

Article

Modeling and Analysis of Vehicle-to-Vehicle Fluid Antenna Communication Systems Aided by RIS

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Abstract

As communication technologies continue to evolve, Reconfigurable Intelligent Surfaces (RISs) have become a crucial and highly potential technology for sixth-generation (6G) mobile communication systems. Their key competitive advantages lie in their cost-effectiveness, minimal power consumption, and simple deployment. To address the limitations of current communication paradigms, this study innovatively integrates RIS technology into vehicle-to-vehicle (V2V) communication systems. Current methodologies fail to comprehensively elucidate the transmission principles underlying RIS-assisted V2V fluid antenna system (FAS) communications. The current channel characteristic analysis techniques and modeling theories struggle to achieve a balance between computational accuracy and computational complexity. To overcome these problems, this study systematically constructed a multipath sub-channel model in RIS-assisted V2V communication. Combining detailed simulation with theoretical analysis, a reliable parametric channel statistical model was established. This progress successfully overcame the main obstacle of the traditional RIS channel modeling method, which was unable to coordinate accuracy and efficiency.

Keywords: reconfigurable intelligent surfaces; channel model; fluid antenna communications; vehicle-to-vehicle wireless communication



Academic Editors: Dimitra I. Kaklamani and Filippo Costa

Received: 28 May 2025

Revised: 1 July 2025

Accepted: 9 July 2025

Published: 11 July 2025

Citation: Pei, Z.; Zhou, B.; Zhou, J. Modeling and Analysis of Vehicle-to-Vehicle Fluid Antenna Communication Systems Aided by RIS. *Electronics* **2025**, *14*, 2804. <https://doi.org/10.3390/electronics14142804>

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1. Introduction

1.1. Background

The emergence of the sixth-generation (6G) wireless communication network marks a paradigm shift toward hyper-connected, intelligent, and immersive digital ecosystems [1]. Envisioned to operate in the 2030s, 6G seeks to overcome the constraints of 5G by achieving unprecedented performance metrics, including terahertz (THz) bandwidths [2], sub-millisecond latency, near-perfect reliability, and global coverage spanning terrestrial, aerial, and maritime domains. These advancements are pivotal for enabling transformative applications such as autonomous vehicular networks, holographic telepresence, tactile internet, and ubiquitous artificial intelligence-driven services [3]. Within this framework, vehicle-to-everything (V2X) communications, particularly V2V interactions, emerge as critical enablers for intelligent transportation systems (ITSs), which demand ultra-reliable low-latency communication (URLLC) and robust connectivity in highly dynamic scenarios [4].

Recent standardization efforts, such as 5G NR V2X [5] and LTE-based V2X services [6], have laid the groundwork for vehicular connectivity, yet challenges persist in adapting these frameworks to 6Gs evolving requirements [7]. For instance, ultra-wideband non-stationary channel modeling for UAV-to-ground communications has revealed critical limitations in current frameworks when addressing high-mobility scenarios [8], while advancements in channel sounding technologies for UAV-assisted systems further highlight the need for adaptive measurement methodologies [9].

However, V2V communication faces inherent challenges due to rapid mobility, dense urban obstructions, and time-varying channel conditions [10]. Traditional cellular architectures struggle to maintain line-of-sight (LoS) links between vehicles, leading to severe signal degradation from shadowing and multipath fading [11]. This is partially addressed in 5G through massive MIMO and beamforming [12], which is a technology direction highlighted as disruptive in early 5G research [13] as efficacy diminishes in non-stationary scenarios with frequent blockages. RISs, a cornerstone of 6Gs smart radio environment vision, offer a revolutionary solution [14]. Through the dynamic manipulation of electromagnetic waves, RIS arrays boost signal propagation, extend coverage, and also help to mitigate interference without active signal amplification, thereby aligning with 6Gs goals of energy efficiency and spectral agility [15]. Recent advancements in RIS hardware designs and optimization algorithms further demonstrate their potential to reshape wireless channels in real time [16], making them ideal for vehicular networks. Notably, physics-based channel modeling for RIS-assisted mmWave systems has shown how RISs can mitigate spatial non-stationarity in aerial environments [17], while hierarchical 3D radio environment maps incorporating channel shadowing provide new insights into urban propagation dynamics [18].

1.2. Related Works

Channel modeling for wireless communication systems has been extensively studied to characterize signal propagation under diverse environments. Traditional approaches for vehicular channels primarily rely on statistical models, geometric stochastic models, and deterministic ray-tracing methods [19]. Models based on statistics, including the 3GPP spatial channel model (SCM) and its extensions, employ empirical distributions to describe path loss, shadowing, and multipath components, offering computational efficiency for system-level simulations [20]. Geometric stochastic models, including the geometry-based stochastic model (GBSM), incorporate spatial consistency by modeling scatterers distributions relative to transceivers, making them suitable for multi-antenna systems in dynamic vehicular scenarios [21]. For example, extended geometric models for UAV-to-UAV communications have introduced adaptive vMF distributions to capture directional scattering in aerial networks [22]. Deterministic methods, such as ray tracing, leverage environmental databases to predict site-specific propagation characteristics, achieving high accuracy at the expense of computational complexity [23]. While these models have been widely adopted for V2X communications, their applicability diminishes in highly dynamic vehicular environments with frequent blockages and non-stationary channel conditions [24]. Recent studies on MIMO multipath channels with aerial intelligent reflecting surfaces further emphasize the limitations of static models in capturing hybrid near-far field interactions [25].

Recent advancements in RISs have spurred new directions in channel modeling. Early works on RIS-assisted channels focused on static or quasi-static scenarios, where RIS elements are optimized to enhance signal strength or mitigate interference through phase-shift adjustments [26]. For instance, the authors of [27] proposed a parametric RIS channel model for indoor environments, integrating far-field approximations and fixed RIS configurations. Similarly, the authors of [28] developed a geometric model for RIS-aided cellular networks,

emphasizing the interplay between RIS4 placement and coverage extension. However, these studies largely assume stationary transceivers and ideal RIS control, overlooking the time-dependent characteristics of vehicular channels and the practical restrictions of RIS sub-array partitioning [29]. Recent efforts have explored dynamic RIS configurations for mobile users [30]. In reference [31] an approach was presented using an algorithm to construct surrogate functions. This method linearizes the objective function and handles the unit modulus constraints via SDP, thus implementing the optimization of phase constraints. Reference [32] proposed two adaptive and robust methods for configuring RISs with more general arbitrary-shaped elements. These approaches reduce complexity while being better suited for highly dynamic communication scenarios. However, the integration with V2V-specific challenges remains limited. Simplified beamspace channel estimation algorithms for mmWave massive MIMO systems have demonstrated potential for reducing computational overhead in RIS-aided networks, while novel beam channel models for UAV-enabled mmWave communications highlight the role of directional beamforming in dynamic environments [33].

In the context of V2V communications, existing channel models often prioritize LOS and NLoS propagation but lack the mechanisms to dynamically adapt to rapid mobility and environmental obstructions. For example, the authors of [34] introduced a twin-cluster model for millimeter-wave V2V channels, capturing spatial-temporal variations through clustered scatterers. Meanwhile, the authors of [35] extended the GBSM framework to incorporate dual mobility and 3D geometry, yet without integrating RISs as a controllable propagation medium. Notably, in RIS-assisted V2V scenarios, hybrid far and near-field modeling has not been thoroughly explored, particularly when sub-array architectures are employed to balance complexity and reconfigurability [36]. Furthermore, existing RIS channel models often neglect the joint impact of time-varying RIS configurations, vehicle kinematics, and scatterer dynamics [37], limiting their practicality for real-time V2V system design. Prior studies on FASs have emphasized their adaptability in dynamic environments [38]; however, their synergistic integration with RIS-aided networks remains an open research challenge [39].

1.3. Main Contributions

The primary contributions are summarized in the following outline:

- A channel model is proposed that jointly captures RIS-enabled far-field reflections and near-field scattering effects in dynamic vehicular environments. This model integrates time-varying RIS configurations, spatially non-stationary scatterer clusters, and dual-mobility kinematics of vehicles, addressing the limitations of existing approaches that either neglect near-field dynamics or assume static RIS deployments.
- Through the derivation of deriving the Space-Time Cross-Correlation Function (ST CCF) and Temporal Auto-Correlation Function (ACF), the non-stationary properties of RIS-assisted vehicle-to-vehicle channels are precisely quantified. Our analysis explicitly incorporates time-varying parameters, including vehicular acceleration, RIS phase profiles, and scatterer dynamics, revealing how temporal evolution and RIS spatial deployment jointly govern channel correlation and attenuation.
- The proposed model supports dynamic port activation in FAS-equipped vehicles, where active port subsets adaptively adjust to channel conditions. This flexibility is formalized through a generalized channel matrix, enabling the real-time optimization of spectral efficiency and reliability under mobility constraints.
- Through comprehensive simulations, we demonstrate that RIS deployment positions and various other variables critically influence ST CCF and temporal ACF performance. Our findings provide actionable insights for RIS-aided V2V system design.

The structure of the remaining part of the paper is arranged as follows. In Section 2 a comprehensive elaboration is provided, which is on the proposed channel model. In Section 3 the physical attributes of the channel model are introduced through the Channel Impulse Response (CIR) function. Subsequently, Section 4 details the specific computational methodologies for deriving the CIR of two distinct transmission links. In Section 5 the transmission characteristics of the proposed channel model were analyzed. Also, the corresponding simulation results and conclusive remarks are presented in Sections 6 and 7, respectively.

Notation: The letters of lowercase (e.g., x), boldface lowercase (e.g., $\mathbf{x}$), and boldface uppercase (e.g., $\mathbf{X}$) represent scalars and vectors, respectively. The symbols $\|\cdot\|$, $(\cdot)^*$, and $[\cdot]^T$ denote the Frobenius norm, the complex conjugate operation, and the transpose operation of matrices, respectively. Finally, $j = \sqrt{-1}$ is the imaginary unit and $\mathbb{E}[\cdot]$ represents the expectation operation.

