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Real-Valued Genetic Algorithm-Based Hybrid Beamforming Optimization in Multi-IRSs-Aided mmWave MIMO-OFDM Systems

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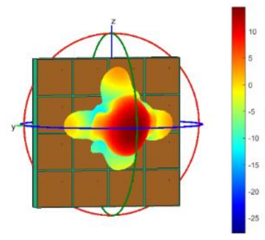
1 Background

Millimeter-wave (mmWave) communication offers vast bandwidth but suffers from severe path loss and sensitivity to blockages. Massive MIMO and hybrid beamforming help address these challenges, yet real-world deployment remains limited by hardware cost and dynamic environments.

Intelligent Reflecting Surfaces (IRSs) can reshape the wireless environment to enhance coverage and signal strength. However, optimizing IRS phase shifts and hybrid beamforming is non-trivial due to non-convexity and hardware constraints. Conventional algorithms often yield suboptimal solutions, dependent on initial conditions.

This research introduces a **Real-Valued Genetic Algorithm (RVGA)**-based optimization framework for joint IRS and hybrid beamforming design. The goal is to maximize spectral efficiency while maintaining low complexity and robustness. We provide practical insights into the deployment of IRS-assisted mmWave MIMO-OFDM systems.

What is IRS?



IRS Hardware Structure:

- **Metasurface layer** – Printed metallic elements on a dielectric substrate for signal interaction
- **Isolation layer** – Copper plate to prevent energy leakage
- **Control layer** – Circuit board to adjust amplitude/phase and connect to controller

IRS Application Scenario:

- Coverage enhancement in blockage scenarios
- Physical layer security enhancement
- Cell-edge user performance optimization

2 System Model and Problem Formulation

System

The total downlink cascade channel on the k^{th} subcarrier through i^{th} IRS equipment:

$$\mathbf{H}_{i,k}^{\text{tot}} = \mathbf{H}_{\text{TI},k}^{\text{H}} \mathbf{\Theta}^i \mathbf{H}_{\text{IU},k}$$

where, $\mathbf{\Theta}^i = diag(\theta_1, \dots, \theta_M)$, the received signal on the k^{th} subcarrier through i^{th} IRS equipment:

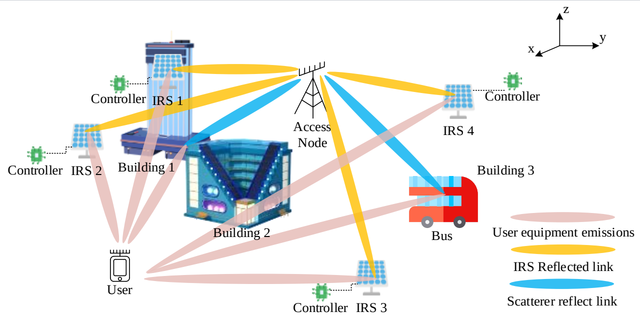
$$\boldsymbol{y}_{i,k} = \mathbf{H}_{i,k}^{\text{tot}} \mathbf{F}_{\text{RF}} \mathbf{F}_{\text{BB},k} \mathbf{s}_{\text{d}} + \mathbf{n}_k$$

$\mathbf{F}_{\text{RF}}$ and $\mathbf{F}_{\text{BB},k}$ are analog and digital hybrid precoder, respectively. $\mathbf{s}_{\text{d}}$ and $\mathbf{n}_k$ and $\mathbf{n}_k \sim \mathcal{CN}(0, \sigma^2)$ denote data symbols vector and Additive White Gaussian Noise matrix.

The achievable spectral efficiency (SE) on the k^{th} subcarrier through i^{th} IRS equipment:

$$R_{i,k} = \log_2 \det\left(\mathbf{I} + \mathbf{R}_{\mathbf{n}_k}^{-1} \mathbf{H}_{i,k}^{\text{tot}} \mathbf{F}_{\text{RF}} \mathbf{F}_{\text{BB},k} \left(\mathbf{H}_{i,k}^{\text{tot}} \mathbf{F}_{\text{RF}} \mathbf{F}_{\text{BB},k}\right)^{\text{H}}\right)$$

where, $\mathbf{R}_{\mathbf{n}_k}^{-1} = \sigma^2$ is the noise covariance matrix of $\mathbf{n}_k$.



