In this paper, we consider the reconfigurable intelligent surface (RIS)-aided MIMO systems to realize a high quality link between the base station (BS) and the users via a RIS. To achieve this goal, the active beamforming at the BS and the passive beamforming at the RIS should be jointly optimized. However, most of the existing joint optimization schemes that maximize the sum-rate have high computational complexity due to the complex derivative calculations and matrix inversion. To this end, a biologically inspired particle swarm optimization (PSO) algorithm is exploited to solve the non-convex sum-rate optimization problem with low-complexity. Simulation results show that the proposed scheme provides a better trade-off between performance and complexity than existing solutions for RIS-aided MIMO systems.

**Introduction:** In the last decade, the network capacity has been significantly improved by using various wireless communication techniques such as multiple-input and multiple-output (MIMO), millimetre wave (mmWave) communications, and ultra-dense networks. However, these techniques require high hardware cost and power consumption [1]. Configurable intelligent surfaces (RIS) are emerging cost-effective techniques to solve the non-convex sum-rate maximization problem for the RIS-aided MIMO systems to realize a high quality link between the base station (BS) and the users via a RIS. To achieve this goal, the active beamforming at the BS and the passive beamforming at the RIS should be jointly optimized. However, most of the existing joint optimization schemes that maximize the sum-rate have high computational complexity due to the complex derivative calculations and matrix inversion. To this end, biologically inspired particle swarm optimization (PSO) algorithm is exploited to solve the non-convex sum-rate optimization problem with low-complexity. Simulation results show that the proposed scheme provides a better trade-off between performance and complexity than existing solutions.

**Notations:** $a$ is a vector and $A$ is a matrix. The transpose and Hermitian (conjugate transpose) of a matrix $A$ is denoted by $A^T$ and $A^H$. $E(\cdot)$ represents the expectation operator, and $CN(0, \sigma^2)$ denotes the Gaussian distribution with zero mean and variance $\sigma^2$. $A^{-1}$, $A^+$, and $\|A\|_F$ indicate the inverse, pseudo-inverse, and Frobenius norm of $A$, respectively. Finally, $\cdot^*$, $\arg(\cdot)$, and $\text{Tr}(\cdot)$ represent the complex conjugate, argument of a complex number, and trace of a matrix.

**System model and problem formulation:** In this section, the system model of RIS-aided MIMO system will be introduced at first, and then we will formulate the capacity maximization problem in the considered system.

**System model:** As illustrated in Figure 1, in this paper we consider a typical downlink RIS-aided MIMO system. The system consists of a BS with $M$ antennas and an RIS with $N$ elements, which simultaneously serve $K$ single-antenna users. Each RIS element is capable of changing its phase shift independently, so that the incident signals can be reflected in some other directions with high array gain [3].

Assuming that the data symbol $x_k$ for the $k$th user has the normalized power, where $k = 1, 2, \ldots, K$, the transmit signal $x \in \mathbb{C}^{M \times 1}$ from $M$ antennas at the BS is

$$x = \sum_{k=1}^{K} g_k x_k,$$

where $g_k \in \mathbb{C}^{M \times 1}$ is the active beamforming vector at the BS. In practise, the power of the transmitted signal at the BS should be constrained as

$$E(\|x\|^2) = \text{Tr}(GG^H) \leq P_t,$$

where $G \triangleq [g_1, g_2, \ldots, g_K] \in \mathbb{C}^{M \times K}$ is the active beamforming matrix at the BS, $P_t$ is the maximum transmission power at the BS. Then, the received signal $y_k$ for the $k$th user is given by

$$y_k = h_{\text{BS-user link}} x + \sqrt{\beta_k} h_{\text{RIS-user link}} \Phi x + n_k,$$

where $h_{\text{BS-user link}} \in \mathbb{C}^{1 \times M}$ denotes the direct channel link between BS and the $k$th user, $\beta_k$ is the channel attenuation coefficient for the $k$th user, and $n_k$ is the noise at the $k$th user. $h_{\text{RIS-user link}} \in \mathbb{C}^{1 \times N}$ denotes the RIS-user link channel between RIS and $N$ elements, and the $k$th single-antenna user; Furthermore, RIS beamforming matrix is denoted by the diagonal matrix $\Phi = \text{diag}(\psi)$ with $\psi = [\psi_1, \psi_2, \ldots, \psi_N]$, where $|\psi_i|^2 = 1$ represents the unit modulus hardware constraint of the $i$th RIS element [4].

