_i, X_i, Y_i)], \quad (2)$$

where  $X_i$  and  $Y_i$  represent the sets of coordinates of the antennas in the  $i$ th logical cell,  $X_i = [x_{i,1}, x_{i,2}, \dots, x_{i,M_i}]$  and  $Y_i = [y_{i,1}, y_{i,2}, \dots, y_{i,M_i}]$ .  $B$  is the bandwidth, and  $\rho = -1.5P/P - 0.2$  represents the performance gap of the coding/modulation scheme [33], which means the difference between the signal to noise ratio (SNR) that needed to be achieved for a practical system and the theoretical Shannon limit  $P$  is the bit error constraint.

Moreover,  $\overline{\text{SNR}}(l, M_i, X_i, Y_i)$  is the average SNR of the receiving terminal. All the antenna units in the same logical

TABLE 1: Introductions of the parameters used in Section 2.

Symbol	Meaning
$L$	Length of the railway
$N$	Total number of antenna units
$I$	Number of logical cells
$M_i$	Number of antenna units in $i$ th logical cell
$X_i, Y_i$	Coordinate sets of antenna units in $i$ th logical cell
$T_r(l, M_i, X_i, Y_i)$	Maximum transmission rate in $(l, 0)$
$B$	Bandwidth of the current system
$\rho$	Performance gap of the coding/modulation scheme
$P$	Bit error constraint
$\overline{\text{SNR}}(l, M_i, X_i, Y_i)$	Average signal to noise ratio in $(l, 0)$
$P_{i,k}$	Transmission power of the $k$ th antenna unit of the $i$ th logical cell
$h(l, x_{i,k}, y_{i,k})$	Channel gain of the $k$ th antenna unit of the $i$ th logical cell
$s$	Small-scale fading
$\text{path loss}(l, x_{i,k}, y_{i,k})$	Path loss of the radio transmission
$d(l, x_{i,k}, y_{i,k})$	Linear distance between the train and the $k$ th antenna unit of the $i$ th logical cell
$H(d_0)$	Constant coefficients
$\kappa$	Path loss exponent

use the same frequency to transmit data, and the signal interferences of the whole network are very small because of using different orthogonal channels for data transmission. The description of SNR is as follows:

$$\text{SNR}(l, M_i, X_i, Y_i) = \frac{\sum_{k=1}^{M_i} P_{i,k} |h(l, x_{i,k}, y_{i,k})|^2}{N_0}, \quad (3)$$

where  $p_{i,k}$  is the transmission power of the  $k$ th antenna unit of the  $i$ th logical cell, and  $N_0$  is the Gaussian white noise.  $h(l, x_{i,k}, y_{i,k})$  represents the channel gain of the  $k$ th antenna unit of the  $i$ th logical cell and it can be described as follows:

$$h(l, x_{i,k}, y_{i,k}) = s * \sqrt{\text{path loss}(l, x_{i,k}, y_{i,k})}, \quad (4)$$

where  $s$  represents the small-scale fading which it can use the Ricean fading model [34],  $\text{path loss}(l, x_{i,k}, y_{i,k})$  is the path loss of the ratio transmission, and it is as follows [35]:

$$\text{path loss}(l, x_{i,k}, y_{i,k}) = H(d_0) + 10 * \kappa \log_{10} \left( \frac{d(l, x_{i,k}, y_{i,k})}{d_0} \right), \quad (5)$$

where  $H(d_0)$  is the constant coefficients, and it represents the actual detected path loss of the close-in reference distance,  $d_0 \cdot d(l, x_{i,k}, y_{i,k})$  represents the linear distance between the locations of high-speed train and the  $k$ th antenna of the  $i$ th logical cell, and  $\kappa$  is the path loss exponent.

### 3. Problem Formulation and Optimization Schemes

In this section, we formulate a DAS deployment optimization problem of the high-speed railway communication networks and prove the proposed problem is NP-hard. The key parameters used in this section are introduced in Table 2.

**3.1. Optimization Problem.** To deploy a mobile network requires a lot of equipment, and we use COST to represent the total cost of the DAS. Specifically,  $P_{\text{cost}}$ ,  $O_{\text{cost}}$ ,  $D_{\text{cost}}$ , and  $L_{\text{cost}}$  represent the cost of the passive optical splitters, the optical line terminal, the antenna units, and the optical fiber, respectively. Moreover, the unit price of the passive optical splitter, the optical line terminal, the antenna unit, and the optical fiber can be set as  $a$ ,  $b$ ,  $c$ , and  $d$ , respectively. Thus, the total cost can be obtained as follows:

$$\begin{aligned} \text{COST} &= O_{\text{cost}} + P_{\text{cost}} + D_{\text{cost}} + L_{\text{cost}} \\ &= a + b * N + c * N + d * (L + N * d_1 + d_2), \end{aligned} \quad (6)$$

where  $N$  represents the total number of antenna units of the network,  $L$  is the length of the railway,  $d_1$  is the distance between the passive optical splitter and each antenna,  $d_2$  is the distance between the passive optical splitter and the optical line terminal, and  $N$  is the only variable and the other parameters are constant. Thus, it can be seen that the way to save the cost of the whole network is to reduce the number of the distributed antennas.

However, two constraints that are the network transmission rate and the hand-off time should be satisfied while reducing  $N$ . These constraints are detailed as follows:

- (1) *The constraint of the network transmission rate.* A network planning can be accepted only when it meets the minimum network transmission rate limit for the entire network. Therefore, the instantaneous rate of the network should be used as the constraint that

aims to meet the minimum network transmission rate limit. Assume  $R_0$  represents the minimum network transmission rate limit, the constraint can be described as

$$T_r(l) \geq R_0, \quad \forall 0 \leq l \leq L, \quad (7)$$

where  $T_r(l)$  is the instantaneous rate of the network.

