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Quantum-Inspired Antenna Subset Selection for IRS-Assisted Wireless Systems

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***Abstract*—Intelligent reflecting surface (IRS) assisted antenna selection systems improve the performance of the wireless communication systems with lower cost and power consumption. We focus on the challenging combinatorial problem of joint optimization of antenna subset at the transmitter and IRS reflection coefficients. Existing approaches, such as manifold optimization based subset selection (MOBSS), rely on exhaustive search over all antenna subsets, resulting in complexity that increases exponentially as the number of radio frequency chains increases. To address this challenge, we propose a quantum-inspired antenna subset selection framework that reformulates the problem as a quadratic unconstrained binary optimization (QUBO) problem. This enables the use of efficient combinatorial solvers, such as simulated annealing and quantum inspired simulated bifurcation, to obtain near-optimal antenna subsets. The reformulated problem is equivalent to the original problem while significantly reducing computational complexity. For a given subset, the IRS reflection coefficients are optimized using a manifold optimization approach. Numerical results demonstrate that the proposed method achieves performance comparable to MOBSS, while offering substantial gains in scalability, making it suitable for large-scale IRS-assisted systems.**

***Index Terms*—IRS, antenna selection, QUBO, quantum inspired simulated annealing, simulated bifurcation, manifold optimization.**

I. Introduction

Intelligent reflecting surface (IRS) is shown to have the potential to enhance next generation wireless communication in a cost and energy efficient manner [1]. It is made up of a large number of passive reflective elements whose reflection coefficients can be configured to beamform the signal in the desired direction. This is referred to as passive beamforming as it is achieved without requiring active radio frequency (RF) chains. It is shown that performing joint active beamforming at the transmitter and passive beamforming at the IRS improves the received signal quality significantly [2], [3].

Among different multiple-antenna techniques, transmit antenna selection (AS) is a technique that preserves diversity and beamforming gain while reducing hardware complexity and power consumption [4], [5]. However, jointly optimizing the antenna subset at the transmitter and reflection coefficients at the IRS is complex due to the combinatorial nature of antenna selection variables and the non-convex unit-modulus constraints imposed by IRS reflection coefficients [1].

Recently, several quantum-inspired (QI) algorithms have attracted significant attention to solve wireless communication problems [6], [7]. Many algorithms inspired by quantum techniques that can be simulated on classical computers are also studied. In this work, we explore QI algorithms to address the combinatorial complexity of joint antenna subset selection and IRS reflection-coefficient optimization.

Conventional Joint AS and IRS Reflection Coefficient Optimization [1]–[5]: Several conventional algorithms have been developed for joint AS and passive beamforming for IRS-assisted systems under different system settings and design objectives. In [1], an exhaustive search-based manifold Optimization based subset selection (MOBSS) scheme is proposed to optimize the antenna subset, beamforming vector at the transmitter, and IRS reflection coefficients jointly. Its computational complexity increases exponentially as number of RF chains increases. A discrete cuckoo optimization based AS scheme was proposed in [4]. In [5], a successive-refinement method was used to iteratively optimize AS and passive beamforming to maximize the sum rate. A successive convex approximation (SCA) based algorithm is developed in [2] and a block coordinate descent (BCD) approach is studied in [3]. These methods typically rely on full CSI and involve iterative optimization procedures.

QI Algorithms [6]–[9]: QI solvers such as the coherent Ising machine (CIM) and quantum annealing (QA) can solve complex combinatorial problems by reformulating them into a quadratic unconstrained binary optimization (QUBO) framework and equivalent Ising models [6]. They have utilized simulated annealing (SA) and the CIM to optimize configuration selection in reconfigurable MIMO arrays, illustrating that QUBO-based solvers can achieve near-optimal capacity. It is shown that the QUBO-based graph partitioning is suited for cell coverage optimization in [7]. A quantum inspired simulated bifurcation (QISB) technique is used to quantize phase-only beamforming [8]. The comparative study between SA and QA for maximizing sum-rates in interference-limited networks has shown that the SA is robust [9].

A. Focus and Contributions

We focus on joint optimization of antenna subset selection and IRS reflection coefficients, which inherently is challenging due to the coupling between discrete selection variables and continuous phase variables. For it, our goal is to develop low complexity near-optimal QI algorithms, unlike the existing approaches that rely on exhaustive search with prohibitive computational complexity [1]. We note that the QI algorithms, which have shown promise for solving large-

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scale combinatorial problems, have not been explored for IRS-assisted antenna subset selection.

