ABSTRACT In this study, the use of intelligent reflecting surfaces (IRSs) to improve the capacity of a multi-user multiple-input-single-output downlink system is investigated. Unlike existing IRS-assisted wireless systems equipped with entirely passive IRS elements or purely active IRS elements, we propose a new IRS architecture in which each IRS element can operate either in active mode or in passive mode. To reduce power consumption, only a small portion of the IRS elements operate in active mode. We seek to maximize the capacity of the proposed IRS-assisted wireless system by jointly optimizing the phase shifts of all IRS elements, the transmit beamforming of the base station, and the IRS active-passive mode vector, which leads to a non-convex problem. In this study, the non-convex problem is addressed by using a probability learning-based algorithm from the cross-entropy optimization framework with an explicit expression for learning the targeted sampling distribution’s tilting parameters. The simulation results reveal that a significant capacity improvement over traditional IRS-assisted wireless systems with entirely passive IRS elements can be achieved using the proposed scheme, which employs only a small portion of active IRS elements.

INDEX TERMS Beamforming optimization, capacity improvement, intelligent reflecting surface, operation mode selection.

I. INTRODUCTION

Intelligent reflecting surfaces (IRSs) are recognized as a suitable technology for the next generation of wireless communications due to their ability to intelligently reconfigure the wireless propagation environment by appropriately adjusting the weight of each IRS element [1], [2], [3], [4], [5], [6], [7], [8], [9], [10]. In an IRS-assisted wireless system, the IRS elements only passively reflect the incident signals from the base station (BS) towards the desired directions. Unfortunately, the use of purely passive IRS elements introduces the double-fading problem, which originates from the product of path losses on the BS-IRS and IRS-user links. Although this problem can be alleviated by increasing the number of passive IRS elements [10], the resulting physical size and power consumption of the IRS module is impractical for some scenarios, and the complexity of IRS optimization increases considerably.

Recent studies propose the use of active elements in IRS-assisted wireless systems [11], [12], [13], [14], [15], [16] to tackle double-fading via the use of low-power reflection-type power amplifiers (PAs) such that the phases and amplitudes of the incident signals from the BS can be simultaneously adjusted. For example, Dong et al. [15] investigate the physical layer security enhancement of active IRS-assisted wireless systems. Moreover, resource allocation algorithm design for active IRS-assisted wireless systems has also been studied [16]. The results indicate that IRS-assisted systems with active elements achieve significantly higher transmission rates than IRS-assisted systems with passive elements. However, although the reflection-type PAs consume low power (e.g., 6–20 mW [17]), their power consumption still exceeds that of a conventional passive IRS element without PA (e.g., 5 mW [18]).
In this study, we propose a novel IRS-assisted architecture to improve the performance of IRS-assisted wireless systems with entirely passive elements while reducing the power consumption of IRS-assisted wireless systems with purely active elements. Accordingly, each IRS element has two modes of operation: passive mode and active mode. In passive mode, the IRS element reflects signals without amplification, whereas when in active mode, an IRS element amplifies the reflected signals. Our objective is to maximize the capacity of the system by jointly optimizing the phase shifts of all IRS elements, the transmit beamforming of the BS, and the IRS active-passive mode vector, where in order to minimize power consumption, only a limited number of IRS elements operate in active mode. This, however, results in a non-convex optimization problem. We address this by first adopting zero-forcing (ZF) beamforming as the transmit beamforming. We then propose a probability learning-based algorithm under a cross-entropy optimization (CEO) framework [24] to simultaneously determine the phase shifts of all IRS elements and their corresponding operation modes. The proposed CEO-based algorithm includes a joint parameterized sampling distribution to generate candidate solutions, that is, the phase shifts of all IRS elements and the associated operational modes. In addition, a restricted operator is proposed to ensure that each generated candidate solution satisfies the constraint that only a fixed number of IRS elements operate in active mode. Finally, a closed-form expression is derived to learn the tilting parameters of the proposed joint-parameterized sampling distribution. Simulation results reveal that replacing a few IRS elements in passive mode with active mode significantly increases system capacity.