1 Access Node (AN) N_{t} antennas, 1 User Equipment (UE) N_{r} antennas

I Intelligent Reflecting Surfaces (IRSs) M elements

Problem Formulation

$$\max_{\mathbf{F}_{\text{BB},k}, \mathbf{F}_{\text{RF}}, \mathbf{\Theta}} \frac{1}{K} \sum_{i=1}^{I} \sum_{k=1}^{K} R_{i,k},$$

$$s.t.\, C1: |\mathbf{F}_{\text{RF}}(x,y)| = \frac{1}{\sqrt{N_t}}, \forall x, y,$$

$$C2: \left\|\mathbf{F}_{\text{BB},k}, \mathbf{F}_{\text{RF}}\right\|_{\text{F}}^2 \le P_{T,k}, C3: |\theta_m| = 1.$$

3 Optimizing Hybrid Precoder and IRS Phase Shifts Matrix

Optimization variables initialization

The digital baseband precoding matrix:

$$\mathbf{F}_{\text{BB},k}(x,y) = f_{x,y}$$

$f_{x,y}$ represents the complex baseband weight applied, controls both the amplitude and phase contribution.

The analog precoding matrix:

$$\mathbf{F}_{\text{RF}}(x,y) = \frac{1}{\sqrt{N_t}} e^{j\varphi_{x,y}}$$

where $\varphi_{x,y} \in [0, 2\pi)$ represents the phase of each phase shifter at the transmitter.

Population initialization

Initialize the chromosome

$$\mathbf{X}_{\text{tot}} = \left[\mathbf{X}_{\text{RF}}^{\text{F}}, \mathbf{X}_{\text{BB},k}^{\text{F}}, \mathbf{X}_{\text{I},i}\right]^{\text{T}} \in \mathbb{R}^{1 \times D_{\text{tot}}}$$

where, $\mathbf{X}_{\text{RF}}^{\text{F}} = \arg(\mathbf{F}_{\text{RF}})$, $\mathbf{X}_{\text{I},i} = \arg\left(\boldsymbol{\theta}^i(:)\right)$, $\mathbf{X}_{\text{BB},k}^{\text{F}} = [\text{Re}(\mathbf{F}_{\text{BB},k}), \text{Im}(\mathbf{F}_{\text{BB},k})]$, $D_{\text{tot}} = N_t^{\text{RF}}(N_t + 2N_s) + N_I$,

where N_t^{RF} denotes the number of RF chain at transmitter and N_s denotes the number of the data stream.

Population initialization

Initialize population for individual

$$\mathbf{x}^p = \mathbf{X}_{\text{tot}} + \boldsymbol{r}, p = 1, \dots, \text{Popsize}$$

