



Robust Movable Antenna Position Optimization Under Imperfect Channel Path Parameters

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Abstract: Movable antenna (MA) systems can reshape the wireless channel by repositioning antenna elements in a confined region, but most existing MA optimization methods depend on perfect channel state information (CSI). This paper studies robust joint transmit beamforming and antenna-position optimization for a downlink multiple-input single-output (MISO) MA system with imperfect CSI. Instead of treating CSI errors as unstructured channel perturbations, we introduce bounded uncertainties directly into physical multipath parameters, including path-gain amplitudes and angular parameters. The resulting worst-case signal-to-noise ratio (SNR) design is approximated through discrete sampling and a harmonic-mean surrogate that penalizes weak channel realizations. An alternating optimization algorithm is then developed, where transmit beamforming is updated on the complex sphere manifold, and antenna positions are optimized via a sequential grid search. Simulation results show that the proposed robust design yields higher SNR performance than non-robust designs and the fixed-position antenna (FPA) baseline.

Keywords: alternating optimization; harmonic mean; imperfect channel state information; movable antenna; robust optimization

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1 Introduction

The rapid growth of sixth generation (6G) and next-generation Wi-Fi services is pushing wireless systems toward higher reliability, higher capacity, and finer spatial control. Conventional multiple-input multiple-output (MIMO) systems improve spatial resolution by deploying more fixed antennas, but continuous scaling of static arrays increases radio-frequency hardware cost, energy consumption, and site constraints. Movable antenna (MA) technology has emerged as a complementary paradigm to conventional fixed-antenna architectures. Instead of solely increasing the number of fixed radiators, MA systems allow antenna elements to be repositioned within a finite local region. Such reconfigurability introduces additional spatial degrees of freedom, enabling the transmitter to better exploit fine-scale electromagnetic-field variations and mitigate unfavorable fading effects^[1–9].

Existing MA research has established field-response channel modeling, capacity characterization, and position optimi-

zation methods for both continuous and sampled movement regions^[8–12]. Recent studies have further expanded MA applications to a wide range of wireless scenarios, including multi-beam coverage, spectrum sharing, and integrated sensing and communication^[13–19]. In parallel, hardware-aware MA designs have been investigated by considering movement delay, mechanical energy consumption, and channel-map estimation^[20–22]. A recent survey has further provided a comprehensive overview of MA and other reconfigurable antenna architectures for next-generation mobile communication networks^[23].

However, a major practical challenge persists, as existing MA optimization frameworks mostly rely on the assumption of perfect channel state information (CSI). In realistic systems, CSI is inevitably degraded by estimation errors, feedback quantization, calibration mismatch, and tracking latency. Since MA performance is highly dependent on the phase relationship between multipath components and antenna coordinates, even small amplitude or angular errors may shift the ap-

parent spatial peaks of the channel field. Consequently, an antenna layout optimized for the estimated channel may suffer significant performance degradation when the actual physical parameters deviate from their nominal values. Robust MA position optimization under norm-bounded and Gaussian channel-vector errors has recently been studied in Ref. [24]. More broadly, robust designs for conventional wireless systems commonly adopt either deterministic norm-bounded uncertainty sets to guarantee performance for all admissible errors^[25], or statistical CSI-error models that control outage probability through chance constraints and tractable conservative approximations^[26]. A globally optimal discrete MA design considering imperfect CSI and power consumption was also investigated in Ref. [27]. These studies establish the importance of CSI-robust transmission and MA position optimization; however, their uncertainty models are mainly imposed on the overall channel responses at each antenna position and do not explicitly preserve the structured dependence of the MA channel on physical path gains and angles.

To address this issue, this paper focuses on robust antenna position optimization with CSI uncertainty of the physical multipath parameters. Specifically, bounded uncertainty sets are considered for path-gain amplitudes, elevation angles, and azimuth angles. Under this structured uncertainty model, we formulate a robust joint beamforming and antenna-position optimization problem for MA-enhanced downlink transmission. The design objective is to maximize the worst-case signal-to-noise ratio (SNR) over uncertain channel realizations. However, the resulting optimization problem is highly non-convex and difficult to solve. To tackle this challenge, we propose a harmonic-mean-based surrogate objective to approximate the finite-scenario worst-case SNR. Furthermore, we develop an alternating optimization algorithm that integrates Riemannian beamforming optimization and sequential grid-based search to optimize the transmit beamforming and antenna positions, respectively. Finally, simulation results demonstrate that the proposed robust design provides notable performance gains over the non-robust MA designs and the fixed-position antenna (FPA) benchmark.