2. System Model

Within V2V wireless communication environments, the unobstructed LoS transmission among vehicles is often obstructed by urban infrastructure such as buildings, owing to the dynamic mobility of both transmitting and receiving nodes. This obstruction significantly degrades communication reliability and stability. To address this issue, the integration of RIS technology can effectively establish an equivalent direct path, thereby enhancing both the quality and efficiency of communication. As illustrated in Figures 1 and 2, we propose a RIS-assisted FAS channel model for V2V communication scenarios. Considering that V2V communications predominantly occur in urban environments with dense obstructions and owing to the real-time mobility characteristics of both transmitting and receiving terminals, we employ RIS-reflected paths to replace conventional LoS propagation. This approach addresses the limitations of LoS blockages caused by dynamic urban obstacles while leveraging the reconfigurability of RISs to enhance signal reliability and adaptability in highly dynamic vehicular networks. Furthermore, FASs offer inherent advantages over traditional linear antennas through their dynamic reconfigurability. During operation they can adaptively modify port configuration based on real-time channel conditions. This capability enables superior handling of time-varying channels in V2V communications, particularly in urban environments with multiple obstructions. Consequently, FASs were selected for the proposed system model. It is supposed that linear FASs are installed on both the transmitting vehicle (MT) and the receiving vehicle (MR). The port lengths are denoted as $W_T\lambda$ and $W_R\lambda$ respectively, and the number of pots is P and Q , respectively. It is worth motioning that W_R is a dimensionless variable, which can be regarded as a coefficient. Consequently, the distances between adjacent ports in the FAS of the transmitting and receiving vehicles can be expressed as follows:

$$\Delta d_{T,p_{sub}} = \frac{W_T\lambda}{P-1} \quad (1)$$

$$\Delta d_{R,q_{sub}} = \frac{W_R\lambda}{Q-1} \quad (2)$$

In the proposed 3D coordinate system, the origin is set as the ground projection of the MT midpoint at the initial motion state. While the z -axis is directed vertically upward, the x -axis is aligned with the direction from MT to MR at the initial motion instant. The y -axis is then determined according to the right-hand rule to ensure orthogonality and coordinate consistency.

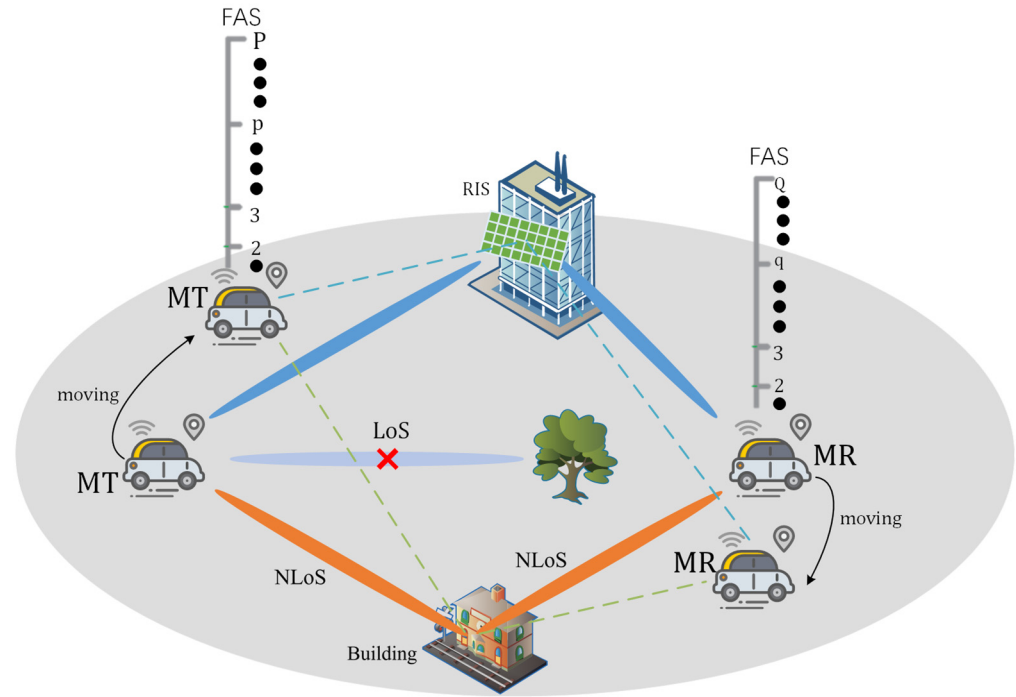


Figure 1. Transmission model of the proposed RIS-assisted V2V fluid antenna system in vehicular communication scenarios.

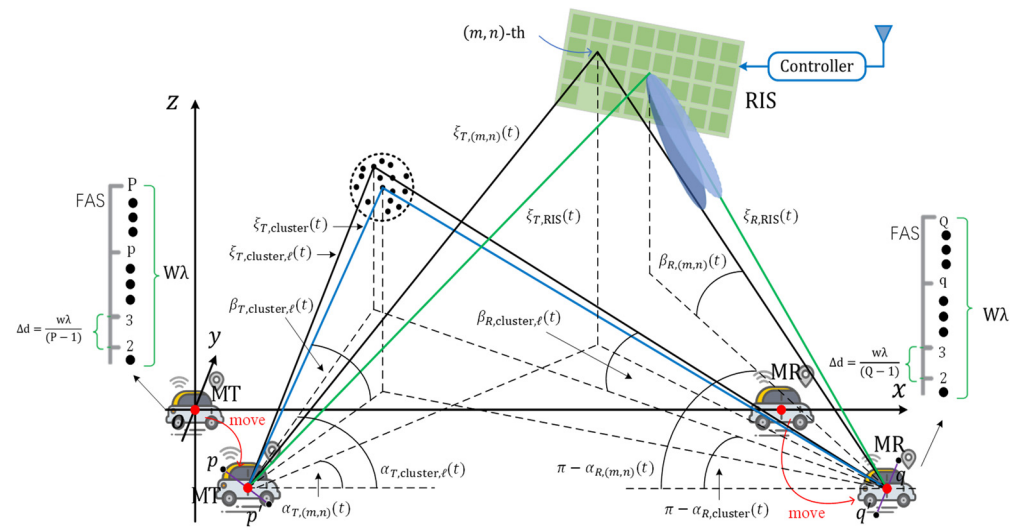


Figure 2. Multipath signal trajectories and spatial angle in the proposed channel model.

In general scenarios where both MT and MR exhibit continuous motion, their velocity vectors are defined as follows: $\mathbf{v}_{T(R)} = [v_{T(R),x}(t), v_{T(R),y}(t), 0]^T$, where $v_{T(R),x}(t)$ and $v_{T(R),y}(t)$, respectively, represent the velocity components of MT (or MR) within both the x - and y -axis. These components are derived through the following formulations:

$$v_{T(R),x}(t) = v_{T(R),x}(0) + \int_0^t a_{T(R),x}(t') dt' \quad (3)$$

$$v_{T(R),y}(t) = v_{T(R),y}(0) + \int_0^t a_{T(R),y}(t') dt' \quad (4)$$

where in Equations (3) and (4) $v_{T(R),x}(0)$ and $v_{T(R),y}(0)$ components in the directions of the x -axis and y -axis represent the MT and MR velocity elements at the initial stage of their motion. Now, let us introduce their relevant situations as follows:

$$a_{T(R),x}(t) = a_{T(R),x}(0) + a'_{T(R),x}(t) \quad (5)$$

$$a_{T(R),y}(t) = a_{T(R),y}(0) + a'_{T(R),y}(t) \quad (6)$$

where the MT and MR initial accelerations along both x - and y -axis are denoted as the variables $a_{T(R),x}(0)$ and $a_{T(R),y}(0)$. As for MT and MR, their distance vectors within this stage of the entire motion can be calculated. The specific calculations are as follows:

$$\mathbf{d}_T(t) = \begin{bmatrix} d_{T,x}(t) \\ d_{T,y}(t) \\ 0 \end{bmatrix} = \begin{bmatrix} v_{T,x}(t)t\cos\eta_T^{\text{ver}}\cos\eta_T^{\text{azi}} \\ v_{T,y}(t)t\cos\eta_T^{\text{ver}}\cos\eta_T^{\text{azi}} \\ 0 \end{bmatrix} \quad (7)$$

$$\mathbf{d}_R(t) = \begin{bmatrix} d_{R,x}(t) \\ d_{R,y}(t) \\ 0 \end{bmatrix} = \begin{bmatrix} D_0 + v_{R,x}(t)t\cos\eta_R^{\text{ver}}\cos\eta_R^{\text{azi}} \\ v_{R,y}(t)t\cos\eta_R^{\text{ver}}\cos\eta_R^{\text{azi}} \\ 0 \end{bmatrix} \quad (8)$$

where D_0 denotes the straight-line distance between MT and MR at the initial motion instant. Respectively, the azimuthal motion directions of both MT and MR in the horizontal plane are represented by the angles η_T^{azi} and η_R^{azi} , while η_T^{ver} and η_R^{ver} are similar enough as to characterize both MT and MR in its vertical motion directions under the elevation plane.

3. Channel Description

In the channel model presented, the MT signal sent reaches the MR via the following two paths: one is the RIS-reflected path, which replaces the LoS; another denotes the NLoS path. For the RIS-reflected path, the signal is reflected and adjusted by the RIS array before arriving at the MR. Regarding the NLoS path, the signal is reflected by scatterers close to the MT and then reaches the MR. The distance vector from the coordinate system origin to the center position of the reconfigurable smart surface RIS array can be represented as follows: $\mathbf{d}_{\text{RIS}} = [x_{\text{RIS}}, y_{\text{RIS}}, z_{\text{RIS}}]$. In the non-line-of-sight path, N scattering clusters are present near the MT. Meanwhile $\mathbf{d}_{n\uparrow} = [x_{n\uparrow}, y_{n\uparrow}, z_{n\uparrow}]$ is denoted as the distance vector in the n -th ($n = 1, 2, \dots, N$) scatterer cluster, which is from the coordinate origin to the $\uparrow$ -th ($\uparrow = 1, 2, \dots, n_{\uparrow}$).

