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Correction of Radio Wave Propagation Prediction Model Based on Improved Seagull Algorithm in Tunnel Environment

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ABSTRACT In the urban rail transit (URT) environment, the radio wave propagation prediction model and communication system planning are very important. However, due to the complexity of the tunnel propagation environment, the current prediction model can not fully cover the radio wave propagation process in the tunnel. In this paper, the propagation mechanism area is divided based on the segmentation approach. Different propagation models are used for different propagation mechanism areas to predict path loss more quickly and accurately. To improve the accuracy of the prediction model, this paper proposes an improved seagull optimization algorithm (ISOA). First, to address the shortcomings of the seagull optimization algorithm (SOA) such as easy premature convergence and slow convergence speeds, two improved methods of random search and periodic disturbance are proposed. Then, in order to verify the effectiveness and feasibility of the improved algorithm, the benchmark function is used to test the optimization performance of the ISOA and gray wolf optimization, the SOA, and particle swarm optimization. The results show that the optimization performance of ISOA is the most significant. Finally, the ISOA is used to fit and correct the continuous wave test data for a rectangular tunnel and an arch tunnel. The results show that the corrected propagation model has a higher degree of fit with the measured data than the single standard propagation model (SPM) model. The modified propagation model thus has guiding significance for the deployment of time-division long-term (TD-LTE) evolution networks in the tunnel environment.

INDEX TERMS Urban rail transit, radio wave propagation prediction model, path loss, seagull algorithm, continuous-wave test.

I. INTRODUCTION

In recent years, due to its advantages in terms of speed and convenience, the utilization rate of urban rail transit (URT) has gradually surpassed taxi, bus, and other travel modes to become the preferred means of transportation for urban citizens. Therefore, it is becoming increasingly urgent to design and build an efficient and reliable URT system. In the URT system, a communication-based train control (CBTC) system is the key to ensuring the safe operation of trains [1]. Most CBTC bearing networks are wireless local area networks (WLAN), but WLAN does not support high-speed movement because it works in a frequency band. Therefore, it is difficult for this type of system to keep up with the improvement of URT operation speeds [2]. Time-division

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long-term evolution (TD-LTE) technology uses a dedicated frequency band for data transmission, which has higher security than a WLAN connection. Therefore, TD-LTE systems have been used to carry CBTC services for some URT projects. TD-LTE supports both same-frequency networking and different-frequency networking. In the URT environment, greater bandwidth and a higher peak rate can be obtained using same-frequency networking; However, there is a problem of co-frequency interference between adjacent cells. Therefore, accurate prediction of path loss is helpful for wireless network planning and reducing the impact of co-frequency interference [3].

The radio wave propagation model is the primary method for predicting path loss. Radio wave propagation in different environments presents different characteristics; therefore, corresponding propagation models need to be established for each environment. Matching the model with the environment

will achieve a more accurate prediction of radio wave propagation and reduce the interference between cells, thus making the network planning more reliable.

There are three main radio wave propagation models: statistical models, deterministic models, and semi-deterministic models [4]. In 2002, Ericolo compared the statistical model with the deterministic model and reached a consistent conclusion [5]. Because empirical models are fast and effective, they are often used in network coverage planning. However, there are some limitations in statistical modeling, which cannot reflect and explain the variation of radio wave jitter in a tunnel environment. In [6], several common statistical models, including the standard propagation model (SPM), are compared under the TD-LTE network, and the SPM is shown to have the highest prediction accuracy and flexibility. In 2014, Hrova *et al.* reviewed the common modeling methods and propagation characteristics in tunnel environments and analyzed the influence of tunnel electrification parameters on radio wave propagation [7]. In the same year, Zhou compared the ray-tracing and modal analysis methods under the environmental conditions of the rectangular tunnel and verified the equivalence and accuracy of the two methods [8]. However, the ray-tracing method requires an accurate geometric description of the propagation environment, involving a huge number of calculations and high demand for memory [9]. Through the research and analysis of the above literature, it is concluded that only one model cannot predict the radio wave transmission loss in a tunnel quickly and accurately. Therefore, this paper combines the SPM and the ray-tracing method to predict radio wave transmission loss in a tunnel environment. Then, based on the test data in the tunnel environment, several optimization algorithms are used to correct the model parameters, and the results are compared to obtain the optimal propagation model for the tunnel environment.