2 System Model and Robust Formulation

2.1 Field-Response Channel Model

Consider a downlink communication system in which a base station equipped with N movable antennas serves a single user terminal equipped with an FPA, as shown in Fig. 1. The n -th MA is located at $\mathbf{t}_n = [x_n, y_n]^T$ in a two-dimensional movement region $\mathcal{C}_t$. The aggregate antenna-position matrix is $\mathbf{T} = [\mathbf{t}_1, \mathbf{t}_2, \dots, \mathbf{t}_N]$. To maintain physical feasibility and reduce severe mutual coupling, each antenna must remain in $\mathcal{C}_t$ and any two antennas must satisfy $\|\mathbf{t}_n - \mathbf{t}_m\|_2 \geq D_{\min}$ for $n \neq m$, where $D_{\min}$ represents the minimum allowable antenna spacing. The

transmit beamforming vector is denoted by $\mathbf{w}$ in $\mathbb{C}^{N \times 1}$, with $\|\mathbf{w}\|_2^2 = 1$, and the transmit power is denoted by P_t .

Under the field-response model, local antenna movement changes the received phase of each multipath component while the large-scale path parameters remain approximately fixed within the small movement region. For L propagation paths, the channel vector from the base station (BS) to the user is modeled as:

$$\mathbf{h}(\mathbf{T}) = \sum_{l=1}^L g_l \mathbf{a}(\mathbf{T}, \theta_l, \phi_l) \quad (1),$$

where g_l is the complex gain of the l -th path, and θ_l and ϕ_l are its elevation and azimuth parameters. The array response $\mathbf{a}(\mathbf{T}, \theta_l, \phi_l)$ contains N unit-modulus components, and the phase of the n -th component is:

$$\psi_n(\theta_l, \phi_l) = \frac{2\pi}{\lambda} (x_n \cos \theta_l \sin \phi_l + y_n \sin \theta_l) \quad (2),$$

where λ denotes the wavelength.

The received signal is expressed as $y = \sqrt{P_t} \mathbf{h}^H(\mathbf{T}) \mathbf{w} s + n$, where s is a unit-power information symbol satisfying $\mathbb{E}[|s|^2] = 1$, and $n \sim \mathcal{CN}(0, \sigma^2)$ is additive white Gaussian noise, where σ^2 denotes the average noise power.

The received SNR is:

$$\gamma(\mathbf{w}, \mathbf{T}) = \frac{P_t}{\sigma^2} \mathbf{w}^H \mathbf{H}(\mathbf{T}) \mathbf{w} \quad (3),$$

where $\mathbf{H}(\mathbf{T}) = \mathbf{h}(\mathbf{T}) \mathbf{h}^H(\mathbf{T})$.

2.2 Structured CSI Uncertainty and Robust Objective

In conventional robust beamforming, the channel is often modeled as $\mathbf{h} = \hat{\mathbf{h}} + \Delta \mathbf{h}$ with $\|\Delta \mathbf{h}\|_2 \leq \epsilon$. Although convenient, this unstructured perturbation does not capture how angular or amplitude errors affect a position-dependent field response. We therefore model uncertainty directly through the

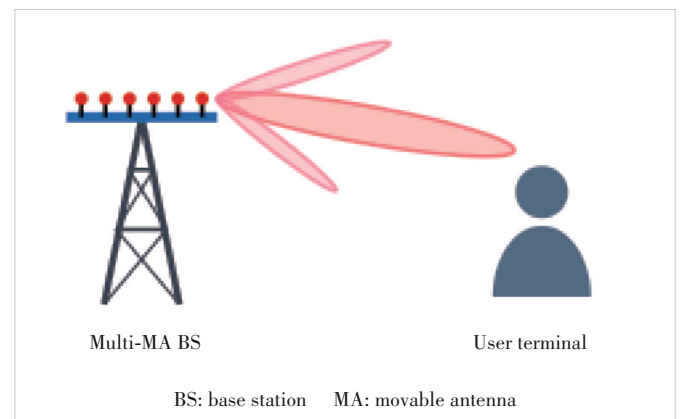


Figure 1. Downlink MA-enhanced communication system

physical path parameters. Let $g_l = \rho_l \exp(j\alpha_l)$, where ρ_l is the path-gain amplitude and α_l is the nominal gain phase. The amplitude and angular parameters obey bounded intervals, i.e.,

$$\rho_l \in [\rho_l^{\min}, \rho_l^{\max}], \theta_l \in [\theta_l^{\min}, \theta_l^{\max}], \phi_l \in [\phi_l^{\min}, \phi_l^{\max}], \forall l \quad (4).$$