Notation: \( \mathbb{R} \) and \( \mathbb{C} \) represent the sets of real and complex numbers, respectively. \( E[\cdot], \left[\cdot\right] \), and \( (\cdot)^H \) represent the expectation operator, ceiling operation, and Hermitian transpose, respectively. \( |\cdot| \) denotes the cardinality of a given set. \( \mathbb{I} \) corresponds to an indicator function of an event \( \cdot \). \( L_n(b) \) is a function used to select the \( n \)-th entry of the vector \( b = \{b_n\}_{n=1}^N \), diag(\( b \)) represents a diagonal matrix composed of elements in \( b \), and \( I \) signifies an identity matrix of an appropriate dimension. \( \mathcal{N}_C(0, \sigma^2) \) represents a complex Gaussian distribution with zero-mean and variance \( \sigma^2 \). \( \sim \) denotes “distributed as.” Lastly, \( j \triangleq \sqrt{-1} \) is an imaginary unit.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. SYSTEM MODEL

As shown in Fig. 1, we consider an IRS-assisted multiuser downlink wireless system that comprises an \( M \)-antenna BS, \( U \) single-antenna users, and an \( N \)-element IRS. In contrast to traditional IRS-assisted wireless systems, each IRS element has two modes of operation: (i) passive mode, where the IRS element is used to reflect the incident signals from the BS, and (ii) active mode, where the IRS element with a low-power reflection-type PA serves as an active relay. In passive mode, an IRS element reflects signals without amplification. Therefore, generally, the reflection amplitude of the IRS element in the passive mode is assumed to be one. However, in active mode, the IRS elements amplify the reflected signals, indicating that the reflection amplitude of the IRS element with the active mode is no smaller than one. In this study, we assume that the reflection amplitude of the IRS element in active mode is fixed (and denoted by \( \eta > 1 \)) to simplify the IRS circuitry [13]. Although the reflection-type PA consumes low power (e.g., 6–20 mW [17]), its power consumption is still higher than that of a conventional passive IRS element without a PA (e.g., 5 mW [18]). Consequently, only the \( K < N \) IRS elements operate in active mode when considering power consumption, while the remaining IRS elements operate in passive mode.

For ease of notation, we introduce a binary diagonal mode selection matrix, denoted by \( \mathbf{B} \triangleq \text{diag}(\mathbf{b}) \) with \( \mathbf{b} = \{b_n\}_{n=1}^N \), to indicate the mode in which the \( n \)-th IRS element operates in, i.e., active or passive mode. Specifically, \( b_n = 1 \) if the \( n \)-th IRS element operates in active mode, and \( b_n = 0 \) if the \( n \)-th IRS element operates in passive mode. In this case, the reflection matrix at the IRS can be written as the product of the reflection amplitude matrix, denoted by \( \mathbf{A} \triangleq \text{diag}(\mathbf{a}) \) with \( \mathbf{a} = \{a_n\}_{n=1}^N \), and the phase shift matrix, denoted by \( \Phi \triangleq \text{diag}(\mathbf{x}) \) with \( \mathbf{x} = \{x_n\}_{n=1}^N = \{e^{j\theta_n}\}_{n=1}^N \). Here, \( a_n \in \{1, \eta\} \) denotes the reflection amplitude of the \( n \)-th IRS element, where \( a_n = 1 \) if \( b_n = 0 \), and \( a_n = \eta \) if \( b_n = 1 \). Alternatively, we can express \( a_n = \eta^b_n \), which indicates that the corresponding reflection amplitude matrix \( \mathbf{A} \) is also determined once the mode selection matrix \( \mathbf{B} \) is determined. \( \theta_n \in [0, 2\pi) \) is the phase shift of the \( n \)-th IRS element. In practice, each phase shift \( \theta_n \) has only a finite resolution. Therefore, \( \theta_n \) is restricted to the values of \( \mathbb{F}_\delta \triangleq \{\Delta, 2\Delta, \ldots, 2\Delta\} \) with \( \Delta = \frac{2\pi}{2^n} \) for the phase shift using \( \lambda \) bits of resolution.

At the BS, the data intended for the \( u \)-th user \( s_u \), with \( E[|s_u|^2] = 1 \) is multiplied by the associated transmit beamforming vector \( \mathbf{w}_u \in \mathbb{C}^M \times 1 \). Thus, the transmit signal vector at the BS is constructed by \( \sum_{u=1}^U w_u s_u \), and the total transmit power constraint is expressed as \( \sum_{u=1}^U |w_u|^2 \leq P \), where

\[ P \] For cost-effective consideration, only the IRS element with the active mode is connected to a low-power reflection-type PA, similar to the antenna selection technique [25]. Therefore, only the \( K < N \) reflection-type PAs are required in the proposed scheme.
\( y_u = \left( h_u^H + f_u^H A \Phi G \right) \sum_{u=1}^{U} w_u s_u + f_u^H B A \Phi z + \sigma_u, \)  

