

Article

Research for Road Scenario-Oriented V2V Small-Scale Channel Model Parameter Extraction and Optimization

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Abstract

V2X communication is crucial for intelligent connected vehicles, but suffers from multipath fading. In existing studies, V2X channel modeling primarily employs 2D models or follows the models specified in 3GPP TR36.885. The reliability has not been verified, and it cannot reflect the small-scale fading of multipath fading. There are also problems, such as easy local optimality and slow convergence in model parameter optimization. Therefore, based on the V2V 3D channel model, this paper uses the K-Means++ algorithm to obtain the main category data, takes the main category data as the input, and then uses the genetic algorithm (GA) to perform multi-parameter optimization of the reflection point M and reflection coefficient μ of six scenarios to obtain the optimal parameters. Based on the China Communications Standards Association (CCSA)'s white paper, the Rice factor K was determined. In-chamber and on-road comparison tests were designed to verify the rationality of the parameters optimized by the GA. The experiments show that this model and method can accurately reproduce the characteristics of V2V channels, support the setting of indoor V2X test parameters, and provide a standardized solution for the verification of V2V communication performance.

Keywords: V2V communication; 3D channel model; K-Means++ clustering; genetic algorithm; parameter optimization



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1. Introduction

As the key technical enabler for the collaborative control of intelligent connected vehicles (ICV), V2X communication enables key functions such as collision warning, collaborative lane change, and platoon driving through the real-time transmission of critical information (e.g., vehicle position, speed, and braking status) [1]. The effectiveness of the progress of the dissemination of the V2X message is a matter of OEM (Original Equipment Manufacturer) enterprise anxiety, which has seriously restricted the scale of the development of intelligent connected vehicles.

In recent years, the variability of V2X channel propagation characteristics, e.g., path loss, shadow fading, and small-scale fading, has attracted increasing attention from

academia and industry. Consequently, shadow fading was taken into account at an early stage of the design of the V2X communication mechanism. By optimizing the deployment of roadside units (RSUs), more continuous and reliable V2X signal coverage can be maintained. However, small-scale fading caused by multipath effects remains a critical factor that affects the quality of V2X communication. Therefore, it is necessary to evaluate the small-scale fading based on the V2X channel model [2].

To dispel the doubts of Original Equipment Manufacturer (OEM) enterprises about the practical applicability of V2X channel models, our research team has focused on the study of V2X small-scale fading characteristics in recent years. In 2021, we proposed a scenario-oriented V2V 3D channel model [3], and completed a series of validation tests for the model [4]. Although both on-road field test and in-chamber simulation test results have verified the basic validity of the proposed V2V 3D channel model, further optimization of the model parameters is still needed to improve its adaptability to different actual road scenarios [5]. Based on this, this paper aims to propose a refined optimization method for the key parameters of the V2V 3D small-scale fading channel model.

Differing from the existing research that only optimizes the V2V channel model for a single scenario or 2D model, this paper takes six typical C-V2X road communication scenarios as the research object, and realizes the unified multi-parameter optimization of the V2V 3D small-scale fading channel model for all scenarios through the K-Means++ GA framework, and verifies the optimized parameters with a unified in-chamber and on-road test scheme, forming a standardized scenario-oriented V2V 3D channel model optimization and verification solution.

For the V2V 3D channel model, three channel parameters, the number of reflection points M , the reflection coefficient μ , and the Rice factor K , are the optimization objectives of this study. These three parameters respectively characterize the multipath propagation structure, signal power attenuation law, and dominant mode of the communication channel, so the optimization of the V2V 3D channel model is essentially a multi-parameter optimization problem.

The only problem is that, on the basis of fully considering the V2V fading channel characteristics [5], the optimization algorithm needs to be selected. Due to the complexity and variability of the wireless communication environment, in many cases, the multipath characteristics are often unpredictable, and the collected channel fading data is dynamic and variable. Therefore, it is difficult to track each reflection path and accurately describe the transmission of wireless signals in the medium.

Therefore, in the algorithm selection process, two problems need to be solved. Firstly, the transmission delay and power attenuation of a specific propagation path in the V2V channel are not fixed values but fluctuate within a certain range with the change of the communication environment, so it is necessary to conduct clustering processing on the channel data to extract the typical characteristic rules of the corresponding propagation path. Secondly, due to the high dynamic characteristics of the V2V fading channel, the traditional optimization algorithm easily falls into a local optimal solution in the process of parameter optimization, which affects the optimization effect of the model.

Specifically, the research contributions of this paper are as follows:

- (1). In order to solve the problem of variable delay and power attenuation of specific paths in the V2V 3D channel, this paper uses K-Means++ for clustering to extract the main class features. Differing from the simple application of general clustering algorithms in existing V2V channel modeling, we customize the K-Means++ clustering process with SSE as the evaluation criterion for six typical road scenarios, which realizes the stable extraction of scenario-specific representative channel features and makes up for

the deficiency that traditional clustering algorithms are prone to local optimum and cannot adapt to the dynamic characteristics of V2V channel data.

- (2). Aiming at solving the problem that the multi-parameter optimization of channels is prone to falling into local extremes and has a slow convergence speed, this paper proposes a model framework for multi-parameter optimization based on GA. We innovatively integrate K-Means++ clustering and GA into a two-stage unified framework, and design a V2V channel characteristic-oriented fitness function and scenario-adaptive iteration strategy for GA, which realizes the precise multi-parameter optimization of V2V 3D channel's key parameters (M , μ , and K) for different scenarios. This integrated framework overcomes the limitations of the independent applications of clustering and optimization algorithms in previous studies, and significantly improves the accuracy and stability of channel parameter estimation.

The remainder of the research is as follows. Section 2 describes relevant work. Section 3 introduces the progress of channel data collection and the details of the datasets, and Section 4 presents the proposed K-Means++ GA algorithm, while the corresponding simulation results are discussed. In Section 5, the progress of the in-chamber test is described, and the test results are analyzed. Section 6 discusses the conclusions and future works.

2. Related Works

Clustering and parameter optimization are critical components for enhancing the accuracy of 3D channel models. The existing research focuses mainly on clustering algorithms and optimization algorithms, and the performance of these two algorithms directly affects the model's scene adaptability.

2.1. Selection of Clustering Algorithms

Due to the vehicle movement in real time, V2V channel data is highly dynamic. It is necessary to extract the most representative main class data through clustering algorithms to avoid redundant data interfering with parameter optimization. The core defect of the traditional K-Means algorithm is that the initial clustering centers are random. If the initial clustering centers are concentrated on a certain local data cluster, the clustering process tends to converge to a local optimum, thereby failing to capture the global channel features [6].

The K-Means++ algorithm addresses this issue by improving the initial center selection strategy [7]. It selects the initial center through distance measurement. Ref. [8] proves that the K-Means++ clustering results have a clear upper bound relative to the global optimal solution, which is significantly more stable than traditional K-Means. Ref. [9] generated more representative initial class centers through the K-Means++ algorithm and combined with CNN for feature extraction and classification, significantly improving the accuracy of image classification. Literature [10] uses the K-Means++ algorithm with a structured initialization of cluster centers, which helps avoid energy imbalance caused by unstable clustering. It is suitable for dynamic underwater sensor networks. Therefore, in this paper, the K-Means++ algorithm is directly adopted for channel data clustering.

For the dynamic time slice data of CIR local peaks in six typical V2V road scenarios, we optimize the clustering implementation process with the sum of squared errors (SSE) as the quantitative evaluation criterion for clustering effectiveness. This scenario-oriented customized application allows K-Means++ to avoid the randomness of initial center selection and the deviation of clustering results in the general application, and can stably extract the main class data with physical meaning for each scenario, which is a key improvement compared with the traditional K-Means and the simple application of K-Means++ in existing wireless channel modeling.

2.2. Multi-Parameter Optimization Algorithm

The optimization of key parameters of the V2V 3D channel model belongs to a multi-parameter optimization problem. The performance differences among the existing mainstream algorithms, namely GA [11], Particle Swarm Optimization (PSO) [12], and Simulated Annealing (SA) [13], are significant.

The Alpha-Beta-Guided PSO (ABGPSO) applied to robot path planning directly points out the fundamental limitations of the standard PSO, which is prone to falling into local optima and exhibits slow convergence [14]. Nevertheless, while PSO has been applied to optimize the t-SNE algorithm (t-SNE-PSO) and can improve visualization by balancing exploration and exploitation, its effectiveness remains highly sensitive to parameter settings [15].

The SA typically suffers from slow convergence, and its performance is notably influenced by the initial temperature and the cooling strategy. In the Simulated Annealing with Variable Neighborhood Descent (SAVND) algorithm, designed for solving heterogeneous fleet vehicle routing, SA provides global search capability. However, it often incurs a high computational cost and converges slowly [16]. Moreover, its slow convergence also limits its applicability in real-time control scenarios [17].