- (2) *The constraint of the hand-off time.* Hand-off often occurs in the high-speed railway due to the high speed of the train. The frequent hand-off may lead to the failure of the network traffic. Though the network planning based on DAS can reduce the number of hand-off, mobile terminals still need to hand-off when crossing the different logical cells, and this can be reflected in Figure 1(b). The time of crossing the two logical cells is expressed as follows:

$$t(u_i^T, u_{i+1}^S) = \int_{u_{i+1}^S}^{u_i^T} \frac{1}{v(l)} dl, \quad \forall i \in \{1, 2, \dots, I-1\}, \quad (8)$$

where  $v(l)$  represents the instantaneous velocity of the train at  $(l, 0)$ ,  $u_i^T$  is the end abscissa of the  $i$ th logical cell, and  $u_{i+1}^S$  is the start abscissa of the  $(i+1)$ th logical cell.

It should be noted that  $t(u_i^T, u_{i+1}^S) > 0$  and  $u_i^T > u_{i+1}^S$ , according to the physical meanings. Moreover, we should set a hand-off time threshold to ensure that the trains have enough time to hand-off. The hand-off time should satisfy the following constraint:

$$\begin{aligned} t(u_i^T, u_{i+1}^S) &\geq \eta * t_0, \quad \forall 0 \leq u_{i+1}^S < u_i^T \leq L, \\ &\forall i \in \{1, 2, \dots, I-1\}, \end{aligned} \quad (9)$$

where  $t(u_i^T, u_{i+1}^S)$  represents the actual hand-off time,  $t_0$  is the theoretical hand-off time,  $\eta$  is the switching regulator, which is a nonnegative constant, the value of  $\eta$  is usually greater than or equal to 1, and the specific value is determined by the network performance.

Accordingly, the optimization of the high-speed railway network planning is to ensure that the network transmission rate meets the limit and to guarantee the hand-off time less than the limit time while reducing the number of antenna units. Thus, the aim of the optimization model is to minimize  $N$ , and the constraints can be expressed as follows:

$$\begin{aligned} T_r(l) &\geq R_0, \quad \forall 0 \leq l \leq L, \\ t(u_i^T, u_{i+1}^S) &\geq \eta * t_0, \quad \forall 0 \leq u_{i+1}^S < u_i^T \leq L, \forall i \in \{1, 2, \dots, I-1\}. \end{aligned} \quad (10)$$

This is a NP-hard problem and it can be proofed in Section 3.2.

TABLE 2: Introductions of the parameters used in Section 3.

Symbol	Meaning
COST	Total cost of the DAS
$P_{\text{cost}}$	Cost of the passive optical splitters
$O_{\text{cost}}$	Cost of the optical line terminal
$D_{\text{cost}}$	Cost of the antenna units
$L_{\text{cost}}$	Cost of the optical fiber
$a$	Unit price of the passive optical splitter
$b$	Unit price of the optical line terminal
$c$	Unit price of the antenna unit
$d$	Unit price of the optical fiber
$d_1$	Distance between the passive optical splitter and antenna unit
$d_2$	Distance between the passive optical splitter and the optical line terminal
$T_r(l)$	Instantaneous rate of the network in $(l, 0)$
$R_0$	Minimum network transmission rate limit
$v(l)$	Instantaneous velocity of the train at $(l, 0)$
$u_i^T$	End abscissa of the $i$ th logical cell
$u_{i+1}^S$	Start abscissa of the $i$ th logical cell
$t(u_i^T, u_{i+1}^S)$	Time of crossing the two logical cells
$t_0$	Theoretical hand-off time
$\eta$	Switching regulator

3.2. *NP-Hard Proof.* To prove the proposed optimization is NP-hard, we first equivalently convert (6) to the following form:

$$\begin{aligned}
\text{COST} &= a + b * N + c * N + d * (L + N * d_1 + d_2) \\
&= N \left( \frac{a}{N} + b + c \right) + \sum_{i=1}^N d \left( l_i + d_1 + \frac{d_2}{N} \right) \\
&= \sum_{i=1}^N \left[ \frac{a}{N} + b + c + d \left( l_i + d_1 + \frac{d_2}{N} \right) \right],
\end{aligned} \tag{11}$$

where  $S$  is the distance between the two passive optical splitters, and it is easy to know that  $L = l_1 + l_2 + \dots + l_N$ ,  $N$  is the required number of antenna units in the system. To simplify the problem, we assume that the solution of the network planning problem is discrete, and we use a set  $D$  to represent the locations of the whole railway. Moreover, we use  $(dx_i, dy_i)$  to represent a location in  $D$ . If  $1 \leq j < i$ ,  $dx_i > dx_j$  and  $dy_i = dy_j$ . Thus, the original continuous optimization problem is converted to a discrete problem that selecting  $N$  antenna units from  $D$ . We introduce another binary set  $X$  that the values of the elements in this set are all 0 or 1.  $X$  is used to represent if the antenna is deployed in  $D$ . If  $x_i = 1$ , it means that the  $i$ th location  $D$  deploys an antenna unit; otherwise, the  $i$ th location does not deploy an antenna unit. Thus, the true solution of the simplified problem is the set  $X$ . Moreover, we assume the number of elements in  $D$  is  $z$ ; hence,  $N = x_1 + x_2 + \dots + x_z$ .

