

Performance Analysis of XL-MIMO With Rotary and Movable Antennas for High-Speed Railway

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Abstract—The rotary and movable antennas (ROMA) technology is efficient in enhancing wireless network capacity by adjusting both the antenna spacing and three-dimensional (3D) rotation of antenna surfaces, based on the spatial distribution of users and channel statistics. Applying ROMA to high-speed rail (HSR) wireless communications can significantly improve system performance in terms of array gain and spatial multiplexing. However, the rapidly changing channel conditions in HSR scenarios present challenges for ROMA configuration. In this correspondence, we propose an analytical framework for configuring ROMA-based extremely large-scale multiple-input-multiple-output (XL-MIMO) systems in HSR scenarios based on spatial correlation. First, we develop a localization model based on a mobility-aware near-field beam training algorithm to determine the real-time position of the train relay antennas. Next, we derive the expression for channel orthogonality and antenna spacing based on the spatial correlation matrix, and obtain the optimal antenna spacing when the transceiver arrays are aligned in parallel. Moreover, we propose an optimization algorithm for the rotation angle of the transceiver arrays, leveraging the differential evolution method, to determine the optimal angles. Finally, numerical results are provided to validate the computational results and optimization algorithm.

Index Terms—XL-MIMO, high-speed railway, ROMA, spatial correlation, capacity.

I. INTRODUCTION

Deploying extremely large-scale multiple-input-multiple-output (XL-MIMO) systems in high-speed railway (HSR) environments significantly improves degrees of freedom (DoFs) and spectral efficiency (SE), which can substantially enhance wireless network coverage [1], [2]. However, this multi-antenna technique essentially represents MIMO with fixed-position antennas. While increasing the number of fixed-position antennas can enhance performance, it also leads to higher hardware costs and increased power consumption. Furthermore, in a wireless network utilizing fixed-position antennas (FPA), the allocation of antenna resources cannot be dynamically adjusted based on the spatial distribution of user channels, beyond the capabilities of traditional adaptive MIMO processing [3]. Especially in the HSR communication scenario, it is not a viable solution to increase the number of fixed-position antennas without limit to improve the signal transmission quality. Furthermore, the fixed-position XL-MIMO

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systems exhibit considerable limitations in flexibility when serving high-speed mobile users. To fully leverage the spatial variations in wireless channels at base stations (BS) and wireless terminals, the rotary and movable antennas (ROMA) technique has been proposed as a novel and cost-effective solution for enhancing wireless network performance [4], [5].

ROMA is an emerging next-generation multiple antenna technology that can flexibly adjust the antenna spacing and array rotation angles of the transceiver. The fundamental idea is to enhance the spatial freedom and channel capacity of the MIMO system without increasing the number of antennas, achieved by adjusting the transceiver antenna units and the 3D geometric features of the entire array. Based on the characteristics above, the ROMA technology has very promising prospects for application in high-mobility scenarios, such as HSR and low-altitude unmanned aerial vehicle (UAV) scenarios. There are several recent studies that adopt similar ideas. In [6], the authors analyzed the performance of a system in which the Access Point (AP) is able to both move and rotate. In [7] and [8], the authors optimized the average network capacity for a random number of users located at random positions by jointly adjusting the 3D positions and rotations of multiple six-dimensional movable antenna (6DMA) surfaces. Besides, the authors of [9] proposed instantaneous and statistical channel estimation algorithms tailored for 6DMA systems by exploiting a new directional sparsity of 6DMA channels. In [10], the authors proposed a fluid antenna system in which the physical position of an antenna can be switched freely to one of the N positions over a fixed-length line space to pick up the strongest signal in the manner of traditional selection diversity. Compared to previous studies, the ROMA technology can adjust the geometric characteristics of the transceiver antenna arrays, enabling the 360-degree rotation of the transceiver antenna arrays and the position movement of the antenna elements on the antenna array. Based on existing research, the ROMA technology increases the spatial variation dimension of the antenna array, thus meeting the growing communication demands of the HSR scenarios. While continuously rotating the ROMA surface offers maximum flexibility and the greatest capacity enhancement, the rapid movement of the HSR leads to frequent changes in channel conditions, making it challenging to determine the optimal rotation angle of the ROMA surface at any given moment.

In this correspondence, we deploy an XL-MIMO system with ROMA in HSR scenario. We then analyze and optimize the system based on spatial correlation, considering factors such as spatial freedom, system capacity, and other relevant metrics. First, we develop a localization model using mobility-aware near-field beam training to predict the XL-MIMO system's position over time. Next, we calculate the antenna spacing that ensures spatial orthogonality of the channel, based on the channel's spatial correlation matrix. Finally, we determine the optimal rotation angles for both the transceiver and the end panels in 3D space using a differential optimization algorithm. Simulation results validate the effectiveness of the optimal antenna spacing expression and the rotation angle optimization algorithm.