In contrast, the Genetic Algorithm (GA) demonstrates a strong global optimization capability and broad applicability [18]. It has been used to tune Deep LSTM hyperparameters for EV energy prediction (GA3P-DLSTM) [19] and to improve ensemble models for flood susceptibility mapping [20]. In wireless sensor networks, optimized deployment can reduce energy use by about 50% [21]. GA can outperform PSO in microgrid management when energy supply and demand fluctuate, and it helps to maintain system stability [22]. For IoT-monitored microgrids, GA can also tune PID controllers effectively [23].

In the dynamic and high-dimensional specific task of the multi-parameter optimization of V2V channel parameters, the inherent defects of the PSO algorithm (prone to local optima) and the SA algorithm (slow convergence) have been verified by relevant research in the field [14,16,24]. GA provides robust global search and stable convergence in complex optimization settings. Based on this, we carry out a targeted customization of GA for the multi-parameter optimization demand of the V2V 3D channel model, by taking the relative power attenuation AT , the core characteristic parameter of V2V multipath fading, as the core index to design the fitness function and designing scenario-adaptive iteration times for six typical road scenarios. This customized design makes GA more suitable for the characteristics of V2V channel data and the multi-scenario optimization demand, and solves the problems of local optimum and slow convergence existing in the application of PSO and SA in V2V channel parameter optimization in previous studies. In addition, the integration of GA with the preprocessed main class data by K-Means++ further improves the efficiency and accuracy of parameter optimization, which differs from the single GA application without targeted data preprocessing in the existing research.

3. Data Collection and Datasets

3.1. Data Collection System

Thanks to the support of the R&S company, a data collection system has been constructed, as shown in Figure 1. The transmit vehicle is equipped with a signal source (R&S SMW200A) generating a PN spread signal. Meanwhile, a Spectrum analyzer (R&S FSW) (Rohde & Schwarz, Munich, Germany) and an IQ recorder (R&S I/Q Recorder) (Rohde & Schwarz, Munich, Germany) are equipped on the receiving vehicle. Two omnidirectional dipole antennas are installed on the roofs of both vehicles. The channel measurement parameter configuration used by the road measurement system is shown in Table 1.

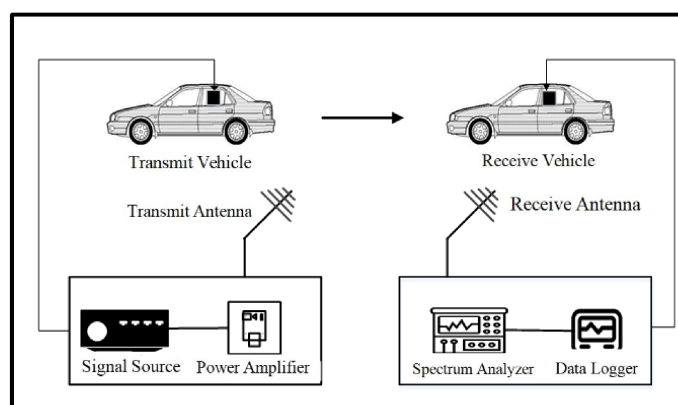


Figure 1. Schematic diagram of the Data collection system.

Table 1. Channel measurement parameter configuration.

Parameter	Configuration
Carrier frequency	5.905 GHz
Frequency bandwidth	20 MHz
Transmission power	18 dBm
Transmitting antenna	omnidirectional dipole antenna
Receiving antenna	omnidirectional dipole antenna
The height of the transmitting/receiving antenna	2 m

According to the suggestion of CCSA, six typical scenarios, which are Low urban canyon, high urban canyon, rural road, tunnel, highway, and overhead bridge, are selected, as shown in Figure 2. The relevant parameters for the above six scenarios are listed in Table 2. For a more concise expression, a low urban canyon is abbreviated as S-1, a high urban canyon is abbreviated as S-2, a rural road is abbreviated as S-3, a tunnel is abbreviated as S-4, a highway is abbreviated as S-5, and an overhead bridge is abbreviated as S-6.

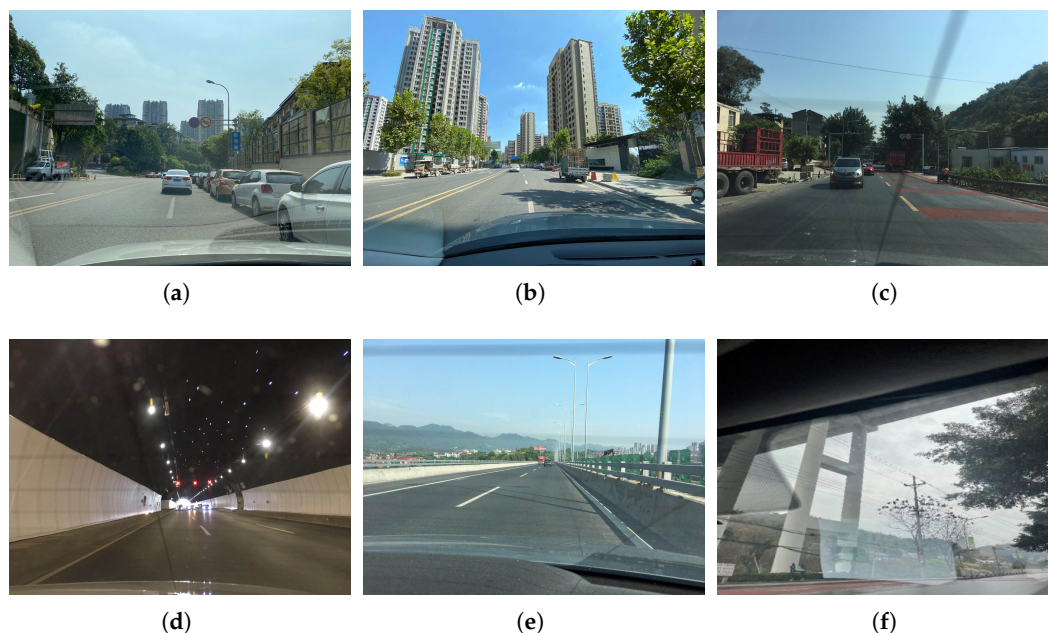


Figure 2. Typical C-V2X communication scenarios' measurement. (a) Low urban scene. (b) High urban scene. (c) Rural road scene. (d) Tunnel scene. (e) Highway scene. (f) Elevated scene.

Table 2. Selected typical scenarios' parameters.

Scene	S-1	S-2	S-3	S-4	S-5	S-6
Test distance	124 m	142 m	100 m	60 m	100 m	100 m
Distance to road-side buildings	7 m/10 m	10 m/12 m	7 m/10 m	5 m/7 m	5 m/7 m	5 m/7 m
Velocity	30 km/h	30 km/h	30 km/h	50 km/h	100 km/h	100 km/h

In our previous research, we determined the range of the number of reflection points M , as detailed in Table 3 [3]. The reflection coefficient μ is classified based on the materials of common existing buildings, and the relevant information is presented in Table 4.

Table 3. Typical C-V2X communication scenarios and scattering points M .

Scene	M Value
S-1	≤ 15
S-2	≤ 50
S-3	≤ 15
S-4	≤ 8
S-5	≤ 9
S-6	≤ 20

Table 4. Typical scene reflection type.

Scene	Reflection Type
S-1	diffuse ¹ , general ² and strong ³
S-2	diffuse, general and strong
S-3	diffuse and general
S-4	diffuse and general
S-5	diffuse and general
S-6	diffuse and general

¹ Diffuse: $\mu \leq 0.1$. ² general: $0.1 \leq \mu \leq 0.6$. ³ strong: $0.6 \leq \mu \leq 1$.

3.2. Collected Data

The on-road V2V channel data acquisition was carried out in July and December 2021, and the single sampling duration of each scenario is set to about 1 min, a scenario-adaptive design tailored to the high mobility of V2V communication nodes and the time-varying characteristics of channel fading—this short time window can avoid the interference of non-scenario-specific factors (e.g., sudden traffic flow changes and random obstacles) and ensure the collection of typical multipath fading data for the target scenario. The data acquisition times of the six typical scenarios are listed in Table 5, and the cumulative measurement duration of each scenario reaches 15–20 min with multiple repeated measurements, forming a large-scale valid dataset for channel parameter estimation.

Table 5. The data acquisition times.

Scene	S-1	S-2	S-3	S-4	S-5	S-6
Value	20	19	18	15	18	15

In the High urban scenario, an example of data collection is shown in Figure 3. The sample data were recorded by an IQ data logger. Each file is named by the data collection time, as shown in Figure 4. The sample data content includes the following:

- (1). Channel parameters: The multipath number of channel impulse response, relative path power loss, relative path delay, noise threshold, maximum delay spread, average delay spread, etc.
- (2). System parameters: The frequency band bandwidth, carrier frequency, transmission power, number of samples, etc.