The parameters of the propagation model are dependent exclusively on human experience, which will significantly affect the predictive accuracy of the model. Some researchers use optimization algorithms to establish optimal parameters. Previous studies have used genetic algorithms [10] and particle swarm optimization (PSO) algorithms [11] to fit and correct the radio wave propagation model in different environments, with more reasonable network planning being realized through the corrected model. However, both of these algorithms have some drawbacks, including slow convergence speeds and tendencies to fall into local optimization.

It is worth noting that in the urban rail environment, the tunnel is not an empty tunnel in the ideal environment. During the train operation, the vehicle body and human body also have an impact on the signal transmission. In this paper, in order to reduce the complexity and verify the proposed algorithm, the influence of human environment is not considered.

The parameters of the propagation model are completely dependent on people's experience, which will significantly affect the prediction accuracy of the model. Some scholars have corrected the propagation model in other ways. In 2014,

Sun used the least square method to correct the TD-LTE network radio wave propagation model in the urban environment [12]. In 2018, Wu used the Gray Verhulst model to predict the propagation path loss of indoor multi-obstacle radio waves working at 9.35GHz [13]. Compared with networks serving ordinary users, the communication network of a URT system has higher requirements for system reliability and real-time performance; therefore, there is a stronger need for algorithm performance in correction. Meta-heuristic approaches receive a great interest in the area of optimization, especially when exact methods are missing, or the cost is extremely high. Besides the possibility to report good solutions in reasonable time, metaheuristic techniques are widely applicable. For example, representative PSO, whale optimization algorithm (WOA) and seagull optimization algorithm (SOA). PSO is used to find the optimal parameter combination, but the author found that although PSO has fast convergence speed and high efficiency, it has poor accuracy and easy divergence. WOA was found to have the advantages of fast convergence speed and high precision, easy to use, but easy to fall into local optimization. SOA is a newly meta-heuristic technique that is proposed by Dhiman and Kumar. Compared with traditional optimization algorithms, SOA has higher optimization performance, strong global search ability, less parameters and easy implementation, which makes it suitable for different jobs. However, it still has the disadvantages of easy ''premature'' and slow convergence. To solve these problems, this paper further proposes the random search and periodic disturbance method to improve SOA. These improvements improve the optimization speed and performance of SOA. In this paper, the use of ISOA further improves the speed of finding the optimal parameters of the propagation model and improves the global search ability, without making the parameter selection of the propagation model fall into the local parameter optimization, which meets the more matching between the corrected prediction model and the measured model.

The main contributions of this paper are as follows:

1) Addressing the issue that the existing radio wave propagation model cannot fully describe the tunnel propagation process; this paper divides the tunnel environment into two propagation mechanism areas to describe the radio wave propagation process more comprehensively in the tunnel. Different models are used for areas with different propagation mechanisms to reduce the calculation time as much as possible under the condition of meeting the engineering indicators.

2) The SOA is improved upon, and the ISOA is compared with the traditional algorithm. The ISOA proposed in this paper can quickly find the optimal solution in many kinds of test functions. It shows the best optimization performance in comparison with other algorithms, and it is suitable for a variety of optimization problems.

3) The ISOA algorithm is used to correct the segmented model, find the optimal parameters, reduce the mean square error between the prediction model and the measured data, and generate more accurate path loss prediction results.

II. TD-LTE TUNNEL COVER

LTE is a technology that enhances and improves 3G air access technology. It introduces multi-input–multi-output (MIMO) and orthogonal frequency division multiple technologies. At present, the global commercial LTE network is deployed at 700MHz–2.6GHz, of which the URT environment is mainly deployed within the 1,785–1,805MHz range. Compared with GSM-R, WLAN and other technologies, TD-LTE has stronger anti-interference ability in the same frequency due to the adoption of Interference Rejection Combining (IRC), Inter-Cell Interference Coordination (ICIC) and other technologies. The comparison between GSM-R and TD-LTD is shown in Table 1.

TABLE 1. Comparison of TD-LTE and GSM-R.

Signal propagation modes in URT systems include infinite free wave, leaky waveguide, and leaky cable types [14]. The tunnel environment tested in this paper is mainly covered by leaky cable. As shown in Figure 1, the baseband processing unit (BBU) is set in the weak current comprehensive equipment room of the station, and the radio frequency remote radio unit (RRU) is set near the leaky cable on the tunnel wall to send the wireless signal into the leaky cable. The schematic diagram of single-network networking is shown in Figure 2.