Then, we use  $x_i$  to represent  $l_m$ , and  $1 \leq i \leq z$ ,  $1 \leq m \leq N$ . The specific correspondence is for  $1 \leq j < i \leq z$ , if  $x_i = 1$ ,  $x_j = 1$ , and it does not exist  $h$  between  $i$  and  $j$  to make  $x_h = 1$ ,  $l_m = dx_i - dx_j$  because of  $dy_i = 0$  and  $dy_j = 0$ ; if  $x_i = 0$ , there is no correspondence between  $x_i$  and  $l_m$ , and it means that the  $i$ th location  $D$  does not deploy an antenna unit. In other words,  $l_m$  is the distance between the locations in  $D$ , and the corresponding element of  $x_i$  in  $X$  is 1. Thus, we can replace the relevant parameters in (11) with  $X$  and assume  $k_i = a / (\sum_{j=1}^z (x_j)) + b + c + d * (x_i - x_j + d_1 + d_2 / \sum_{j=1}^z (x_j))$ , and then (11) can be rewritten as follows:

$$\text{COST}(X) = \sum_{i=1}^z x_i k_i. \tag{12}$$

Moreover, the constraints can be also represented by  $x_i$ . We use  $p_i$  to represent the transmit power of  $i$ th antenna units, and according to the conversions above, (2), (3), (4), and (5) can be rewritten as follows:

$$T_r(l, X) = B \log_2 [1 + \rho \overline{\text{SNR}}(l, X)],$$

$$\text{SNR}(l, X) = \frac{\sum_{i \in \{x_i=1\}} x_i * p_i |h(l, dx_i, dy_i)|^2}{N_0},$$

$$h(l, dx_i, dy_i) = s * \sqrt{\text{path loss}(l, dx_i, dy_i)},$$

$$\text{path loss}(l, dx_i, dy_i) = H(d_0) + 10 * \kappa \log_{10} \left( \frac{d(l, dx_{i,k}, dy_{i,k})}{d_0} \right). \tag{13}$$

Thus, a simplified version of the proposed optimization problem can be expressed as follows:

$$\text{Minimize } \text{COST}(X) = \sum_{i=1}^z x_i k_i,$$

$$\text{Subject to } T_r(l, X) \geq R_0, \quad \forall 0 \leq l \leq L, x_i \in X, 1 \leq i \leq z. \tag{14}$$

According to [36], the optimization problem above is a 0-1 knapsack problem which has been proved as a NP-hard problem. Thus, the optimization problem proposed in this paper is a NP-hard problem.

To simplify the design, we assume the number of the antennas in each logic cell is fixed. Thus, the optimization problem is converted to minimize the total number of the logic cells. Hence, the coverage area of each logic cell should be extended while meeting the transmission rate requirements. Therefore, we propose a scheme to reformulate the aforementioned optimization problem and it will be detailed in the next section.

3.3. *DAS Deployment Scheme.* The practical high-speed railway network planning based on the DAS includes two main items that are deploying the distributed antenna units and deploying the logical cells, respectively. Thus, we propose a practical DAS deployment scheme that includes a hybrid

logical cell antenna deployment method. The main steps of this scheme are as follows:

*Step 1.* Determine the start location of the logical cell. Assume that the coordinates of the start point of the first logical cell are (0, 0). However, the start point of the other logical cells is uncertain. Thus, the locations of the other logical cells should be determined while guaranteeing that the time of the train crosses the overlapping region between the two logical cells meets the maximum time limit. The start location of the  $i$ th logical cell  $u_i^S$  can be described as follows:

$$u_i^S = \begin{cases} 0, & i = 1, \\ u_{i-1}^T - d_{i-1}^{\text{hand-off}}, & i = 2, 3, \dots, I, \end{cases} \quad (15)$$

where  $d_{i-1}^{\text{hand-off}}$  represents the distance that the train travels during the hand-off time. Correspondingly,  $u_i^T$  represents the end location of  $i$ th logical cell.

By introducing the velocity function  $v(l)$ ,  $d_{i-1}^{\text{hand-off}}$  can be further deformed to the following form:

$$d_{i-1}^{\text{hand-off}} = \int_{u_i^S}^{u_{i-1}^T} v(l) t(u_{i-1}^T, u_i^S) dl, \quad \forall i = 2, 3, \dots, I. \quad (16)$$

*Step 2.* Determine the end location of the logical cell and the locations of the antenna units in the logical cell. The end location and locations of the antenna unit determination of logical cells should guarantee two conditions that are (a) the network transmission rate of each logical cell meets the rate limit and (b) expand the coverage of the antennas as much as possible. The overall number of the distributed antennas can be reduced by achieving these two goals.

## 4. Algorithms

In this section, a novel ICSDC algorithm is proposed to solve the optimization problems formulated in Section 3. ICSDC is based on the conventional CS algorithm, and the details of the CS as well as the ICSDC algorithms will be introduced as follows.

*4.1. CS Algorithm.* CS algorithm is a swarm intelligence optimization algorithm proposed by Yang and Deb [37], and it uses nests to represent solutions. The simplest case shows only one egg in each nest, and the cuckoo's egg represents a new solution. The purpose of the algorithm is to use the new and potentially more ideal solutions to replace poor ones. This algorithm is based on three ideal rules:

- (1) Each cuckoo lays one egg at a time and then dumps its egg into a randomly chosen nest.
- (2) The best nests with high-quality eggs are passed over to the next generations.
- (3) The number of the available host nests is fixed, and the egg laid by a cuckoo is discovered by the host bird with a probability  $P_a$ .