We assume that the gain phase is kept at its nominal value. This assumption focuses the study on the dominant amplitude and angular uncertainty while preserving the deterministic field-response structure. For a given $\mathbf{T}$, we define an uncertainty set $\Lambda(\mathbf{T})$ that consists of all possible channel covariance matrices $\mathbf{H}(\mathbf{T})$ generated by parameters satisfying Eq. (4).

The robust design objective is to maximize the worst-case SNR over the structured uncertainty set:

$$\begin{aligned} \max_{\mathbf{w}, \mathbf{T}} \quad & \min_{\mathbf{H}(\mathbf{T}) \in \Lambda(\mathbf{T})} \frac{P_t}{\sigma^2} \mathbf{w}^H \mathbf{H}(\mathbf{T}) \mathbf{w} \\ \text{s.t.} \quad & \mathbf{t}_n \in \mathcal{C}_t, \forall n, \\ & \|\mathbf{t}_n - \mathbf{t}_m\|_2 \geq D_{\min}, n \neq m, \\ & \|\mathbf{w}\|_2^2 = 1. \end{aligned} \quad (\text{P1})$$

However, (P1) is difficult to handle because the uncertainty set is continuous; the channel depends nonlinearly on the antenna coordinates, and $\mathbf{w}$ and $\mathbf{T}$ are coupled. Therefore, a tractable approximation is needed.

3 Harmonic-Mean Robust Optimization

3.1 Discretization and Surrogate Objective

The continuous uncertainty set is first approximated by a finite set of representative discrete points. For each path, the amplitude, elevation angle, and azimuth angle are uniformly sampled inside their intervals. To avoid an exorbitant number of discrete points, a coupled sampling strategy is adopted, where a common index is used for amplitude, elevation, and azimuth perturbations, and each index triplet is applied jointly to all L paths. Specifically, let $\xi_s = \{g_l^{(s)}, \theta_l^{(s)}, \phi_l^{(s)}\}_{l=1}^L$ denote the S -th sampled parameter triple, and S denote the total number of sampled parameter triples. The corresponding channel vector and covariance matrix are:

$$\mathbf{h}_s(\mathbf{T}) = \sum_{l=1}^L g_l^{(s)} \mathbf{a}(\mathbf{T}, \theta_l^{(s)}, \phi_l^{(s)}), \quad \mathbf{H}_s(\mathbf{T}) = \mathbf{h}_s(\mathbf{T}) \mathbf{h}_s^H(\mathbf{T}) \quad (5).$$

For the s -th representative channel realization, we define the received channel gain as $x_s(\mathbf{w}, \mathbf{T}) = \mathbf{w}^H \mathbf{H}_s(\mathbf{T}) \mathbf{w}$.

Because P_t/σ^2 is a positive constant independent of $\mathbf{w}$ and $\mathbf{T}$, it is omitted in the surrogate objective without loss of optimality. A direct robust objective would maximize the minimum of $x_s(\mathbf{w}, \mathbf{T})$ over all representative channel realizations. However, the minimum operator is non-smooth. We therefore

adopt the following regularized harmonic mean:

$$\text{HM}_\delta = \left[\frac{1}{S} \sum_{s=1}^S \frac{1}{x_s(\mathbf{w}, \mathbf{T}) + \delta} \right]^{-1} \quad (6),$$

to approximate the minimum, where $\delta > 0$ is a small positive regularization constant introduced to prevent numerical singularities.

The harmonic mean is strongly affected by small elements, so it penalizes the parameter triple with poor channel quality more effectively than an arithmetic-mean objective. It is not identical to the strict minimum; instead, it provides a smooth robustness-promoting surrogate.