II. SYSTEM MODEL

We consider a downlink XL-MIMO system for HSR scenario, wherein the transmitter and receiver are UPAs with $M = M_H \times M_V$ and $N = N_H \times N_V$ antenna elements, respectively, where $M_H (N_H)$ is the number of the antenna elements in the horizontal direction and

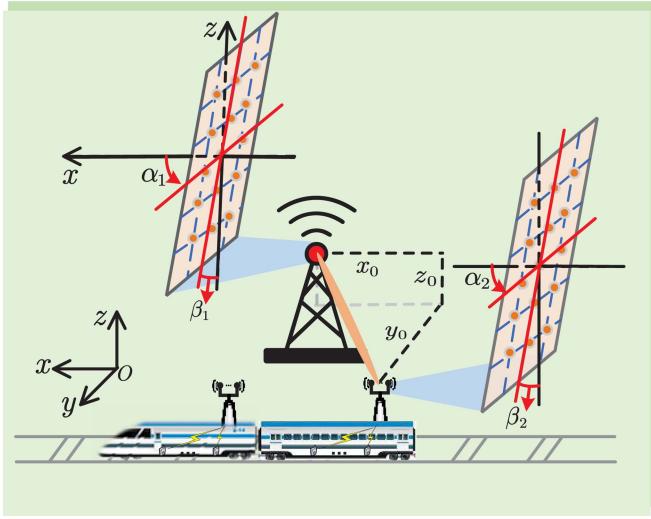


Fig. 1. ROMA-enabled HSR XL-MIMO communication systems.

$M_V(N_V)$ is the number of elements in the vertical direction. The uniform antenna spacing between adjacent transmit (TX) antennas is denoted as d_{tv} in the vertical direction and d_{th} in the horizontal direction, while the spacing between adjacent receive (RX) antennas is denoted as d_{rv} in the vertical direction and d_{rh} in the horizontal direction. As shown in Fig. 1, the geometric relationship between the transmitting and receiving UPA is defined by four 3D rotation angles: α_1 , β_1 , α_2 , and β_2 , representing the transmitter's rotation about the x -axis and z -axis, and the receiver's rotation about the x -axis and z -axis, respectively. The transmitter is centered in $\mathbf{r}^t = [0, 0, 0]^T$, while the receiver is centered in $\mathbf{r}^r = [x_0, y_0, z_0]^T$. Hence, the distance between the center points of the antenna arrays is

$$D = |\mathbf{r}^t - \mathbf{r}^r| = \sqrt{x_0^2 + y_0^2 + z_0^2}. \quad (1)$$

The positions of the m -th transmit antenna element and the n -th receive antenna element are denoted by $\mathbf{r}_m^t = [\Delta_{xm}^t, \Delta_{ym}^t, \Delta_{zm}^t]^T$ and $\mathbf{r}_n^r = [x_0 + \Delta_{xn}^r, y_0 + \Delta_{yn}^r, z_0 + \Delta_{zn}^r]^T$, respectively. Δ_{an}^r and Δ_{am}^t for the a -axis with $a = \{x, y, z\}$ are the coordinates with respect to the center of the transmitter and receiver, respectively. Δ_{am}^t can be shown as

$$\begin{cases} \Delta_{xm}^t = \left(m_1 - \frac{M_H-1}{2}\right) d_{th} \cos \alpha_1 - \left(m_2 - \frac{M_V-1}{2}\right) d_{tv} \sin \beta_1 \sin \alpha_1 \\ \Delta_{ym}^t = \left(m_1 - \frac{M_H-1}{2}\right) d_{th} \sin \alpha_1 + \left(m_2 - \frac{M_V-1}{2}\right) d_{tv} \sin \beta_1 \cos \alpha_1, \\ \Delta_{zm}^t = \left(m_2 - \frac{M_V-1}{2}\right) d_{tv} \cos \beta_1 \end{cases} \quad (2)$$

where $m_1 = \text{mod}(m-1, M_H)$ and $m_2 = \lfloor (m-1)/M_H \rfloor$ are the row and column indexes of the m -th transmit antenna. Based on the number of antennas and the antenna spacing of the receiver panel defined above, we can represent Δ_{an}^r in exactly the same form as Δ_{am}^t [11].

The channel matrix between the transmitter and the receiver is $\mathbf{H} \in \mathbb{C}^{N \times M}$. Since we consider HSR communication in the open scenario, the power of LoS path is much higher than that of the non-LoS (NLoS) paths. Accordingly, the channel matrix between the m -th transmitting antenna and the n -th receiving antenna can be modeled as

$$[\mathbf{H}]_{nm} = \frac{e^{-jk|\mathbf{r}_m^t - \mathbf{r}_n^r|}}{4\pi|\mathbf{r}_m^t - \mathbf{r}_n^r|}, \quad (3)$$

where $k = c/f$ is the wavenumber with c is the speed of the light, $f = f_c + f_d$ is the propagation frequency, f_c is the carrier frequency,