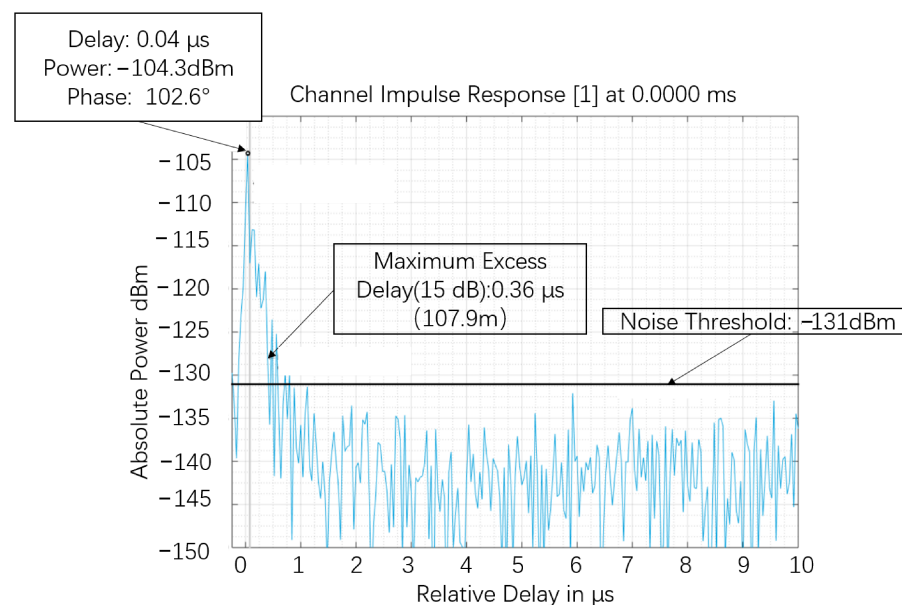


Figure 3. Schematic diagram of road measurement data.

0828gaoj	2020/11/24 22:19	Microsoft Acces...	48,950 KB
0828gaoj2	2020/11/25 16:03	Microsoft Acces...	48,950 KB
0828gaoj3	2020/11/25 16:04	Microsoft Acces...	48,950 KB
0828gs09	2020/11/24 22:24	Microsoft Acces...	48,950 KB
08251023	2020/11/25 11:24	Microsoft Acces...	48,950 KB
08251026	2020/11/25 11:28	Microsoft Acces...	48,950 KB
08251028	2020/11/25 11:31	Microsoft Acces...	48,950 KB
08251030	2020/11/25 11:34	Microsoft Acces...	48,950 KB
08251033	2020/11/25 11:36	Microsoft Acces...	48,950 KB
08251035	2020/11/25 13:33	Microsoft Acces...	48,950 KB
08251041	2020/11/24 19:20	Microsoft Acces...	48,950 KB
08251043	2020/11/25 13:36	Microsoft Acces...	48,950 KB
08251045	2020/11/25 10:33	Microsoft Acces...	48,950 KB
08251048	2020/11/24 20:16	Microsoft Acces...	48,950 KB
08251051	2020/11/24 20:31	Microsoft Acces...	48,950 KB
08251054	2020/11/24 18:56	Microsoft Acces...	48,950 KB
08251056	2020/11/24 19:37	Microsoft Acces...	48,950 KB
08251100	2020/11/24 19:52	Microsoft Acces...	48,950 KB

Figure 4. Schematic diagram of export data.

The collected dataset is preprocessed by the channel impulse response (CIR) extraction software package provided by R&S. We selected the data obtained from a single collection, and the detailed information is shown in Figure 5. The CIR curve is obtained from ChannelSnapshots and the involved fields are shown in Figure 6. For the noise threshold, it was calculated based on the R&S I/Q recorder.

We took the first sample of each scenario as an example, extracted the measured data above the noise threshold, and plotted the CIR curve, as shown in the Figure 7. The CIR curve exhibits numerous local peaks that generally correspond to propagation paths, which exert a significant impact on the received signal quality.

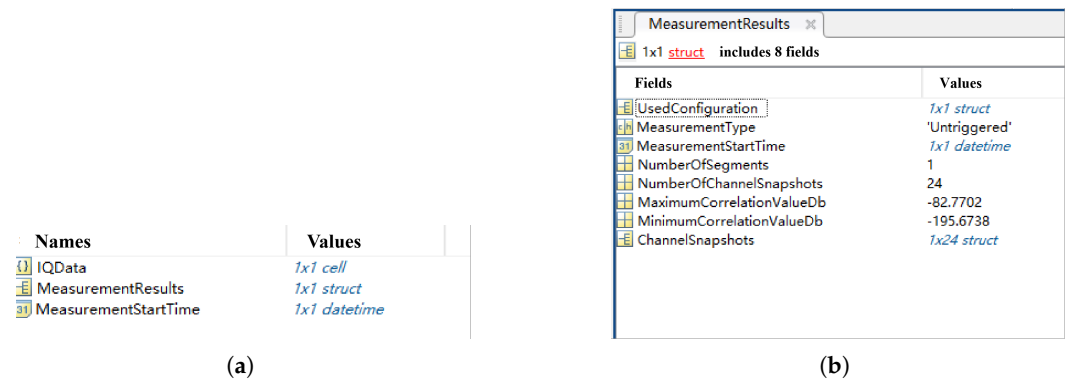


Figure 5. Details of a single snapshot. (a) Overview of the single Snapshot. (b) Details of the MeasurementResults.

MeasurementResults.ChannelSnapshots			
Fields	ComplexLinearPdpValues	DelayValues	DetectedNoiseThreshold
1	1x257 complex double	1x257 double	-128.5348
2	1x257 complex double	1x257 double	-129.0213
3	1x257 complex double	1x257 double	-128.9974
4	1x257 complex double	1x257 double	-128.6736
5	1x257 complex double	1x257 double	-129.0713
6	1x257 complex double	1x257 double	-128.6741
7	1x257 complex double	1x257 double	-129.3049
8	1x257 complex double	1x257 double	-128.6245
9	1x257 complex double	1x257 double	-128.6663
10	1x257 complex double	1x257 double	-129.8563
11	1x257 complex double	1x257 double	-128.9975
12	1x257 complex double	1x257 double	-129.3394
13	1x257 complex double	1x257 double	-128.9363
14	1x257 complex double	1x257 double	-129.1430
15	1x257 complex double	1x257 double	-128.7028
16	1x257 complex double	1x257 double	-129.7700
17	1x257 complex double	1x257 double	-129.5924
18	1x257 complex double	1x257 double	-129.3226
19	1x257 complex double	1x257 double	-130.2013
20	1x257 complex double	1x257 double	-129.2295
21	1x257 complex double	1x257 double	-128.6359

Figure 6. Schematic diagram of export data.

The characteristic information of the local peak points on the CIR curve can be characterized by two key factors: the normalized power attenuation (AT) and normalized delay (TD). Therefore, the whole CIR curve can be converted into discrete time slice data in the form of (AT, TD) . In this paper, the duration of a single time slice is set to 0.0048 s to balance the data resolution and calculation efficiency.

Then, the raw data slice is expressed as

$$DATA = \{(AT, TD)_1, (AT, TD)_2, \dots, (AT, TD)_N\} \quad (1)$$

where N is the number of valid local peak points.

Based on the construction of road scene data fragments, the raw dataset is expressed as follows:

$$D_{data} = \{DATA_1, DATA_2, \dots, DATA_N\} \quad (2)$$

where N is the number of datasets.

Due to the time-varying characteristics of the V2V channel, the local peak points on the CIR curve also show dynamic changes, but the (AT, TD) characteristic values of the peak

points in the same propagation path fluctuate within a relatively narrow range. Based on this characteristic, we can carry out similarity clustering classification on the time slice data, and the clustering results are used as the data basis for the subsequent multi-parameter optimization of channel model parameters.

Therefore, the proposed K-Means++ GA algorithm includes two key steps, which are K-Means++ clustering and GA multi-parameter optimization.