(1)

where \( z \sim \mathcal{CN}(0, \sigma_z^2 I) \) and \( \sigma_u \sim \mathcal{CN}(0, \sigma_u^2) \) denote the dynamic noise introduced at the IRS elements in active mode and the additive Gaussian noise received at the \( u \)-th user, respectively. \( h_u^H \in \mathbb{C}^1 \times M, f_u^H \in \mathbb{C}^{1 \times N}, \) and \( G \in \mathbb{C}^{N \times M} \) represent the channel gains for the direct BS-user link, IRS-user link, and BS-IRS link, respectively. On the basis of (1) and the definition above, the signal-to-interference-plus-noise ratio at the \( u \)-th user can be expressed as

\[
\gamma_u = \frac{\left| \left( h_u^H + f_u^H A \Phi G \right) w_u \right|^2}{\sum_{i=1}^{U} \left| \left( h_u^H + f_u^H A \Phi G \right) w_i \right|^2 + \left| f_u^H B A \Phi \right|^2 \sigma_z^2 + \sigma_u^2}.
\]

(2)

III. PROBLEM FORMULATION

Our objective is to maximize the sum-rate of an IRS-assisted wireless system by jointly optimizing the transmit beamforming matrix \( W = [w_1, \ldots, w_U] \), the mode selection matrix \( B \), and the phase shift matrix \( \Phi \), which can be represented mathematically as

\[
(P1): \max_{W, B, \Phi} f(W, B, \Phi) = \sum_{u=1}^{U} \log_2 \left( 1 + \gamma_u \right)
\]

(3a)

subject to \( \sum_{u=1}^{U} \| w_u \|^2 \leq P \),  

(3b)

\(| \theta_n | \leq \pi, \forall n \),  

(3c)

\(| b | = K. \)  

(3d)

The optimization problem in (3) is non-convex because of the coupled optimization variables and the non-convex constraints in (3c) and (3d). We adopt a classical ZF-based transmit beamforming matrix \( W = H_{\text{eff}}^H \left( H_{\text{eff}} H_{\text{eff}}^H \right)^{-1} \) at the BS to simplify the optimization problem in (3), where \( H_{\text{eff}} = H^H + F^H A \Phi G \) with \( H = [h_1, \ldots, h_U] \) and \( F = [f_1, \ldots, f_U] \) is the effective channel matrix from the BS to all users. In addition, the obtained transmit beamforming matrix \( W \) must be normalized by a factor of \( \sqrt{\frac{\| H_{\text{eff}}^H (H_{\text{eff}} H_{\text{eff}}^H)^{-1} \|_F^2}{\| H_{\text{eff}}^H (H_{\text{eff}} H_{\text{eff}}^H)^{-1} \|_F}} \) to fulfill the power constraint in (3c). Accordingly, the objective function in (3a) can be represented solely in terms of \( B \) (or \( b \)) and \( \Phi \) (or \( x \)), and P1 is recast as

\[
(P2): \max_{b, x} f(b, x) = \sum_{u=1}^{U} \log_2 \left( 1 + \gamma_u \right) \quad (4a)
\]

subject to \( | \theta_n | \leq \pi, \forall n \),  

(4b)

\(| b | = K. \)  

(4c)

which can be solved using an exhaustive search. However, the search size of P2 is up to \( \frac{N^N}{(N-K)^K} \times 2^{KN} \), which is prohibitively high when \( N \) is large.

IV. ALGORITHMS

CEO is an effective probability learning-based framework for solving complex optimization problems [24].
fundamental idea of the CEO-based framework is to approximate the solution of the optimization problem at hand with a sequence of samples from a sequence of predesigned parameterized sampling distributions governed by the tilting parameters \( \pi \). Here, the tilting parameters are the iterates of the CEO-based framework. More specifically, in each iteration \( t \), the CEO-based framework generates a set of sample solutions \( \{ Y^{(t)}_{\ell} \}_{\ell=1}^L \) from the sampling distribution of the previous iteration \( \mathcal{P}(\cdot; \pi^{(t-1)}) \), after which it evaluates the function of those samples to obtain a set of objective function values \( f( Y^{(t)}_{\ell} ) \), and finally re-fits the sampling distribution to the elite samples by solving the following maximization problem [24]:

\[
\pi^{(t)} = \arg\max_{\pi} \frac{1}{L} \sum_{\ell=1}^L \mathcal{I}(f( Y^{(t)}_{\ell} ) \in \mathcal{E}(t)) \ln \mathcal{P}( Y^{(t)}_{\ell} ; \pi),
\]

(5)

where \( \mathcal{E}(t) \) denotes the elite set constituted by the \( L_{\text{elite}} \) top-performing samples. These samples are referred to as elite samples, and \( 0 < \xi < 1 \) is called the elite ratio. Similar to other reinforcement learning methods, instead of directly updating the parameters from \( \pi^{(t-1)} \) to \( \pi^{(t)} \), the tilting parameters \( \pi^{(t)} \) obtained in (5) are smoothed via

\[
\pi^{(t)} := \phi \times \pi^{(t)} + (1 - \phi) \times \pi^{(t-1)},
\]

(6)

where \( 0 < \phi \leq 1 \) is a fixed smoothing parameter.