Given Eq. (6), the robust joint design problem is reformulated as (P2). Fig. 2 summarizes the resulting robust optimization flow.

$$\begin{aligned} \max_{\mathbf{w}, \mathbf{T}} \quad & - \sum_{s=1}^S \frac{1}{\mathbf{w}^H \mathbf{H}_s(\mathbf{T}) \mathbf{w} + \delta} \\ \text{s.t.} \quad & \mathbf{t}_n \in \mathcal{C}_t, \forall n, \\ & \|\mathbf{t}_n - \mathbf{t}_m\|_2 \geq D_{\min}, n \neq m, \\ & \|\mathbf{w}\|_2^2 = 1. \end{aligned} \quad (\text{P2})$$

3.2 Alternating Optimization

The surrogate problem in (P2) remains non-convex. We therefore adopt an alternating optimization framework, in

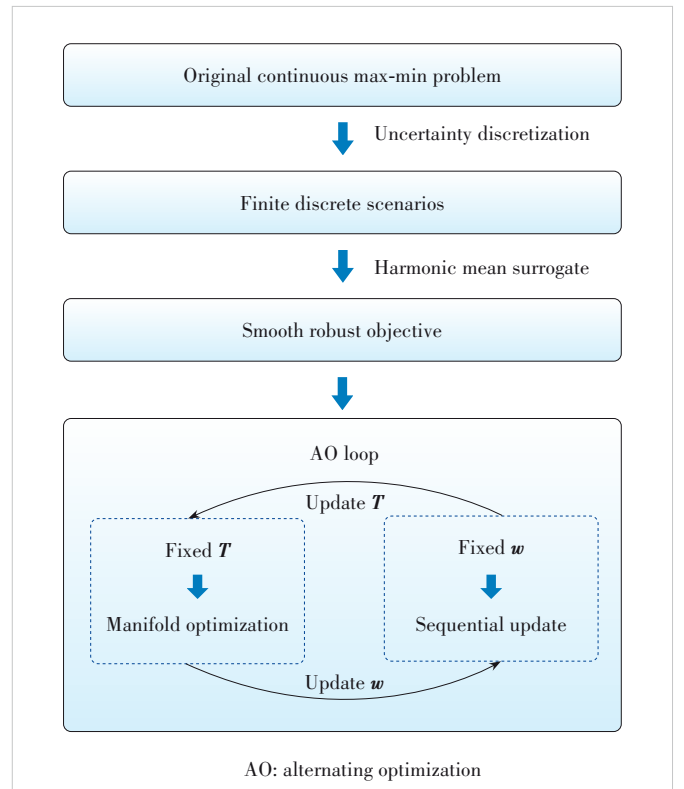


Figure 2. Robust joint beamforming and MA-position optimization flow

which the transmit beamforming vector and the antenna positions are optimized alternately while the other variable is kept fixed.

With fixed antenna positions $\mathbf{T}$, the beamforming vector is optimized on the complex unit sphere $\mathcal{M} = \{\mathbf{w} \in \mathbb{C}^N : \|\mathbf{w}\|_2 = 1\}$.

Recall that $x_s(\mathbf{w}|\mathbf{T}) = \mathbf{w}^H \mathbf{H}_s(\mathbf{T}) \mathbf{w}$ denotes the received channel power gain under the s -th representative channel realization. Since maximizing the harmonic-mean objective in Eq. (6) is equivalent to minimizing its reciprocal-sum denominator, the beamforming subproblem is implemented as:

$$\min_{\mathbf{w} \in \mathcal{M}} F(\mathbf{w}; \mathbf{T}) = \kappa \sum_{s=1}^S \frac{1}{x_s(\mathbf{w}, \mathbf{T}) + \delta} \quad (7),$$

where κ is a positive numerical scaling factor that does not affect the optimal beamforming vector, and it is set as 10^6 in the simulation.

The Euclidean gradient of $F(\mathbf{w}; \mathbf{T})$ supplied to the manifold solver is given by:

$$\nabla_{\mathbf{w}} F(\mathbf{w}; \mathbf{T}) = -2\kappa \sum_{s=1}^S \frac{\mathbf{H}_s(\mathbf{T}) \mathbf{w}}{[x_s(\mathbf{w}, \mathbf{T}) + \delta]^2} \quad (8).$$

The Euclidean gradient in Eq. (8) is projected onto the tangent space of the complex unit sphere to obtain the Riemannian gradient as $\text{grad } F(\mathbf{w}; \mathbf{T}) = \nabla_{\mathbf{w}} F(\mathbf{w}; \mathbf{T}) - \mathbf{w} \text{Re}\{\mathbf{w}^H \nabla_{\mathbf{w}} F(\mathbf{w}; \mathbf{T})\}$.