CS uses Lévy flight to update the solutions. Lévy flight is helpful to improve the population diversity of the algorithm, and it can further improve the accuracy of solution as well as the convergence rate. The solution update formula is as follows:

$$X_i^{\text{iter}+1} = X_i^{\text{iter}} + \text{step}, \quad (17)$$

$$\text{step} = \alpha \otimes s, \quad (18)$$

where  $\text{iter}$  is the current iteration and  $\text{step}$  represents the update length;  $\alpha$  is the step factor and it can be chosen as 1 for most of the applications [31].  $s$  represents the random step of Lévy flight and it is taken from the Lévy distribution:

$$s = \frac{\mu}{|\nu|^{1/\beta}}, \quad (19)$$

$$\mu \sim N(0, \sigma_\mu^2), \quad (20)$$

$$\nu \sim N(0, \sigma_\nu^2)$$

$$\sigma_\mu = \left\{ \frac{\Gamma(1 + \beta) \sin(\pi\beta/2)}{\Gamma[(1 + \beta)/2] 2^{(\beta-1)/2} \beta} \right\}^{\frac{1}{\beta}}, \quad (21)$$

$$\sigma_\nu = 1$$

where  $\mu$  and  $\nu$  obey the normal distributions shown in (20); the standard deviations  $\sigma_\mu$  and  $\sigma_\nu$  of the normal distribution corresponding to (20) are shown in (21).  $\beta$  is a parameter of Lévy distribution, and it is usually 1.5 in CS algorithm. The flow chart of CS algorithm is shown in Figure 2.

*4.2. ICSDC Algorithm.* Each dimension of a solution in CS is updated by the same step length simultaneously, thereby causing the mutual interference between different dimensions. To solve this problem, we propose a novel solution update mechanism based on the dimension cell evolution.

Figure 3 shows the basic principle of the dimension cell. It can be seen that all the dimensions of a solution are not updated at the same time. We divide the  $n$ -dimensional solution into  $Q$  cells. In each cell, the numbers of the cells are different, and the algorithm updates the solutions in each cell one by one.  $Q$  is expressed as follows:

$$Q = \lambda + \omega \cdot \ln(n) + \gamma, \quad (22)$$

where  $\lambda$ ,  $\omega$ , and  $\gamma$  are the growth factors. When  $n$  is increased by 1%,  $Q$  increases  $\omega$  units correspondingly. According to this method, the number of the cells increases with the increasing of  $n$ . The increasing process is nonlinear in order to ensure the number of cells is not increasing rapidly, thereby reducing the evaluation times of the objective function and improving the efficiency of the algorithm. By using this mechanism, when several dimensions in a cell are updated, they will generate a new solution with other dimensions in the other cells. In a certain iteration, the updated cell can be accepted only when this cell could improve the value of the objective function. By introducing the update mechanism based on the dimension cells, the evolution of the solution will be unaffected by the degradation of other

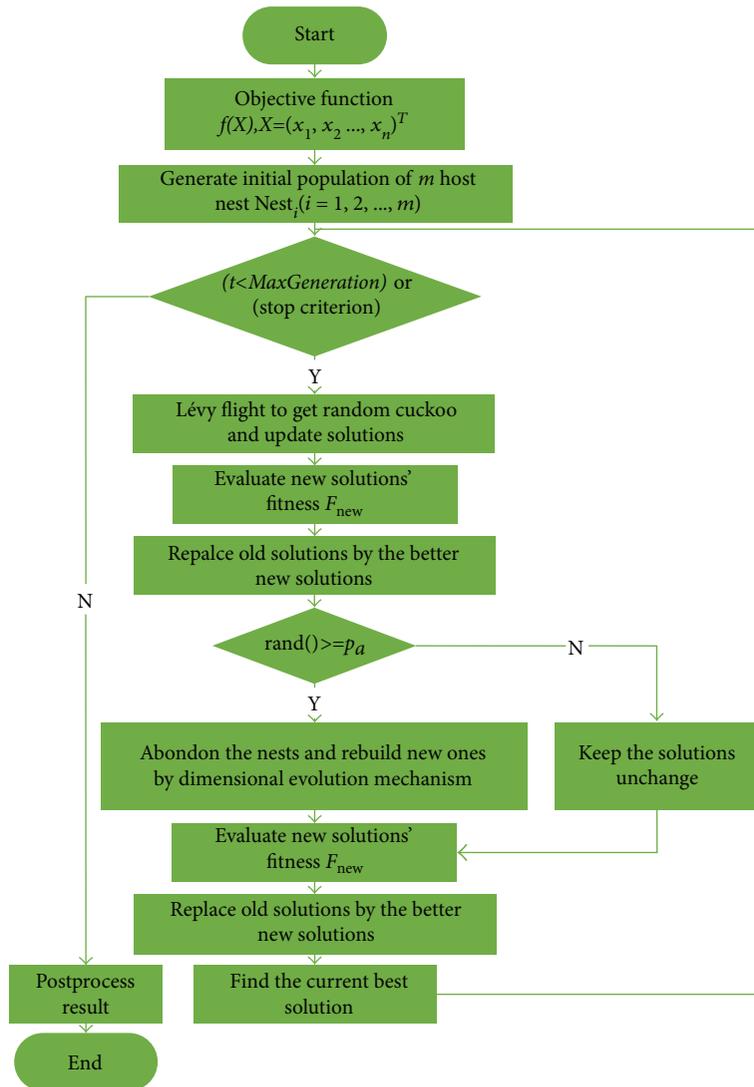


FIGURE 2: The flow chart of the conventional CS algorithm.