We must first design a conveniently parameterized sampling distribution to generate samples to use the CEO framework to solve (4), that is, the mode selection vector \( b \) and the phase shift vector \( x \). Given that the mode selection of each IRS element \( b_n \) is a binary variable, we model the \( n \)-th element of \( b \) using an independent Bernoulli random variable with a probability mass function defined by \( \Pr[ I_n(b) = 1] = 1 - \Pr[ I_n(b) = 0] = I_n(\psi) \) for \( n = 1, 2, \ldots, N \). Here, \( \psi = |v| \) is a probability vector whose entry \( \nu_n \) denotes the probability of the \( n \)-th IRS element being chosen as the active mode. Accordingly, the sampling distribution for generating a random mode selection vector, \( b \), can be expressed as

\[
\mathcal{P}(b; \psi) \triangleq \prod_{n=1}^N I_n(b) (1 - \nu_n)^{1 - I_n(b)}.
\]

(7)

Unlike binary variables used in the mode selection of each IRS element, the phase shift of each IRS element \( x_n \) has \( |F| \) candidate discrete phase shifts. Thus, we model the \( n \)-th element of \( x \) by an independent discrete random variable with a probability mass function defined by \( p_{nk} = \Pr[ x_n = \theta^k ] \) for \( n = 1, 2, \ldots, N \) and \( k = 1, 2, \ldots, |F| \). Here, \( p_{nk} \) denotes the probability of the \( k \)-th element in the set \( F \) being chosen as \( x_n \), and the probability mass of each \( p_{nk} \) is constrained to a sum of one, that is, \( \sum_{k=1}^{|F|} p_{nk} = 1 \). Consequently, the sampling distribution for generating a random phase shift vector \( x \), which is governed by a probability parameter matrix \( \mathbf{P} \triangleq [p_{nk}] \in \mathbb{R}^{N \times |F|} \), is given by

\[
\mathcal{P}(x; \mathbf{P}) \triangleq \prod_{n=1}^N \sum_{k=1}^{|F|} p_{nk} \mathbb{I}[ x_n = \theta^k ].
\]

(8)

Therefore, based on (7) and (8), the joint sampling distribution of problem (4) parameterized by the metaparameters \( \pi \triangleq [v, \mathbf{P}] \) can be expressed as

\[
\mathcal{P}(Y; \pi) \triangleq \mathcal{P}(b; v) \times \mathcal{P}(x; \mathbf{P}),
\]

(9)

where \( Y \triangleq [b, x] \) is the sample solution generated from the joint sampling distribution \( \mathcal{P}(\cdot; \pi) \).

Once the parameterized sampling distribution is established, in each iteration \( t \), a collection of random samples \( \{ Y^{(t)}_{\ell} \}_{\ell=1}^L = \{ b^{(t)}_{\ell}, x^{(t)}_{\ell} \}_{\ell=1}^L \) is sampled from the pre-designed parameterized sampling distribution \( \mathcal{P}(\cdot; \pi^{(t-1)}) = \mathcal{P}(\cdot; v^{(t-1)}, \mathbf{P}^{(t-1)}) \) defined in (9). However, the generated samples \( \{ b^{(t)}_{\ell} \}_{\ell=1}^L \) cannot guarantee that the constraint in (4c) is satisfied, that is, \( \| b^{(t)}_{\ell} \|_0 \neq K \), we propose a restricted operator to ensure that each generated sample \( b^{(t)}_{\ell} \) is feasible without changing the distribution of \( \mathcal{P}(\cdot; v^{(t-1)}) \) as follows:

- If \( \| b^{(t)}_{\ell} \|_0 < K \), we sequentially flip the zero entry in \( b^{(t)}_{\ell} \) corresponding the highest probability in \( v^{(t-1)} \) to one until the constraint in (4c) is satisfied.
- If \( \| b^{(t)}_{\ell} \|_0 > K \), we sequentially flip the nonzero entry in \( b^{(t)}_{\ell} \) corresponding the lowest probability probability in \( v^{(t-1)} \) to zero until the constraint in (4c) is satisfied.