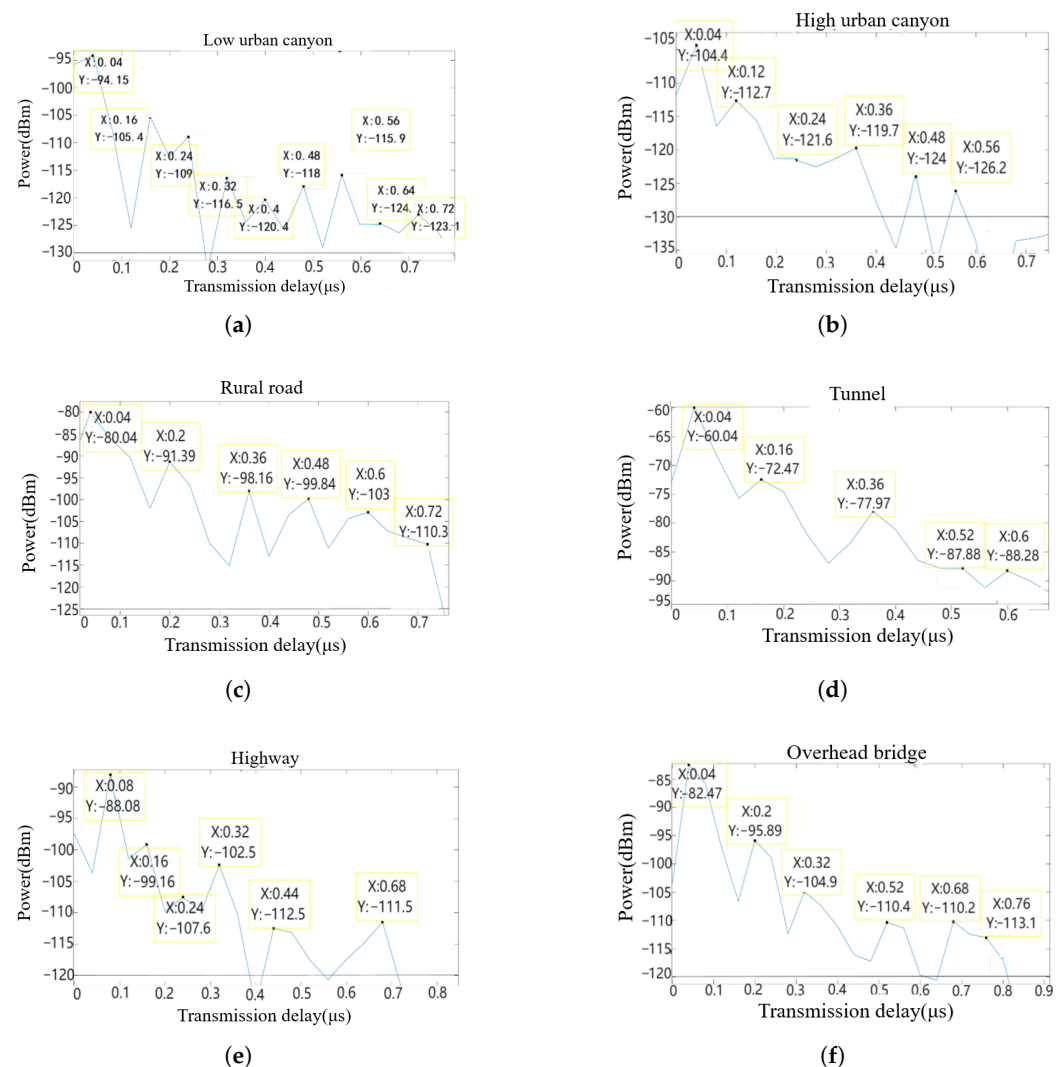


Figure 7. Channel impulse response of different scenes (a) S-1, (b) S-2, (c) S-3, (d) S-4, (e) S-5, and (f) S-6.

4. K-Means++ GA Algorithm

4.1. 3D Small-Scale Fading Channel

In our previous research [4], based on the 2D channel model, a 3D channel model was proposed by adding the elevation angle parameter. Thus, under small-scale fading, the channel exhibits frequency non-selectivity, and the cOmplex Channel Fading Envelope $h(t)$ can be denoted as

$$3D_h(t) = 3D_h_{LOS}(t) + 3D_h_{NLOS}(t) \quad (3)$$

(1). LOS component:

The core of the LOS component lies in the power ratio and spatial phase characterization. The 3D model fully inherits the power ratio logic of the 2D model, only extending the planar distance to 3D spatial distance and optimizing the phase term. The 3D Complex Channel Fading Envelope (LOS) focuses on the core characteristics of fading, simplifying the Doppler frequency shift term, with the following formula:

$$3D_h_{LOS}(t) = \sqrt{\frac{K}{K+1}} e^{-j2\pi f_c D_{LOS}/c} \quad (4)$$

where K is the Rice factor and f_c is the carrier frequency, which is set to 5.9 GHz; D_{LOS} is the distance between transmitter T_x and receiver R_x , $c = 3 \times 10^8$ m/s, which is the wave velocity.

(2). NLOS component:

The NLOS component characterizes the characteristics of reflected/scattered links. Based on the multipath superposition logic of the 2D model, the 3D model achieves 3D adaptation through path decomposition and spatial extension.

The 3D Complex Channel Fading Envelope (NLOS) focuses on the core characteristics of fading, simplifying the Doppler frequency shift term and the number of planar scatterers N , with the following formula:

$$3D_h_{NLOS}(t) = \sqrt{\frac{1}{K+1}} \lim_{M \rightarrow \infty} \frac{1}{\sqrt{M}} \sum_{i=1}^M \mu e^{j(\theta_i - 2\pi f_c D_{pmi}^{NLOS}/c)} \quad (5)$$

where θ_i is the phase difference between LOS path and NLOS path, and obeys uniform distribution between $[0, 2\pi]$, μ is the reflection coefficient, and M is the number of reflection points. D_{pmi}^{NLOS} is the length of one reflection path, and is denoted as

$$D_{pmi}^{NLOS} = D_{pli}^{NLOS} + D_{lmi}^{NLOS} \quad (6)$$

D_{pli}^{NLOS} and D_{lmi}^{NLOS} can be obtained according to the 2D model D_{pli}^{NLOS} , D_{lmi}^{NLOS} and ϵ_i , as shown in Figure 8 [4].

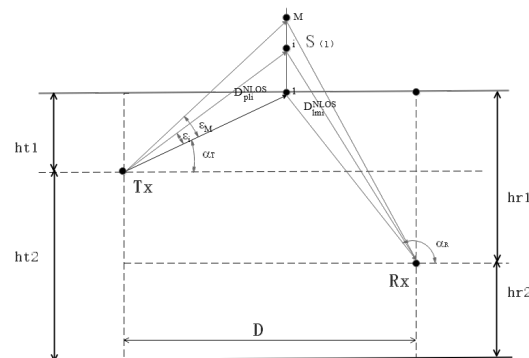


Figure 8. Schematic diagram of 2D model.

4.2. K-Means++

K-Means requires the initial cluster centers to be specified manually. Different initial clustering centers may lead to completely different clustering results. However, in the dataset of this paper, the power and delay of the same peak vary. As a result, the cluster centers cannot be set in advance. The K-Means++ [8], which randomly selects a data point as the first cluster center, meets the requirements of this experiment.

The core idea of the K-Means++ algorithm is as follows:

Step 1: Randomly select a point from the constructed dataset as the first clustering center.

Step 2: The remaining centers are chosen using a distance-based probability. For each sample, the shortest distance to the current centers is computed. The next center is selected by wheel sampling, where samples farther away have a higher selection probability. This is repeated until all k centers are obtained.

Step 3: If the cluster number is less than a given value k_m , go back to step 2, until the k_m -th cluster center is selected.

Step 4: The K-Means clustering process is performed on the basis of previous experience and knowledge (clustering center and clustering number).

To determine the appropriate number of clustering centers, the sum of squared errors (SSE) was adopted as the measurement criterion. Its calculation involves the total of the Euclidean distances between the current available clustering centers and their respective center point clusters. The specific calculation method is as follows:

$$SSE = \sum_{s=1}^{k_m} \sum_{pos \in c_s} |pos - m_s|^2 \quad (7)$$

where pos represents the position of the current point, m_s represents the position of the corresponding cluster center point, k_m represents the number of cluster centers, and c_s represents the specific cluster. A simple schematic diagram is shown as Figure 9:

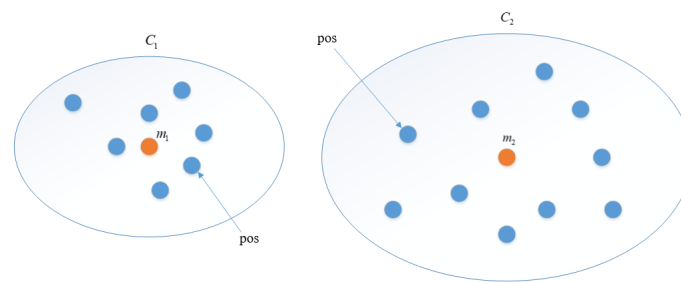


Figure 9. SSE schematic diagram.

We take the measured data of the second peak in the scene of a Low urban canyon as an example. From this, we can obtain the second peak's SSE and the number of categories after clustering based on SSE, as shown in the Figure 10.

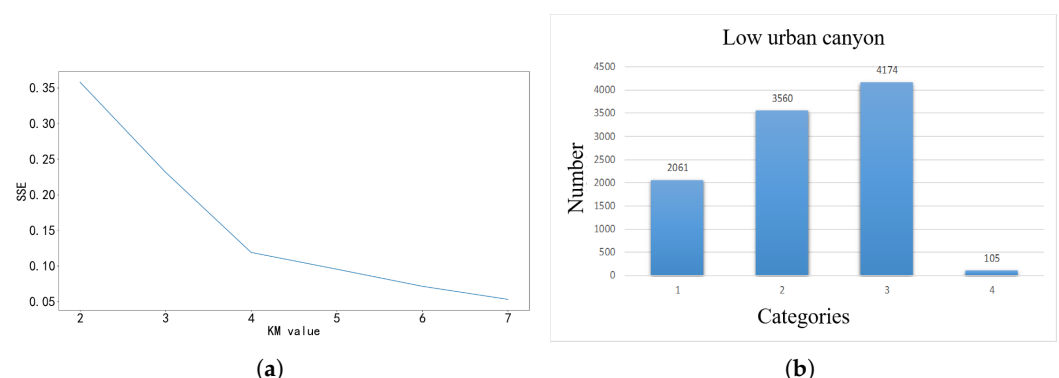


Figure 10. The second peak clustering effect of the Low urban scene. (a) The second peak SSE. (b) Number of second peak categories.