To comprehensively characterize the transmission characteristics of this model, the matrix formula $\mathbf{H}(t) = [h_{p_{\text{sub}}, q_{\text{sub}}}(t, \tau)]$ is utilized as the impulse response to complex channels is denoted by $h_{p_{\text{sub}}, q_{\text{sub}}}(t, \tau)$. The model comprises two distinct links, each contributing its own propagation component of the RIS-reflected component (equivalent to the LoS component) and the NLoS component. Assuming mutual independence between these two propagation components, the summation of their individual complex channel impulse responses can be used to express the overall complex CIR. The calculation method is as follows [40]:

$$h_{p_{\text{sub}}, q_{\text{sub}}}(t, \tau) = \sqrt{\frac{K}{K+1}} h_{p_{\text{sub}}, q_{\text{sub}}}^{\text{RIS}}(t) \delta\left(\tau - \frac{\xi_{T,\text{RIS}}(t) + \xi_{R,\text{RIS}}(t)}{c}\right) + \sqrt{\frac{1}{K+1}} h_{p_{\text{sub}}, q_{\text{sub}}}^{\text{cluster}}(t) \delta\left(\tau - \frac{\xi_{T,\text{cluster}}(t) + \xi_{R,\text{cluster}}(t)}{c}\right) \quad (9)$$

where K is the Rice factor and the distances from MT and MR to the midpoint of the RIS array are represented by the formulas $\xi_{T,\text{RIS}}(t) = \|\mathbf{d}_{\text{RIS}} - \mathbf{d}_T\|$ and $\xi_{R,\text{RIS}}(t) = \|\mathbf{d}_{\text{RIS}} - \mathbf{d}_R\|$. As the same, the formulas $\xi_{T,\text{cluster}}(t) = \|\mathbf{d}_{\text{RIS}} - \mathbf{d}_T\|$ and $\xi_{R,\text{cluster}}(t) = \|\mathbf{d}_{\text{cluster}} - \mathbf{d}_R\|$ stand for both distances to the scattering cluster's geometric center.

It is important to note that the dimension of $\mathbf{H}(t)$ is $Q_{sub} \times P_{sub}$, where Q_{sub} and P_{sub} represent the number of active ports at MR and MT sides, respectively. Given that fluid antennas can dynamically activate one or multiple communication ports for signal transmission, the values of Q_{sub} and P_{sub} are variable. In this work we introduce the general form of the FAS channel matrix, where Q_{sub} and P_{sub} denote the number of active ports. Thus, the sets of $\mathbf{Q}_{sub}$ and $\mathbf{P}_{sub}$ are given by the following:

$$\mathbf{Q}_{sub} = \{q_{sub,1}, q_{sub,2}, \dots, q_{sub,Q_{sub}}\}, \mathbf{Q}_{sub} \in \mathbf{Q} \quad (10)$$

$$\mathbf{P}_{sub} = \{p_{sub,1}, p_{sub,2}, \dots, p_{sub,P_{sub}}\}, \mathbf{P}_{sub} \in \mathbf{P} \quad (11)$$

where $\mathbf{Q} = \{1, 2, \dots, Q\}$ and $\mathbf{P} = \{1, 2, \dots, P\}$ represent the port sets of the MR and MT, respectively. The positions of the q_{sub} -th port at the MR side ($q_{sub} = 1, 2, \dots, Q_{sub}$) and the p_{sub} -th port at the MT side ($p_{sub} = 1, 2, \dots, P_{sub}$) are calculated as follow:

$$\mathbf{d}_{q_{sub}}(t) = \begin{bmatrix} d_{q_{sub},x}(t) \\ d_{q_{sub},y}(t) \\ d_{q_{sub},z}(t) \end{bmatrix} = \begin{bmatrix} d_{R,x}(t) \\ d_{T,x}(t) \\ (q_{sub} - 1)\Delta d_{R,q_{sub}} \end{bmatrix} = \begin{bmatrix} D_0 + v_{R,x}(t)\cos\eta_R^{\text{ver}}\cos\eta_R^{\text{azi}} \\ v_{R,y}(t)\cos\eta_R^{\text{ver}}\sin\eta_R^{\text{azi}} \\ (q_{sub} - 1)\Delta d_{R,q_{sub}} \end{bmatrix} \quad (12)$$

$$\mathbf{d}_{p_{sub}}(t) = \begin{bmatrix} d_{p_{sub},x}(t) \\ d_{p_{sub},y}(t) \\ d_{p_{sub},z}(t) \end{bmatrix} = \begin{bmatrix} d_{T,x}(t) \\ d_{R,y}(t) \\ (p_{sub} - 1)\Delta d_{T,p_{sub}} \end{bmatrix} = \begin{bmatrix} v_{T,x}(t)\cos\eta_T^{\text{ver}}\cos\eta_T^{\text{azi}} \\ v_{R,x}(t)\cos\eta_T^{\text{ver}}\sin\eta_T^{\text{azi}} \\ (p_{sub} - 1)\Delta d_{T,p_{sub}} \end{bmatrix} \quad (13)$$

4. The CIR for the Two Transmission Links

In the preceding analysis the CIR function was employed to characterize the channel response between the MT's p -th and the MR's q -th antennas. The resultant value is derived from the summation of the CIR functions under both LoS and NLoS propagation conditions. The mathematical expressions for these two scenarios are formulated as follows:

$$\begin{aligned} h_{p_{sub},q_{sub}}^{\text{RIS}} &= \sum_{m=1}^M \sum_{n=1}^N \chi_{m,n}(t) \\ &\times e^{j(\varphi_{m,n}(t) - \frac{2\pi}{\lambda}(\xi_{T,(m,n)}(t) + \xi_{R,(m,n)}(t)))} \\ &\times e^{j\frac{2\pi}{\lambda}(p_{sub}-1)\Delta d_{T,p_{sub}}\sin\beta_{T,(m,n)}(t)} \\ &\times e^{j\frac{2\pi}{\lambda}(q_{sub}-1)\Delta d_{R,q_{sub}}\sin\beta_{R,(m,n)}(t)} \\ &\times e^{j\frac{2\pi}{\lambda}v_R t \cos(\alpha_{R,(m,n)}(t) - \eta_R^{\text{azi}})\cos\beta_{R,(m,n)}(t)} \\ &\times e^{j\frac{2\pi}{\lambda}v_T t \cos(\alpha_{T,(m,n)}(t) - \eta_T^{\text{azi}})\cos\beta_{T,(m,n)}(t)} \end{aligned} \quad (14)$$

Recent research achievements, such as those reported in [31], demonstrate that in general scenarios the reflection phases of RIS elements can be optimized by constructing surrogate functions via specific algorithms, transforming the objective function and subsequently handling the unit-modulus constraints. For analytical tractability in the context, the variables $\chi_{(m,n)}(t)$ and $\varphi_{(m,n)}(t)$, respectively, represent the reflection amplitude and reflection phase of the (m,n) -th element in the RIS array and we adopt the simplifying assumption of perfect phase alignment among all RIS sub-arrays. The parameters $\xi_{T,(m,n)}$ and $\xi_{R,(m,n)}$ are used to denote both MT and MR path lengths of the (m,n) -th element to the coordinate origin. The angles $\beta_{T,(m,n)}$ and $\alpha_{T,(m,n)}$ are used to describe the two charac-

teristics of time-varying vertical and horizontal azimuth deviations. Their mathematical expressions are formulated as follows:

$$\alpha_{T,(m,n)} = \tan^{-1} \frac{y_{(m,n)} - d_{T,y}(t)}{x_{(m,n)} - d_{T,x}(t)} \quad (15)$$

$$\beta_{T,(m,n)} = \tan^{-1} \frac{z_{(m,n)}}{\sqrt{(y_{(m,n)} - d_{T,y}(t))^2 + (x_{(m,n)} - d_{T,x}(t))^2}} \quad (16)$$

where $\beta_{R,(m,n)}$ and $\alpha_{R,(m,n)}$, respectively, represent all the vertical azimuth angles that change over time and the horizontal azimuth angles that change over time in the RIS array for the (m,n) -th element. These angles are represented in the following way:

$$\alpha_{R,(m,n)} = \tan^{-1} \frac{y_{(m,n)} - d_{R,y}(t)}{x_{(m,n)} - d_{R,x}(t)} \quad (17)$$

$$\beta_{R,(m,n)} = \tan^{-1} \frac{z_{(m,n)}}{\sqrt{(y_{(m,n)} - d_{R,y}(t))^2 + (x_{(m,n)} - d_{R,x}(t))^2}} \quad (18)$$

In the case of the presence of scatterer clusters, how the CIR function is divided between the p -th and the q -th port for MT and MR is as follows:

$$\begin{aligned} h_{p_{sub},q_{sub}}^{\text{cluster}} = & \sum_{n \in N} \sum_{\downarrow=1}^{n_{\downarrow}} e^{j(\varphi_{n_{\downarrow}}(t) - \frac{2\pi}{\lambda}(\xi_{T,n_{\downarrow}}(t) + \xi_{R,n_{\downarrow}}(t)))} \\ & \times e^{j\frac{2\pi}{\lambda}(p_{sub}-1)\Delta d_{T,p_{sub}} \sin \beta_{T,n_{\downarrow}}(t)} \\ & \times e^{j\frac{2\pi}{\lambda}(q_{sub}-1)\Delta d_{R,q_{sub}} \sin \beta_{R,n_{\downarrow}}(t)} \\ & \times e^{j\frac{2\pi}{\lambda}v_T t \cos(\alpha_{T,n_{\downarrow}}(t) - \eta_T^{\text{azi}}) \cos \beta_{T,n_{\downarrow}}(t)} \\ & \times e^{j\frac{2\pi}{\lambda}v_R t \cos(\alpha_{R,n_{\downarrow}}(t) - \eta_R^{\text{azi}}) \cos \beta_{R,n_{\downarrow}}(t)} \end{aligned} \quad (19)$$

where $\varphi_{n_{\downarrow}}(t)$ represents an independent and uniformly distributed random phase. The variables $\xi_{T,n_{\downarrow}}(t)$ and $\xi_{R,n_{\downarrow}}(t)$ denote the straight-line distances from the $\downarrow$ -th scatterer to MT and MR, respectively. The scatterer path signal has time-varying deviations from the vertical azimuth angle and the horizontal azimuth angle. These two angles are represented by angles $\beta_{T,n_{\downarrow}}(t)$ and $\alpha_{T,n_{\downarrow}}(t)$, respectively. Let us specifically explain how they are defined through the following:

$$\alpha_{T,n_{\downarrow}} = \tan^{-1} \frac{y_{n_{\downarrow}} - d_{T,y}(t)}{x_{n_{\downarrow}} - d_{T,x}(t)} \quad (20)$$

$$\beta_{T,n_{\downarrow}} = \tan^{-1} \frac{z_{n_{\downarrow}}}{\sqrt{(y_{n_{\downarrow}} - d_{T,y}(t))^2 + (x_{n_{\downarrow}} - d_{T,x}(t))^2}} \quad (21)$$