The main contributions of this paper are as follows:

i) QUBO-Based Reformulation: First, we decompose the joint optimization into a discrete antenna subset selection stage and a continuous IRS phase optimization stage. We reformulate the antenna subset selection problem into the QUBO framework by mapping the signal-to-noise ratio (SNR) maximization objective into an equivalent energy minimization problem.

ii) QI Antenna Subset Selection and IRS Reflection Coefficient Optimization: We employ optimization techniques such as SA and QISB to solve the formulated QUBO problem. These methods enable near-optimal subset selection with polynomial complexity significantly reduced complexity. Given the selected subset, the IRS reflection coefficients are obtained using manifold optimization under unit-modulus constraints.

iii) Reduced Complexity: We show that the proposed QI subset selection framework has polynomial-time complexity significantly lower than the conventional algorithms, whose complexity grows exponentially as the number of RF chains increases.

iv) Benchmarking: We show that the performance of the proposed QISB algorithm matches the conventional MOBSS algorithms in the literature with significantly lower complexity. Furthermore, SA performs very close to the MOBSS.

II. System Model

We consider an IRS-assisted wireless communication system consisting of a transmitter (Tx), an IRS, and a receiver (Rx). The Tx is equipped with N_{t} antennas and N_{RF} RF chains with $N_{\mathrm{RF}} < N_{\mathrm{t}}$. The Rx has N_r receive antennas and one RF chain. It performs single antenna selection. The IRS comprises N passive reflecting elements with unit-modulus reflection coefficients. Let $\mathcal{N}_t = \{1, 2, \ldots, N_t\}$ denote the set of antennas at the Tx. The Tx dynamically selects a subset $\mathcal{S} \subset \mathcal{N}_t$ consisting of N_{RF} antennas and connects them to the available RF chains. Let $\mathbf{w} \in \mathbb{C}^{N_{\mathrm{RF}} \times 1}$ denote the transmit beamforming vector applied to the selected antennas.

Channel Model: We consider a quasi-static flat-fading channel model, where channel coefficients remain constant within a transmission block and change independently across blocks. Let $h_{rk} \in \mathbb{C}$ denote the complex channel gain of the direct link from the k^{th} Tx antenna to the r^{th} Rx antenna. Let $\mathbf{H} = [h_{rk}] \in \mathbb{C}^{N_r \times N_{\mathrm{t}}}$ denote the channel gain matrix of the direct link from the Tx and Rx. Let $\mathbf{G} \in \mathbb{C}^{N \times N_{\mathrm{t}}}$ denote the complex channel gain matrix between the Tx and the IRS and $\mathbf{f}_r \in \mathbb{C}^{N \times 1}$ denotes the complex channel gain vector from the IRS to the r^{th} Rx antenna, where $r \in \{1, 2, \ldots, N_r\}$. We consider Rayleigh fading for the direct link. The IRS is placed such that it has a strong line-of-sight (LoS) to both Tx and Rx. So we model the Tx to IRS and IRS to Rx channel gains as Rician fading. Let x_n denote the reflection coefficient of the n^{th} IRS element and $\mathbf{x} = [x_1, x_2, \ldots, x_N]^T$ denote the reflection coefficient vector.

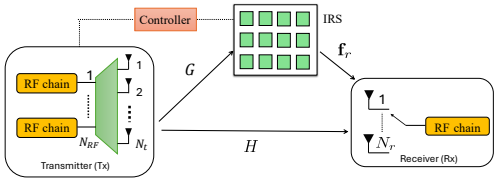


Fig. 1. IRS-assisted antenna selection system with N_{t} transmit antennas, N_{RF} RF chains at the Tx, and N_r receive antennas with a single RF chain at the Rx.