Based on the signal model (3), the signal-to-interference-plus-noise ratio (SINR) for the $k$th user is written by

$$\text{SINR}_k = \frac{|h_{\text{BS-user link}} x + \sqrt{\beta_k} h_{\text{RIS-user link}} \Phi x|}{\sum_{j=1, j \neq k}^{K} |h_{\text{BS-user link}} x + \sqrt{\beta_j} h_{\text{RIS-user link}} \Phi x| + \sigma^2}.$$

---

**Fig. 1 RIS-aided MIMO communication system**
Based on the SINR in (4), the achievable sum-rate $R$ of all $K$ users in the RIS-aided MIMO system can be obtained as

$$R = \sum_{k=1}^{K} \log_2(1 + \text{SINR}_k). \quad (5)$$

**Problem formulation:** For the considered RIS-aided MIMO system, our objective is to jointly optimize the active beamforming matrix $\Phi$ at the BS and the passive beamforming matrix $\Psi$ at the RIS to maximize the achievable sum-rate $R$. Mathematically, the sum-rate optimization problem can be formulated as

$$(\Psi^\text{opt}, G^\text{opt}) = \arg \max_{\Psi, G} R$$

s.t. $c_1 : \Psi \in \mathcal{F}$,

$$c_2 : \text{Tr}(GG^H) \leq P_t,$$

where $\mathcal{F}$ denotes all possible passive beamformers that satisfy the unit modulus hardware constraint. In this paper, we assume that the channel state information (CSI) is perfectly known, e.g. the channels information can be retrieved by a technique discussed in [7]. With the known channel information, BS exploits the classical zero-forcing (ZF) as the active beamforming scheme for the signal transmissions. To this end, for a given passive beamforming matrix $\Psi$, we obtain the equivalent channel matrix $\tilde{H} = H + \sqrt{P_t} \Psi H$, where $H = [h_{11}, h_{12}, \ldots, h_{1K}]^T \in \mathbb{C}^{1 \times K}$ and $\Psi = [\Psi_1, \Psi_2, \ldots, \Psi_K]^T \in \mathbb{C}^{K \times K}$. Then, the pseudo-inverse of the equivalent channel $\tilde{H}$ gives the ZF beamforming matrix $G$, i.e. $G = \tilde{H}^+$. Substituting $G = \tilde{H}^+$ into (6), we can rewrite the sum-rate maximization problem (6) as

$$(\Psi^\text{opt}, \gamma) = \arg \max_{\Psi, \gamma} R$$

s.t. $c_1 : \Psi \in \mathcal{F}$,

$$c_2 : \text{Tr}(\tilde{H}^+ \tilde{H}) \leq \gamma P_t,$$

where $\gamma = \|G\|_F^2/P_t$ is the optimal scaling factor, so the optimal active beamforming matrix at the BS is given by $\hat{G} = \gamma G$.

However, the reformulated problem (7) is still non-convex due to the unit modulus constraint of $\Psi$ in $c_1$. In the following, we present a computationally efficient algorithm to solve this non-convex problem (7).

**RIS beamforming design:** In this section, we use the particle swarm optimization (PSO) algorithm to solve the non-convex sum-rate maximization problem (7) with low-complexity.

**PSO for RIS design:** PSO is a stochastic iterative optimization technique, which is inspired by the social behavior of birds flocking. The population of individual candidates, like birds, are called particles. These particles are randomly initialized within the search space. The coordinate of a particle that represents a solution to a problem is called the position of a particle. Moreover, in each iteration, the velocity of each particle is adjusted towards the best position, and the best suboptimal particle can be finally obtained after several iterations.

Specifically, the PSO algorithm (summarized in Algorithm 1) works in the following steps. First, the PSO algorithm generates $O$ particle swarms (e.g., possible passive beamformers in our problem (7)) with random positions as $\hat{\Psi}^0(0), \hat{\Psi}^1(0), \ldots, \hat{\Psi}^O(0)$. All positions are normalized to ensure the unit power. Subsequently, the velocity of all $O$ passive beamformers is randomly initialized, where the velocity of the $o$th passive beamformer is represented by $v_o$. Based on each passive beamformer, we can easily obtain the active beamforming matrix $G$ from the equivalent channel matrix. Then, the value of the objective function (e.g. the achievable sum-rate $R$ in our problem (7)) can be computed. For all $O$, compare the objective function values. The $o$th beamformer $\hat{\Psi}_o$ that maximizes the objective function in (7) is denoted by $\hat{w}_\text{best}$, and is regarded as the best particle in one iteration.

### Algorithm 1: PSO algorithm

**Input:** Channel matrices $H_1, H_2, H$. Number of iterations $I$, Number of candidates $O$.

**Output:** Passive beamformer $\Psi$

**Stage 1 (initialization):**
1. Generate $O$ particles with random positions as $\hat{\Psi}^0(0), \hat{\Psi}^1(0), \ldots, \hat{\Psi}^O(0)$ based on initial velocities $v_1(0), v_2(0), \ldots, v_O(0)$.
2. Compute $O$ corresponding active beamforming matrices $G$ based on equivalent channel matrix $\tilde{H} = H_1 + H_2, H$.
3. Update the objective function value.
4. Find $\hat{w}_\text{best}$ among all particles.