FIGURE 1. Leaky cable coverage scheme.

The cell networking mode is shown in Figure 3. Accurate prediction of path loss can help to provide more accurate wireless network planning, improve the quality of information transmission, and ensure driving safety.

III. STUDY ON TUNNEL PROPAGATION MODEL

There are three kinds of radio wave propagation models: empirical models. The empirical models are easy to implement, but their prediction accuracy is lower than the deterministic model. deterministic models, and hybrid models. Empirical models are easy to implement, but their prediction accuracy is not high. Examples include the Okumura model, the Okumura–Hata model, the Cost231–Hata model, and the SPM. Deterministic modeling is based on electromagnetic wave propagation theory, and path loss is calculated according to the basic conditions and boundary conditions of radio wave propagation, including the ray-tracing method and the finite difference time domain method. The response of the ray-tracing model to radio wave propagation characteristics is more accurate, but the calculation process is complex. Therefore, this paper uses the hybrid propagation model and combines the empirical propagation model with the ray-tracing method to reduce computational complexity and improve prediction accuracy.

By comparing several common empirical models, [15] shows that SPM has the best performance under both lineof-sight and non-line-of-sight conditions, and this model is suitable for TD-LTE networks with an operating frequency of 1.8GHz. However, the default parameters of SPM are not applicable to any propagation environment. Therefore, SPM parameters need to be corrected to make them suitable for each different propagation environments. In [16], a PSO algorithm is used to correct the propagation of the SPM for an urban and hilly environment. In [17], the researchers improved and corrected the SPM in the marine propagation environment, obtaining a prediction model that was more consistent with the measured data. However, the above studies were not established in the tunnel environment, and the obtained models are not suitable for a tunnel propagation environment. The closed and narrow environment of the tunnel is different from the urban and marine propagation environments. Reflection from the tunnel wall has a significant impact on radio wave propagation. To obtain a suitable radio wave propagation model for the tunnel environment and improve planning speed for the wireless network of the URT system, this paper corrects the SPM in the tunnel environments.

A. STANDARD PROPAGATION MODEL

SPM is improved on the basis of the Cost-231–Hata model. A set of parameters are added on the basis of the Cost-231 model, taking into account the diffraction loss of the ground object environment, which is more flexible. SPM is mainly used for channel transmission loss prediction in code-division multiple access and LTE network bands. SPM considers the correction coefficient of each parameter and improves the measurement accuracy by fitting and calibrating with the measured data. The mathematical expression of the model is shown in equation [\(1\)](#page-3-0). The significance of

FIGURE 3. Schematic diagram of TD-LTE wireless network architecture.

TABLE 2. SPM parameters and significance.

parameters in the model is shown in Table 2.

$$
L_{s} = A_{1} + A_{2} \log (d) + A_{3} \log (H_{t}) + A_{4} diff
$$

+ $A_{5} \log (d) \log (H_{t}) + A_{6} H_{r} + A_{7} f$ (clutter) (1)

The empirical values of the parameters are shown in Table 3. In the tunnel environment, $H_t = 4m$, $H_r = 1.5m$, $f_c = 1$, 800MHz, and the values of cluster and diffusion are 1. Equation [\(1\)](#page-3-0) shows that the values of A_1 , A_4 , A_6 , and A_7 are linearly and positively correlated with the path loss. Fixing other parameters, we take different values of *A*2, *A*3, *A*5, and *H*^b following [5] and [12] for simulation comparison.

The simulation results are shown in Figure 4. The setting of parameter values has a great impact on the predicted value of path loss, but the overall prediction trend is consistent:

FIGURE 4. SPM simulation comparison diagram.

path loss increases with the increase of propagation distance. Under other fixed conditions, the values of *A*2, *A*3, and *A*⁵ parameters have varying degrees of influence on the prediction of path loss.

To obtain an accurate radio wave propagation model in a tunnel environment, this paper uses CW test data to correct and optimize the seven parameters A_1 – A_7 simultaneously. This will help to obtain a more suitable model for the actual measurement environment.

SPM can predict the overall propagation trend of radio waves in the tunnel environment. However, when radio waves propagate in a tunnel, the signal fluctuates violently over the first 500m due to the influence of antenna gain, polarization mode, diffraction loss, etc., so SPM cannot predict this pattern. To more accurately predict radio wave loss in the first 500m of a tunnel, the deterministic model is selected for modeling. The ray-tracing method can more accurately reflect the influence of tunnel wall thickness, the dielectric constant, and conductivity on radio waves.