Let $h_{r\mathcal{S}} \in \mathbb{C}^{N_{RF} \times 1}$ denote the direct link channel gain vector corresponding to the subset of antennas at Tx and the r^{th} antenna at Rx. Similarly, let $G_{\mathcal{S}} \in \mathbb{C}^{N \times N_{RF}}$ denote the submatrix of G corresponding to the subset of antennas $\mathcal{S}$. The received signal at the r^{th} Rx antenna is given by

$$y_r = \left(\mathbf{h}_{r\mathcal{S}}^T + \mathbf{x}^T \mathbf{F}_r \mathbf{G}_{\mathcal{S}}\right) \mathbf{w} d + z, \tag{1}$$

where $\mathbf{F}_r = \mathrm{diag}(\mathbf{f}_r)$, d is the transmitted symbol with unit power, and z is the additive white Gaussian noise with variance σ^2.

A. Problem Formulation

From (1), the instantaneous SNR is given by:

$$\mathrm{SNR}(\mathcal{S}, r, \mathbf{w}, \mathbf{x}) = \frac{1}{\sigma^2} \left| \left(\mathbf{h}_{r\mathcal{S}}^T + \mathbf{x}^T \mathbf{F}_r \mathbf{G}_{\mathcal{S}}\right) \mathbf{w} \right|^2. \tag{2}$$

Constraints:

i) Peak Transmit Power Constraint: This constraint limits total transmit power across the selected N_{RF} antennas, i.e., $\|\mathbf{w}\|^2$, to be below the maximum permissible power $P_{\max}$. It is given by $\|\mathbf{w}\|^2 \leq P_{\max}$. *ii) Unit Modulus Constraint:* In order to maximize the SNR at Rx, the reflection coefficients of the IRS are subject to a unit-modulus constraint, where the magnitude of the reflection coefficient of each IRS element remains unity, i.e., $|x_n| = 1, \forall n$.

Optimization Problem: The objective is to jointly optimize subset $\mathcal{S}$ at Tx, antenna index r at the Rx, transmit beamforming vector $\mathbf{w}$ and IRS reflection coefficient vector $\mathbf{x}$ to maximize the received SNR in (2). The optimization problem can be written as

$$\mathcal{P}: \max_{\mathcal{S}, r, \mathbf{w}, \mathbf{x}} \quad \left| \left(\mathbf{h}_{r\mathcal{S}}^T + \mathbf{x}^T \mathbf{F}_r \mathbf{G}_{\mathcal{S}}\right) \mathbf{w} \right|^2, \tag{3}$$

$$\text{s.t.} \quad \|\mathbf{w}\|^2 \leq P_{\max}, \tag{4}$$

$$|x_n| = 1, \ \forall \ n = 1, 2, ..., N, \tag{5}$$

$$|\mathcal{S}| = N_{\mathrm{RF}}. \tag{6}$$

This problem is non-convex due to the discrete antenna subset constraint and the unit-modulus IRS constraints.

III. Proposed Algorithms

In this Section, we first decompose the above problem $\mathcal{P}$ into subset optimization and IRS reflection coefficient optimization problems. We then formulate QUBO problem for antenna subset selection and present two algorithms. We then present a manifold optimization based technique to optimize IRS reflection coefficients.

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For a Tx subset $\mathcal{S}$, Rx antenna r and IRS reflection coefficient vector $\mathbf{x}$, we know that the maximum-ratio transmission (MRT) beamforming vector

$$\mathbf{w}_{\mathrm{MRT}} = \sqrt{P_{\max}} \frac{\left(\mathbf{h}_{r\mathcal{S}}^T + \mathbf{x}^T \mathbf{F}_r \mathbf{G}_{\mathcal{S}}\right)^H}{\|\mathbf{h}_r^T + \mathbf{x}^T \mathbf{F}_r \mathbf{G}_{\mathcal{S}}\|}. \tag{7}$$

maximizes the SNR. Up on substituting $\mathbf{w}_{\mathrm{MRT}}$ in (2), the SNR reduces to $\frac{P_{\max}}{\sigma^2} \left\|\mathbf{x}^T \mathbf{F}_r \mathbf{G}_{\mathcal{S}} + \mathbf{h}_{r\mathcal{S}}^T\right\|^2$. Therefore, the optimization problem $\mathcal{P}$ reduces to

$$\mathcal{P}_1 : \max_{\mathcal{S},\mathbf{x},r} \quad \left\|\mathbf{x}^T \mathbf{F}_r \mathbf{G}_{\mathcal{S}} + \mathbf{h}_{r\mathcal{S}}^T\right\|^2 \tag{8}$$

$$\text{s.t.} \quad |\mathcal{S}| = N_{\mathrm{RF}}, r \in \{1, 2, \ldots, N_r\}, \tag{9}$$

$$|x_n| = 1, \ \forall n, \tag{10}$$

Problem Decomposition: The joint optimization problem involves both discrete and continuous variables, making it computationally intractable. To address this, we decompose the problem into two stages: 1) Antenna subset selection, 2) IRS reflection coefficient optimization