Subsequently, the feasible sampled solutions are evaluated using (4a) to obtain the corresponding objective function values \( f( Y^{(t)}_{\ell} ) \). A sorting process is then used to identify the elite samples \( \mathcal{E}^{(t)} \triangleq \{ Y^{(t)}_{\ell} \}_{\ell=1}^{L_{\text{elite}}} \) by ranking the performance of the sampled solutions \( \{ Y^{(t)}_{\ell} \}_{\ell=1}^L \) based on their objective function values \( f( Y^{(t)}_{\ell} ) \): from largest to smallest as \( f( Y^{(t)}_{1} ) \geq \cdots \geq f( Y^{(t)}_{L_{\text{elite}}} ) \geq \cdots \geq f( Y^{(t)}_{L} ) \), where \( f( Y^{(t)}_{\ell} ) \) denotes the \( \ell \)-th largest function value of \( f( Y^{(t)}_{\ell} ) \). Based on the \( \mathcal{E}^{(t)} \), the \( \{ Y^{(t)}_{\ell} \}_{\ell=1}^{L_{\text{elite}}} \) thus obtained, the parameterized sampling distribution \( \pi^{(t-1)} \) is updated to \( \pi^{(t)} \) by solving the problem in (5). Proposition 1 provides an optimal update formula.

**Proposition 1:** For the multivariate isotropic sampling distribution defined in (9), we have \( \pi = [v, \mathbf{P}] \) with \( v = \{ \nu_n \}_{n=1}^N \) and \( \mathbf{P} = [p_{nk}] \), and (5) has a closed-form solution given by

\[
v_n = \frac{\sum_{\ell=1}^L \mathbb{I}( f( Y^{(t)}_{\ell} ) \in \mathcal{E}(t) ) I_n(b^{(t)}_{\ell})}{\sum_{\ell=1}^L \mathbb{I}( f( Y^{(t)}_{\ell} ) \in \mathcal{E}(t) )},
\]

(10a)

\[
p_{nk} = \frac{\sum_{\ell=1}^L \mathbb{I}( f( Y^{(t)}_{\ell} ) \in \mathcal{E}(t) ) I_{n}(x^{(t)}_{\ell} = \theta^k)}{\sum_{\ell=1}^L \mathbb{I}( f( Y^{(t)}_{\ell} ) \in \mathcal{E}(t) )},
\]

(10b)

for \( n = 1, 2, \ldots, N \) and \( k = 1, 2, \ldots, |F| \).

**Proof:** See Appendix A.

**Remark 1:** In each iteration \( t \), the dominant complexity of Algorithm 1 originates from the evaluation of the objective function in Line 14. This step requires the complexity order of \( \mathcal{O}(L) \). Therefore, the complexity of Algorithm 1 can be approximated as \( \mathcal{O}(L_{\text{max}}) \), where \( L_{\text{max}} \) denotes the
number of iterations. Indeed, the complexity of Algorithm 1 is considerably lower than that of an exhaustive search. The parameter settings for the CEO-based framework are problem-dependent. However, the desired performance can be obtained in conformity with the recommendation of [24]. It is suggested to set $L = 8N$ with $1 < \varepsilon < 10$ and $\zeta = 0.1$. The parameters of Algorithm 1 are thus run with $\varepsilon = 4$, $\varphi = 0.6$, $\zeta = 0.1$, and $I_{\text{max}} = 50$.

V. SIMULATION RESULTS AND DISCUSSION

In this study, we consider a hot spot scenario in which the BS and the IRS are located at (0, 0) and (50 m, 2 m), respectively, and $K$ single-antenna users are randomly scattered within a circle centered at (50 m, 0). The noise power at the user is set to $\sigma_u^2 = -80$ dBm. Small-scale fading is modeled using a Rayleigh distribution. Moreover, the large-scale fading of the BS-user link is modeled as $L_\text{d}(\delta_{d,u}) = C_d \delta_{d,u}^{-\gamma_{d,u}}$, where $\delta_{d,u}$ represents the distance between the BS and the $u$-th user, $\gamma_{d,u} = 3.5$ is the path loss exponent, and $C_d = -30$ dB is the effect of channel fading and antenna gain. Similarly, the large-scale fading of the BS-IRS-user link can be expressed as $L_\text{G}(\delta_{G,u}) = C_G \delta_{G,u}^{-\gamma_{G,u}}$, where $\delta_{G,u}$ denotes the distance between the BS and the IRS, $\gamma_{G,u}$ denotes the distance between the IRS and the $u$-th user, and $C_G = -60$ dB denotes the effect of channel fading and antenna gain, and $\gamma_{G} = \gamma_{G,u} = 2$ is the path loss exponents. For comparison, a simple successive refinement (SA) algorithm [5] was applied to a traditional IRS-assisted wireless system with $N$ fully passive reflecting elements and $N$ fully active reflecting elements. In addition, the proposed CEO-based algorithm can be applied to a scenario where the mode selection vector $b$ is fixed. In such a scenario, the indexes of the IRS elements chosen as the active mode are predefined, for example, equipped active mode placement.