$f_d = \frac{f_c}{c} \frac{(\mathbf{r}_n^r - \mathbf{r}_m^t) \mathbf{v}}{|\mathbf{r}_n^r - \mathbf{r}_m^t|}$ is the Doppler frequency offset, and $\mathbf{v} = [v, 0, 0]^T$ is the velocity of the train. Hence, the channel correlation matrix is given by $\mathbf{G} = \mathbf{H}^* \mathbf{H} \in \mathbb{C}^{M \times M}$. According to the considered system model, the channel capacity is given as follows:

$$C = \sum_{i=1}^R \log_2 \left(1 + \frac{P_i}{\sigma^2} \lambda_i \right), \quad (4)$$

where λ_i is the i -th largest eigenvalue of \mathbf{G} , R is the rank of \mathbf{G} , σ^2 is the additive white Gaussian noise power, and P_i is the power allocated to the i -th communication mode. In the high SNR regime and LoS conditions, as considered in this system, the capacity is maximized when \mathbf{H} is an orthogonality matrix, rank of \mathbf{G} is $R = M$ and the R eigenvalues have the same magnitude. Therefore, we need to fulfill the following condition to ensure the matrix \mathbf{H} is orthogonal [12]:

$$\mathbf{G}(u, v) = \sum_{n=1}^N [\mathbf{H}(n, u)]^* \mathbf{H}(n, v) = 0 \quad \forall u \neq v = 1, 2, \dots, M. \quad (5)$$

III. ROMA-HSR XL-MIMO SYSTEMS

In this section, we describe our proposed framework for optimizing the deployment of antennas for UPA-based XL-MIMO HSR communication systems. Firstly, the moving receiver is localized with the predictive beam training algorithm mentioned in [13]; then we analyze the conditions that make the channel matrix \mathbf{H} orthogonal; finally, the channel capacity is maximized by optimizing the antenna configuration.

A. Localization Model

We construct the localization model of the user's location based on the predictive beam training model of our previous work [13]. Considering the speed stability and the small curvature of the track during operation, the channel parameters can be obtained from the first two near-field beam training after the receiver enters the sender's coverage area.

First, with the receiver position at time $t \in \{0, \Delta t, \dots, T\}$ as (θ_t, R_t) , we conduct beam training to maximize the downlink beam focusing gain [14], and obtain the angle and distance parameters corresponding to the optimal near-field beam:

$$(\hat{\theta}_t, \hat{R}_t) = \underset{\mathbf{y} \in \mathbb{C}^N}{\text{argmax}} \|\mathbf{y}\|_F^2, \quad (6)$$

where $\mathbf{y} \in \mathbb{C}^N$ is the received signal.

Then, these parameters obtained from the first two beam training can be used to predict the train's subsequent motion state while enabling real-time error correction. We can obtain the speed and position of the receiver at that moment as

$$\begin{cases} \hat{v} = \frac{R_0 \cos \theta_0 - R \Delta t \cos \theta_{\Delta t}}{\Delta t} \\ (\hat{\theta}_t, \hat{R}_t) = \left(\text{atan} \left(\frac{R_0 \sin \theta_0}{R_0 \cos \theta_0 - v t} \right), \sqrt{(vt)^2 - 2vtR_0 \cos \theta_0 + R_0^2} \right) \end{cases}, \quad (7)$$

where $(\hat{\theta}_t, \hat{R}_t) = (\text{arc tan} \frac{y_0}{x_0}, \sqrt{x_0^2 + y_0^2})$ is the receiver's position at the moment t in the form of angle and distance, Δt is the time interval between the first and second beam training, and $[0, T]$ is the time range when the train passes through the coverage area of the BS.

Based on the principle that near-field beam training can be accurate to both angle and distance dimensions, this localization scheme improves the existing near-field hierarchical beam training and achieves position prediction for mobile users targeting HSR scenarios with low-frequency

beam training, and at the same time can correct the error to a certain extent. This scheme provides the basis of user location for subsequent channel correlation analysis.

B. Channel Correlation Model

Based on the system model shown in Fig. 1, the apertures of the antenna arrays are sufficiently small compared with the distance between their center points. Therefore, the amplitude of (3) changes slowly and it can be approximated as $1/D$. Moreover, the phase in (3) is very sensitive to the variations of $|\mathbf{r}_m^t - \mathbf{r}_n^r|$. By denoting $f(x) = 2x_0\Delta_{xn}^r - 2x_0\Delta_{xm}^t + (\Delta_{xn}^r)^2 - 2\Delta_{xn}^r\Delta_{xm}^t + (\Delta_{xm}^t)^2$ and $g(x) = 2x_0\Delta_{xn}^r - 2x_0\Delta_{xm}^t + (\Delta_{xn}^r)^2 - 2\Delta_{xn}^r\Delta_{xm}^t$, the distance $|\mathbf{r}_m^t - \mathbf{r}_n^r|$ in the phase term can be approximated as

$$\begin{aligned} d_{nm} &= |\mathbf{r}_m^t - \mathbf{r}_n^r| \\ &= \sqrt{D^2 + \rho(\mathbf{r}_m^t - \mathbf{r}_n^r)} \\ &\approx D \left[1 + \frac{\rho(\mathbf{r}_m^t - \mathbf{r}_n^r)}{2D^2} - \frac{\rho^2(\mathbf{r}_m^t - \mathbf{r}_n^r)}{8D^4} \right], \end{aligned} \quad (8)$$

where

$$\rho(\mathbf{r}_m^t - \mathbf{r}_n^r) = f(x) + f(y) + f(z), \quad (9)$$

$$\rho^2(\mathbf{r}_m^t - \mathbf{r}_n^r) \approx (g(x) + g(y) + g(z))^2. \quad (10)$$