B. RAY-TRACING MODEL

As a deterministic modeling method, the ray-tracing approach is more complex than the empirical propagation model. It is designed to predict radio wave loss by simplifying the propagation path of the electromagnetic wave into direct reflection and diffraction and tracking each ray emitted by the transmitting end. Ray-tracing methods are divided into shooting and bouncing ray launching algorithms and imaging. The mirror image method assesses whether the electromagnetic wave emitted by the source point acts on the receiving point according to the mirror image principle. In this paper, a combination of the ray-shooting and imaging methods is adopted, the schematic diagrams of the ray-shooting method and the ray-image method are shown in Figure 5 and Figure 6, respectively.

Network deployment based on a prediction model can improve stability of the physical communication links [18]. Compared with other environments, the tunnel environment is more closed and narrow; consequently, the modeling is more complex. In this section, the ray tracing method is

FIGURE 5. Schematic diagram of ray-shooting method.

FIGURE 6. Schematic diagram of ray–image method.

combined with ISOA to recalibrate the radio wave propagation model at 500m in front of the tunnel (the SPM model has a large error in this correction area) [19]. The path loss *P^L* expression of the radio wave in the near-field region is shown in formula [\(2\)](#page-4-0), where P_t and P_r are the transmission power and the reception power, respectively.

$$
P_L (dB) = 10lg \left(\frac{P_t}{P_r}\right) \tag{2}
$$

The meaning of each parameter in equation [\(3\)](#page-5-0) is shown in Table 4.

TABLE 4. SPM parameters and significance.

The expression of received signal power at the receiving end is shown in equation [\(3\)](#page-5-0):

$$
P_r = P_t \left(\frac{\lambda}{4\pi}\right)^2 G_t G_r \times \left| \frac{\exp\left(\frac{-j2\pi d}{\lambda}\right)}{d} + \sum_{i=2}^q R_i \left| \frac{\exp\left(\frac{-j2\pi d_i}{\lambda}\right)}{d_i} \right| \right|
$$
\n(3)

In tunnel environments, the propagation model is complex. In addition to the direct path, there are also a large number of multiple reflection paths and diffraction paths. As the real environment is complex, it is not possible to accurately track each radio wave. To avoid excessive consumption of time and resources, this paper only considers the direct and reflection conditions and uses an approximate method to reasonably set the maximum reflection times. In this study, the maximum number of reflections is set at 5 [7]. Because the TD-LTE 's carrying frequency in the URT environment is 1800 MHz, the frequency $f = c/l$, *c* is the electromagnetic wave velocity, the value is 3e^8, so $l = 0.17$. R_i is the reflection coefficient of the *i*th reflected wave, which can be solved by equation [\(4\)](#page-5-1):

$$
R_i = R_h \cos(\theta_i) + R_v \sin(\theta_i) \tag{4}
$$

In formula [\(4\)](#page-5-1), R_h and R_v represent the reflection coefficients of the parallel and vertical polarization of the antenna, respectively, $\theta_i = 90 - \alpha_i$, and α_i is the angle of incidence during the *i*th reflection, as shown in Figure 5. R_h and R_v are calculated as equation (10) and equation (11) :

In equation [\(12\)](#page-6-0), ε , ε _r, and δ represent the relative permittivity, complex permittivity, and conductivity of the tunnel wall, respectively.

The ray-shooting method is shown in Figure 5. The ray2 and ray3 emitted by T_x at the transmitting end will be successfully received by the receiving end. It should be noted that, when the ray-tracing method is used to set the receiving sphere radius, the setting of this parameter has a great impact on the path loss prediction accuracy. If the radius is too small, some effective rays will be lost, while if the radius of the receiving sphere is set too large, some invalid rays will be received. In [20], it is proposed that in the tunnel environment, the attenuation coefficient of the antenna's horizontal polarization is much smaller than that of the vertical polarization. The horizontal polarization coefficient is thus ignored in this paper. Additionally, [21] points out that the dielectric constant of the tunnel has a greater impact on prediction results than the conductivity. Therefore, this paper mainly corrects the two parameters of receiving sphere radius: r and ε_r .

Due to the complexity of various environments, existing models cannot accurately describe the actual communication environment. To reduce path loss prediction error, the model parameters need to be corrected by using the test data in a specific environment. Therefore, the optimization performance of the algorithm used in the correction process also determines the prediction accuracy of the model.