The beamforming subproblem is then solved using the Riemannian conjugate-gradient method implemented in Manopt, which performs the search-direction update, step-size selection, and retraction onto the complex unit sphere. The beamforming solution obtained in the preceding alternating optimization (AO) iteration is used as the initial point of the current beamforming update. The inner solver terminates when the cost reduction over two consecutive iterations is less than a prescribed value (set as 10^{-6} in the simulation).

With fixed beamforming $\mathbf{w}$, the antenna-position optimization subproblem is solved by sequential grid search. The movement region $\mathcal{C}_l$ is discretized into K candidate points $\mathbf{q}_k \in \mathcal{C}_l$, $k = 1, \dots, K$, and the resulting grid set is denoted by $\mathcal{Q} = \{\mathbf{q}_1, \mathbf{q}_2, \dots, \mathbf{q}_K\}$.

During one antenna-position sweep, the antennas are updated sequentially from $n = 1$ to N . When optimizing the position of the n -th antenna, the positions of the other $N - 1$ antennas are temporarily fixed. The feasible candidate set is constructed as:

$$\mathcal{Q}_n^{\text{feas}}(\mathbf{T}_{-n}) = \left\{ \mathbf{q} \in \mathcal{Q} : \|\mathbf{q} - \mathbf{t}_m\|_2 \geq D_{\min}, \forall m \neq n \right\} \quad (9),$$

where $\mathbf{T}_{-n}$ denotes the positions of all antennas except the n -th antenna.

For each $\mathbf{q} \in \mathcal{Q}_n^{\text{feas}}(\mathbf{T}_{-n})$, let $\mathbf{T}_n(\mathbf{q})$ denote the antenna-

position matrix obtained by replacing $\mathbf{t}_n$ with $\mathbf{q}$, while keeping the other antenna positions unchanged. The channel matrices $\mathbf{H}_s(\mathbf{T}_n(\mathbf{q}))$, $s = 1, \dots, S$, are recalculated, and the reciprocal-sum objective $F(\mathbf{w}|\mathbf{T}_n(\mathbf{q}))$ is evaluated. The position of the n -th antenna is then updated according to:

$$\mathbf{t}_n \leftarrow \arg \min_{\mathbf{q} \in \mathcal{Q}_n^{\text{feas}}(\mathbf{T}_{-n}) \cup \{\mathbf{t}_n\}} F(\mathbf{w}; \mathbf{T}_n(\mathbf{q})) \quad (10).$$

Before evaluating the feasible grid candidates, the current position of the n -th antenna is retained as the incumbent solution. Therefore, if none of the feasible candidates improves the objective value, the antenna remains at its current position. Each updated antenna position is immediately used when constructing the feasible candidate set for the subsequent antenna. The outer loop of the alternating optimization alternates between the manifold beamforming update and the sequential antenna-position sweep until the relative objective change is below a tolerance or the maximum number of iterations is reached.

The complexity of the proposed algorithm is analyzed next. If I_w inner iterations are used for beamforming optimization, the beamforming update costs $\mathcal{O}(I_w SN^2)$. For the antenna position optimization, a full antenna-position sweep costs $\mathcal{O}(NKS)$. With I_{A0} outer iterations, the overall complexity is thus given by $\mathcal{O}(I_{A0} SN(I_w N + K))$.