The approximation in (8) stems from Taylor's approximation $\sqrt{1+x} \approx 1 + x/2 - x^2/8$, and the approximation in (10) can be applied when antenna array dimensions are much smaller than the center distance between the transceiver and the receiver. The channel matrix in (3) with the approximated antenna distance is equivalent as

$$\mathbf{H} \approx \frac{1}{4\pi D} \mathbf{F}_{\text{RX}} \mathbf{P} \mathbf{F}_{\text{TX}}^*, \quad (11)$$

where $\mathbf{F}_{\text{RX}} \in \mathbb{C}^{N \times N}$ and $\mathbf{F}_{\text{TX}} \in \mathbb{C}^{M \times M}$ are diagonal matrices representing the phase shifts caused by the receiver and transmitter independently. Upon defining an expression as

$$\begin{aligned} \zeta(\Delta_x, \Delta_y, \Delta_z) &= \exp \left\{ -\frac{jk}{2D} \left[-2x_0\Delta_x + (\Delta_x)^2 - 2y_0\Delta_y \right. \right. \\ &\quad \left. \left. + (\Delta_y)^2 - 2z_0\Delta_z + (\Delta_z)^2 - \frac{(\Delta_x x_0 + \Delta_y y_0 + \Delta_z z_0)^2}{D^2} \right] \right\}, \end{aligned} \quad (12)$$

we can represent the (m, m) -th element of \mathbf{F}_{TX} is $\mathbf{F}_{\text{TX}}(m, m) = \zeta(\Delta_{xm}^t, \Delta_{ym}^t, \Delta_{zm}^t)$ and the (n, n) -th element of \mathbf{F}_{RX} is $\mathbf{F}_{\text{RX}}(n, n) = \zeta(\Delta_{xn}^r, \Delta_{yn}^r, \Delta_{zn}^r)$. Besides, \mathbf{P} is the channel matrix contributed by spatial multiplexing and is a non-diagonal matrix, given by

$$\begin{aligned} \mathbf{P}(n, m) &= \exp \left\{ \frac{jk}{D} \left[\Delta_{xn}^r \Delta_{xm}^t + \Delta_{yn}^r \Delta_{ym}^t + \Delta_{zn}^r \Delta_{zm}^t \right. \right. \\ &\quad \left. \left. - \frac{(\Delta_{xm}^t x_0 + \Delta_{ym}^t y_0 + \Delta_{zm}^t z_0)(\Delta_{xn}^r x_0 + \Delta_{yn}^r y_0 + \Delta_{zn}^r z_0)}{D^2} \right] \right\}. \end{aligned} \quad (13)$$

Therefore, \mathbf{G} can be written as follows

$$\begin{aligned} \mathbf{G} &= \frac{1}{(4\pi D)^2} [\mathbf{F}_{\text{RX}} \mathbf{P} \mathbf{F}_{\text{TX}}^*]^* \mathbf{F}_{\text{RX}} \mathbf{P} \mathbf{F}_{\text{TX}}^* \\ &= \frac{1}{(4\pi D)^2} \mathbf{F}_{\text{TX}} \mathbf{P}^* \mathbf{P} \mathbf{F}_{\text{TX}}^*. \end{aligned} \quad (14)$$

Because \mathbf{F}_{TX} is a diagonal matrix, it doesn't have any impact on the diagonalization of \mathbf{G} . Let $\mathbf{R} = \mathbf{P}^* \mathbf{P}$ denote the channel gain matrix, which the rank of \mathbf{R} being equal to that of \mathbf{G} [15]. Therefore, by denoting $p(x) = \Delta_{xv}^t - \Delta_{xu}^t$, the (u, v) -th element of the channel gain matrices \mathbf{R} is given by

$$\begin{aligned} \mathbf{R}(u, v) &= \sum_{n=1}^N [\mathbf{P}(n, u)]^* \mathbf{P}(n, v) \\ &= \sum_{n=1}^N \exp \left(\frac{jk}{D} [\Delta_{xn}^r p(x) + \Delta_{yn}^r p(y) + \Delta_{zn}^r p(z) \right. \\ &\quad \left. - \frac{(\Delta_{xn}^r x_0 + \Delta_{yn}^r y_0 + \Delta_{zn}^r z_0)(p(x)x_0 + p(y)y_0 + p(z)z_0)}{D^2}] \right) \end{aligned} \quad (15)$$