Similarly, the symbol $\beta_{R,n_{\downarrow}}(t)$ represents the vertical azimuth of arrival of the scatterer's path signal, which changes over time. The symbol $\alpha_{R,n_{\downarrow}}(t)$ indicates the horizontal azimuth variation in the scatterer's path signal which arrives over time. The values involved here are determined as follows:

$$\alpha_{R,n_{\downarrow}} = \tan^{-1} \frac{y_{n_{\downarrow}} - d_{R,y}(t)}{x_{n_{\downarrow}} - d_{R,x}(t)} \quad (22)$$

$$\beta_{R,n_{\downarrow}} = \tan^{-1} \frac{z_{n_{\downarrow}}}{\sqrt{\left(y_{n_{\downarrow}} - d_{R,y}(t)\right)^2 + \left(x_{n_{\downarrow}} - d_{R,x}(t)\right)^2}} \quad (23)$$

In this work, the von Mises distribution is introduced to determine the position of each scatterer, and is shown as follows:

$$f(\alpha) = \frac{e^{\kappa \cos(\alpha - \mu_{\alpha})}}{2\pi I_0(\kappa)} \quad (24)$$

where κ is the environmental factor [41]. Considering that V2V communication scenarios are predominantly deployed in highly scattered urban environments, κ typically takes smaller values, ranging between 0.5 and 2. This range indicates dispersed scattering directions, as documented in relevant literature. μ_{α} represents the mean value of α , and $I_0(\cdot)$ stands for the order 0 within adjusted Bessel function. Furthermore, existing studies (e.g., [32]) commonly model scatterer elevation angles using uniform distributions. Consistent with this approach, our work generates scatterer elevation angles according to $U(-1/2, 1/2)$.

5. Propagation Characteristics of the Proposed Channel Model

In contemporary research endeavors the wireless channel models' accuracy is typically validated through the derivation of the CCF. This metric is evaluated by determining the correlation between two distinct complex CIRs, denoted as $h_{p_{sub},q_{sub}}(t)$ and $h_{p'_{sub},q'_{sub}}(t + \Delta t)$. Here, p'_{sub} and q'_{sub} represent the p'_{sub} -th port at the MT side ($p'_{sub} = 1, 2, \dots, P_{sub}$) and the q'_{sub} -th port at the MR side ($q'_{sub} = 1, 2, \dots, Q_{sub}$), respectively. The CCF can be derived using the following formula:

$$\rho_{h_{p_{sub},q_{sub}} h_{p'_{sub},q'_{sub}}} (t, \Delta p_{sub}, \Delta q_{sub}, \Delta t) = \mathbb{E} \left[\frac{h_{p_{sub},q_{sub}}(t) h_{p'_{sub},q'_{sub}}^*(t + \Delta t)}{|h_{p_{sub},q_{sub}}(t)| |h_{p'_{sub},q'_{sub}}(t + \Delta t)|} \right] \quad (25)$$

where Δp_{sub} represents the MT normalized antenna spacing between both the ports of p_{sub} -th and p'_{sub} -th, while Δq_{sub} denotes the values of MR. Therefore, the ST CCF of this channel model can be decomposed into the following two components:

$$\begin{aligned} \rho_{h_{p_{sub},q_{sub}} h_{p'_{sub},q'_{sub}}} (t, \Delta p_{sub}, \Delta q_{sub}, \Delta t) &= \rho_{h_{p_{sub},q_{sub}} h_{p'_{sub},q'_{sub}}}^{\text{RIS}} (t, \Delta p_{sub}, \Delta q_{sub}, \Delta t) \\ &+ \rho_{h_{p_{sub},q_{sub}} h_{p'_{sub},q'_{sub}}}^{\text{cluster}} (t, \Delta p_{sub}, \Delta q_{sub}, \Delta t) \end{aligned} \quad (26)$$

where $\rho_{h_{p_{sub},q_{sub}} h_{p'_{sub},q'_{sub}}}^{\text{RIS}} (t, \Delta p_{sub}, \Delta q_{sub}, \Delta t)$ and $\rho_{h_{p_{sub},q_{sub}} h_{p'_{sub},q'_{sub}}}^{\text{cluster}} (t, \Delta p_{sub}, \Delta q_{sub}, \Delta t)$ represent the ST CCF divided to the RIS and the cluster propagation link, respectively. Their expressions are as follows:

$$\begin{aligned}
\rho_{h_{p_{sub}q_{sub}}h_{p'_{sub}q'_{sub}}}^{RIS}(t, \Delta p_{sub}, \Delta q_{sub}, \Delta t) &= \frac{K}{K+1} \sum_{m=1}^M \sum_{n=1}^N (\chi_{m,n}(t) - \chi_{m',n'}(t + \Delta t)) \\
&\times e^{j(\varphi_{m,n}(t) - \varphi_{m',n'}(t + \Delta t))} \\
&\times e^{-j\frac{2\pi}{\lambda}(\xi_{T,(m,n)}(t) + \xi_{R,(m,n)}(t) - \xi_{T,(m',n')}(t + \Delta t) - \xi_{R,(m',n')}(t + \Delta t))} \\
&\times e^{j\frac{2\pi}{\lambda}(p_{sub}-1)\Delta d_{T,p_{sub}}\sin\beta_{T,(m,n)}(t)} \\
&\times e^{-j\frac{2\pi}{\lambda}(p'_{sub}-1)\Delta d_{T,p'_{sub}}\sin\beta_{T,(m',n')}(t + \Delta t)} \\
&\times e^{j\frac{2\pi}{\lambda}(q_{sub}-1)\Delta d_{R,q_{sub}}\sin\beta_{R,(m,n)}(t)} \\
&\times e^{-j\frac{2\pi}{\lambda}(q'_{sub}-1)\Delta d_{R,q'_{sub}}\sin\beta_{R,(m',n')}(t + \Delta t)} \\
&\times e^{j\frac{2\pi}{\lambda}v_T t \cos(\alpha_{T,(m,n)} - \eta_T^{azi})\cos\beta_{T,(m,n)}(t)} \\
&\times e^{-j\frac{2\pi}{\lambda}v_T(t + \Delta t)\cos(\alpha_{T,(m',n')} - \eta_T^{azi})\cos\beta_{T,(m',n')}(t + \Delta t)} \\
&\times e^{j\frac{2\pi}{\lambda}v_R t \cos(\alpha_{R,(m,n)} - \eta_R^{azi})\cos\beta_{R,(m,n)}(t)} \\
&\times e^{-j\frac{2\pi}{\lambda}v_R(t + \Delta t)\cos(\alpha_{R,(m',n')} - \eta_R^{azi})\cos\beta_{R,(m',n')}(t + \Delta t)}
\end{aligned} \tag{27}$$

$$\begin{aligned}
\rho_{h_{p_{sub}q_{sub}}h_{p'_{sub}q'_{sub}}}^{RIS}(t, \Delta p_{sub}, \Delta q_{sub}, \Delta t) &= \frac{1}{K+1} \sum_{n \in N} \sum_{\downarrow=1}^{n_{\downarrow}} e^{j(\varphi_{n_{\downarrow}}(t) - \varphi_{n'_{\downarrow}}(t + \Delta t))} \\
&\times e^{-j\frac{2\pi}{\lambda}(\xi_{T,n_{\downarrow}}(t) + \xi_{R,n_{\downarrow}}(t) - \xi_{T,n'_{\downarrow}}(t + \Delta t) - \xi_{R,n'_{\downarrow}}(t + \Delta t))} \\
&\times e^{j\frac{2\pi}{\lambda}(p_{sub}-1)\Delta d_{T,p_{sub}}\sin\beta_{T,n_{\downarrow}}(t)} \\
&\times e^{-j\frac{2\pi}{\lambda}(p'_{sub}-1)\Delta d_{T,p'_{sub}}\sin\beta_{T,n'_{\downarrow}}(t + \Delta t)} \\
&\times e^{j\frac{2\pi}{\lambda}(q_{sub}-1)\Delta d_{R,q_{sub}}\sin\beta_{R,n_{\downarrow}}(t)} \\
&\times e^{-j\frac{2\pi}{\lambda}(q'_{sub}-1)\Delta d_{R,q'_{sub}}\sin\beta_{R,n'_{\downarrow}}(t + \Delta t)} \\
&\times e^{j\frac{2\pi}{\lambda}v_T t \cos(\alpha_{T,n_{\downarrow}} - \eta_T^{azi})\cos\beta_{T,n_{\downarrow}}(t)} \\
&\times e^{-j\frac{2\pi}{\lambda}v_T(t + \Delta t)\cos(\alpha_{T,n'_{\downarrow}} - \eta_T^{azi})\cos\beta_{T,n'_{\downarrow}}(t + \Delta t)} \\
&\times e^{j\frac{2\pi}{\lambda}v_R t \cos(\alpha_{R,n_{\downarrow}} - \eta_R^{azi})\cos\beta_{R,n_{\downarrow}}(t)} \\
&\times e^{-j\frac{2\pi}{\lambda}v_R(t + \Delta t)\cos(\alpha_{R,n'_{\downarrow}} - \eta_R^{azi})\cos\beta_{R,n'_{\downarrow}}(t + \Delta t)}
\end{aligned} \tag{28}$$

Furthermore, upon applying the conditions $\Delta p_{sub} = \Delta q_{sub} = 0$, we can derive (27) and (28) to represent the temporal ACFs of the communication model.