In Figure 10a, it can be seen that for the second peak of the measured data of the Low urban canyon, when the number of clusters (k_m value) is four, there is a significant inflection point in the SSE, and the slope undergoes a significant change; at this time, the clustering

effect is relatively good. According to the elbow rule, the number of main class data and non-main class data of the peak can be obtained, as shown in Figure 10b.

The corresponding clustering results of all six scenarios are listed in Table 6.

Table 6. Peak data clustering in typical C-V2X communication scenarios.

Scene	Peak	1	2	3	4	5	6	7	8	9
S-1	$N_{clusters}$	/	4	3	3	3	4	4	4	3
	R_{main}	/	0.417	0.642	0.401	0.599	0.398	0.584	0.391	0.606
S-2	$N_{clusters}$	/	3	3	4	4	3	/	/	/
	R_{main}	/	0.823	0.875	0.889	0.812	0.789	/	/	/
S-3	$N_{clusters}$	/	4	3	3	3	3	/	/	/
	R_{main}	/	0.503	0.672	0.526	0.493	0.512	/	/	/
S-4	$N_{clusters}$	/	3	3	3	4	/	/	/	/
	R_{main}	/	0.503	0.672	0.526	0.493	/	/	/	/
S-5	$N_{clusters}$	/	3	3	4	3	3	/	/	/
	R_{main}	/	0.631	0.642	0.596	0.693	0.612	/	/	/
S-6	$N_{clusters}$	/	3	3	4	3	3	/	/	/
	R_{main}	/	0.624	0.678	0.682	0.602	0.712	/	/	/

4.3. Multi-Parameter Optimization of Model Based on GA

In this work, GA is applied to the clustered dominant peak data to optimize three channel parameters: the number of reflection points M , the reflection coefficient μ , and the Rice factor K . The specific implementation of the GA is as follows:

(1). Population initialization:

Each individual represents a feasible solution, with two parameters, M and μ . Consequently, the initial population is generated as a matrix $100 \times 2 [M, \mu]$.

(2). Population fitness:

The fitness function measures how well an individual parameter set $[M, \mu]$ matches the observed channel characteristics, which is denoted as follows:

$$Opt_{M,\mu} = |AT_i - AT_i^{cal}(M, \mu)| \quad (8)$$

where AT_i is the relative power attenuation of the NLOS and LOS paths for the i -th peak main class data, and AT_i^{cal} is the calculated relative power attenuation for the same paths. The power and power attenuation corresponding to different NLOS and LOS paths can be obtained:

$$G_R^i = G_T * \mu^{N_{ref}^i} \quad (9)$$

$$AT_i^{cal} = 10lg\left(\frac{G_R^i}{G_t}\right) \quad (10)$$

where G_R^i is the power of the i -th NLOS path and N_{ref}^i is the number of reflections experienced by the i -th NLOS path, which is denoted as follows:

$$N_{ref}^i = floor\left(\frac{P_i^{NLOS}}{D_{pmi}^{NLOS}}\right) + 1 \quad (11)$$

where D_{pmi}^{NLOS} is defined in Equation (6) and floor is rounding down. P_i^{NLOS} is the length of each NLOS path and is denoted as

$$P_i^{NLOS} = P_i^{LOS} + TD_i * c \quad (12)$$

where P_i^{LOS} is the length of the LOS path, and TD_i is the relative delay between the NLOS and LOS paths for the i -th peak main class data.

(3). Selection:

Based on the fitness function in Equation (8), a population of 100 individuals, whose fitness is denoted by p , is evaluated. The survival number of each individual in the next generation is determined by

$$Number = 100 * \frac{\frac{1}{Opt_i}}{\sum \frac{1}{Opt_i}} \quad (13)$$

Then, the integer part of the number is taken as the confirmed survival count for each individual in the next generation. To keep the population size fixed at 100, the roulette selection method [25] is adopted to fill the remaining individuals.

(4). Crossover:

Based on the crossover probability, the individuals of the next-generation population are randomly paired. Subsequently, a single-point crossover strategy is applied to each paired individual [26]. When the crossover probability is between 0.9 and 1 [27], it can effectively avoid entering the local optimum.

(5). Mutation:

Based on the mutation probability, this paper randomly modifies the parameter values at specific positions in an individual. To avoid a local optimum, the selected mutation probability is 0.01 in this experiment.

(6). Generation:

After completing the selection, crossover, and mutation operations of the population, the fitness value of all individuals in the new generation population is re-evaluated, and the individual with the minimum fitness value (i.e., the maximum matching degree with the actual channel data) is selected as the optimal individual of this iteration. The above steps are repeated for iterative optimization until the maximum number of iterations is reached, and the optimal individual of the final iteration is the optimal parameter combination of the channel model.

The optimizing iteration progress is shown in Figure 11. For the relative attenuation power (AT) and relative delay (TD) measured in the typical six scenarios, we used GA, SA, and PSO to conduct optimization searches for M and μ , and then calculated the predicted relative attenuation power in reverse. Finally, we obtained the relative predicted power error, as shown in Figure 12. It is clearly evident that in almost all six classic scenarios, the relative error of GA is smaller than that of PSO and SA. The corresponding algorithm is given in Algorithm 1, while the variable explanation is listed in Table 7. Iterations of all six scenarios are listed in Table 8.

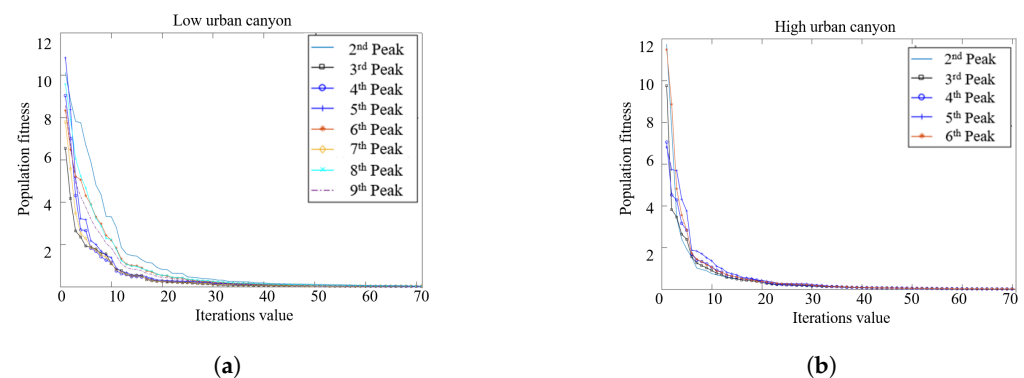


Figure 11. Cont.

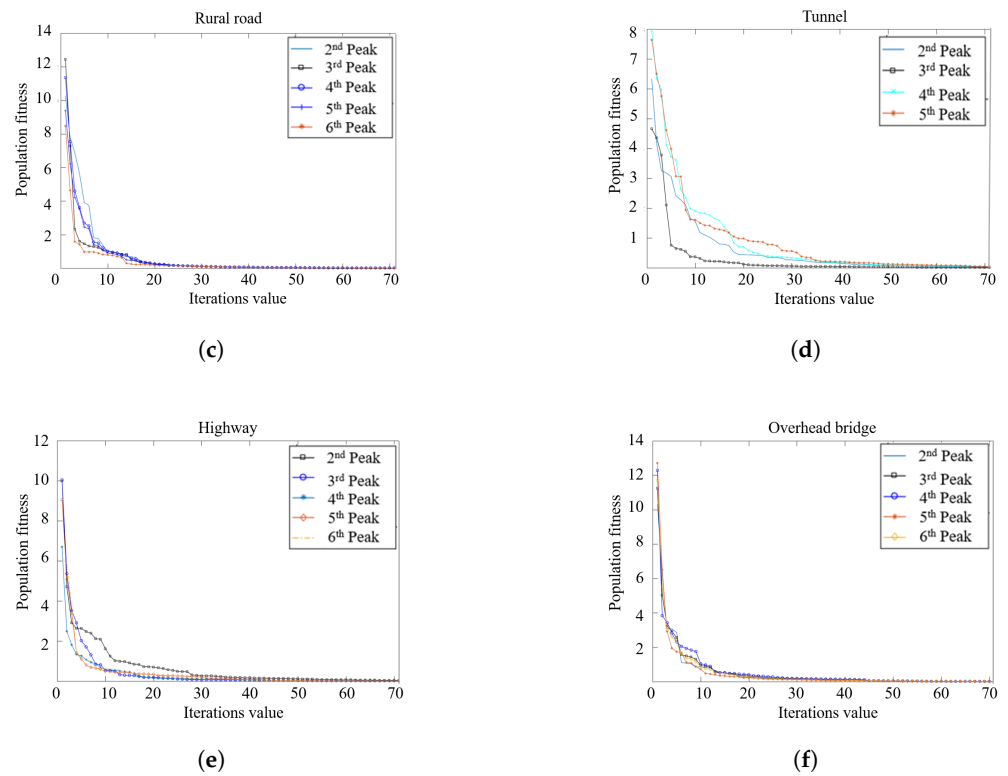


Figure 11. Algorithm iteration diagram for different typical C-V2X communication scenarios: (a) S-1, (b) S-2, (c) S-3, (d) S-4, (e) S-5, and (f) S-6.