According to (2), we denote the position indices of the u -th antenna, v -th antenna and n -th antenna as (u_1, u_2) , (v_1, v_2) and (n_1, n_2) , respectively. Then substituting the antenna-specific coordinates, we expand and simplify (15), shown as

$$\begin{aligned} \mathbf{R}(u, v) &= \sum_{n_1=0}^{N_H-1} \sum_{n_2=0}^{N_V-1} \exp \left\{ jk \left\{ [\eta_{11}(v_1 - u_1) + \eta_{12}(v_2 - u_2)] \right. \right. \\ &\quad \left. \left. \left(n_1 - \frac{N_H-1}{2} \right) + [\eta_{21}(v_1 - u_1) + \eta_{22}(v_2 - u_2)] \right. \right. \\ &\quad \left. \left. \times \left(n_2 - \frac{N_V-1}{2} \right) \right\} \right\}, \end{aligned} \quad (16)$$

where

$$\begin{aligned} \eta_{11} &= d_{rh} d_{th} \frac{1}{D^3} (\sigma_1(\alpha_1, \alpha_2) + y_0^2 \sin \alpha_1 \sin \alpha_2 + x_0 y_0 \\ &\quad \times \sin(\alpha_1 - \alpha_2)), \end{aligned} \quad (17)$$

$$\begin{aligned} \eta_{12} &= d_{rh} d_{tv} \frac{1}{D^3} (\sin \beta_1 \sigma_2(\beta_1, \alpha_1, \alpha_2) - z_0 \cos \beta_1 (x_0 \cos \alpha_2 \\ &\quad + y_0 \sin \alpha_2)), \end{aligned} \quad (18)$$

$$\begin{aligned} \eta_{21} &= d_{rv} d_{th} \frac{1}{D^3} (\sin \beta_1 \sigma_2(\beta_2, \alpha_2, \alpha_1) - z_0 \cos \beta_1 (x_0 \cos \alpha_2 \\ &\quad + y_0 \sin \alpha_2)), \end{aligned} \quad (19)$$

$$\begin{aligned} \eta_{22} &= d_{rv} d_{tv} \frac{1}{D^3} (\sin \beta_1 \sin \beta_2 (\sigma_1 \left(\alpha_1 + \frac{\pi}{2}, \alpha_2 + \frac{\pi}{2} \right) + \sigma_4(\alpha_1, \alpha_2)) \\ &\quad + x_0 z_0 \sigma_3(\alpha_1, \alpha_2) - y_0 z_0 \sigma_3 \left(\alpha_1 + \frac{\pi}{2}, \alpha_2 + \frac{\pi}{2} \right)), \end{aligned} \quad (20)$$

with $\sigma_1(\alpha_1, \alpha_2) = D^2 \cos(\alpha_1 - \alpha_2) - x_0^2 \cos \alpha_1 \cos \alpha_2$, $\sigma_2(\beta_1, \alpha_1, \alpha_2) = -D^2 \sin(\alpha_1 - \alpha_2) + x_0^2 \sin \alpha_1 \cos \alpha_2 - y_0^2 \cos \alpha_1 \sin \alpha_2 - x_0 y_0 \cos(\alpha_1 + \alpha_2)$, $\sigma_3(\alpha_1, \alpha_2) = \sin \alpha_1 \sin \beta_1 \cos \beta_2 + \sin \alpha_2 \cos \beta_1 \sin \beta_2$, and $\sigma_4(\alpha_1, \alpha_2) = -y_0^2 \cos \alpha_1 \cos \alpha_2 + D^2 \cos \beta_1 \cos \beta_2 - z_0^2 \cos \beta_1 \cos \beta_2 + x_0 y_0 \sin(\alpha_1 + \alpha_2)$.

With $\chi_b = k[\eta_{b1}(v_1 - u_1) + \eta_{b2}(v_2 - u_2)]$ ($b \in \{1, 2\}$), we can simplify (16) using the geometric sum formula $\sum_{n=0}^{M-1} x^n = (1 - x^M)/(1 - x)$, which is shown as

$$\begin{aligned} \mathbf{R}(u, v) &= \sum_{n_1=0}^{N_H-1} (e^{jk[\eta_{11}(v_1 - u_1) + \eta_{12}(v_2 - u_2)]})^{\left(n_1 - \frac{N_H-1}{2}\right)} \\ &\quad \times \sum_{n_2=0}^{N_V-1} (e^{jk[\eta_{21}(v_1 - u_1) + \eta_{22}(v_2 - u_2)]})^{\left(n_2 - \frac{N_V-1}{2}\right)} \end{aligned}$$

$$\begin{aligned}
&= \frac{(1 - e^{j\chi_1 N_H}) e^{j\chi_1 \left(-\frac{N_H-1}{2}\right)}}{1 - e^{j\chi_1}} \frac{(1 - e^{j\chi_2 N_V}) e^{j\chi_2 \left(-\frac{N_V-1}{2}\right)}}{1 - e^{j\chi_2}} \\
&= \frac{(e^{-j\chi_1 \frac{N_H}{2}} - e^{j\chi_1 \frac{N_H}{2}})(e^{-j\chi_2 \frac{N_V}{2}} - e^{j\chi_2 \frac{N_V}{2}})}{(e^{-j\frac{1}{2}\chi_1} - e^{j\frac{1}{2}\chi_1})(e^{-j\frac{1}{2}\chi_2} - e^{j\frac{1}{2}\chi_2})}. \quad (21)
\end{aligned}$$