6. Simulation Results and Analysis

In existing research on channel modeling, key metrics such as attenuation rate—referring to the degree of signal power loss per unit distance or unit time during channel transmission and sensitivity—and the minimum input power required for a receiver to correctly demodulate a signal are typically addressed through channel measurements. However, as this study focuses on investigating channel transmission characteristics via simulation,

we prioritize the analysis of spatiotemporal correlation properties within the proposed channel model. Here, the spatial–temporal correlation of the model formed in this paper is simulated and analyzed under various configurations. The initial parameter settings for the simulations are defined as follows: operating frequency $f = 5$ GHz, parameter settings $P = 10$ and $Q = 10$, reference distance $D_0 = 150$ m, and initial time instant $t = 0$ s. The RIS array is positioned at coordinates $(x_{\text{RIS}}, y_{\text{RIS}}, z_{\text{RIS}}) = (60 \text{ m}, 25 \text{ m}, 20 \text{ m})$ with element spacings $d_x = d_z = \frac{\lambda}{2}$ and array dimensions $M \times N = 50 \times 50$.

Figure 3 demonstrates the time autocorrelation characteristics under the various RIS array deployment configurations of this model. The simulation results reveal that as time elapses the characteristics exhibit a progressively declining trend. Notably, when the RIS array deployment positions vary the evolutionary patterns of the channel's time autocorrelation characteristics also differ. For example, in scenarios where RIS arrays are deployed in close proximity the rate of decline in the channel's time autocorrelation characteristics increases markedly. Due to the normalization applied during simulation, the time correlation starts at 1 at the initial time instance and continuously decreases. At $x_{\text{RIS}} = 20$ m the time autocorrelation exhibits the most significant decrease—dropping from 1 to approximately 0.6 within a short duration. From these observations, it can be inferred that the non-stationary features in the time domain are possessed by this model and are highly sensitive to the deployment positions of RIS arrays.

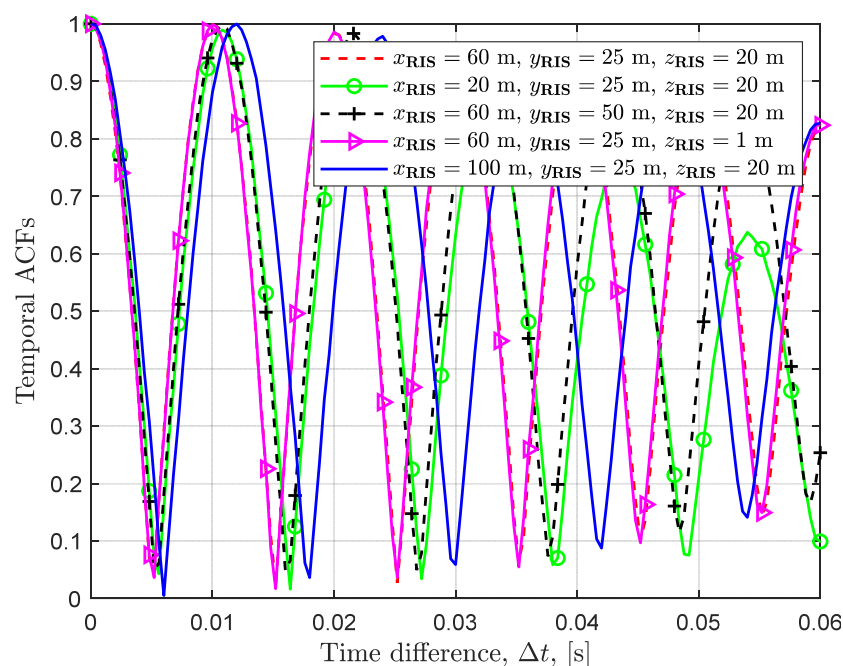


Figure 3. The characteristics of temporal autocorrelation characteristics under the proposed channel model within RIS array deployment positions.

The temporal autocorrelation characteristics of the proposed channel model under varying initial distance settings are illustrated by Figure 4. It is revealed by the simulation results that distinct variation trends in the temporal autocorrelation properties depend on the initial distance configurations. Notably, significant differences are observed between scenarios with smaller and larger initial distances. For instance, the temporal autocorrelation trends diverge markedly when comparing small and large initial distance regimes. However, in cases where both initial distances are sufficiently large, the temporal autocorrelation characteristics exhibit similar evolutionary patterns. Numerically, this difference manifests as a faster decay of time autocorrelation at smaller initial distance parameters, accompanied by an increasing time offset (starting from approximately 0.002 s). Quantitatively, the

simulation shows that by $t = 0.07$ s the time autocorrelation value decays from 1 to 0.5 across all configurations. This observation further corroborates the inherent non-stationary features in the time domain, highlighting its sensitivity to spatial initialization conditions.

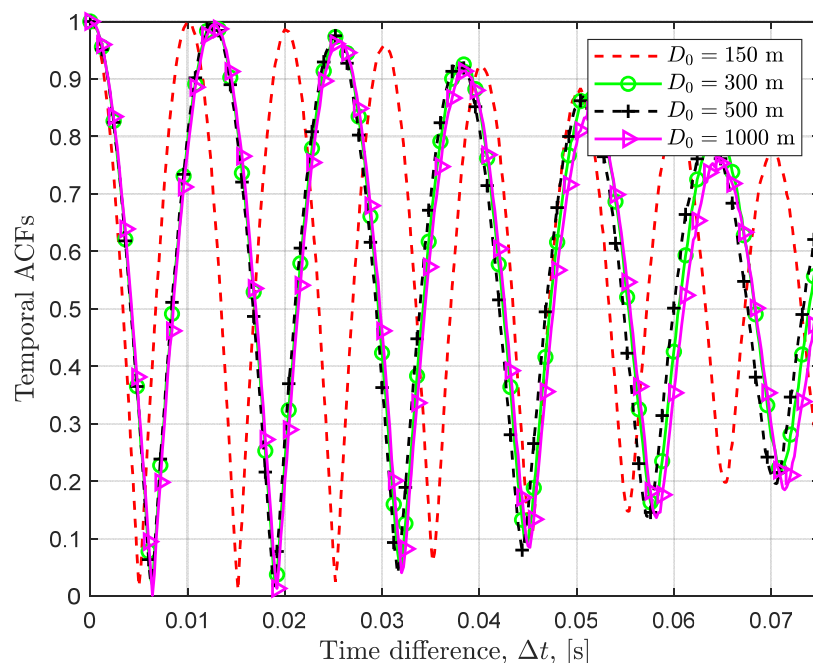


Figure 4. The characteristics of temporal autocorrelation characteristics under the proposed channel model within initial distance configurations.

The temporal autocorrelation characteristics of the proposed channel model under different mobility speeds of the MR along the x -axis, taking into account the complex motion dynamics inherent to V2V communication scenarios, are presented in Figure 5. It is demonstrated that the temporal autocorrelation properties of the channel generally exhibit a declining trend. Notably, the MR's velocity exerts a significant influence on these characteristics. Specifically, at lower MR speeds the temporal autocorrelation displays heightened punctuations, whereas at higher MR velocities the rate of autocorrelation decay diminishes markedly. The simulation results demonstrate distinct autocorrelation behaviors at different MR velocities. At higher speeds (5 m/s and 7 m/s) the time autocorrelation decays rapidly from 1 to 0.5 within 0.02 s before stabilizing. Conversely, at lower velocities we observe significant autocorrelation fluctuations with poor stability despite larger variation amplitudes. This behavior highlights the model's sensitivity to mobility conditions and further corroborates its inherent non-stationary characteristics in the temporal domain.

Figure 6 illustrates the characteristics of temporal autocorrelation for the diverse time parameter t . It demonstrates a pronounced declining trend in the temporal autocorrelation properties as t evolves. Specifically, as t increases from 0 s to 3 s the autocorrelation trend becomes more gradual, with a significant reduction in the rate of decline. This behavior highlights the non-stationary nature in the time domain regions, consistent with its inherent temporal variability. Simulation results reveal significant variation in the autocorrelation decay rate across different parameter configurations. When $t = 0$ the time autocorrelation decays slowly from 1 to 0.5. By contrast, at $t = 1$ this decay occurs rapidly within 0.02 s. At higher values ($t = 2$ and $t = 3$) the decay accelerates further, completing in just 0.015 ms. Furthermore, these observations align closely with the findings reported in [42], thereby validating the theoretical derivations and numerical simulations of this model. The consistency with previous studies verifies the reliability and precision of the proposed approach.

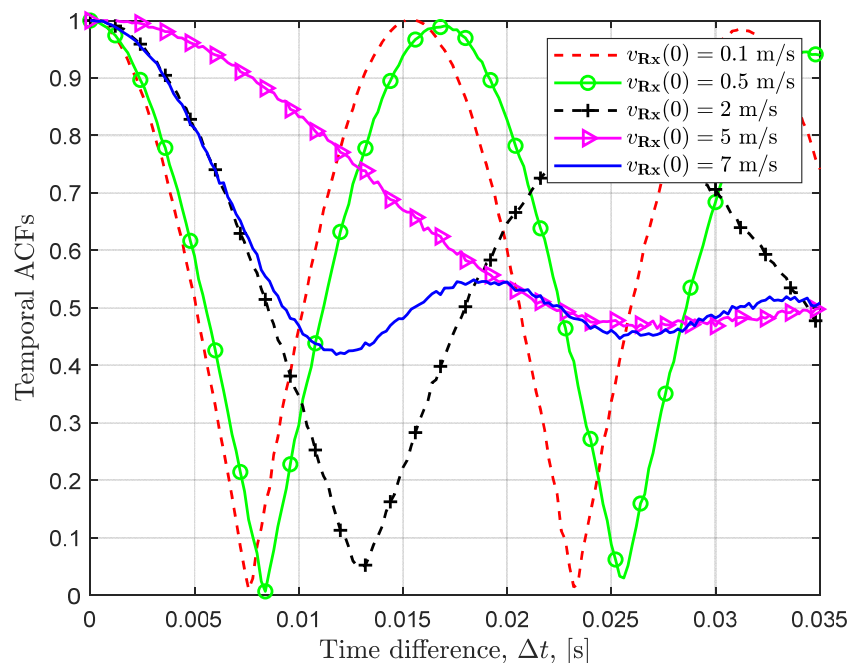


Figure 5. The characteristics of temporal autocorrelation characteristics under the proposed channel model within varying MR mobility speeds.