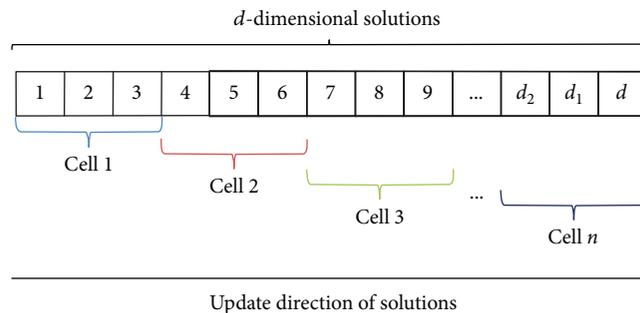


FIGURE 3: Updating mechanism based on evolution of dimension cell.

dimensions. Moreover, the dimension cell mechanism can also prevent the algorithm generated too many extra repeated computations because the algorithm can use the evolution of partial dimensions as the guide information for local search and then obtain the global optimal solution to improve the convergence rate of the algorithm. The steps of ICSDC algorithm are shown in Algorithm 1.

4.3. *DAS Deploying Optimization with ICSDC.* In this section, a specific optimization method based on the proposed ICSDC algorithm for solving the network planning problem in high-speed railways is presented.

The start location of the logical cell scheme can be obtained by (15). Figure 4 shows the mapping method between the antennas and the solutions of the proposed

```

Input:
 $f(x)$ : objective function determined by practical problems
 $X_i$ : initial solutions of  $m$  host nests;
while  $t < MaxGeneration$  do
    Lévy flights to get random cuckoo;
    Updating the solutions according the random cuckoo;
    Evaluate its quality/fitness  $F_i$ ;
    for each nest among  $m(F_{old})$  do
        if  $F_i > F_{old}$  then
            replace  $i$  by the new solution;
        end if
    end for
    for each nest among  $m$  host nests do
        if  $rand() \geq p_a$  then
            Abandon the current nest and rebuild new nest by
            dimensional evolution mechanism;
        end if
    end for
    Evaluate its quality/fitness  $F_i$ ;
    for each nest among  $m(F_{old})$  do
        if  $F_i > F_{old}$  then
            replace  $i$  by the new solution;
        end if
    end for
    Find the current best  $x_{best}$ ;
end while
return  $x_{best}$ 
    
```

ALGORITHM 1: ICSDC.

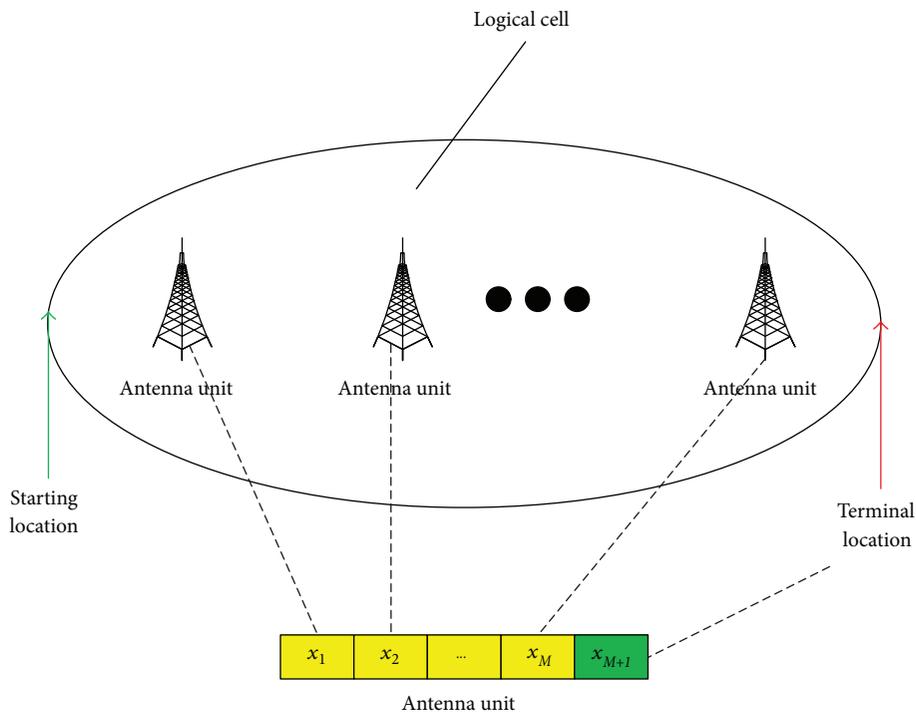


FIGURE 4: The encoding of solution.

**Input:**Initialize the parameters:  $u_i^S = 0, i = 1, u_i^T tmp = u_i^S + L_{\max}$ ;**while**  $u_i^T \neq L$  **do**

Using ICSDC algorithm to obtain the antenna location

 $X_i$  and new end location of logical cell  $u_i^T$ ; $Plan(i) = [u_i^S, u_i^T, X_i]$ ; $i = i + 1$ ;Generate the value of  $u_i^S$  through (17); $u_i^T tmp = u_i^S + L_{\max}$ ;**end while****return**  $Plan$ 

ALGORITHM 2: Network planning algorithm based on ICSDC.

TABLE 3: Parameter setups of the simulation.

Parameter	Symbol	Value
Length of the railway	$L$	30 km
Transmit power	$P_{i,k}$	15 dBm
White Gaussian noise	$N_0$	-104 dBm
Bit error rate constraint	$P$	0.01
Hand-off factor	$\eta$	2
Hand-off time	$t_0$	2 s
Velocity of the train	$v(l), l \in [0, L]$	300 km/h
Network rate limit	$R_0$	1 Mbit/s
Path loss exponent	$\kappa$	3.665
Distance between the antennas of the DAS and the train	$d_v$	50 m
Network bandwidth	$B$	106 Hz
The number of the antennas within a single cell	$M$	4
Oscillation factor	$r$	0.01
Close-in reference distance	$d_0$	100 m
Path loss for distance $d_0$	$H(d_0)$	71.83

ICSDC algorithm. As can be seen, the end location of the logical cell is also encoded as a dimension in the solution.