Figure 2 illustrates the sum-rate versus transmit power for an IRS-assisted wireless system with $M = 4$, $U = 4$, $N = 64$, $K = 8$, and $\lambda = 1$, where the convergence behavior of the proposed algorithm is also provided in Fig. 2(b) when $\varphi = 10$ dBm. Accordingly, the CEO with a fixed mode selection significantly outperforms the SA with $N$ entirely passive reflecting elements. For instance, the sum-rate of the CEO with a fixed mode selection and $\eta = 2$ increases by 31.76% at a transmit power of 10 dBm. Moreover, the CEO with dynamic mode selection enhances the performance of the CEO with fixed mode selection under the same $\eta$. This

![Figure 2](image-url)
observation is expected because the CEO with dynamic mode selection provides more spatial degrees of freedom than fixed mode selection. Furthermore, for a fixed \( \eta \), the SA with \( N \) entirely active reflecting elements presents the best performance. Interestingly, the CEO with dynamic mode selection achieves near the same performance as the SA with purely active reflecting elements when \( \eta = 2 \). This phenomenon is due to the fact that the active elements introduce additional amplification noise. Therefore, to compensate for the larger noise, the amplification factors the SA with \( N \) entirely active reflecting elements cannot be too small. In addition, Fig. 3 shows that the proposed algorithm converges within 40 iterations whether active or passive modes.

Figure 4 illustrates the influence of the different number of IRS elements operating in active mode on the sum-rate for an IRS-assisted wireless system with \( M = 4 \), \( U = 4 \), \( N = 64 \), \( \lambda = 1 \), and \( \varphi = 10 \) dBm, wherein the performance of the SA with \( N \) entirely active reflecting elements is also included for ease of comparison. As expected, as \( K \) increases, the performance of all schemes improves. However, for a fixed \( \eta \), the performance gap between the CEO with dynamic mode selection and that with fixed mode selection gradually widens as \( K \) increases. This finding is because the CEO with dynamic mode selection exploits spatial diversity gain. Furthermore, for a fixed \( \eta = 2 \) (\( \eta = 3 \)), the CEO with dynamic mode selection and \( K = 8 \) (\( K = 16 \)) achieves performance comparable with the SA with \( N \) entirely active reflecting elements while reducing power consumption. Notably, the CEO with dynamic mode selection and \( K = 16 \) even performs better than the SA with purely active reflecting elements when \( \eta = 2 \). This phenomenon is due to the fact that SA may lead to premature convergence when an inappropriate initial guess is applied. Additionally, as plotted in Fig. 5, the performance of the CEO with dynamic mode selection is further improved by increasing \( \lambda \).

Figure 6 compares the energy efficiency of the test algorithms with transmission power, where the energy efficiency is defined as [16], [21], [22], [23], [26], [27], [28]

\[
\xi = \frac{\sum_{u=1}^{U} \log_2 (1 + \gamma_u)}{P_{\text{total}}} \quad \text{(bits/Hz)}. \quad (11)
\]

Here, \( P_{\text{total}} \) is the total power consumption and is given by (12), as shown at the bottom of the page, where \( P_{\text{BB}}, P_{\text{RFchain}}, P_{\lambda, \text{PS}}, \) and \( P_{\text{SW}} \) are the power consumptions of the baseband processor, a single RF chain, a \( \lambda \)-bit phase shifter, and a switch, respectively. \( P_1 \) is the circuit power required to support one IRS element. In the simulation, the power consumption values of these components are set to \( P_{\text{BB}} = 200 \) mW, \( P_{\text{RFchain}} = 300 \) mW, \( P_{\lambda, \text{PS}} = 10 \) mW, \( P_{\text{SW}} = 5 \) mW, and \( P_1 = 2 \) mW [16], [21], [22], [23], [27], [28]. In addition,

\[
P_{\text{total}} = \begin{cases} 
\frac{1}{\tau} \sum_{u=1}^{U} \| w_u \|_2^2 + P_{\text{BB}} + MP_{\text{RFchain}} + NP_{\lambda, \text{PS}} + NP_1, & \text{for the purely passive IRS,} \\
\frac{1}{\tau} \sum_{u=1}^{U} \| w_u \|_2^2 + P_{\text{BB}} + MP_{\text{RFchain}} + NP_{\lambda, \text{PS}} + NP_1 + \frac{1}{\tau} P_A, & \text{for the purely active IRS,} \\
\frac{1}{\tau} \sum_{u=1}^{U} \| w_u \|_2^2 + P_{\text{BB}} + MP_{\text{RFchain}} + NP_{\lambda, \text{PS}} + NP_1 + \frac{1}{\tau} P_A, & \text{for the fixed mode IRS,} \\
\frac{1}{\tau} \sum_{u=1}^{U} \| w_u \|_2^2 + P_{\text{BB}} + MP_{\text{RFchain}} + NP_{\lambda, \text{PS}} + NP_1 + \frac{1}{\tau} P_A + \tau P_{\text{SW}}, & \text{for the dynamic mode IRS.} 
\end{cases} 
\]
a restricted operator under the CEO framework. The simulation results indicate that the proposed scheme with only a few active IRS elements significantly outperforms traditional IRS-assisted wireless systems composed of entirely passive IRS elements. Moreover, the proposed CEO with dynamic mode selection can offer comparable performance to the SA with purely active reflecting elements at a lower power consumption.