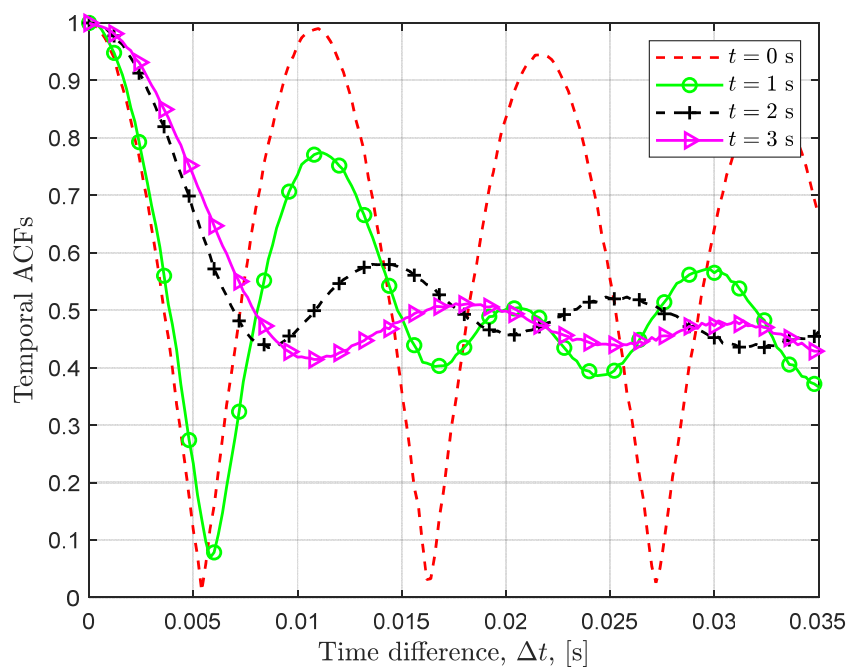


Figure 6. The characteristics of temporal autocorrelation characteristics under the proposed channel model within varying time parameters.

Figure 7 demonstrates the characteristics of temporal autocorrelation within diverse Rician factor K values. The simulation results reveal the significant influence of K on the channel's temporal autocorrelation behavior. Overall, the temporal autocorrelation exhibits a declining trend across all K configurations. Specifically, for smaller K values the temporal autocorrelation degrades rapidly, accompanied by pronounced punctuations. In contrast, for larger K values the autocorrelation decay rate slows considerably, with reduced punctuation magnitudes while maintaining elevated autocorrelation levels. Simulation results demonstrate distinct K -factor dependencies in time autocorrelation behavior. At $K = 0.1$ the most pronounced decay occurs—rapidly dropping from 1 to approximately 0.5.

For $K = 0.5$, while the peak autocorrelation decreases from 1 to 0.7, substantial fluctuations dominate the decay process. At $K \geq 1$, increasing K values progressively reduce fluctuation amplitude while maintaining peak autocorrelation above 0.8. These findings are in close agreement with the conclusions presented in Ref [43], thus confirming both the proposed channel model accuracy and its theoretical derivations. The observed dependency on K underscores the model's capability to capture nuanced temporal dynamics in Rician fading environments, reinforcing its applicability to scenarios requiring the precise characterization of non-stationary channel behaviors.

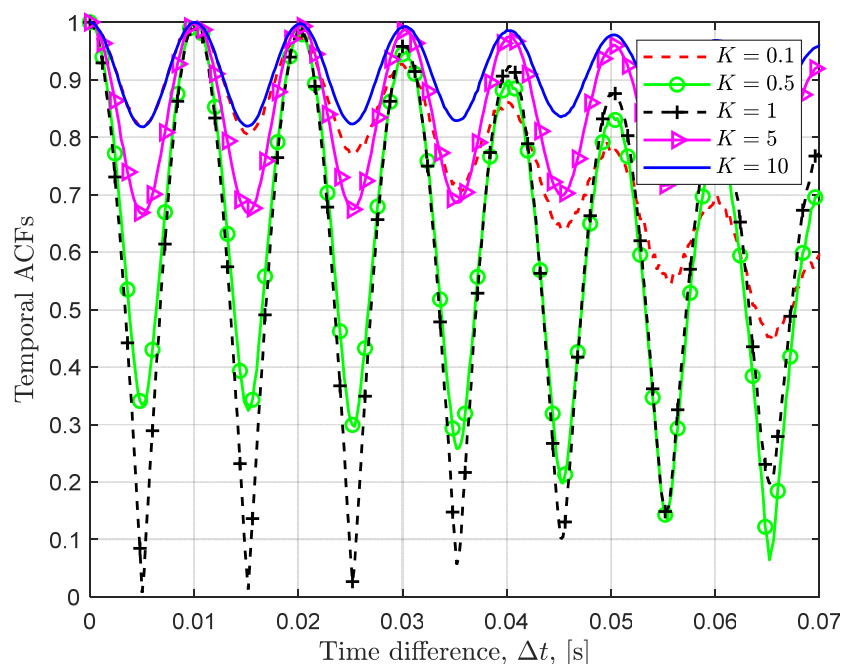


Figure 7. The characteristics of temporal autocorrelation characteristics under the proposed channel model within varying factor K .

The spatial cross-correlation features for various deployment locations of the RIS array are shown in Figure 8. It emphasizes that the RIS positioning has a substantial influence on the spatial cross-correlation properties. Overall, the spatial cross-correlation exhibits a declining trend across varying deployment configurations. Notably, distinct variation patterns emerge depending on the RIS array positioning. For instance, certain deployment geometries induce sharper cross-correlation decay, while others result in more gradual reductions. This divergence underscores the non-stationary nature in the spatial domain, emphasizing its sensitivity to environmental layout dynamics. Simulation results show that increasing the antenna size reduces peak spatial cross-correlation from 1 to approximately 0.7. The most rapid decrease occurs at $z_{\text{RIS}} = 1$. These observations align closely with the conclusions drawn in [44], thereby validating the theoretical framework and simulation accuracy of the proposed channel model's spatial cross-correlation properties. The consistency with prior research reinforces the model's capability to capture complex spatial interactions in RIS-aided communication systems, especially within the non-stationary propagation states.

Figure 9 shows the spatial cross-correlation properties under various initial distance parameters D_0 . It depicts a general declining trend in spatial cross-correlation across varying D_0 . Notably, distinct variation patterns emerge depending on the initial distance configuration. Specifically, smaller spatial cross-correlation values are observed when the initial distance is shorter, whereas larger cross-correlation magnitudes persist for longer initial distances. This divergence highlights the spatial non-stationary characteristics

of the channel, reflecting its sensitivity to geometric configurations in the propagation environment. Simulation results show that increasing the antenna size reduces peak spatial cross-correlation from 1 to approximately 0.7. These findings align closely with the conclusions reported in [44], thereby validating the theoretical framework and numerical accuracy under this model. This established literature consistency underscores the model's capability to capture complex spatial dependencies, particularly under dynamically varying initial distance conditions.

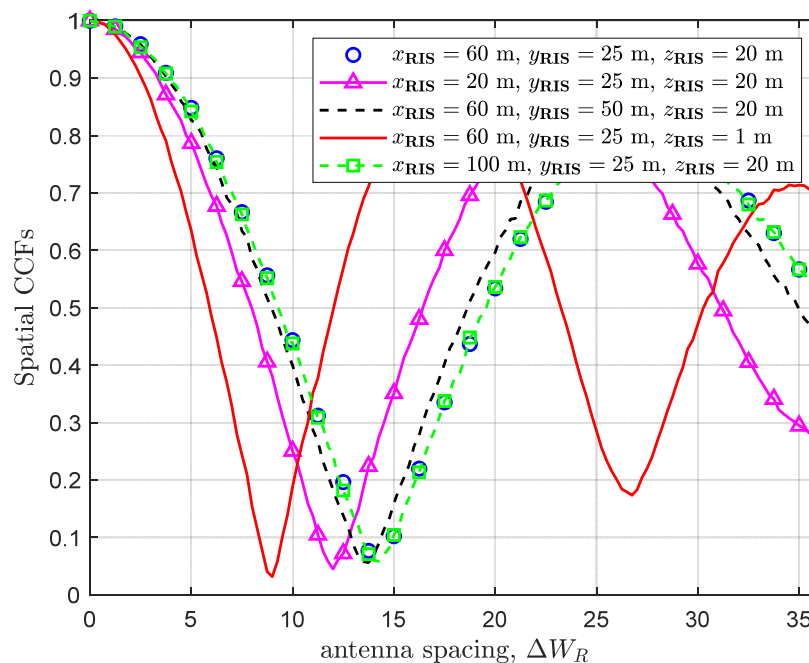


Figure 8. The characteristics of spatial cross-correlation under the proposed channel model within RIS array deployment configurations.

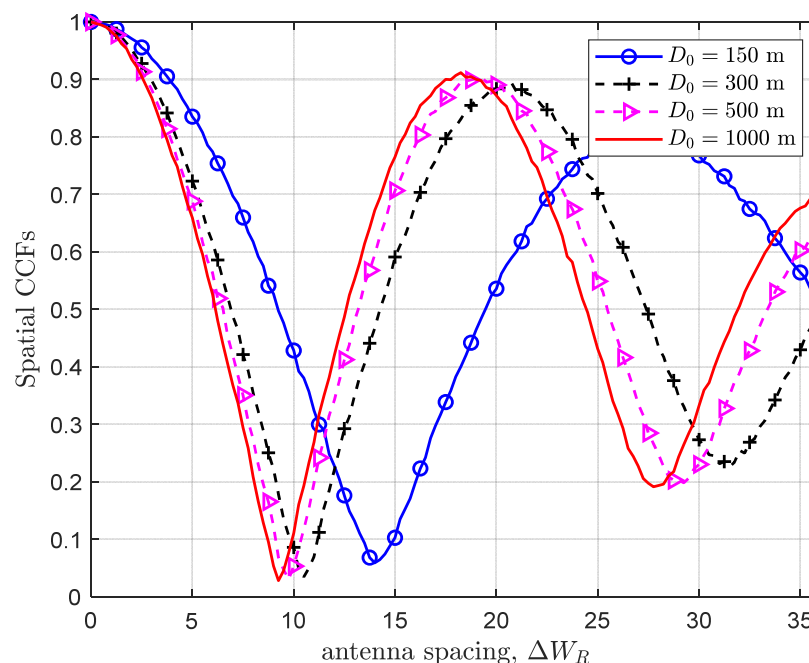


Figure 9. The characteristics of spatial cross-correlation under the proposed channel model within initial distance parameters.