A. QUBO Formulation for Antenna Subset Selection

For a given Rx antenna r and IRS reflection coefficient vector $\mathbf{x}$ the optimization problem $\mathcal{P}_1$ reduces to

$$\mathcal{P}_2 : \max_{\mathcal{S}} \quad \left\|\mathbf{x}^T \mathbf{F}_r \mathbf{G}_{\mathcal{S}} + \mathbf{h}_{r\mathcal{S}}^T\right\|^2 \tag{11}$$

$$\text{s.t.} \quad |\mathcal{S}| = N_{\mathrm{RF}}, \tag{12}$$

To handle the above combinatorial optimization problem, we introduce binary variables

$$z_k = \begin{cases} 1, & \text{if antenna } k \text{ is selected,} \\ 0, & \text{otherwise,} \end{cases} \quad k = 1, 2, \ldots, N_{\mathrm{t}}. \tag{13}$$

Therefore, the subset cardinality constraint in (12) reduces to

$$\sum_{k=1}^{N_{\mathrm{t}}} z_k = N_{\mathrm{RF}}. \tag{14}$$

Let $\mathbf{z} = [z_1, z_2, \ldots, z_{N_t}]^T \in \{0,1\}^{N_{\mathrm{t}}}$ denote vector of binary selection variables. For fixed IRS reflection coefficient vector $\mathbf{x}$ and Rx antenna r, let c_k denote the effective channel gain corresponding to the k^{th} Tx antenna. It is given by

$$c_k = \mathbf{x}^T \mathbf{F}_r \mathbf{g}_k + h_{rk}, \tag{15}$$

where $\mathbf{g}_k \in \mathbb{C}^{N \times 1}$ is the k^{th} column of $\mathbf{G}$ matrix denoting the channel gain vector between k^{th} Tx antenna and IRS. We know that

$$\left\|\mathbf{x}^T \mathbf{F}_r \mathbf{G}_{\mathcal{S}} + \mathbf{h}_{r\mathcal{S}}^T\right\|^2 = \sum_{k \in \mathcal{S}} \left|\mathbf{x}^T \mathbf{F}_r \mathbf{g}_k + h_{rk}\right|^2. \tag{16}$$

Therefore, the objective function in (11) can be expanded in terms of binary variables z_k and the effective channel gain c_k as follows:

$$\left\|\mathbf{x}^T \mathbf{F}_r \mathbf{G}_{\mathcal{S}} + \mathbf{h}_{r\mathcal{S}}^T\right\|^2 = \sum_{k=1}^{N_{\mathrm{t}}} z_k \left|\mathbf{x}^T \mathbf{F}_r \mathbf{g}_k + h_{rk}\right|^2 = \sum_{k=1}^{N_{\mathrm{t}}} z_k |c_k|^2. \tag{17}$$

In the reformulated objective in (17), we only have linear terms of the binary variables z_k and no terms with interactions between two different variables z_i and z_j. However, the QUBO formulation requires an objective with interaction terms.

The square of the channel power in (17) is given by

$$\left(\sum_{k=1}^{N_{\mathrm{t}}} z_k |c_k|^2\right)^2 = \sum_{k=1}^{N_{\mathrm{t}}} |c_k|^4 z_k + \sum_{\substack{i,j=1 \\ i \neq j}}^{N_{\mathrm{t}}} |c_i|^2 |c_j|^2 z_i z_j, \tag{18}$$

where we have the pairwise interaction terms. From now on, we consider the square of the channel power in (18) as our objective function. We note that maximizing this square of the channel power yields the same optimal solution as maximizing the channel power in (17), as the function $f(x) = x^2$ is monotonically increasing in x for $x \geq 0$.This is similar to the reformulation done in [10].