With the trigonometric identity $\sin(x) = (e^{jx} - e^{-jx})/(2j)$, the expression can be shown as

$$\begin{aligned}
\mathbf{R}(u, v) &= \frac{\sin(k(\eta_{11}(u_1 - v_1) + \eta_{12}(u_2 - v_2))\frac{N_H}{2})}{\sin(k(\eta_{11}(u_1 - v_1) + \eta_{12}(u_2 - v_2)\frac{1}{2}))} \\
&\times \frac{\sin(k(\eta_{21}(u_1 - v_1) + \eta_{22}(u_2 - v_2))\frac{N_V}{2})}{\sin(k(\eta_{21}(u_1 - v_1) + \eta_{22}(u_2 - v_2)\frac{1}{2}))}. \quad (22)
\end{aligned}$$

To satisfy the channel orthogonality condition of (5), the matrix elements represented by \mathbf{R} as shown in (22) have to be equal to zero at non-diagonal positions. Then, the condition can be given by

$$\mathbf{R}(u, v) = \sum_{n=1}^N [\mathbf{P}(n, u)]^* \mathbf{P}(n, v) = 0 \quad \forall u \neq v = 1, 2, \dots, M. \quad (23)$$

According to [16], the orthogonality condition presented in (23) admits a solution provided that at least one η_{ab} ($a, b = 1, 2$) is equal to zero.

Corollary 1: When the transceiver planes are parallel and the antenna spacing is uniform with $\alpha_1, \beta_1, \alpha_2, \beta_2 = 0$ and $d_{th} = d_{tv} = d_{rh} = d_{rv} = d$, the antenna spacing can be expressed as

$$d = \sqrt{\left| \frac{\lambda D^3}{N_H (x_0 z_0)} \right|}. \quad (24)$$

Proof: Based on the parameter conditions shown in Corollary 1, η_{ab} can be simplified as follows:

$$\eta_{11} = \frac{1}{D^3} (D^2 d^2 - x_0^2 d^2), \quad (25)$$

$$\eta_{12} = -x_0 z_0 d^2 \frac{1}{D^3}, \quad (26)$$

$$\eta_{21} = -x_0 z_0 d^2 \frac{1}{D^3}, \quad (27)$$

$$\eta_{22} = \frac{1}{D^3} (D^2 d^2 - z_0^2 d^2). \quad (28)$$

Based on the system model shown in Fig. 1, $\eta_{11} \approx 0$. Besides, the function $\sin(\pi N_H \eta_{12}(u_2 - v_2)/\lambda)/\sin(\pi \eta_{12}(u_2 - v_2)/\lambda)$ with $\lambda = 2\pi/k$ is a periodic function with period λ/η_{12} and it has a zero in q/η_{12} for $q \in (\lambda/N_H, (N_H - 1)\lambda/N_H)$. Then, we can ensure the channel orthogonality condition is fulfilled when $|N_H \eta_{12}/\lambda| = 1$. Then, the expression of antenna spacing can be proved. ■

Remark 1: In practical research, solving the solution of the channel orthogonality condition is too complicated, so we only perform a simple analysis here for the state where the rotation angles $(\alpha_1, \beta_1, \alpha_2, \beta_2)$ are all zero. In the case of considering arbitrary rotation angles, in order to simplify the calculation, we use the rank of the \mathbf{R} as the optimization index.

C. Differential Evolution Algorithm for ROMA

Based on the channel correlation analysis, we propose a framework, shown in Algorithm 1, for the optimization of movable antenna

Algorithm 1: Differential Evolution Algorithm for ROMA.

Input: The range of values for $\alpha_1, \beta_1, \alpha_2, \beta_2$, population number num , variable dimension de in each individual, maximum number of evolutionary generations gen , initial variation operator F_0 , and crossover operator C_R .

1: **Initialisation** : Assign each dimension to each individual in the population randomly within a range of values, shown as $\mathbf{x} \in \mathbb{R}^{de \times num}$.

2: **for** $i=1,2,\dots, num$ **do**

3: Evaluation of the i -th individual in the original population according to (29).

4: **end for**

5: Track optimal individuals in $trace(1)$.

6: **for** $g=1,2,\dots, gen$ **do**

7: Dynamically set the variation operator according to the number of iterations:

$$lamb = \exp(1 - gen/(gen + 1 - g)), F = F_0 2^{lamb}.$$

8: **for** $i=1,2,\dots, num$ **do**

9: Randomly take three unequal integers $r_1, r_2, r_3 \neq i$ within the population size. Then, calculate the variant individual as: $\mathbf{y}(:, i) = \mathbf{x}(:, r_1) + F(\mathbf{x}(:, r_2) - \mathbf{x}(:, r_3))$, and verify the range of values.

10: **end for**

11: Iterate through each individual of population \mathbf{x} , and generate a random probability each time. If the random probability is greater than C_R , exchange the individuals of population \mathbf{x} with the individuals of population \mathbf{y} at the corresponding index.

12: **for** $i=1,2,\dots, num$ **do**

13: Evaluation of the i -th individual in the population \mathbf{x} according to (29).

14: **end for**

15: Track optimal individuals in $trace(g + 1)$.