The proposed channel model shows its spatial cross-correlation properties within diverse MR mobility speeds along the x -axis, presented in Figure 10. While the antenna port spacing grows larger, a decreasing trend in the simulation results demonstrate a declining trend in spatial cross-correlation, as revealed by the simulation results. Of the channel in the spatial domain, the intrinsic non-stationarity is confirmed by distinct variation patterns observed under different MR velocities. Specifically, higher MR mobility speeds induce a faster decay rate in spatial cross-correlation, whereas lower speeds result in a more gradual reduction. Simulation results indicate that increasing the antenna size causes peak spatial cross-correlation to fluctuate while declining from 1. Each successive peak appears to decrease by approximately 10%. This differential behavior highlights the model's sensitivity to dynamic spatial configurations caused by MR motion, further emphasizing its capability to capture non-stationary propagation effects.

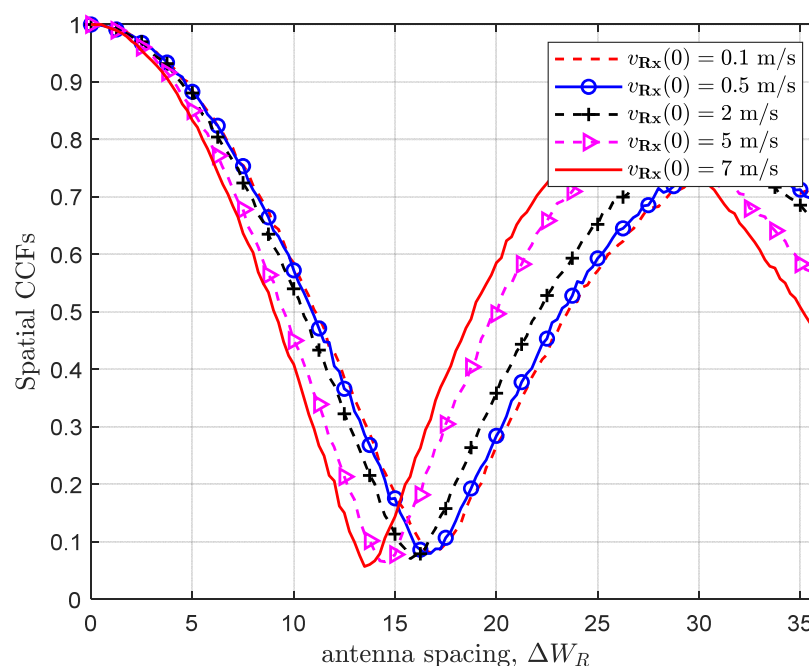


Figure 10. The characteristics of spatial cross-correlation under the proposed channel model within varying MR mobility speeds.

The spatial cross-correlation performance of this model under various Rician factor K values is depicted by Figure 11. The simulation results highlight distinct variation trends in spatial cross-correlation characteristics across varying K , thereby underscoring the non-stationary behavior of the channel in this spatial domain. More precisely, for smaller K values the spatial cross-correlation exhibits a rapid decay accompanied by pronounced punctuations. In contrast, for larger K values the decay rate slows significantly, with the cross-correlation curve demonstrating a smoother decline while maintaining elevated correlation magnitudes. These observations align with the theoretical expectations of Rician fading environments, where a dominant LoS component (associated with higher K) stabilizes spatial interactions, whereas a weaker dominant path (lower K) amplifies stochastic variations. Simulation results reveal the K -factor dependent effects of antenna size on spatial cross-correlation. At $K = 0.1$, cross-correlation decreases from 1 to approximately 0.3. For $K \geq 0.5$, the correlation decay rate significantly slows while fluctuation amplitude increases. At $K \geq 1$, spatial cross-correlation stabilizes within the 0.8–0.9 range. The results further validate the model's capability to emulate spatially non-stationary channel behaviors under diverse propagation conditions, reinforcing its applicability to advanced wireless communication systems requiring precise spatial correlation modeling.

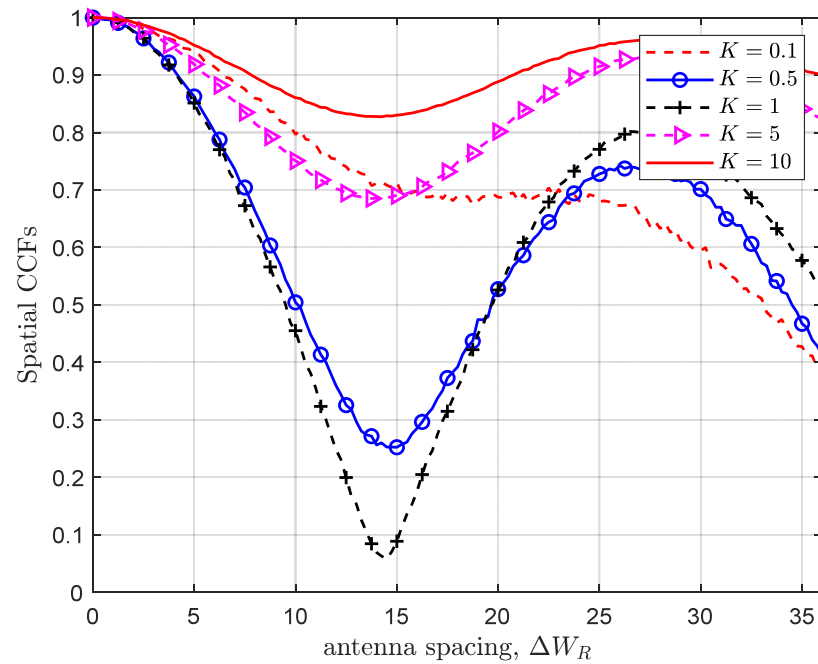


Figure 11. The characteristics of spatial cross-correlation under the proposed channel model within varying K factors.

7. Conclusions

This paper proposes a RIS-assisted V2V fluid antenna channel model, where RIS-reflected paths replace conventional LoS propagation. The ST CCF is derived to characterize the channels non-stationary properties. Comprehensive simulations were conducted under varying parameters, including RIS deployment positions, initial distance D_0 , MR mobility speeds, time parameter t , and Rician factor K . The results demonstrated that these parameters significantly influence both temporal autocorrelation and the channel's spatial cross-correlation characteristics. In particular, the non-stationary behavior of RIS-aided V2V channels in dynamic environments is effectively quantified by the proposed model. The simulations reveal distinct trends in temporal autocorrelation decay rates and spatial cross-correlation attenuation, governed by RIS positioning, mobility dynamics, and scattering conditions. Notably, the non-stationary features in both temporal and spatial domains are rigorously validated, highlighting the model's robustness under rapidly changing propagation scenarios. These findings underscore the model's capability to emulate real-world vehicular communication challenges, offering a theoretical foundation for optimizing RIS configurations and adaptive beamforming strategies in 6G-enabled intelligent transportation systems. Future work may extend this framework to multi-RIS collaboration and hybrid near-far field scenarios to further enhance practicality and scalability.

The following directions merit further investigation and refinement in subsequent studies: (i) Develop lightweight real-time RIS-phase optimization algorithms for high-mobility V2V, leveraging ML-based adaptive control. (ii) Investigate multi-RISs deployment impact on V2V in dense urban V2V, addressing Doppler shifts, delays, pilot overhead, and channel complexity. (iii) Co-design RIS reconfiguration with FAS port activation via real-time joint optimization for 6G vehicular latency-constrained applications. (iv) To enhance system performance and general applicability, future work will consider optimizing the reflection phases of individual RIS elements within more generalized communication scenarios. (v) Enhance our channel measurement efforts to incorporate metrics such as attenuation rate and sensitivity, thereby optimizing the performance of the channel model.

Author Contributions: Data curation, B.Z.; Writing—original draft, Z.P.; Writing—review & editing, J.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data are contained within the article.