Thus, for fixed IRS beamforming vector $\mathbf{x}$ and receive antenna index r, the optimization problem can be written as

$$\mathcal{P}_3 : \max_{\mathbf{z} \in \{0,1\}^{N_{\mathrm{t}}}} \quad \sum_{k=1}^{N_{\mathrm{t}}} |c_k|^4 z_k + \sum_{\substack{i,j=1 \\ i \neq j}}^{N_{\mathrm{t}}} |c_i|^2 |c_j|^2 z_i z_j, \tag{19}$$

$$\text{s.t.} \quad \sum_{k=1}^{N_{\mathrm{t}}} z_k = N_{\mathrm{RF}}. \tag{20}$$

Now, we incorporate the cardinality constraint in the above optimization problem as a penalty term in order to formulate the unconstrained binary optimization. It is as follows

$$\mathcal{P}_4 : \min_{\mathbf{z} \in \{0,1\}^{N_{\mathrm{t}}}} \left(- \sum_{k=1}^{N_{\mathrm{t}}} |c_k|^4 z_k - \sum_{i \neq j} |c_i|^2 |c_j|^2 z_i z_j + \lambda \left(\sum_{k=1}^{N_{\mathrm{t}}} z_k - N_{\mathrm{RF}} \right)^2 \right), \tag{21}$$

where $\lambda > 0$ is a penalty parameter. After expanding and collecting terms, the problem can be written compactly as

$$\mathcal{P}_5 : \min_{\mathbf{z} \in \{0,1\}^{N_{\mathrm{t}}}} \mathbf{z}^T \mathbf{Q} \mathbf{z}, \tag{22}$$

where $\mathbf{Q}$ is the QUBO matrix with entries given as

$$Q_{kk} = -|c_k|^4 + \lambda(1 - 2N_{\mathrm{RF}}), \ \text{for } k \in \mathcal{N}_t \tag{23}$$

$$Q_{ij} = -|c_i|^2 |c_j|^2 + \lambda, \quad i \in \mathcal{N}_t, j \in \mathcal{N}_t, i \neq j. \tag{24}$$

The reformulated QUBO preserves optimality since it is derived directly from the original effective channel power in (11) without relaxation.

1) Simulated Annealing for QUBO Optimization [6]: This is a widely used stochastic optimization algorithm for solving combinatorial problems such as QUBO formulations. It is inspired by the annealing process in statistical physics, wherein a system evolves toward a low-energy state through controlled cooling. The QUBO problem $\mathcal{P}_5$ in (22) can be interpreted as minimizing an energy function over binary

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variables z_k. To approximate the solution, we employ SA, a stochastic optimization method. Let the energy function be defined as $E(\mathbf{z}) = \mathbf{z}^T\mathbf{Q}\mathbf{z}, \quad \mathbf{z} \in \{0,1\}^{N_t}$.

Using a Markov chain, SA generates a sequence of candidate solutions $\{\mathbf{z}^{(t)}\}$. At each iteration, it randomly flips one or more components of the current solution $\mathbf{z}^{(t)}$ within its Hamming neighborhood to obtain a new candidate solution $\mathbf{z}'$. Then the change in energy is computed as $\Delta E = E(\mathbf{z}') - E(\mathbf{z}^{(t)})$, and the next candidate solution is obtained below:

$$\mathbf{z}^{(t+1)} = \begin{cases} \mathbf{z}', & \text{if } \Delta E \leq 0, \\ \mathbf{z}', & \text{if } \Delta E \geq 0 \text{ and p}> \text{rand}(0,1), \\ \mathbf{z}^{(t)}, & \text{otherwise} \end{cases} \tag{25}$$

where $p = \exp(-\Delta E/T_t)$ represents the acceptance probability and T_t denotes the temperature parameter at iteration t. The temperature is initialized to T_0 and is decreased after every iteration using $T_t = \alpha^t T_0, \quad 0 < \alpha < 1$. This probabilistic nature of the update in (25) enables the algorithm to escape local minima at high temperatures and allows a gradual convergence to low-energy solutions as the temperature decreases.