Then, we need to design the fitness function. Two objectives that are keeping the network transmission rate and extending the length of logical cell as long as possible should be considered. Thus, the fitness function can be designed as follows:

$$\begin{aligned} \text{fitness}(x_1, x_2, \dots, x_M, x_{M+1}) &= \omega_1 * T_1 + \omega_2 * T_2, \\ T_1 &= \left| \min \left\{ T_r(l, x_1, x_2, \dots, x_M), u^S \leq l \leq x_{M+1} \right\} - R \right|, \\ T_2 &= \frac{|x_{M+1} - u^S|}{L_{\max}}, \\ R &= R_0 + r, \end{aligned} \quad (23)$$

where  $x_i (1 \leq i \leq M)$  represents the location of the  $i$ th antenna, and  $x_{M+1}$  is the end location of a logical cell.  $T_1$  is

used to meet the minimum transmission rate limit, and  $T_2$  is used to maximize the length of logical cell.  $\omega_1$  and  $\omega_2$  are weighting factors and they can be chosen as -1 and 1, respectively.  $r$  is the oscillation factor which is used to ensure that the optimal solution meet the network transmission rate limit.  $L_{\max}$  is the theoretical maximum coverage distance of a single logical cell.

Thus, the optimization problem can be expressed as follows:

$$\begin{aligned} \max \quad & \text{fitness}(x_1, x_2, \dots, x_M, x_{M+1}), \\ \text{subject to} \quad & T_r(l) \geq R_0, \forall 0 \leq l \leq L, \\ & t(u_i^T, u_{i+1}^S) \geq \eta * t_0, \forall i \in \{1, 2, \dots, I-1\}. \end{aligned} \quad (24)$$

The steps of the network planning algorithm for solving the optimization problem formulated in (24) of the proposed scheme are shown in Algorithm 2.

## 5. Simulations

In this section, the DAS deployment optimization for the high-speed railway communication system based on ICSDC algorithm is simulated using MATLAB. The CPU of the computer used for the simulation is Intel CORE i5, and the RAM is 8 GB. The parameters used in this simulation are listed in Table 3.

The reasons for selecting the values of some key parameters are as follows. The values of  $\kappa$  and  $H(d_0)$  are cited from [35], and  $M$  is cited from [32]. For  $v(l)$ , it is cited from [38], and it is a realistic value of the high-speed trains used in many countries such as China. In our work, we set  $v(l)$  as a fixed value and do not consider the acceleration and the deceleration of the train. This is because the trains are able to speed up from 0 km/h to 300 km/h in just a few minutes, and train is moving at the high speed for most of the time during the whole journey. Thus, it makes sense to set the velocity as the constant. Moreover, the acceleration and the deceleration often appear near the stations in the real-life scenarios, and the communication infrastructures of the stations are always abundant. For example, it may have several base stations so that the passengers can access the Internet directly. Thus, using the DAS may be not necessary when the train is within the scope of the stations. Moreover,  $d_v$  is actually the distance between the electric centers of the TX (DAS) antenna and RX (train) antenna, and it has been chosen as several different values in previous work, for example, 50 m [39], 60 m [40], and 100 m [41]. In our simulation, we set it as a fixed value of 50 m for simplification. The selections of the rest parameter values are the same with [26].

**5.1. Network Planning Results.** In this section, the results obtained by the proposed scheme are presented. First, the parameters used in ICSDC algorithm are tuned for achieving the best performance. Then, GA, PSO, the accelerated PSO (APSO) [42], and the firefly algorithm (FA) [43] are used as the benchmark algorithms, and the configurations and setups of these algorithms are described. Finally, the network planning results obtained by the proposed ICSDC and the benchmark algorithms are shown, respectively.

**5.1.1. Parameter Tuning of ICSDC Algorithm.** Similar to the parameter settings of CS and other CS-based algorithms,  $\alpha$  and  $p_a$  can be set as 1 and 0.25, respectively, because these settings have been proved that they can achieve the best results in most optimization problems. Moreover, the values corresponding to the dimension cells should be determined by performing the setup tests for  $\lambda$ ,  $\omega$ , and  $\gamma$ . We use a semilogarithmic growth model to determine the number of the dimension cells. Thus,  $\lambda$  and  $\gamma$  are just the fine tuning factors that do not play a decisive role. Therefore, we set them to be 0.5 and 0.5, respectively.  $\omega$  needs to be tested to obtain the value that provides the optimal solution. Moreover, in order to obtain the optimal parameter settings, we jointly tune the population size  $n$  and  $\omega$ . Figure 5 shows the average tuning results obtained from 50 independent tests. It can be seen from the figure that when  $\omega = 1.5$  and  $n = 30$ , ICSDC can

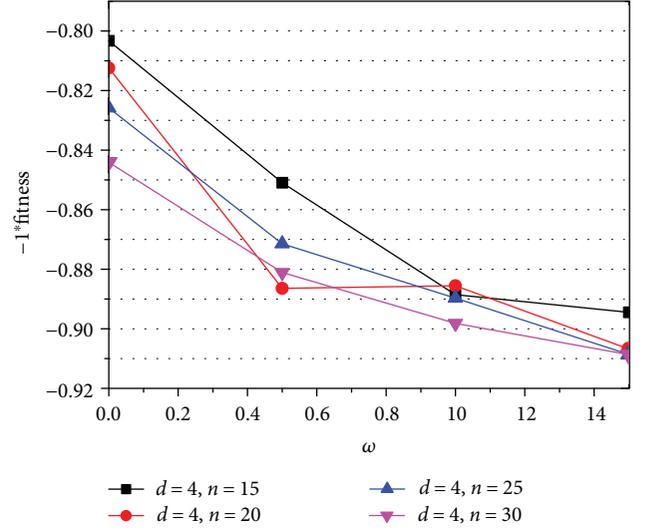


FIGURE 5: Joint parameter sensitivity test for  $\omega$  and  $n$  of the ICSDC for the scheme.