4 Simulation Results

4.1 Setup and Benchmarks

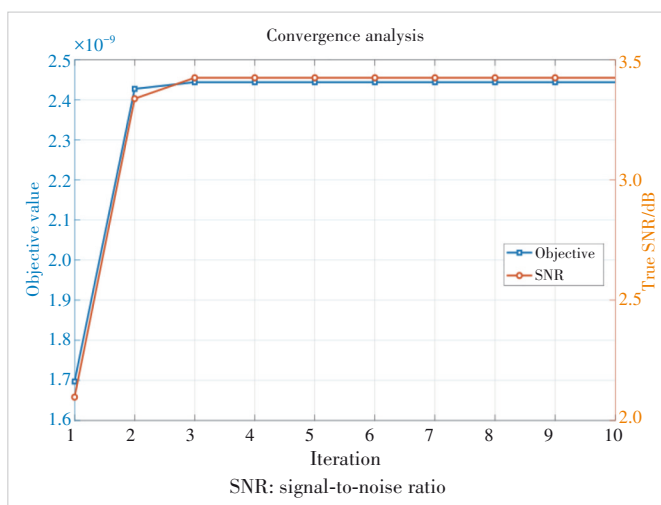
Numerical results are provided in this section to evaluate convergence, robustness against CSI uncertainty, and scalability with the number of antennas. Unless otherwise stated, the carrier frequency is 5 GHz, the wavelength is 0.06 m, the number of paths is $L = 3$, and the base-station-to-user distance is 50 m. The transmit region is a square of $4\lambda \times 4\lambda$, and the minimum antenna spacing is $\lambda/2$. Furthermore, the interval bounds in Eq. (4) are generated by introducing a scaling factor Δ . Specifically, let $\bar{\rho}_l$, $\bar{\theta}_l$, and $\bar{\phi}_l$ denote the estimated amplitude, elevation angle, and azimuth angle of the l -th path, respectively. The bounds in Eq. (4) are set as $\theta_l^{\min} = \bar{\theta}_l - \frac{\pi}{12} \Delta$, $\theta_l^{\max} = \bar{\theta}_l + \frac{\pi}{12} \Delta$, $\phi_l^{\min} = \bar{\phi}_l - \frac{\pi}{12} \Delta$, $\phi_l^{\max} = \bar{\phi}_l + \frac{\pi}{12} \Delta$, $\rho_l^{\min} = (1 - 0.1\Delta) \bar{\rho}_l$, and $\rho_l^{\max} = (1 + 0.1\Delta) \bar{\rho}_l$. It follows that a larger value of Δ produces wider amplitude and angular uncertainty intervals and represents more severe CSI mismatch. The main simulation parameters are listed in Table 1.

4.2 Convergence Behavior

First, Fig. 3 presents the convergence plot of the proposed alternating optimization algorithm in terms of the objective function and actual received SNR with $\Delta = 1$.

Table 1. Summary of simulation parameters

Parameter	Default Value
Carrier frequency (f_c)	5 GHz
Wavelength (λ)	0.06 m
Default number of MAs (N)	4
Number of paths (L)	3
BS-user distance (d)	50 m
Path-loss exponent (α)	2.8
Transmit region ($A \times A$)	$4\lambda \times 4\lambda$
Minimum spacing ($D_{\min}$)	$\lambda/2$
Transmit power (P_t)	46 dBm
Noise power (σ^2)	-44 dBm

**Figure 3. Convergence behavior of the proposed alternating optimization algorithm**

It is shown that the harmonic-mean surrogate objective increases rapidly at the early iterations and gradually reaches a stable plateau, verifying the effectiveness of the alternating updates. The actual received SNR follows a similar trend, which demonstrates that the surrogate objective provides a reliable optimization direction for performance improvement. Moreover, the smooth convergence behavior indicates favorable numerical stability, which is desirable for MA systems to avoid unnecessary antenna movement caused by oscillations.

tory updates.

4.3 Benchmark Schemes

To comprehensively evaluate the performance of the proposed algorithm, it is compared against three benchmark schemes in the following. These benchmark schemes are selected to distinguish the effects of three key factors: perfect versus imperfect CSI, movable versus fixed antenna architectures, and robust versus non-robust position optimization.

First, the Perfect-CSI+MA scheme assumes that true channel parameters are available during optimization and employs the graph-based dynamic programming algorithm (Graph-DP) proposed in Ref. [11] to optimize MA positions. However, since the conventional Graph-DP algorithm was originally developed for one-dimensional linear antenna arrangements, it cannot be directly applied to the two-dimensional planar deployment considered in this study due to the increased geometric complexity. To address this, we incorporate a greedy collision-resolution mechanism into the discrete dynamic programming procedure, ensuring that the minimum-distance constraint is satisfied while pursuing high field-response values. Its performance serves as an upper bound for the proposed scheme and other benchmark schemes.

Second, the Imperfect-CSI+MA (Graph-DP) scheme represents a conventional non-robust MA design. It employs the same two-dimensional Graph-DP implementation described above. However, instead of using the true channel parameters, this scheme is directly fed with the imperfectly estimated CSI.

Third, the Imperfect-CSI+FPA scheme acts as the traditional static-array baseline. It utilizes a fixed-position antenna array without spatial mobility. The estimated channel vector is constructed based on the imperfect path parameters, and standard maximum ratio transmission (MRT) precoding is then applied to align the beamforming vector with the estimated channel. For clarity, the main characteristics of the proposed method and all benchmark schemes are summarized in Table 2.