IV. ISOA

A. SOA

Based on research on optimization algorithms, this paper selects the SOA to correct the prediction model, and we put forward two methods to improve its optimization performance.

The SOA is an optimization algorithm proposed by Gaurav Dhiman in 2018 [22], [23]. It was primarily inspired by the migration and foraging behavior of seagull populations as a basis for constructing the optimization process. Migratory behavior refers to the migration of seagull populations to their habitats, and foraging behavior refers to seagull populations hunting their prey in these habitats. The specific optimization process is as follows.

1) MIGRATORY BEHAVIOR

The following three conditions constitute the migratory behavior of seagull populations.

1) Avoiding collisions: To avoid collisions between individual seagulls, in equation [\(5\)](#page-5-2), variable *A* is used to adjust the seagull position.

$$
\overrightarrow{C_S} = A \times \overrightarrow{P_S}(t) \tag{5}
$$

 $\overrightarrow{C_S}$ represents the new location of seagulls, $\overrightarrow{P_S}(t)$ represents the current location of seagulls, and *A* represents the search behavior of seagulls in the search space.

In equation [\(6\)](#page-5-3), the value of f_c is 2, t is the current number of iterations, and *Tmax* is the maximum number of iterations.

$$
A = f_c - f_c(t/T_{\text{max}})
$$
 (6)

2) Movement toward best neighbor's direction: After ensuring that there is no collision between seagulls, individual seagulls move toward the best seagull position, As shown in equation [\(7\)](#page-5-4):

$$
\overrightarrow{M}_s = B \times (\overrightarrow{P_{best}}(t) - \overrightarrow{P}_s(t))
$$
\n(7)

 $P_{best}(t)$ indicates the best position of seagulls, and $\frac{M_s}{M_s}$ indicates that the seagull population moves toward $\overrightarrow{P_{best}}$. *B* is a random number with the function of balanced algorithm exploration. The calculation method is shown in equation [\(8\)](#page-5-5).

$$
B = 2 \times A^2 \times rand \tag{8}
$$

3) Remain close to the best search agent: An individual seagull starts to move in the calculated convergence direction, and the formula is as follows as equation [\(9\)](#page-5-6): \overrightarrow{D}_s A new position for each seagull after moving.

$$
\overrightarrow{D}_{s} = \left| \overrightarrow{C}_{s} + \overrightarrow{M}_{s} \right| \tag{9}
$$

B. FORAGING BEHAVIOR

$$
R_h = \frac{\varepsilon \cos(\theta_i) - \sqrt{(\varepsilon - 1 + \cos^2(\theta_i))}}{\varepsilon \cos(\theta_i) + \sqrt{(\varepsilon - 1 + \cos^2(\theta_i))}} \tag{10}
$$

$$
R_{\nu} = \frac{\cos(\theta_i) - \sqrt{(\varepsilon - 1 + \cos^2(\theta_i))}}{\cos(\theta_i) + \sqrt{(\varepsilon - 1 + \cos^2(\theta_i))}}
$$
(11)

$$
\varepsilon = \varepsilon_r - j60\delta\lambda\tag{12}
$$

The foraging behavior of a seagull population depends on the experience gained by its migratory behavior. The attack angle and flight speed of the population will constantly change and spiral in the air.

$$
\begin{cases}\nx' = r \times \cos(k) \\
y' = r \times \sin(k) \\
z' = r \times k \\
r = u \times e^{kv}\n\end{cases}
$$
\n(13)

In equation (13) , r is the helix radius, which is controlled by *u* and *v*, the correlation constants of the helix shape. *k* is the random angle between [0,2 π]. By combining these processes, the seagull position update formula is obtained.

$$
\overrightarrow{P}_s(t) = (\overrightarrow{D}_s \times x \times y \times z) + \overrightarrow{P}_{best}(t)
$$
 (14)

As equation [\(14\)](#page-6-2), $\overrightarrow{P}_s(t)$ is the position of the seagull population after an iteration. In the SOA, variable *A* decays linearly, and variable *B* is responsible for controlling the optimization stability of migration behavior and foraging behavior.