16: **end for**

Output: The optimal individual $trace(gen + 1)$; the optimal rotation angle in this individual $\hat{\alpha}_1, \hat{\beta}_1, \hat{\alpha}_2$, and $\hat{\beta}_2$.

configurations to calculate the optimal rotation angles of the transmitting and receiving surface panels for the positional variations brought about by the train running in an HSR scenario. We use the rank of the channel correlation matrix as an optimization variable. It is an important indicator of channel capacity. An increase in the rank usually indicates that the channel can provide more independent information dimensions, thereby enhancing its transmission capacity. In optimization problems, using the rank as the objective can enhance the effectiveness of the system, improve transmission efficiency, optimize system design, and reduce the computational complexity. The optimization problem can be written as

$$\begin{aligned}
(\hat{\alpha}_1, \hat{\beta}_1, \hat{\alpha}_2, \hat{\beta}_2) &= \underset{\alpha_1, \beta_1, \alpha_2, \beta_2}{\operatorname{argmax}} \{ \text{rank}(\mathbf{R}) \} \\
\text{subject to } \alpha_1, \alpha_2 &\in [-\pi/2, \pi/2], \\
\beta_1, \beta_2 &\in [0, \pi/2], \quad (29)
\end{aligned}$$

where the range of values for the rotation angle is based on the physical scenario in the system model.

In Algorithm 1, we use adaptive differential evolution [17] to solve the above optimization problem. The genetic difference method is an efficient global optimization algorithm, which is widely used because it is less affected by parameters and is suitable for solving the optimal value

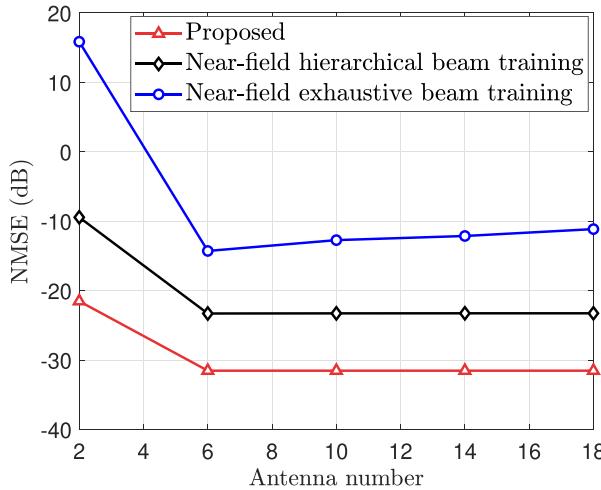


Fig. 2. Localization NMSE against the antenna number of the transmitter and receiver with different near-field beam training algorithms.

in multi-dimensions. The algorithm performs parallel computation from a population, where each individual in the population corresponds to a solution vector represented in the optimization problem, generates new individuals through mutation, hybridization and selection operations, and evaluates and compares the different individuals using a greedy criterion, which guides the search process towards the optimal solution. At the same time, we use a dynamically changing mutation factor F to improve the quality of individual searches. Specifically, we can define the combination of arbitrarily selected values for α_1 , α_2 , β_1 , and β_2 as a four-dimensional individual. Each population consists of num individuals, and the population undergoes gen generations of evolutionary iterations. With the control of the initial variation operator F_0 and crossover operator C_R , global optimal individuals are obtained. This algorithm is developed from traditional genetic algorithms and enhances the diversity of individuals within the population through adaptive mutation and genetic operations, enabling global optimization within a limited number of iterations. In future research, the algorithm can be integrated with deep learning techniques to improve the accuracy and efficiency.

IV. SIMULATION RESULTS AND DISCUSSIONS

In this section, we provide the simulations to demonstrate the performance of the ROMA-HSR XL-MIMO framework. We consider a down-link XL-MIMO system where the transmitter and receiver are equipped with the same square UPA. We denote the carrier frequency $f_c = 20$ GHz, the wavelength $\lambda_c = c/f_c$, the train speed $v = 350$ km/h, and $\sum P_i = P_{\max}$, where P_{\max} is the maximum transmit power. Then, we consider each transmitted data stream with the same power and the signal-to-noise ratio (SNR) is 15 dB. Besides, the relative height between the transmitter and receiver is $|z_0| = 10$ m, and the horizontal distance from BS to train is $|y_0| = 4$ m.

To quantify the accuracy of the localization model, we use the normalized mean square error (NMSE) as the metric:

$$NMSE = \frac{\sum_{t=0}^T |(\theta_t, R_t) - (\hat{\theta}_t, \hat{R}_t)|^2}{\sum_{t=0}^T |(\theta_t, R_t)|^2}. \quad (30)$$

In Fig. 2, we simulate the accuracy of the localization model by leveraging the characteristics of near-field beam training for train relay localization. The train moves along a trajectory within a 2000 m