**APPENDIX A: PROOF OF PROPOSITION 1**

In contrast to (5), an additional constraint is required to ensure that the sum total probability of an element in set \( F_n \) being chosen as \( x_n \) is one, that is, \( \sum_{k=1}^{\mid F_n \mid} p_{nk} = 1 \). Therefore, the optimal update problem in our case can be expressed as

\[
\text{(P3)}: \quad \text{maximize} \quad \pi \quad \frac{1}{L} \sum_{\ell=1}^{L} \mathbb{1}_{(\mathbf{Y}_\ell^{(n)}) \in \mathcal{D}^{(n)}} \ln \mathcal{P}(\mathbf{Y}_\ell^{(n)}; \pi) \\
\text{subject to} \quad \sum_{k=1}^{\mid F_n \mid} p_{nk} = 1, \quad \text{for} \quad n = 1, \ldots, N. \tag{A.1b}
\]

By introducing the Lagrange multipliers \( \mathcal{L}_n \), we can rewrite (A.1) as an unconstrained problem given by

\[
\text{(P4)}: \quad \text{maximize} \quad \pi \quad \frac{1}{L} \sum_{\ell=1}^{L} \mathbb{1}_{(\mathbf{Y}_\ell^{(n)}) \in \mathcal{D}^{(n)}} \ln \mathcal{P}(\mathbf{Y}_\ell^{(n)}; \pi) \\
+ \sum_{n=1}^{N} \mathcal{L}_n \left( \sum_{k=1}^{\mid F_n \mid} p_{nk} - 1 \right). \tag{A.2}
\]

To proceed with this optimization, we first calculate the partial derivatives of \( \ln \mathcal{P}(\mathbf{Y}_\ell^{(n)}; \pi) \) with respect to \( v_n \) and \( p_{nk} \), yielding

\[
\frac{\partial}{\partial v_n} \ln \mathcal{P}(\mathbf{Y}_\ell^{(n)}; \pi) = \frac{\mathcal{I}_n(\mathbf{b}_\ell^{(n)}) - v_n}{(1 - v_n) v_n} \tag{A.3a}
\]

\[
\frac{\partial}{\partial p_{nk}} \ln \mathcal{P}(\mathbf{Y}_\ell^{(n)}; \pi) = \frac{\mathbb{1}_{(\mathcal{I}_n(x_n^{(n)}) = e^{k\lambda})}}{p_{nk}}. \tag{A.3b}
\]

Next, differentiating (A.2) with respect to \( v_n \) and applying the result of (A.3a) yields

\[
\sum_{\ell=1}^{L} \mathbb{1}_{(\mathbf{Y}_\ell^{(n)}) \in \mathcal{D}^{(n)}} \frac{\mathcal{I}_n(\mathbf{b}_\ell^{(n)}) - v_n}{(1 - v_n) v_n} = 0. \tag{A.4}
\]

Subsequently, solving for \( v_n \) of (A.4) yields the following analytic expression for \( v_n \):

\[
v_n = \frac{\sum_{\ell=1}^{L} \mathbb{1}_{(\mathbf{Y}_\ell^{(n)}) \in \mathcal{D}^{(n)}} \mathcal{I}_n(\mathbf{b}_\ell^{(n)})}{\sum_{\ell=1}^{L} \mathbb{1}_{(\mathbf{Y}_\ell^{(n)}) \in \mathcal{D}^{(n)}}}. \tag{A.5}
\]

Similarly, differentiating (A.2) with respect to \( p_{nk} \) and using the result of (A.3b) yields

\[
\frac{1}{L} \sum_{\ell=1}^{L} \mathbb{1}_{(\mathbf{Y}_\ell^{(n)}) \in \mathcal{D}^{(n)}} \mathbb{1}_{(\mathcal{I}_n(x_n^{(n)}) = e^{k\lambda})} + \mathcal{L}_n p_{nk} = 0. \tag{A.6}
\]
Summing (A.6) over \( k = 1, 2, \ldots, |\mathcal{I}| \) together yields
\[
L_{\rho} = -\frac{1}{\ell} \sum_{\ell=1}^{L} \mathbf{I}((\gamma^{p}_{\ell})_{e|d|^{(\nu)}}, \),\]  
(A.7)

Substituting (A.7) into (A.6) leads to the following closed-form expression for \( p_{\text{hk}} \):
\[
p_{\text{hk}} = \frac{\sum_{\ell=1}^{L} \mathbf{I}((\gamma^{p}_{\ell})_{e|d|^{(\nu)}},)}{\sum_{\ell=1}^{L} \mathbf{I}((\gamma^{p}_{\ell})_{e|d|^{(\nu)}},)} .\]  
(A.8)

**ACKNOWLEDGMENT**

The author would like to thank the editor, Dr. Xujie Li, and all the anonymous reviewers for their valuable comments and suggestions for enhancing the readability and technical quality of the paper.