**Stage 2 (iterative refinement):**
5: for $o = 1: O$ do
6: Refine the $o$th particle velocity using (8);
7: Update the $o$th particle via (9);
8: Compute the new objective function value;
9: if (updated objective function value $> $ previous best value)
   $\hat{\Psi}_o(i) = \hat{\Psi}_o(\text{current})$;
10: end for
11: Find $\hat{w}_\text{best}$;
12: $i = i + 1$

After that, we update the velocity and corresponding position of the $o$th particle for the next iteration as

$$v_o(i + 1) = v_o(i) + c_1 u_1 \odot (\hat{\Psi}_\text{best}(i) - \hat{\Psi}_o(i))$$

$$+ c_2 u_2 \odot (\hat{w}_\text{best} - \hat{\Psi}_o(i)),$$

$$\hat{\Psi}_o(i + 1) = \hat{\Psi}_o(i) + v_o(i + 1),$$

where $u_1$ and $u_2$ are the uniformly distributed random vectors, $\hat{\Psi}_\text{best}$ is the best and $\hat{w}_\text{best}$ is the current position of the $o$th particle. The $c_1$ and $c_2$ are positive acceleration coefficients, and the element-wise multiplication is denoted by $\odot$. In the first iteration when $i = 0$, we set $\hat{\Psi}_\text{best}(0) = \hat{\Psi}_\text{best}(0)$ for any $o$. In the following iterations, each particle keeps track of its own best position that can achieve the maximum objective function value. Whenever the $o$th particle position is refined, its new objective function value will be updated accordingly. If the updated objective function value is larger than the previous best value of the candidate, then we set $\hat{\Psi}_o(i) = \hat{\Psi}_o(i)$. Finally, for all $O$ new positions, we again compare the objective function values, and the particle that maximizes $R$ in (7) will also be compared with the previous best $\hat{w}_\text{best}$ and the one that maximizes (7) will become the best particle $\hat{w}_\text{best}$. These steps will be repeated, until the number of iterations $I$ is satisfied. In the end, $\hat{w}_\text{best} = \hat{w}_\text{best}$.

**Computational analysis:** In this subsection, we provide the computational complexity comparison between the PSO algorithm and an existing scheme in [6]. It is observed that the computational complexity of the PSO algorithm mainly involves the computation of fitness values of $O$ passive beamformers for $K$ users. Thus, the computational complexity is $O(OK \log(O))$. On the other hand, the complexity of the scheme in [6] is $O(N^3 + N^2 + N)$. It is clear that the complexity of the existing scheme [6] grows fast with $N$ RIS elements, while the complexity of the PSO algorithm is only linearly increasing with the particles number $O$.

**Simulation results:** In this section, simulation results are provided to validate the performance of the RIS-aided MIMO communication system. We compare the spectral efficiency performance of the PSO algorithm with the existing work [6]. The configuration of the simulated scenario is shown in Figure 2, where BS and RIS are located at $(0, -20 \text{ m})$ and $(30 \text{ m}, 3 \text{ m})$ respectively. Four users are randomly distributed in a uniform region with radius $1 \text{ m}$. The distance between the BS and the uniform region is denoted as the horizontal distance $D$. 

ELECTRONICS LETTERS April 2021 Vol. 57 No. 9 wileyonlinelibrary.com/iet-el 385
Simulation setup: We consider a large-scale channel model as discussed in [3]. Let $d_{\text{BS},k}$, $d_{\text{RS},k}$, and $d_{\text{BS,RS},k}$ denote the distance between BS-kth user, BS-RIS and RIS-kth user, respectively. Thus, the distance-dependent path loss (PL) for the BS-user link can be written as

$$\text{PL}(d_{\text{BS},k}) = C_{\text{BS}}G_{\text{BS}}G_{\text{RS}}G_{\text{LoS,fad}}d_{\text{BS,LoS,fad}}^{-\nu_{\text{BS}}},$$

and the PL for the BS-RIS-user link can be written as

$$\text{PL}(d_{\text{BS-RIS,k},k}) = C_{\text{BS}}G_{\text{BS}}G_{\text{RS}}G_{\text{LoS,fad}}d_{\text{BS-RIS,LoS,fad}}^{-\nu_{\text{BS-RIS}}},$$

where $C_{\text{BS}}$ and $G_{\text{BS}}$ are the channel fading variables depending on the wavelength, channel status, and angle of departure (AoD); Moreover, $C_{\text{RS}}$ is also related to the angle of arrival (AoA), the material and size of RIS element; $G_{\text{RS}}$ and $G_{\text{RS}}$ denote the antenna gain of the BS and the k-th user; Here, we assume $C_{\text{BS}}G_{\text{BS}} = -30 \, \text{dB}$ and $C_{\text{RS}}G_{\text{RS}} = -40 \, \text{dB}$ [6]. The PL exponents for the BS-RIS link and RIS-user link are set as $\nu_{\text{BS-RIS}} = 2$, while BS-user link is set as $\nu_{\text{BS}} = 3$ [6].