TABLE 4: Parameters of the ICSDC algorithm.

Parameter	Value
$n$	30
$\beta$	1.5
$\alpha$	0.01
$I_{\text{iter}_{\max}}$	100
$p_a$	0.25
$\omega$	1.5
$\gamma$	0.5
$\lambda$	0.5

achieve the best performance. The parameters used in ICSDC algorithm are shown in Table 4.

**5.1.2. Configurations and Setups of the Benchmark Algorithms.** GA is a heuristic search algorithm and it is first proposed in [44]. This algorithm uses the selection, the crossover, and the mutation operations to update the solutions, and the solving procedure can be regarded as a genetic process. The key parameter setups of GA used in the simulations are as follows: the individual chromosome length  $\text{indivlength} = 65$ , the crossover probability  $p_c = 0.8$ , and the mutation probability  $p_m = 0.05$ , respectively.

PSO is proposed in [45], and the basic idea of PSO is derived from the foraging behavior of the birds. In PSO, each potential solution of the optimization problem can be regarded as a point on the  $d$ -dimensional search space, and these solutions are called particles. Moreover, each particle has a fitness value determined by the objective function and a speed that determines its direction and distance of flight. The particles follow the current best particle iteratively to find the optimal solution, and hence, PSO is also a kind of

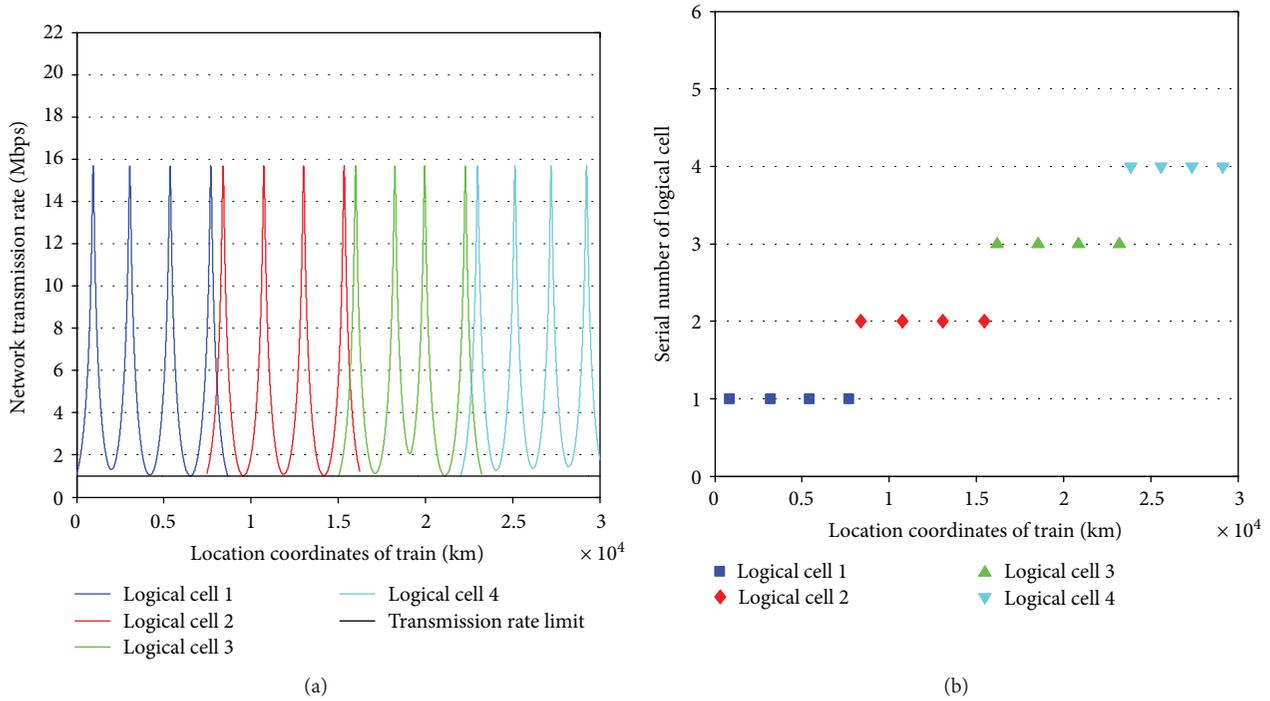


FIGURE 6: DAS deployment optimization results based on ICSDC algorithm: (a) network transmission rate along the railway, (b) DAS planning results, and (c) convergence rates of different algorithms for the scheme.

evolutionary algorithm. The key parameter setups of PSO used in the simulation are as follows: the inertia factor  $w = 0.7$ , the learning factors  $c_1 = 2$ , and  $c_2 = 2$ .

APSO is an enhanced version of the conventional PSO; the solution updated method of PSO is improved in APSO so that it has better performance in terms of the global optimization capability and the flexibility in some optimization problems [42]. The key parameter setups of APSO are as follows: the initial randomization parameter  $\alpha_0 = 1$ , the attraction parameter  $\beta_0 = 0$ , and the control parameter  $\gamma = 0.91$ . The rest parameter values are the same with the conventional PSO.

FA is inspired by the fireflies in nature and it is proposed in [43]. FA treats the candidate solutions as the fireflies and let the brighter fireflies to attract darker fireflies in order to find the optimal solution iteratively. The main parameter setups of FA in this work are as follows: the light absorption coefficient  $\gamma = 1$ , the maximum attractiveness  $\beta_0 = 1$ , and the minimum attractiveness  $\beta_{\min} = 0.2$ .