C. RESEARCH ON IMPROVED METHODS 1) RANDOM POSITION FORMULA

This paper proposes a random location equation to maximize the global optimization of the SOA before and in the middle of the iteration and to avoid premature convergence. In the optimization process, we set the parameter *p* at $p = 0.1$, and then improve the random equation.

$$
\overrightarrow{D_{\text{rand}}} = \left| C \cdot \overrightarrow{X_{\text{rand}}} - \overrightarrow{P_s} \right| \tag{15}
$$

In equation [\(15\)](#page-6-3), C is the random number between $(0, 2)$, X_{rand} is the random seagull position, and D_{rand} is the random distance between individual seagulls.

In equation [\(16\)](#page-6-4), *G* is the random number in $(-A, A)$, and P_{rand} is the randomly generated seagull position.

$$
\overrightarrow{P_{rand}} = \overrightarrow{X_{rand}} - G \cdot \overrightarrow{D_{rand}} \tag{16}
$$

In equation [\(17\)](#page-6-5), *rand* is a random number between (0, 1).

$$
\overrightarrow{P}(t) = \begin{cases} Eq.(16), & rand < p \\ Eq.(14), & rand > p \end{cases}
$$
 (17)

In order to ensure that the SOA can quickly and reliably avoid premature convergence and increase the optimization speed, a periodic disturbance improvement method is proposed, which is improved based on equation [\(14\)](#page-6-2). The specific equation is as follows:

$$
\overrightarrow{P_{TT}}(t) = \begin{cases} \overrightarrow{P_s}(t) \cdot (1 + V \cdot (0.5 - rand)), & T = TT \\ \overrightarrow{Eq.}(14), & T \neq TT \end{cases}
$$
(18)

In equation [\(18\)](#page-6-6), *V* is the disturbance coefficient (set to 1), *TT* is the disturbance period, and *T* is the current iteration period.

The ISOA process is shown in pseudo-code algorithm 1.

3) ISOA OPTIMIZATION PERFORMANCE TEST

To verify the optimization performance of the proposed ISOA, six benchmark functions are used to test each of four optimization algorithms: PSO, GWO, the SOA, and the ISOA. Each algorithm is tested 10 times, and the average value and standard deviation of the optimal value of each optimization are recorded. The specific test results are shown in Table 6. The six benchmark function equations are shown in Appendix A, and the parameter settings of the four optimization algorithms are shown in Table 5.

In Table 6, the optimal values in all test results are marked in bold type. The results show that the average value and

TABLE 5. Optimization algorithm parameter setting.

	PSO	WOA	SOA	ISOA
c1	1.2			
c2	1.2			
\mathcal{W}_{max}	0.9			
\mathcal{W}_{min}	0.2			
v_{max}	6			
\boldsymbol{a}		$2\rightarrow 0$		
Fc			$\overline{2}$	$\overline{2}$
\mathcal{U}			$\mathbf{1}$	$\mathbf{1}$
\mathcal{V}			$\mathbf{1}$	1
$\cal T\cal T$				10
V				1

TABLE 6. Specific test results of optimization algorithm.

standard deviation of the ISOA are the best in single-peak reference functions F1 and F2. The ISOA also obtains the best results in multi-peak reference functions F3, F4, and F5, but in F5, WOA obtains equally high results. In the fixed dimensional multimodal reference function F6, the ISOA also obtains the best mean and standard deviation. Thus, compared with the other three algorithms, the ISOA shows better optimization performance. Figure 7 shows the test results of the four algorithms to further demonstrate the optimization performance of the ISOA.

Figure 7 shows that, in the testing of six test functions, the ISOA not only finds the optimal fitness value, but also has the fastest convergence speed. In F_5 , although GWO sometimes finds the optimal fitness value, it is not stable, and the convergence speed of the ISOA is significantly better than that of GWO. These test results show that the ISOA can find the minimum values of multiple test functions and is relatively stable, thus demonstrating its excellent optimization performance.

From the test results of the test function of section 3, it can be found that the ISOA has good convergence performance and optimization accuracy. In the second and third sections of this paper, we establish two tunnel propagation models respectively. Obviously, some parameters in the model are not fixed, in other words, different parameters correspond to different propagation environments. This paper uses the excellent global search ability and fast solution performance of ISOA to find practical parameters, so that the model established above can best match the actual propagation situation.

V. SIMULATION VERIFICATION AND CONCLUSION

A. CORRECTION OF TUNNEL PROPAGATION MODEL

The basic process of propagation model correction is as follows:

Step 1. Select test path for the CW test.

Step 2. Data sampling and filtering (filtering out abnormal data).