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

References

1. Saad, W.; Bennis, M.; Chen, M. A vision of 6G wireless systems: Applications, trends, technologies, and open research problems. *IEEE Netw.* **2020**, *34*, 134–142. [\[CrossRef\]](#)
2. Rappaport, T.S.; Xing, Y.; Kanhere, O.; Ju, S.; Madanayake, A.; Mandal, S. Wireless communications and applications above 100 GHz: Opportunities and challenges for 6G and beyond. *IEEE Access* **2019**, *7*, 78729–78757. [\[CrossRef\]](#)
3. Tang, W.; Chen, X.; Chen, M.; Dai, J.; Han, Y.; Renzo, M.D. Path loss modeling and measurements for reconfigurable intelligent surfaces in the millimeter-wave band. *IEEE Trans. Antennas. Propag.* **2021**, *69*, 8329–8343. [\[CrossRef\]](#)
4. Alexandropoulos, G.C.; Shlezinger, N.; Hougne, P. Reconfigurable intelligent surfaces for rich scattering wireless communications: Recent experiments and challenges. *IEEE Wirel. Commun.* **2021**, *28*, 118–125. [\[CrossRef\]](#)
5. Wymeersch, H.; Seco-Granados, G.; Garcia, G.F.; Steinmetz, M.; Silven, M.; Polese, M. 5G NR V2X communications for connected and automated mobility. *IEEE Commun. Stand. Mag.* **2021**, *5*, 48–54.
6. 3GPP TR 36.885; Study on LTE-Based V2X Services. 3GPP: Sophia Antipolis, France, 2016.
7. Jiang, H.; Shi, W.; Chen, X.; Zhu, Q.; Chen, Z. High-efficient near-field channel characteristics analysis for large-scale MIMO communication systems. *IEEE. Internet Things J.* **2025**, *12*, 7446–7458. [\[CrossRef\]](#)
8. Hua, B.; Han, L.; Zhu, Q.; Wang, C.; Mao, K.; Bao, J. Ultra-Wideband Nonstationary Channel Modeling for UAV-to-Ground Communications. *IEEE Trans. Wirel. Commun.* **2025**, *24*, 4190–4204. [\[CrossRef\]](#)
9. Mao, K.; Zhu, Q.; Wang, C.; Ye, X.; Gomez-Ponce, J.; Cai, X. A survey on channel sounding technologies and measurements for UAV-assisted communications. *IEEE Trans. Instrum. Meas.* **2024**, *73*, 1–24. [\[CrossRef\]](#)
10. Mecklenbräuker, C.F.; Laura, B.; Jesus, G.; Thomas, Z.; Andreas, F.; Johan, K.; Fredrik, T.; Lorenzo, R.; Jose-Maria, M. Non-stationary vehicle-to-vehicle channel modeling using geometry-based stochastic approach. *IEEE Trans. Veh. Technol.* **2017**, *66*, 6703–6716.
11. Molisch, A.F. *Wireless Communications*, 2nd ed.; Wiley: Hoboken, NJ, USA, 2011.
12. Björnson, E.; Larsson, E.G.; Marzatta, T.L. Massive MIMO: Ten myths and one critical question. *IEEE Commun. Mag.* **2016**, *54*, 114–123. [\[CrossRef\]](#)
13. Boccardi, F.; Heath, R.W.; Lozano, A.; Marzetta, T.L.; Popovski, P. Five disruptive technology directions for 5G. *IEEE Commun. Mag.* **2014**, *52*, 74–80. [\[CrossRef\]](#)
14. Di Renzo, M.; Renzo, M.D.; Zappone, A.; Debbah, M.; Alouini, M.S.; Yuen, C.; Rosny, J.D. Smart radio environments empowered by reconfigurable intelligent surfaces: How it works, state of research, and road ahead. *IEEE Access* **2020**, *8*, 45974–45995. [\[CrossRef\]](#)
15. Ruan, C.; Zhang, Z.; Jiang, H.; Dang, J.; Wu, L.; Zhang, H. Wideband near-field channel covariance estimation for XL-MIMO systems in the face of beam split. *IEEE Trans. Veh. Technol.* **2025**, *74*, 2912–2926. [\[CrossRef\]](#)
16. Jiang, H.; Shi, W.; Zhang, Z.; Pan, C.; Wu, Q.; Shu, F. Large-scale RIS enabled air-ground channels: Near-field modeling and analysis. *IEEE Trans. Wirel. Commun.* **2025**, *24*, 1074–1088. [\[CrossRef\]](#)
17. Lian, Z.; Lian, Z.; Zhang, W.; Wang, Y.; Su, Y.; Zhang, B.; Biao, J. Physics-based channel modeling for IRS-assisted mmWave communication systems. *IEEE Trans. Commun.* **2024**, *72*, 2687–2700. [\[CrossRef\]](#)
18. Wang, J.; Zhu, Q.; Lin, Z.; Chen, J.; Ding, G.; Wu, Q. Sparse Bayesian learning-based hierarchical construction for 3D radio environment maps incorporating channel shadowing. *IEEE Trans. Wirel. Commun.* **2024**, *23*, 14560–14574. [\[CrossRef\]](#)
19. Tse, D.; Viswanath, P. *Fundamentals of Wireless Communication*; Cambridge University Press: Cambridge, UK, 2005.
20. 3GPP TR 38.901; Study on Channel Model for Frequencies from 0.5 to 100 GHz. 3GPP: Sophia Antipolis, France, 2020.
21. Zajic, A.; Gallagher, M.D.; Miletic, N.M.; West, J.; Zhang, J.; Mckaughlin, S.W.; Tranter, G.K. A 3-D geometry-based stochastic model for vehicle-to-vehicle MIMO channels. *IEEE Trans. Veh. Technol.* **2019**, *7*, 8674–8687.
22. Zeng, L.; Liao, X.; Ma, Z.; Liu, W.; Jiang, H.; Chen, Z. Toward more adaptive UAV-to-UAV GBSMs: Introducing the extended vMF distribution. *IEEE Wirel. Commun. Lett.* **2025**, *14*, 260–264. [\[CrossRef\]](#)
23. Abbas, T.; Karedal, J.; Tufvesson, F.; Palsson-Svensson, A.; Larsson, K. Measurement-based ray launching for V2V channel modeling. *IEEE Trans. Antennas. Propag.* **2017**, *65*, 6752–6766.
24. Chen, Z.; Guo, Y.; Zhang, P.; Jiang, H.; Xiao, Y.; Haung, L. Physical layer security improvement for hybrid RIS-assisted MIMO communications. *IEEE Commun. Lett.* **2024**, *28*, 2493–2497. [\[CrossRef\]](#)

25. Ma, Z.; Ai, B.; He, R.; Mi, H.; Yang, M.; Wang, N. Modeling and analysis of MIMO multipath channels with aerial intelligent reflecting surface. *IEEE J. Sel. Areas. Commun.* **2022**, *40*, 3027–3040. [\[CrossRef\]](#)
26. Basar, E.; Renzo, M.D.; Rosny, J.D.; Debbah, M.; Alouini, M.; Zhang, R. Wireless communications through reconfigurable intelligent surfaces. *IEEE Access* **2019**, *7*, 116753–116773. [\[CrossRef\]](#)
27. Huang, C.; He, R.; Ai, B.; Li, G.Y.; Zhong, Z. RIS-enhanced wideband coverage: A geometric channel modeling approach. *IEEE J. Sel. Areas. Commun.* **2022**, *40*, 1967–1981.
28. Cheng, L.; Yu, Z.; Yang, L.; Chen, B.; Zhong, Z. Millimeter-wave V2V channel modeling with cluster dynamics. *IEEE Trans. Intell. Transp. Syst.* **2021**, *22*, 6813–6827.
29. Hu, S.; Yuen, C.; Renzo, M.D.; Shi, Y. Dynamic RIS configuration for mobile users: A deep reinforcement learning approach. *IEEE Trans. Commun.* **2022**, *70*, 1905–1918.
30. Chen, Z.; Huang, L.; So, H.C.; Jiang, H.; Zhang, X.; Wang, J. Deep reinforcement learning over RIS-assisted integrated sensing and communication: Challenges and opportunities. *IEEE Veh. Technol. Mag.* **2024**, early access. [\[CrossRef\]](#)
31. Chu, H.; Yang, M.; Pan, X.; Ge, X. Joint active and passive beamforming design for hybrid RIS-aided integrated sensing and communication. *China Commun.* **2024**, *21*, 1–12.
32. Chu, H.; Pan, X.; Jiang, J.; Li, X.; Zheng, L. Adaptive and robust channel estimation for IRS-aided millimeter-wave communications. *IEEE Trans. Veh. Technol.* **2024**, *73*, 9411–9423. [\[CrossRef\]](#)
33. Lian, Z.; Wang, Y.; Su, Y.; Ji, P. A novel beam channel model and capacity analysis for UAV-enabled millimeter-wave communication systems. *IEEE Trans. Wirel. Commun.* **2024**, *23*, 3617–3632. [\[CrossRef\]](#)
34. Yuan, Y.; Wang, C.; Yang, Y.; Li, Y.; Ge, X. 3D geometry-based vehicle-to-vehicle channel modeling with dual mobility. *IEEE Trans. Veh. Technol.* **2020**, *69*, 8329–8343.
35. Gershman, A.B.; Sanguinetti, L.; Debbah, M.; Fischione, C. MIMO systems for vehicle-to-vehicle communications. *IEEE Commun. Mag.* **2016**, *54*, 98–105.
36. Ruan, C.; Zhang, Z.; Jiang, H.; Zhang, H.; Dang, J.; Wu, L. Simplified learned approximate message passing network for beamspace channel estimation in mmWave massive MIMO systems. *IEEE Trans. Wirel. Commun.* **2024**, *23*, 5142–5156. [\[CrossRef\]](#)
37. Wang, J.; Xiao, J.; Zou, Y.; Xie, W.; Liu, Y. Wideband beamforming for RIS assisted near-field communications. *IEEE Trans. Wirel. Commun.* **2024**, *23*, 16836–16851. [\[CrossRef\]](#)
38. Yang, N.; Jiang, H.; Guo, D.; Liu, Y.; Ding, G.; Chen, Z. Proof of reputation: A blockchain-based countermeasure to defend against massive SSDF in cognitive radio networks. *IEEE Commun. Lett.* **2024**, *28*, 2693–2697. [\[CrossRef\]](#)
39. Zhang, J.; Zhang, S.; Zhang, Y.; Yuen, C.; Zhang, W.; Guan, Y. Dynamic port selection in fluid antenna systems for mobile communications. *IEEE Trans. Veh. Technol.* **2021**, *70*, 6345–6359.
40. Zeng, L.; Liao, X.; Xie, W.; Ma, Z.; Xiong, B.; Jiang, H. UAV-to-ground channel modeling: (Quasi-)Closed-form channel statistics and manual parameter estimation. *China. Commun.* **2024**, *21*, 100–115. [\[CrossRef\]](#)
41. Jiang, H.; Xiong, B.; Zhang, H.; Basar, E. Physics-based 3D end-to-end modeling for double-RIS assisted non-stationary UAV-to-ground communication channels. *IEEE Trans. Commun.* **2023**, *71*, 4247–4261. [\[CrossRef\]](#)
42. Lian, Z.; Jiang, L.; He, C.; He, D. A non-stationary 3-D wideband GBSM for HAP-MIMO communication systems. *IEEE Trans. Veh. Technol.* **2019**, *68*, 1128–1139. [\[CrossRef\]](#)
43. Mao, K.; Zhu, Q.; Qiu, Y.; Liu, X.; Song, M.; Fan, W. A UAV-aided real-time channel sounder for highly dynamic nonstationary A2G scenarios. *IEEE Trans. Instrum. Meas.* **2023**, *72*, 1–15. [\[CrossRef\]](#)
44. Sun, G.; He, R.; Ma, Z.; Ai, B.; Zhong, Z. A 3D geometry-based non-stationary MIMO channel model for RIS-assisted communications. In Proceedings of the IEEE VTC2021-Fall, Norman, OK, USA, 27–30 September 2021; pp. 1–5.

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