Moreover, for a fair comparison, the population size  $pops$  and the maximum number of iterations  $Iter_{\max}$  of ICSDC and the benchmark algorithms above are set to be 30 and 100, respectively. Note that using 100 iterations is a common

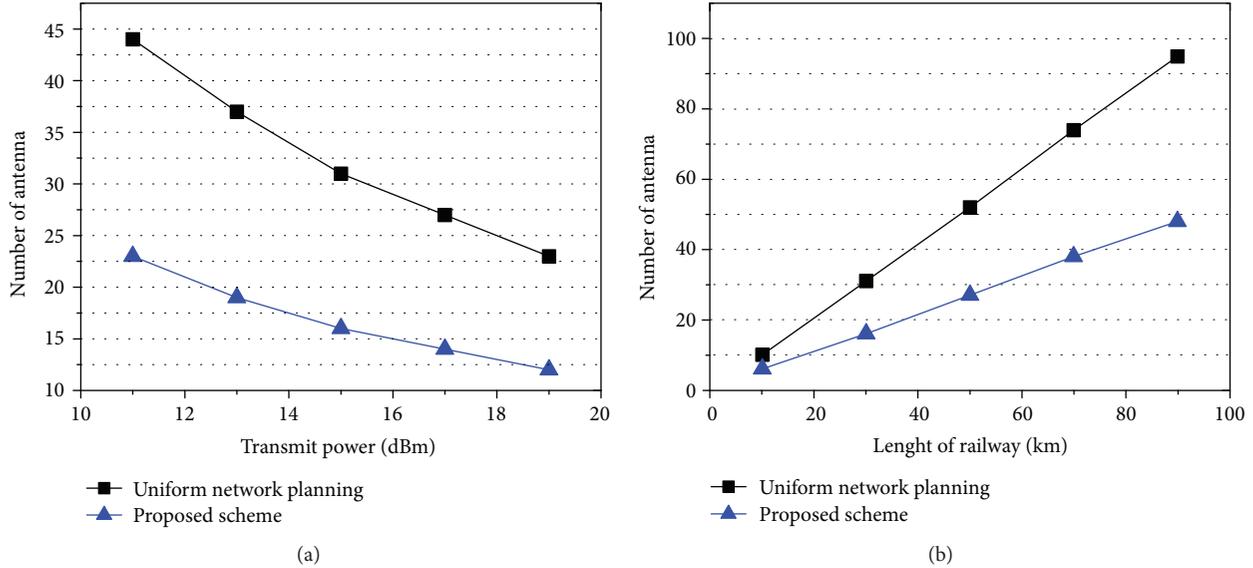


FIGURE 7: Comparisons of proposed scheme and uniform scheme. (a) Transmit power impact on the network planning. (b) Railway length impact on the network planning.

simulation setup in this research field [46–48]. Moreover, the DAS planning optimization problem of the high-speed railway has been demonstrated as NP-hard. Thus, using 100 iterations is able to obtain an acceptable optimization result within the reasonable time.

**5.1.3. DAS Deployment Optimization Results.** Figure 6(a) shows the network transmission rate of the whole railway obtained by the proposed ICSDC algorithm. Figure 6(b) shows the optimized locations of the logical cells and the antenna locations in each logical cell obtained by the ICSDC algorithm. As can be seen, the antenna units are deployed along the railway and they are divided into many logical cells. Moreover, each position of the railway can meet the network transmission rate restriction. Figure 6(c) shows the convergence rate obtained by different algorithms. It can be seen from the figure that the proposed ICSDC has the best performance in terms of the convergence rate and the accuracy compared with GA, FA, CS, conventional PSO, and APSO. Moreover, the accuracy of ICSDC is better than the other algorithms which means that it can get the highest network transmission rate and the larger coverage range of the DAS deployment. Thus, the overhead of the DAS deployment obtained by ICSDC is less than the other algorithms.

**5.2. Comparisons of Proposed Scheme and Uniform Scheme.** In this section, the optimization results in terms of the number of antennas of proposed scheme and uniform scheme are compared.

Figure 7(a) shows the relationship between the required numbers of antennas obtained by proposed scheme based on ICSDC algorithm and the uniform antenna deployment method and the changing of the transmit power. It can be seen from the figure that the required numbers of antennas of the two methods decrease with the increasing of the transmit power. This is because the higher transmission power will increase the coverage region of a single antenna unit,

thereby reducing the number of the antennas. However, the proposed scheme uses the less number of the required antennas compared with the uniform approach.

Figure 7(b) shows the relationship between the required numbers of antennas obtained by the above mentioned two methods and the length of the railway. As can be seen, the proposed scheme can reduce the number of the antennas compared with the uniform deployment method. Moreover, with the increase of the length of the railway, the difference between the numbers of the antennas obtained by the two schemes is increasing, which means that the proposed scheme has a better performance than the uniform scheme.

## 6. Conclusion

In this paper, an antenna deployment optimization problem is formulated for the DAS-based high-speed railway communication networks. The objective of this optimization problem is to minimize the total system cost under the constraints of network transmission rate, the hand-off time, and the number of the antennas. Since the problem is proved as NP-hard, a scheme based on an ICSDC algorithm is proposed for solving this problem. ICSDC introduces the dimension cell mechanism to avoid the internal dimension interferences, thereby improving the performance of the algorithm. Simulation results show that the proposed scheme can obtain a lower network cost compared with the uniform antenna deployed method. Moreover, compared to the GA, PSO, FA, CS, and APSO, ICSDC algorithm has better performance in terms of the convergence rate and the accuracy for optimizing DAS-based high-speed railway communication networks.

## Conflicts of Interest

All of the authors declare that they have no conflict of interest.

## Acknowledgments

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