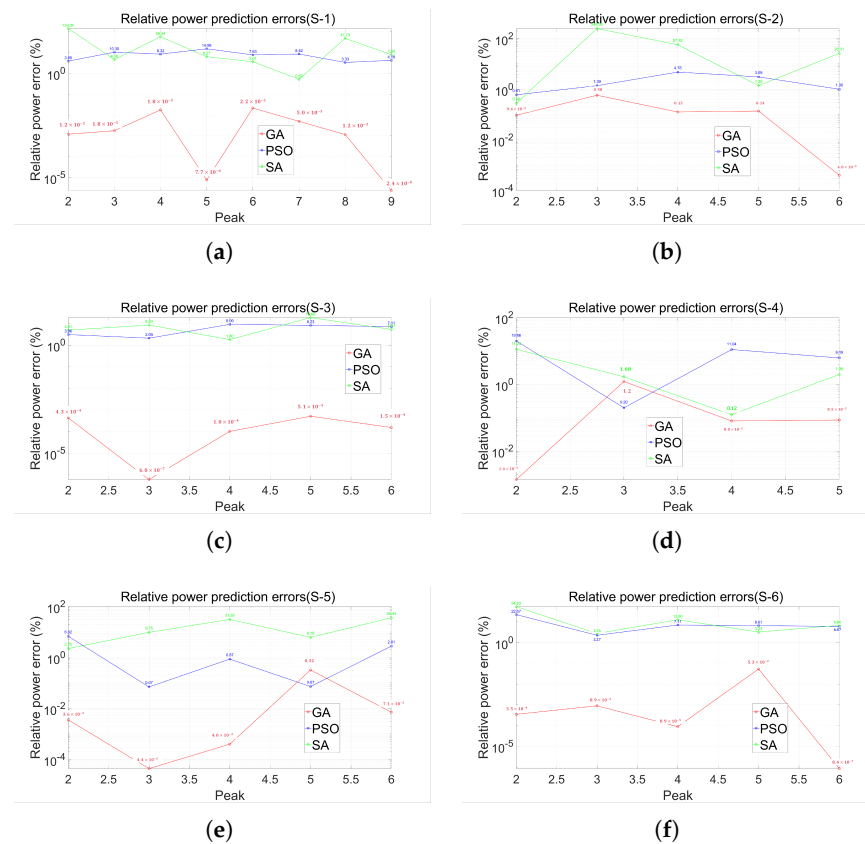


Figure 12. The relative error of predicted attenuation power for the three algorithms: (a) S-1, (b) S-2, (c) S-3, (d) S-4, (e) S-5, and (f) S-6.

Algorithm 1: Parameter optimization methods for different typical C-V2X communication scenario models based on GA.

Require: $Major_{data} \leftarrow \emptyset$
Ensure: Optimal vector: M, μ vector

```

1: for  $i = 1$  to  $N$  do
2:    $t = 0$ 
3:    $Pop\_vector(t) \leftarrow Initialize()$ 
4:    $AT_i, TD_i \leftarrow Get(Major_{data})$ 
5:   while  $t \leq T$  do
6:     for  $j = 1$  to  $Num$  do
7:        $Opt\_vector \leftarrow Evaluate\_fitness(Pop\_vector(t), AT_i, TD_i)$ 
8:     end for
9:      $new\_Pop\_vector(t) \leftarrow Select(Opt\_vector)$ 
10:    if  $random(0, 1) < P_c$  then
11:       $Crossover(new\_Pop\_vector(t))$ 
12:    end if
13:    if  $random(0, 1) < P_b$  then
14:       $Mutation(new\_Pop\_vector(t))$ 
15:    end if
16:     $Pop\_vector(t + 1) \leftarrow new\_Pop\_vector(t)$ 
17:     $t = t + 1$ 
18:  end while
19:   $best\_M, \mu \text{ vector} \leftarrow GetBest(Pop\_vector(t))$ 
20:   $M, \mu \text{ vector.push\_back}(best\_M, \mu \text{ vector})$ 
21: end for
22: return  $M, \mu$  vector

```

Table 7. Explanation of variables and functions in the Algorithm 1.

Variables/Functions	Explanation
$Major_{data}$	Main class datasets with different peaks
M, μ vector	The vector of the optimal values of M and μ for all the peaks in this scene
t	Number of population iterations
N	The number of peaks in the main class dataset
$Pop_vector(t)$	The vector of the M, μ population
$Initialize()$	Initialize the population and output $Pop_vector(t)$
$Get(d)$	Obtain AT_i and TD_i from dataset d
T	The maximum number of iterations of the population
Num	The total number of individuals in the population
Opt_vector	Population individual fitness vector
$Evaluate_fitness(a, b, c)$	Calculate the fitness of individuals in the population and output Opt vector
$new_Pop_vector(t)$	New population vector
$Select(F)$	Based on the fitness F selection, output $new_Pop_vector(t)$
$random(0,1)$	Randomly generate a random number between 0 and 1
P_c / P_b	Population crossover probability/mutation probability
$Crossover(x)$	Perform a crossover operation on population x and update population x
$Mutation(x)$	Perform mutation operations on population x and update population x
$best_M, \mu$ Vector	The optimal value vector of M, μ corresponding to a certain peak
$GetBest(p)$	Obtain the best M, μ vector in the population vector p at the end of the iteration

Table 8. The value of iterations.

Scene	S-1	S-2	S-3	S-4	S-5	S-6
Value	60	60	50	70	60	50

4.4. K Value

The Rice factor K is used to describe the channel quality, and its value is the power ratio of the LOS propagation component to the NLOS propagation component. In this paper, the multipath component method is adopted to calculate K , and the calculation formula is as follows:

$$K = 10 \log_{10} \left(\frac{G_1}{\sum_{i=2}^n G_i} \right) \quad (14)$$

where G_1 is the power of the first peak, and G_i represents the power of the i -th peak. Furthermore, according to the CCSA white paper, the Rice factor K of different typical C-V2X communication scenarios was extracted. This K value serves as the criterion for fitting the Rice factor in the channel model, as shown in Table 9.

Table 9. Rice factor K effective range.

Scene	K Value
S-1	$8.92 \pm \sqrt{3.46}$
S-2	$8.92 \pm \sqrt{3.46}$
S-3	$8.92 \pm \sqrt{3.46}$
S-4	$7.44 \pm \sqrt{2.55}$
S-5	$12.48 \pm \sqrt{3.51}$
S-6	$12.48 \pm \sqrt{3.51}$

4.5. Reference Value

On the basis of the above, the reference values of the 3D small-scale V2V channel model parameters are listed in Table 10. After fitting and optimization, the optimal number of reflection points M and the reflection coefficient μ corresponding to different peaks in different typical C-V2X communication scenarios are reported in Table 10 together with AT , TD , and K . The fitted K values for all six scenarios fall within the valid range and meet the required criteria.

Table 10. Results of channel model fitting and optimization in different typical C-V2X scenarios.

Scene	Peak	1	2	3	4	5	6	7	8	9
S-1	M	/	2	3	4	5	6	7	9	10
	μ	/	0.271	0.317	0.273	0.300	0.396	0.424	0.453	0.504
	AT	0	−11.34	−14.96	−22.57	−26.14	−24.11	−26.12	−30.96	−29.72
	TD	0	0.12	0.20	0.28	0.36	0.44	0.52	0.60	0.68
	K					9.1489				
S-2	M	/	1	2	2	3	4	/	/	/
	μ	/	0.092	0.185	0.172	0.230	0.277	/	/	/
	AT	0	−10.37	−14.64	−15.30	−19.13	−22.29	/	/	/
	TD	0	0.11	0.20	0.32	0.44	0.52	/	/	/
	K					7.5932				

Table 10. Cont.

Scene	Peak	1	2	3	4	5	6	7	8	9
S-3	M	/	3	4	6	7	9	/	/	/
	μ	/	0.364	0.309	0.401	0.390	0.456	/	/	/
	AT	0	−13.16	−20.39	−23.45	−28.61	−30.72	/	/	/
	TD	0	0.16	0.32	0.44	0.56	0.68	/	/	/
	K					10.5416				
S-4	M	/	2	5	7	8	/	/	/	/
	μ	/	0.377	0.485	0.418	0.480	/	/	/	/
	AT	0	−8.47	−15.71	−26.55	−25.54	/	/	/	/
	TD	0	0.12	0.32	0.48	0.56	/	/	/	/
	K					7.5933				
S-5	M	/	2	3	4	6	9	/	/	/
	μ	/	0.305	0.259	0.324	0.387	0.528	/	/	/
	AT	0	−10.32	−17.61	−19.60	−24.77	−24.99	/	/	/
	TD	0	0.08	0.16	0.24	0.36	0.6	/	/	/
	K					12.2433				
S-6	M	/	2	4	6	8	8	/	/	/
	μ	/	0.230	0.243	0.354	0.431	0.397	/	/	/
	AT	0	−12.77	−24.60	−27.08	−29.24	−32.12	/	/	/
	TD	0	0.16	0.28	0.48	0.64	0.72	/	/	/
	K					12.2146				

5. In-Chamber Test Verification

To validate the actual application effect of the optimized V2V 3D small-scale fading channel model proposed in this paper, we designed a set of in-chamber simulation verification tests, with CAERI (China Automotive Engineering Research Institute Co., Ltd., Chongqing, China), which provided the anechoic chamber test environment and the professional V2X communication test system required for the test. The overall layout of the in-chamber test environment is shown in Figure 13, and the detailed installation of the test equipment is shown in Figure 14.