Specify fitness function

The fitness function is defined as

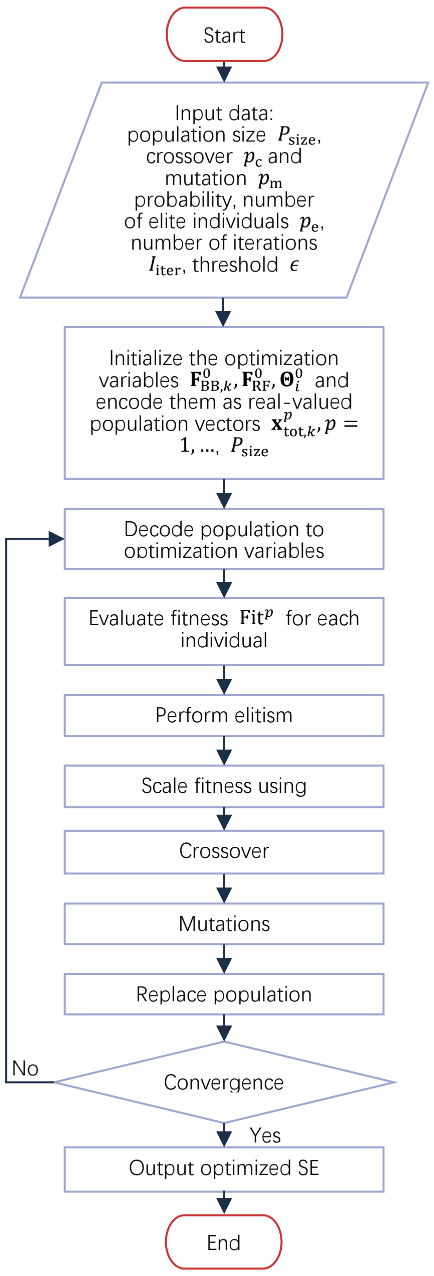
$$\text{Fit}^p = R_{i,k}$$

Compute selection, crossover, and mutation

The sum of fitness values and the selection probability of the p^{th} individual

$$\text{Fit}_{\text{sum}} = \sum_{p}^{D_{\text{tot}}} \text{Fit}^p, P(p) = \frac{\text{Fit}^p}{\text{Fit}_{\text{sum}}}.$$

4 RVGA Algorithm Flowchart



5 Result

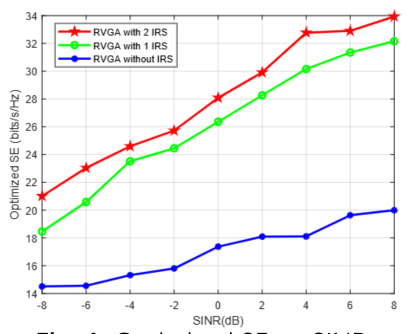


Fig. 1. Optimized SE vs. SINR

Fig.1 presents the optimized spectral efficiency (SE) vs. SINR conditions, comparing scenarios without IRS, 1 IRS, and 2 IRSs. The RVGA algorithm with 1 and 2 IRSs improves SE by 9.09- and 10.95-bits/s/Hz, respectively, compared to no IRS.

Fig. 2 compares SE performance of RVGA, CCPSO, and PSO in an ablation study. SE increases with SINR for all algorithms, with RVGA performing best, followed by steadily improving CCPSO. PSO shows the lowest performance but maintains an upward trend.

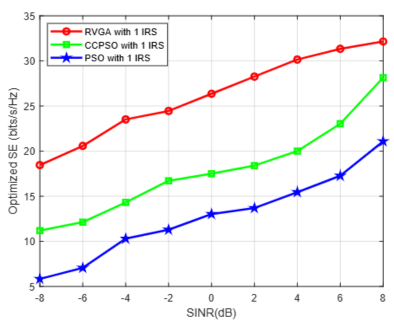


Fig. 2. Algorithms comparison

References

1. S. H. Hong, J. Park, S.-J. Kim, and J. Choi, "Hybrid Beamforming for Intelligent Reflecting Surface Aided Millimeter Wave MIMO Systems," IEEE Trans. Wireless Commun.
2. L. Yang, J. Wang, X. Xue, J. Shi, and Y. Wang, "Secure Hybrid Beamforming for IRS-Assisted Millimeter Wave Systems," IEEE Trans. Wireless Commun.
3. I. Ahmed, K. Shahid, and H. Khammari, "DRL based Beam Selection and Hybrid Beamforming for Intelligent Reflective Surface assisted Massive MIMO System," in 2023 IEEE 97TH VEHICULAR TECHNOLOGY CONFERENCE, VTC2023-SPRING, Huawei.
4. K. Ikeagu, M. R. A. Khandaker, C. Song, and Y. Ding, "Deep LearningBased Hybrid Beamforming Design for IRS-Aided MIMO Communication," IEEE Commun. Lett.
5. J. Lee and S. Hong, "Asymptotically Near-Optimal Hybrid Beamforming for mmWave IRS-Aided MIMO Systems," IEEE Trans. on Veh. Technol.
6. F. Sohrabi and W. Yu, "Hybrid Digital and Analog Beamforming Design for Large-Scale Antenna Arrays," IEEE J. Sel. Topics Signal Process.

Why RVGA Works?

Unlike closed-form derivation methods, this approach does not require the optimization problem to be convex, nor does it reduce the problem's dimensionality to obtain a suboptimal closed-form solution. Instead, the algorithm can directly optimize the variables to determine the desired solution structure.

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