**REFERENCES**

[1] C. Huang, A. Zappone, G. C. Alexandropoulos, M. Debbah, and C. Yuen, “Reconfigurable intelligent surfaces for energy efficiency in wireless communication,” IEEE Trans. Wireless Commun., vol. 18, no. 8, pp. 4157–4170, Aug. 2019.

[2] E. Basar, M. Di Renzo, J. De Rosny, M. Debbah, M. Alouini, and R. Zhang, “Wireless communications through reconfigurable intelligent surfaces,” IEEE Access, vol. 7, pp. 116753–116773, 2019.

[3] S. Gong, X. Lu, D. T. Hoang, D. Niyato, L. Shu, D. I. Kim, and Y.-C. Liang, “Toward smart wireless communications via intelligent reflecting surfaces: A contemporary survey,” IEEE Commun. Surveys Tuts., vol. 22, no. 4, pp. 2283–2314, 4th Quart., 2020.

[4] Q. Wu, S. Zhang, B. Zheng, C. You, and R. Zhang, “Intelligent reflecting surface aided wireless communications: A tutorial,” IEEE Trans. Commun., vol. 69, no. 5, pp. 3313–3351, May 2021.

[5] Q. Q. Wu and R. Zhang, “Beamforming optimization for wireless network aided by intelligent reflecting surface with discrete phase shifts,” IEEE Trans. Commun., vol. 68, no. 3, pp. 1838–1851, Mar. 2020.

[6] M. D. Renzo, A. Zappone, M. Debbah, M.-S. Alouini, C. Yuen, J. De Rosny, and S. Tretjakov, “Smart radio environments empowered by reconfigurable intelligent surfaces: How it works, state of research, and the road ahead,” IEEE J. Sel. Area Commun., vol. 38, no. 11, pp. 2450–2525, Nov. 2020.

[7] C. Huang, R. Mo, and C. Yuen, “Reconfigurable intelligent surface assisted multiuser MISO systems exploiting deep reinforcement learning,” IEEE J. Sel. Area Commun., vol. 38, no. 8, pp. 1839–1850, Aug. 2020.

[8] G. Zhou, C. Pan, H. Ren, K. Wang, and A. Nallanathan, “Intelligent reflecting surface aided multigroup multicast MISO communication systems,” IEEE Trans. Signal Process., vol. 68, pp. 3236–3251, 2020.

[9] X. Yuan, Y.-J. A. Zhang, Y. Shi, W. Yan, and H. Liu, “Reconfigurable intelligent-surface empowered wireless communications: Challenges and opportunities,” IEEE Wireless Commun., vol. 28, no. 2, pp. 136–143, Apr. 2021.

[10] H. Guo, Y.-C. Liang, J. Chen, and E. G. Larsson, “Weighted sum-rate maximization for reconfigurable intelligent surface aided wireless networks,” IEEE Trans. Wireless Commun., vol. 19, no. 5, pp. 3064–3076, May 2020.

[11] R. Long, Y.-C. Liang, Y. Pei, and E. G. Larsson, “Active reconfigurable intelligent surface aided wireless communications,” IEEE Trans. Wireless Commun., vol. 20, no. 8, pp. 4962–4975, Aug. 2021.

[12] M. H. Khoshafa, T. M. N. Ngatché, M. H. Ahmed, and A. R. Ndiuji SHE, “Active reconfigurable intelligent surfaces-aided wireless communication system,” IEEE Commun. Lett., vol. 25, no. 11, pp. 3699–3703, Nov. 2021.

[13] C. You and R. Zhang, “Wireless communication aided by intelligent reflecting surface: Active or passive?” IEEE Wireless Commun. Lett., vol. 10, no. 12, pp. 2659–2663, Dec. 2021.

[14] Z. Zhang, L. Dai, X. Chen, C. Liu, F. Yang, R. Schoder, and H. V. Poor, “Active RIS vs. passive RIS: Which will prevail in 6G?” 2021, arXiv:2103.15154.

[15] L. Dong, R.-M. Wang, and J. Bai, “Active reconfigurable intelligent surface aided secure transmission,” IEEE Trans. Veh. Technol., vol. 71, no. 2, pp. 2181–2186, Feb. 2022.