4.4 Robustness Against CSI Uncertainty

Fig. 4 plots the average actual received SNR versus the CSI error-bound scaling factor Δ , averaged over 100 independent Monte Carlo realizations. In each realization, the actual elevation and azimuth angles are independently and uniformly gen-

Table 2. Summary of the proposed method and benchmark schemes

Scheme	CSI Assumption	Antenna Type	Design Principle
Proposed robust MA	Imperfect CSI	Movable	Harmonic-mean robust AO
Perfect-CSI+MA	Perfect CSI	Movable	Graph-DP with true CSI
Imperfect-CSI+MA	Imperfect CSI	Movable	Graph-DP with estimated CSI
Imperfect-CSI+FPA	Imperfect CSI	Fixed	MRT with estimated CSI

AO: alternating optimization

FPA: fixed-position antenna

MA: movable antenna

CSI: channel state information

Graph-DP: graph-based dynamic programming algorithm

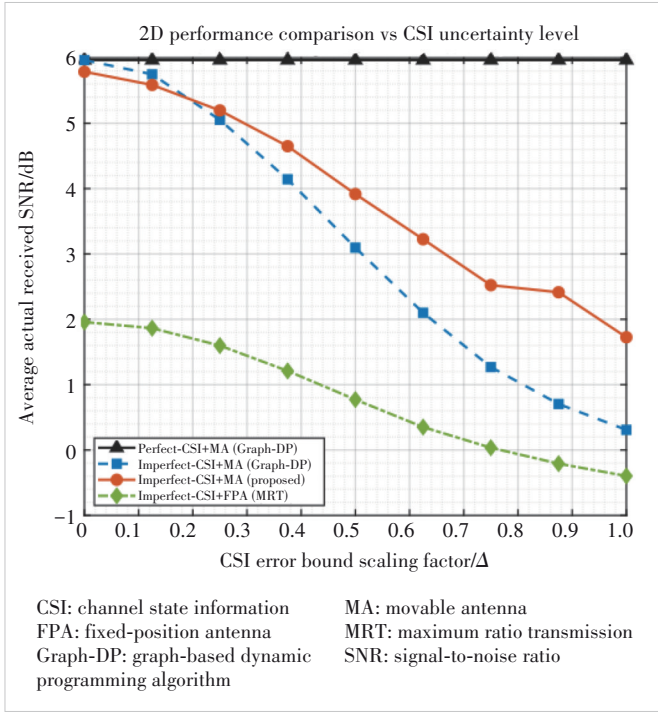


Figure 4. Average actual received SNR versus CSI uncertainty level

erated within $[0, \pi/2]$ and $[-\pi, \pi]$, respectively. The complex path gains are generated according to independent circularly symmetric complex Gaussian (CSCG) distributions and normalized based on the large-scale path loss. The estimated channel parameters are obtained by introducing bounded perturbations into the actual parameters. The elevation- and azimuth-angle errors are bounded by $(\pi/12)\Delta$, while the relative path-gain amplitude error is bounded by 0.1Δ . The path phases remain unchanged. Within each Monte Carlo realization, the perturbation directions are fixed as Δ varies, and only their magnitudes are scaled.

It should be noted that the worst-case SNR over the continuous uncertainty set in (P1) is also a widely adopted performance metric. However, in the proposed algorithm, the continuous uncertainty set is approximated by a finite number of representative channel realizations, and the non-smooth minimum operator is further replaced by the harmonic-mean surrogate in Eq. (6). Therefore, the proposed method promotes worst-case robustness by assigning greater penalties to weak channel realizations, rather than directly obtaining the exact worst-case SNR. In view of this, the average actual received SNR is adopted to evaluate the practical performance of the proposed scheme.

Several observations can be made from Fig. 4. First, the Perfect-CSI+MA (Graph-DP) scheme achieves the best SNR performance among the considered schemes since it optimizes the antenna positions using the true channel parameters. Second, the Imperfect-CSI+FPA (MRT) baseline exhibits the low-

est performance across the considered uncertainty range. The gap between the MA-based schemes and the FPA baseline confirms the fundamental benefit of antenna mobility: spatial movement provides additional degrees of freedom to avoid unfavorable fading, even when CSI is imperfect.

A clear performance crossover is observed between the proposed robust MA scheme and the Imperfect-CSI+MA (Graph-DP) benchmark. In the extremely low-uncertainty regime, the proposed robust design exhibits a marginal performance loss compared with the non-robust Graph-DP benchmark. This is expected because the Graph-DP scheme directly optimizes the antenna positions according to the estimated field-response peak when the nominal CSI is almost accurate. However, as the uncertainty level Δ increases, the non-robust Graph-DP scheme suffers from more rapid performance degradation, whereas the proposed robust design maintains a slower decay rate and achieves a clear SNR advantage under moderate and severe uncertainty.