To exploit the small-scale fading, we adopt a Rician fading channel model for the BS-user channel $h_{\text{BS,k}}$ as

$$h_{\text{LoS,k}} = \sqrt{\frac{\alpha_{\text{BS,k}}}{1 + \alpha_{\text{RS,k}}}} h_{\text{LoS,k}}^{\text{LoS,fad}} + \sqrt{\frac{1}{1 + \alpha_{\text{RS,k}}}} h_{\text{LoS,k}}^{\text{Ray,fad}},$$

where $\alpha_{\text{RS,k}}$ is the Rician factor, and $h_{\text{LoS,k}}^{\text{LoS,fad}}$ and $h_{\text{LoS,k}}^{\text{Ray,fad}}$ denote the LoS and Rayleigh fading components.

In the simulation, we consider $M = 8$, $N = 64$, $K = 4$ and $\sigma = 40$. The number of iterations is $I = 30$ and the noise power is set as $\sigma^2 = -120$ dBm. The distance between BS and RIS is defined as 30m. Finally, the channel attenuation coefficient $b$ in (3) is set as 1.

Achievable spectral efficiency comparison: The spectral efficiency performance of the PSO algorithm is shown in Figure 3, [6] in the whole transmit power range. Moreover, the PSO algorithm achieves about 93% of the spectral efficiency achieved by the existing scheme [6], but with much lower complexity as we have discussed before.

Figure 4 shows the spectral efficiency performances against the horizontal distance $D$ between BS and users. From this figure, it is observed that as the horizontal distance $D$ between the BS and users increases, the achievable spectral efficiency performance decreases rapidly due to the serious attenuation of the signals. However, a peak at $D = 30 \, \text{m}$ indicates that the spectral efficiency of both PSO and existing scheme [6] increases when the users approach the RIS, since the users receive strong signals reflected from the RIS. On the other hand, no peak is observed for the conventional without RIS scheme.

Conclusions: In this letter, we focused on the joint active and passive beamforming problem for the RIS-aided MIMO system. We formulated the sum-rate optimization problem with practical hardware constraints. To solve this non-convex problem, the biologically inspired low-complexity PSO algorithm was adopted. Complexity analysis showed the advantage of the presented scheme over the recently proposed solution for real-time implementation. Simulation results demonstrated that, PSO algorithm achieves about 93% of the spectral efficiency achieved by the existing scheme but with low-complexity.

Acknowledgement: This work was supported in part by the National Key Research and Development Program of China (Grant No. 2020YFB1805005).

© 2021 The Authors. Electronics Letters published by John Wiley & Sons Ltd on behalf of The Institution of Engineering and Technology. This is an open access article under the terms of the Creative Commons Attribution License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

References
1 Wang, C., et al.: Cellular architecture and key technologies for 5G wireless communication networks. *IEEE Commun. Mag.* **52**(2), 122–130 (2014)
2 Tan, X., et al.: Enabling indoor mobile millimeter-wave networks based on smart reflect-arrays. in Proc. IEEE INFOCOM’18, pp. 270-278.IEEE, Piscataway, NJ (2018)
3 Yu, X., Xu, D., Schober, R.: Optimal beamforming for MISO communications via intelligent reflecting surfaces. in Proc. IEEE ICC’19, pp. 735–740.IEEE, Piscataway, NJ (2019)
4 Guo, C., et al.: Maximum ergodic capacity of intelligent reflecting surface assisted MIMO wireless communication system. *Commun. Network.* **312**, 331–343 (2019)
5 Huang, C., et al.: Large intelligent surfaces for energy efficiency in wireless communication. *IEEE Trans. Wireless Commun.* **18**(8), 4157–4170 (2019)
6 Zhang, Z., Dai, L.: Capacity improvement in wideband reconfigurable intelligent surface-aided cell-free network. In: Proc. IEEE 21st Int. Workshop on Signal Process. Advances in Wireless Communications, pp. 1–5.IEEE, Piscataway, NJ (2020)
7 Wei, X., Hu, C., Dai, L.: Deep learning for beamspace channel estimation in millimeter-wave massive MIMO systems. *IEEE Trans. Commun.* **69**(1), 182–193 (2021)