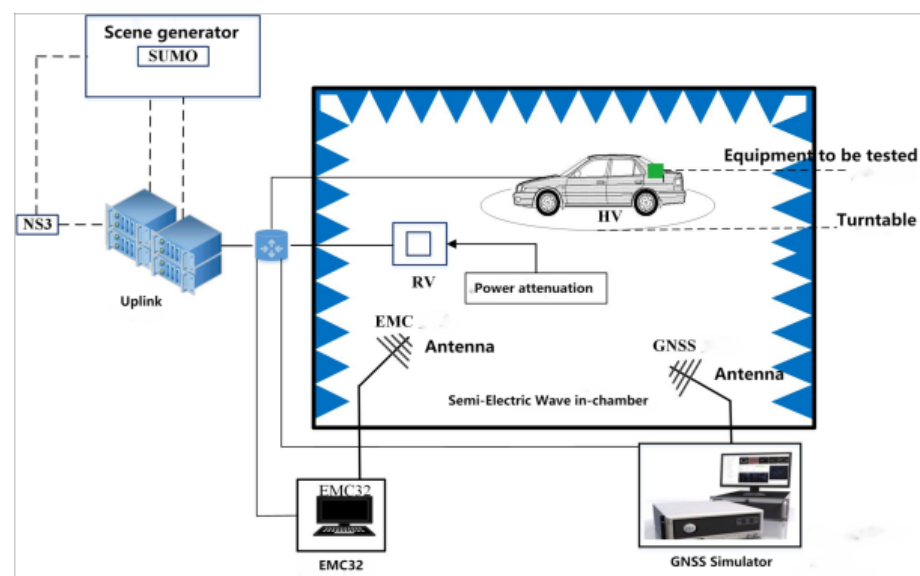


Figure 13. Schematic diagram of anechoic chamber test environment layout.

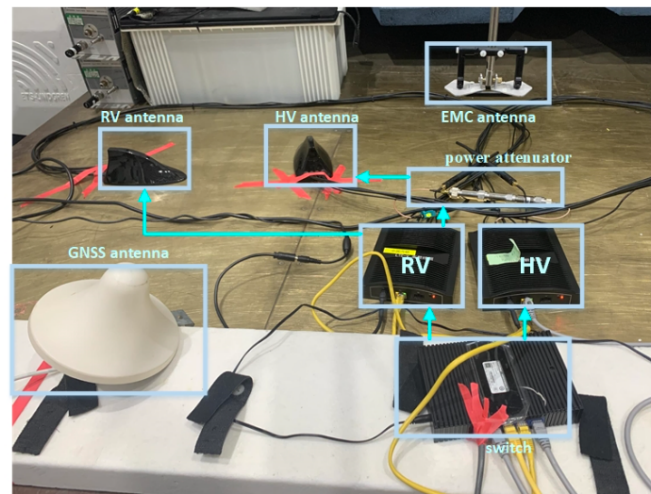


Figure 14. Actual layout of anechoic chamber test equipment.

Five typical C-V2X scenarios were selected for on-road field testing. Significantly, tunnel tests were excluded due to GPS timing loss and unstable data. The verification procedure was as follows:

- (1). Collect on-road V2V performance metrics (e.g., packet loss rate and transmission delay) at the same locations as channel data acquisition.
- (2). Integrate the proposed channel model into the test control platform to configure the testbed's transmission parameters.
- (3). Collect the corresponding V2V performance data in the anechoic chamber environment.
- (4). Compare the anechoic chamber test results with the on-road field results.

There is a problem relating to GPS timing loss in the tunnel scenario, which leads to unstable response characteristics and the inability to upload the test data normally. Therefore, only the remaining five scenarios are considered here. The corresponding results are shown in Figure 15, and the relative error of packet loss and transmission delay are shown in Table 11.

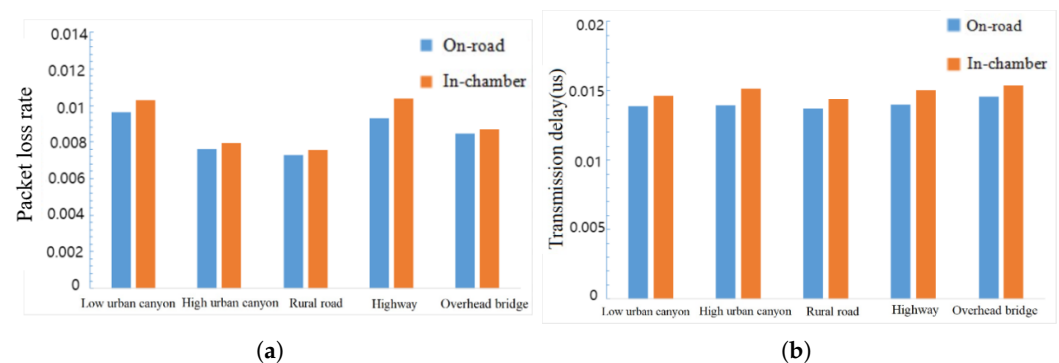


Figure 15. Test verification results. (a) Packet loss rate. (b) Transmission delay.

Table 11. The relative error value of packet loss and transmission delay.

Sence	S-1	S-2	S-3	S-5	S-6
packet loss	2%	1%	1%	4%	1%
Transmission delay	3%	7%	3%	7%	3%

As shown in Figure 15 and Table 11, the packet loss rate in outdoor tests across the six typical scenarios (excluding the tunnel) ranges from 0.7% to 1%, which is consistently lower than in the anechoic chamber tests, with a maximum difference of 4% between indoor and

outdoor results. Meanwhile, the delay in outdoor tests is consistently lower than in the anechoic chamber tests, which indicates that real road factors, such as roadside trees and traffic, affect transmission latency.

Tables 12 and 13 present the statistical results of the packet loss rate and transmission delay in the outdoor and indoor test scenarios, respectively. For all scenarios, both the outdoor and indoor measurements yield small standard deviation values and narrow 95% confidence intervals, indicating high data stability and reliability. The mean values of PLR and the delay between the indoor and outdoor tests are extremely close across all environments, demonstrating the strong consistency between the laboratory and real-world conditions. The overall statistical distribution further verifies the accuracy and robustness of the proposed channel modeling method in practical V2X communication scenarios.

Table 12. Statistical results of packet loss rate (PLR).

Scenario	Out-M	Out-SD	Out-95CI	In-M	In-SD	In-95CI
Low urban canyon	0.0096	0.00019	[0.0095, 0.0097]	0.0102	0.00020	[0.0101, 0.0103]
High urban canyon	0.0076	0.00015	[0.0075, 0.0077]	0.0080	0.00016	[0.0079, 0.0081]
Rural Road	0.0074	0.00015	[0.0073, 0.0075]	0.0076	0.00015	[0.0075, 0.0077]
Highway	0.0094	0.00019	[0.0093, 0.0095]	0.0104	0.00021	[0.0103, 0.0105]
Overhead Bridge	0.0084	0.00017	[0.0083, 0.0085]	0.0086	0.00017	[0.0085, 0.0087]

Notes: M = mean, SD = standard deviation, and 95CI = 95% confidence interval.

Table 13. Statistical results of transmission delay (unit: s).

Scenario	Out-M	Out-SD	Out-95CI	In-M	In-SD	In-95CI
Low urban canyon	0.0140	0.00028	[0.0138, 0.0142]	0.0145	0.00029	[0.0143, 0.0147]
High urban canyon	0.0140	0.00028	[0.0138, 0.0142]	0.0150	0.00030	[0.0148, 0.0152]
Rural Road	0.0140	0.00028	[0.0138, 0.0142]	0.0145	0.00029	[0.0143, 0.0147]
Highway	0.0138	0.00028	[0.0136, 0.0140]	0.0150	0.00030	[0.0148, 0.0152]
Overhead Bridge	0.0145	0.00029	[0.0143, 0.0147]	0.0155	0.00031	[0.0153, 0.0157]

Notes: M = mean, SD = standard deviation, and 95CI = 95% confidence interval.