4.5 Performance Scalability with Antenna Array Size

Next, we evaluate how the performance of the proposed scheme scales with the number of transmit antennas N . To isolate the impact of array size under imperfect CSI, this evaluation is conducted at a fixed moderate uncertainty level of $\Delta = 0.5$. In this setting, each uncertain parameter is discretized into 8 points in its interval, and the results are averaged over 100 independent Monte Carlo realizations.

Fig. 5 plots the average actual received SNR as a function of N . It is observed that all considered schemes achieve

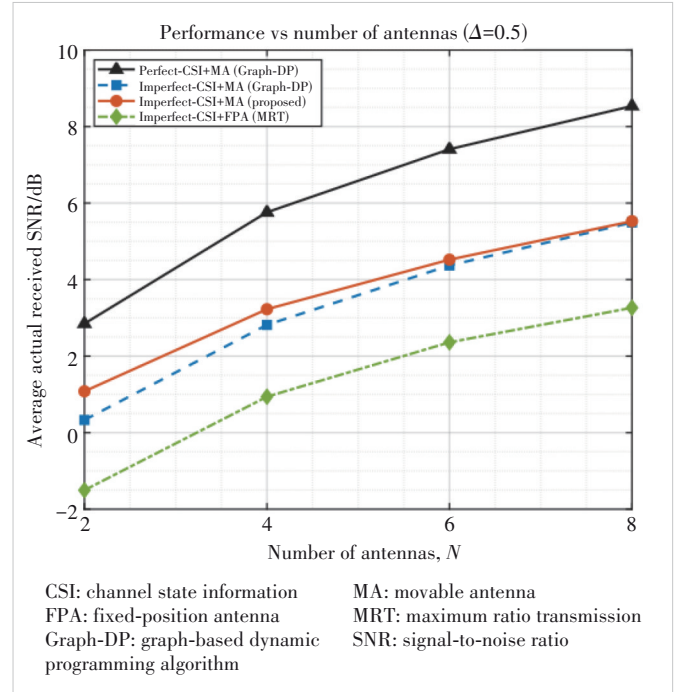


Figure 5. Average actual received SNR versus the number of transmit antennas at $\Delta=0.5$

higher received SNR as the number of antennas increases. This trend is consistent with the fact that additional antennas enhance the array gain and improve the signal-combining capability. As expected, the Perfect-CSI+MA (Graph-DP) scheme provides the best SNR performance among the considered schemes. In contrast, the Imperfect-CSI+FPA (MRT) baseline remains at the bottom due to the absence of spatial mobility. The substantial gap between the FPA baseline and the MA-based schemes further confirms that movable antennas provide an important spatial degree of freedom for combating fading and CSI mismatch. Furthermore, for smaller arrays, such as $N = 2$ and $N = 4$, the proposed robust design noticeably outperforms the non-robust Graph-DP benchmark. However, as N further increases, the performance gap between the two imperfect-CSI MA schemes gradually narrows. This is because the feasible movement space becomes increasingly crowded as N increases. The minimum-distance constraint restricts the permissible displacement of each antenna, forcing both robust and non-robust algorithms into similar dense geometric configurations. In this regime, the gain from position optimization becomes less dominant, while the array gain associated with more antennas becomes the primary source of SNR improvement.

5 Conclusions

This paper presented a robust joint beamforming and antenna-position optimization framework for MA-enhanced MISO downlink transmission under imperfect estimates of path parameters. The CSI uncertainty was embedded into physical multipath parameters, including path-gain amplitudes and angular parameters. To make the continuous worst-case SNR maximization problem tractable, the uncertainty region was sampled into finite parameter triples and optimized through a harmonic-mean-based surrogate. An alternating optimization algorithm was developed by combining Riemannian beamforming on the complex sphere and a sequential grid search for antenna positions.

Simulation results demonstrated stable convergence of the proposed robust MA optimization algorithm and showed that the proposed algorithm outperformed the non-robust MA benchmark when uncertainty increased. Future work will consider more practical aspects, including joint amplitude-phase-angle uncertainty, movement delay, mechanical energy consumption, mutual coupling, multi-user interference, and wide-band channel models.

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