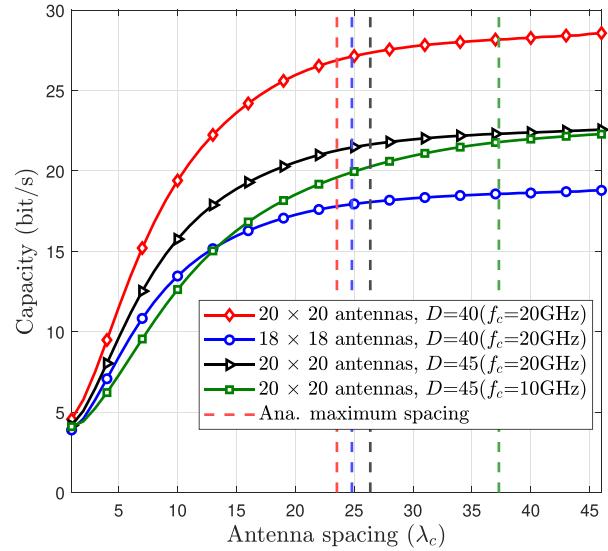


Fig. 3. Capacity versus normalized antenna spacing for different antenna numbers, physical distances and carrier frequencies.

radius centered on the base station at a constant speed, with the base station recording the position of the train relay every second. By comparing our proposed localization model with two widely used near-field beam training algorithms, we demonstrate that our model significantly reduces the localization error, enabling more precise positioning of the train relay. Additionally, it is observed that increasing the number of antennas reduces the error in the near-field beam training algorithms. This improvement arises because a larger antenna array expands the near-field range, assuming fixed antenna spacing.

In Fig. 3, we compare the relationship between antenna spacing and channel capacity by varying antenna configurations, assuming the receivers and transmitters are parallel to each other. As shown by the solid line, for a given number of antennas, the channel capacity increases with antenna spacing until it converges. The larger the number of antennas, the higher the maximum channel capacity that can be achieved. Additionally, the greater the distance between the receiver and transmitter, the lower the maximum achievable channel capacity. When other parameters remain constant, a decrease in carrier frequency results in a slower convergence rate, though it does not affect the convergence value. The dashed line represents the optimal antenna spacing, calculated using the analytical expression in (24), which closely approaches the minimum antenna spacing required for channel capacity convergence. This confirms the accuracy of Corollary 1. In Fig. 4, we compare the relationship between channel capacity and location under three different conditions, with 20×20 movable antennas configured at both the transmitter and receiver. For the analysis, we set $F_0 = 0.5$, $C_R = 0.2$, and assume the train travels at a constant speed to various positions. The x-axis positions correspond to the train's relay positions, as y_r and z_r remain fixed. The channel capacity is normalized by using the scenario where both the receivers and transmitters are parallel and fixed as the reference. The results indicate that system performance improves when both the receivers and transmitters can rotate within a certain range. Specifically, configurations where the panels can rotate outperform the fixed setup. For instance, when the train reaches the x-axis position of 40 m, the channel capacity of both bilateral XL-MIMOs equipped with ROMA is 1.4 times greater than that with FPA, and the single-sided XL-MIMO with ROMA yields a channel capacity 1.15 times higher than that with FPA. However,

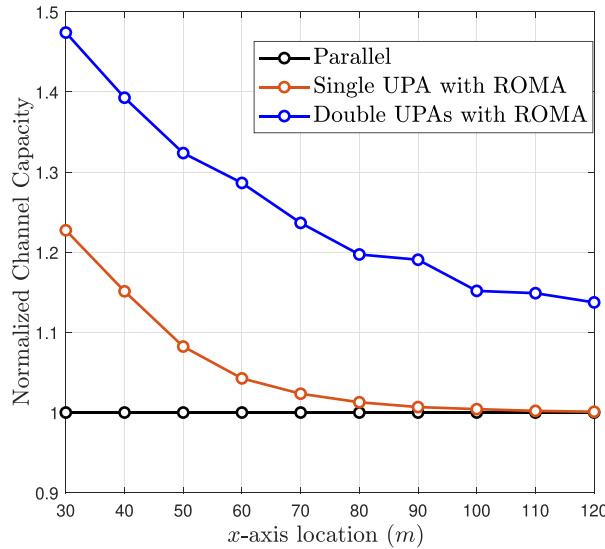


Fig. 4. Normalized channel capacity versus the x -axis location for three cases: parallel receiver and transmitter with FPA, one-sided plane with ROMA, and both planes with ROMA.

this performance gain diminishes as the distance increases, due to the growing influence of large-scale fading.

V. CONCLUSION

In this correspondence, we investigate the performance of the XL-MIMO system with ROMA in the HSR communication scenario, focusing on channel correlation and channel capacity. We first adopt a mobility-aware near-field beam training approach to locate the train. Subsequently, by analyzing the channel correlation matrix, we derive the channel orthogonality condition and determine the optimal antenna spacing expression under specific conditions. Furthermore, we employ the differential evolution method to optimize the rotation angles of the receiver and transmitter panels. Finally, simulation experiments are conducted to validate the performance gains achieved by ROMA in the HSR communication system. In future work, we will conduct a detailed analysis of the specific physical implementation and mechanical principles of the ROMA technology. Additionally, we will study the low-complexity signal processing techniques for ROMA based on the large-scale path loss models in the 3GPP protocol [18], and explore the application prospects of the ROMA technology in more complex scenarios.

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