Step 3. Improve and test the optimization algorithm.

Step 4. Use the ISOA algorithm with the best test results to correct the parameters.

Step 5. Obtain corrected prediction model.

The CW test is conducted to collect data through software and hardware equipment after the test station and route are selected. It is carried out by transmitting a CW wave through the transmitter, setting the frequency to 1,800MHz, and filtering out abnormal data after the test.

B. RESEARCH ON IMPROVED METHODS

This section uses the ISOA to optimize and correct the radio wave propagation model and verify it in the environment of a rectangular tunnel and an arch tunnel. First, the SPM is corrected using the ISOA. The correction environment is a complete tunnel with a total length of 1,200m. Second, in the environment of severe radio wave jitter within the first 500m of the tunnel, the ray-tracing model is corrected using the ISOA. Third, we segment the model and correct the near and far regions with different propagation mechanisms. The final results show that the hybrid propagation model has higher prediction accuracy than the empirical model. The simulation environment of this paper is carried out under MATLAB version 2019a, with an i7-9750H processor.

First, the SPM is corrected for the complete tunnel. Second, the CW wave test data is imported and the parameters are set. Third, the coefficients A_1 – A_7 are calculated by correction.

The diagrams in Figure 8 show a comparison of path loss prediction results between uncorrected SPM and ISOAcorrected SPM. Diagrams a) and b) show the relationship between the fitness function of the ISOA and the number of iterations. It can be seen that the convergence performance of ISOA is good and that it needs a longer iteration time when correcting the arch. The latter is because the propagation path of radio waves in the arch tunnel is more complex and changeable than in the rectangular tunnel. In diagrams c) and d), using the ISOA to correct SPM, we see that the propagation

FIGURE 7. Test results of different algorithms (a) Test function F1 and its performance; (b) Test function F2 and its performance; (c) Test function F3 and its performance; (d) Test function F4 and its performance; (e) Test function F5 and its performance; (f) Test function F6 and its performance.

model after ISOA correction is closer to the measured data, and the error between the SPM and the measured data before correction reaches 20dB. In diagrams e) and f), the errors between the model before and after correction and the measured data under the two tunnel environmental conditions are more intuitively displayed, and it is clear that the path loss prediction of the SPM after ISOA correction is more accurate than before correction. As shown in c) and d), in the near area, the error between the model and the measured data before and after correction is relatively large, while in the far area, the mean square error between the corrected model and the measured data is much smaller than that before correction. Therefore, the IOSA proposed in this paper can accurately optimize the parameters and correct the model.

However, it is worth noting that, as seen in e) and f), while the coefficient of the SPM obtained by applying the ISOA algorithm is more suitable for the tunnel environment, the error is still large in the first 500m. This does not meet the engineering requirements. In both the rectangular tunnel and the arch tunnel environment, when the radio wave propagates in the near region, the antenna polarization mode, antenna gain, and pitch angle will affect the radio wave propagation characteristics, and the waveguide effect has not yet appeared. The SPM cannot reflect the multipath effect caused by the tunnel wall. To predict the near-field path loss more accurately, we will thus use the ray-tracing model for the first 500m and correct the model with ISOA to further improve prediction accuracy. The calculation equation of absolute value error (AE) is as follows equation [\(19\)](#page-8-0). Among them, \hat{p}_n is the predicted propagation loss value, p_n^* is the test propagation loss value.

$$
AE_n = \left| \frac{\hat{p}_n - p_n^*}{p_n^*} \right| \times 100\%
$$
\n(19)

The results from the ray-tracing model after ISOA correction are shown in Figure 9. The prediction accuracy of the ray-tracing model is shown to be significantly higher than the SPM within the first 500m, and the error reaches 2.63, which is lower than the SPM. Compared with the SPM, the parameters of the ray-tracing model have clearer physical

(a) Iterative graph of fitness function of rectangular tunnel

(c) Comparison diagram of SPM model correction of rectangular tunnel

rectangular tunnel

(b) Iterative diagram of fitness function of arch tunnel

(d) Comparison diagram of SPM model correction of arch tunnel

(f) Mean square error between calibration model and measured data of arch tunnel

As shown in Figure 8 9 and 10, the red part is the correction amount. It can be found that, firstly, the correction amount between the first 500 m and the last 500 m of the

in Table 7 for both tunnel environments. The results show that using the ISOA to correct the hybrid propagation model