Overall, the V2V communication performance in road tests closely matches indoor test results, with similar packet loss trends across different scenarios. This consistency validates the effectiveness of the proposed 3D channel model. More importantly, the high consistency of the key V2V communication performance indicators (packet loss rate with relative error 1–4%; transmission delay with relative error 3–7%) between the in-chamber and on-road tests is the ultimate verification of the statistical representativeness and validity of the dataset. It proves that the channel parameters estimated from the dataset can accurately reproduce the typical multipath fading characteristics of actual road scenarios, and that the estimated parameters have high statistical stability and practical applicability.

6. Conclusions

This paper selects six typical C-V2X communication scenarios and conducts outdoor channel data collection. A multi-parameter channel parameter optimization method combining the K-Means++ algorithm and GA is proposed to optimize the established channel models, yielding the optimal C-V2X channel model parameters for these six scenarios. To verify the effectiveness of the proposed scheme, an in-chamber and on-road cross-test verification method based on the C-V2X off-road test platform is implemented, and the

test results confirm the high accuracy of the optimized parameter models. Additionally, future research will expand this work to the evaluation criteria of channel scenarios, parameter model optimization, and the correlation between channel characteristics and application responses.

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References

1. Al-Yarimi, F.A. Enhancing Road Safety through Advanced Predictive Analytics in V2X Communication Networks. *Comput. Electr. Eng.* **2024**, *115*, 109134. [[CrossRef](#)]
2. Gifford, W.M.; Dardari, D.; Win, M.Z. The Impact of Multipath Information on Time-of-Arrival Estimation. *IEEE Trans. Signal Process.* **2020**, *70*, 31–46. [[CrossRef](#)]
3. Ye, L.; Liu, E.; Han, Q.; Sun, Q.; Zeng, L.; Liu, F. Scenarios Oriented V2V 3D Channel Model Optimization. In *Proceedings of the 2021 IEEE International Intelligent Transportation Systems Conference (ITSC)*; IEEE: New York, NY, USA, 2021; pp. 3204–3209.
4. Han, Q.; Yuan, X.; Zeng, L.; Zu, H.; Ye, L.; Lin, L. Scenario Oriented V2v Field Test Scheme with Dense Node Array. In *Proceedings of the 2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC)*; IEEE: New York, NY, USA, 2020; pp. 1–6.
5. Yang, M.; Ai, B.; He, R.; Chen, L.; Li, X.; Li, J.; Zhang, B.; Huang, C.; Zhong, Z. A Cluster-Based Three-Dimensional Channel Model for Vehicle-to-Vehicle Communications. *IEEE Trans. Veh. Technol.* **2019**, *68*, 5208–5220. [[CrossRef](#)]
6. Xu, Y.; Qu, W.; Li, Z.; Min, G.; Li, K.; Liu, Z. Efficient k -Means++ Approximation with MapReduce. *IEEE Trans. Parallel Distrib. Syst.* **2014**, *25*, 3135–3144. [[CrossRef](#)]
7. Arthur, D.; Vassilvitskii, S. *K-Means++: The Advantages of Careful Seeding*; Technical Report; Stanford InfoLab Publication Server: Stanford, CA, USA, 2006.
8. Lattanzi, S.; Sohler, C. A Better K-Means++ Algorithm via Local Search. In *Proceedings of the International Conference on Machine Learning*, Long Beach, CA, USA, 9–15 June 2019; pp. 3662–3671.
9. Zhao, X.; Zhang, L.; Ling, Y.; Zhang, Z.; He, Y.; Wang, F. Research on Image Classification Enhancement Method Based on K-means++ Clustering and CNN. In *Proceedings of the 2024 IEEE 6th International Conference on Civil Aviation Safety and Information Technology (ICCASIT)*; IEEE: New York, NY, USA, 2024; pp. 1411–1415.
10. Yang, J.; Wu, Z.; Huang, Y.; Gong, M.; Zhang, X.; Ma, Y.; Han, G. K-Means++-Based Secure and Efficient Routing Protocol Design for Underwater Sensor Networks. *IEEE Internet Things J.* **2025**, *13*, 1702–1717. [[CrossRef](#)]
11. Song, J.; Wang, Z.; Niu, Y.; Dong, H. Genetic-Algorithm-Assisted Sliding-Mode Control for Networked State-Saturated Systems over Hidden Markov Fading Channels. *IEEE Trans. Cybern.* **2020**, *51*, 3664–3675. [[CrossRef](#)] [[PubMed](#)]

12. Liu, W.; Wang, Z.; Yuan, Y.; Zeng, N.; Hone, K.; Liu, X. A Novel Sigmoid-Function-Based Adaptive Weighted Particle Swarm Optimizer. *IEEE Trans. Cybern.* **2019**, *51*, 1085–1093. [[CrossRef](#)] [[PubMed](#)]
13. Melouki, Y.; Omari, M. Simulated Annealing Approach for Clustering in Wireless Sensor Networks. In *Proceedings of the 2020 2nd International Conference on Mathematics and Information Technology (ICMIT)*; IEEE: New York, NY, USA, 2020; pp. 216–219.
14. Ahmad, J.; Ab Wahab, M.N.; Ramli, A.; Misro, M.Y.; Ezza, W.Z.; Hasan, W.Z.W. Enhancing Performance of Global Path Planning for Mobile Robot through Alpha-Beta Guided Particle Swarm Optimization (ABGPSO) Algorithm. *Measurement* **2025**, *257*, 118633. [[CrossRef](#)]
15. Allaoui, M.; Belhaouari, S.B.; Hedjam, R.; Bouanane, K.; Kherfi, M.L. T-SNE-PSO: Optimizing t-SNE Using Particle Swarm Optimization. *Expert Syst. Appl.* **2025**, *269*, 126398. [[CrossRef](#)]
16. Vincent, F.Y.; Anh, P.T.; Gunawan, A.; Han, H. A Simulated Annealing with Variable Neighborhood Descent Approach for the Heterogeneous Fleet Vehicle Routing Problem with Multiple Forward/Reverse Cross-Docks. *Expert Syst. Appl.* **2024**, *237*, 121631.
17. Qi, W.; Zhang, N.; Zong, G.; Su, S.F.; Yan, H.; Yeh, R.H. Event-Triggered SMC for Networked Markov Jumping Systems with Channel Fading and Applications: Genetic Algorithm. *IEEE Trans. Cybern.* **2023**, *53*, 6503–6515. [[CrossRef](#)] [[PubMed](#)]
18. Wright, A.H. Genetic Algorithms for Real Parameter Optimization. In *Foundations of Genetic Algorithms*; Elsevier: Amsterdam, The Netherlands, 1991; Volume 1, pp. 205–218.
19. Jlifi, B.; Ferjani, S.; Duvallet, C. A Genetic Algorithm Based Three Hyperparameter Optimization of Deep Long Short Term Memory (GA3P-DLSTM) for Predicting Electric Vehicles Energy Consumption. *Comput. Electr. Eng.* **2025**, *123*, 110185. [[CrossRef](#)]
20. Razavi-Termeh, S.V.; Sadeghi-Niaraki, A.; Seo, M.; Choi, S.M. Application of Genetic Algorithm in Optimization Parallel Ensemble-Based Machine Learning Algorithms to Flood Susceptibility Mapping Using Radar Satellite Imagery. *Sci. Total Environ.* **2023**, *873*, 162285. [[CrossRef](#)] [[PubMed](#)]
21. Bahadur, D.J.; Lakshmanan, L. A Novel Method for Optimizing Energy Consumption in Wireless Sensor Network Using Genetic Algorithm. *Microprocess. Microsyst.* **2023**, *96*, 104749. [[CrossRef](#)]
22. EL-Qasery, M.; Abbou, A.; Laamim, M.; Id-Khajine, L.; Rochd, A. Comparative Analysis of GA and PSO Algorithms for Optimal Cost Management in On-Grid Microgrid Energy Systems with PV-battery Integration. *Glob. Energy Interconnect.* **2025**, *8*, 572–580. [[CrossRef](#)]
23. Vijayalakshmi, N.; Yuvaraj, S.; Baskar, V.V.; Krishnaswamy, R.; Sasikala, K.; Srinivasan, C. Optimized Control of IoT-Monitored Microgrid Systems Using Genetic Algorithm. In *Proceedings of the 2023 International Conference on Power Energy, Environment & Intelligent Control (PEEIC)*; IEEE: New York, NY, USA, 2023; pp. 1014–1018.
24. Katoch, S.; Chauhan, S.S.; Kumar, V. A Review on Genetic Algorithm: Past, Present, and Future. *Multimed. Tools Appl.* **2021**, *80*, 8091–8126. [[CrossRef](#)] [[PubMed](#)]
25. Cantú-Paz, E. A Survey of Parallel Genetic Algorithms. *Calc. Paralleles Reseaux Syst. Repartis* **1998**, *10*, 141–171.
26. Semenkin, E.; Semenkina, M. Self-Configuring Genetic Algorithm with Modified Uniform Crossover Operator. In *Proceedings of the International Conference in Swarm Intelligence*; Springer: Berlin/Heidelberg, Germany, 2012; pp. 414–421.
27. Mirjalili, S. Evolutionary Algorithms and Neural Networks. *Stud. Comput. Intell.* **2019**, *780*, 43–53.

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