FIGURE 8. SPM correction, a) Iterative graph of fitness function of rectangular tunnel; b) Iterative diagram of fitness function of arch tunnel; c) Comparison diagram of SPM correction of rectangular tunnel; d) Comparison diagram of SPM correction of arch tunnel; e) Mean square error between calibration model and measured data of rectangular tunnel; f) Mean square error between calibration model and measured data of archtunnel.

meaning and can better reflect the multipath effect in the tunnel. However, the calculations involved in the ray-tracing method are complex, and the high-order waveguide gradually disappears when the radio wave propagates in the far region. Therefore, this method is generally not used across a whole communication area. To quickly and accurately predict the radio wave propagation of the whole tunnel, the ray-tracing model and the SPM are thus combined and corrected using the ISOA algorithm. The ray-tracing model that can reflect multipath effects is used in the near area, and the SPM, which uses convenient and rapid calculations, is used in the far area. The prediction accuracy of the corrected SPM in the far area meets the engineering requirements, and the root mean square error (RMSE) is less than 8dB. The simulated hybrid propagation model is shown in Figure 10 below:

tunnel propagation model is different, which shows that the piecewise establishment of the prediction model proposed in this manuscript is of great significance, and this method can better match the actual propagation situation. Second, the red line changes the error between the corrected model and the uncorrected model, which reflects the excellent performance of the optimization algorithm proposed in this paper. The corrected model is consistent with the test data. The RMSE corrected by the mixed model using the ISOA algorithm and that corrected by the single SPM are shown

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FIGURE 9. Ray tracing model correction, a) Correction model and measured data points under rectangular tunnel; b) Correction model and measured data points under arch tunnel.

(b) Relationship between propagation distance and path loss in arch tunnel

FIGURE 10. Hybrid model correction, a) Relationship between propagation distance and path loss in rectangular; b) Relationship between propagation distance and path loss in arch tunnel.

	TABLE 7. Comparison of RMSE before and after correction.				
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COMPARISON OF RMSE BEFORE AND AFTER CORRECTION

reduces the computational complexity and improves the accuracy of path loss prediction. This approach thus meets the requirements of rapid train operation on the performance of communication systems in the URT environment. Using the corrected hybrid propagation model for coverage planning in a tunnel environment could reduce the interference caused by TD-LTE co-frequency networking and reduce or avoid safety issues caused by poor train communication. The calculation equation of RMSE is shown in equation [\(20\)](#page-10-0).

RMSE =
$$
\sqrt{\frac{\sum_{n=1}^{N} (\hat{p}_n - p_n^*)^2}{N}}
$$
 (20)

C. CONCLUSION

As the main operating environment of urban rail transit, tunnels have the characteristics of limited visible space and multiple reflections of wireless signals. These characteristics make the propagation model different from other environments. The propagation model is an important basis for the design of communication systems and can effectively reduce interference. There have been many accidents in the Shenzhen Metro that caused trains to stop suddenly due to communication interference. In order to enhance the communication security of the tunnel environment and maintain the communication security of the tunnel environment, it is necessary to correct the propagation model in the tunnel environment.

Taking into account the waveguide effect on electromagnetic wave propagation in the far region in a tunnel and the propagation characteristics of intense signal fluctuation within the first 500m of the tunnel due to the influence of antenna gain, polarization mode, and diffraction loss, we divided the radio wave propagation range into two mechanism regions. We then integrated the advantages of an empirical model and a deterministic model, and proposed the use of an ISOA to correct the model.

In this paper, the mixed propagation model was corrected using the ISOA, and it was shown that the deployment of a communication network using the corrected propagation model could effectively ensure the safety of train operation.

Pay attention to the idea of establishing the prediction model in sections and the improved algorithm proposed in this paper. They help obtain the parameters more in line with the actual propagation conditions, improve the accuracy of

TABLE 8. Six benchmark function equations.

the prediction model, and improved the safety performance of trains during operation. In future work, the prediction model and optimization algorithm need to be studied in more detail to continuously improve the correction accuracy to ensure driving safety. Based on this modelling method, this idea is also used in complex environments such as mine, sea, indoor, forest and so on. At the same time, the ISOA proposed in this paper has excellent performance. It can be applied to all occasions suitable for group optimization, such as the selection of optimal parameters of controller, the location selection of distributed devices, some programming problems, and the solution of equations, etc.

APPENDIX

See Table 8.

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