2) Ising Formulation and Simulated Bifurcation: The QUBO problem in (22) can be equivalently represented using the Ising model, a widely used combinatorial optimization formulation. In it, the binary variables $z_i \in \{0,1\}$ are mapped to spin variables $s_i \in \{-1,1\}$ using $s_i = 2z_i - 1, \quad \forall i \in \mathcal{N}_t$. Let $\mathbf{s} = [s_1, s_2, \ldots, s_{N_t}]^T \in \{-1,1\}^{N_t}$ denote the corresponding spin vector. Expressing (21) in $\mathcal{P}_4$ in terms of s_i yields the following Ising energy minimization problem

$$\min_{\mathbf{s}\in\{-1,1\}^{N_t}} E(\mathbf{s}) = \sum_{i<j} J_{ij}s_is_j + \sum_i h_is_i, \tag{26}$$

where J_{ij} represents the interaction between spins s_i and s_j, and h_i denotes the local bias term. We ignore constant offset term arising from the transformation. The Ising parameters can be expressed in terms of elements of the QUBO matrix $\mathbf{Q}$ as $J_{ij} = 0.5Q_{ij}, \forall i \neq j$ and $h_i = 0.5Q_{ii} + 0.5\sum_{j\neq i} Q_{ij}$. The mapping $s_i = 2z_i - 1$ is bijective and does not affect the optimal solution of the original problem. To solve the Ising problem in (26), we employ the QISB algorithm [11]. It is a quantum-inspired optimization method designed to efficiently minimize Ising energy. The QISB algorithm models each spin variable as a continuous dynamical variable and evolves the system according to nonlinear differential equations. The system evolves towards low-energy configurations that correspond to near-optimal solutions of the Ising problem.

In practice, the Ising parameters J_{ij} and h_i are provided as inputs to a simulated bifurcation solver in quadratic form. Upon convergence, the algorithm returns spin variables $s_i \in \{-1,1\}$, which are then mapped back to original binary variables using $z_i = (1+s_i)/2$.

B. IRS Reflection Coefficient Optimization

The above algorithms output the binary vector $\mathbf{z}$. The corresponding subset of antennas is given by

$$\mathcal{S}(\mathbf{z}) = \{\, k \in \mathcal{N}_t \;:\; z_k = 1 \,\}. \tag{27}$$

For a given receive antenna $r \in \{1,2,\ldots,N_r\}$ and antenna subset $\mathcal{S}(\mathbf{z})$ obtained from (27), the IRS reflection coefficient optimization problem $\mathcal{P}_6$ can be written as

$$\mathcal{P}_6 : \max_{\mathbf{x}} \quad \left\| \mathbf{x}^T\mathbf{F}_r\mathbf{G}_{\mathcal{S}(\mathbf{z})} + \mathbf{h}^T_{r\mathcal{S}(\mathbf{z})} \right\|^2, \tag{28}$$

$$\text{s.t.} \quad |x_n| = 1, \ \forall n. \tag{29}$$

We define

$$\mathbf{u}(\mathbf{x})^H \triangleq \mathbf{x}^T\mathbf{F}_r\mathbf{G}_{\mathcal{S}(\mathbf{z})} + \mathbf{h}^T_{r\mathcal{S}(\mathbf{z})}, \tag{30}$$

so that $\mathbf{u}(\mathbf{x}) \in \mathbb{C}^{N_{\text{RF}}\times 1}$ and the objective in (28) can be written as

$$f(\mathbf{x}) = \|\mathbf{u}(\mathbf{x})\|^2 = \mathbf{u}^H(\mathbf{x})\mathbf{u}(\mathbf{x}). \tag{31}$$

Let $\mathbf{A} \triangleq \mathbf{F}_r\mathbf{G}_{\mathcal{S}(\mathbf{z})}$ and $\mathbf{b} \triangleq \mathbf{h}_{r\mathcal{S}(\mathbf{z})}$. Using (30), the objective in (31) can be expanded as

$$f(\mathbf{x}) = \mathbf{x}^T\mathbf{A}\mathbf{A}^H\mathbf{x}^* + \mathbf{x}^T\mathbf{A}\mathbf{b}^* + \mathbf{b}^T\mathbf{A}^H\mathbf{x}^* + \mathbf{b}^T\mathbf{b}^*. \tag{32}$$

We now compute the gradient of $f(\mathbf{x})$ with respect to $\mathbf{x}^*$ using Wirtinger calculus. The Euclidean gradient is given by

$$\nabla f(\mathbf{x}) = (\mathbf{A}\mathbf{A}^H)^T\mathbf{x} + \mathbf{A}^*\mathbf{b}. \tag{33}$$

The constraint in (29) defines the complex circle manifold

$$\mathcal{M} = \left\{ \mathbf{x} \in \mathbb{C}^N : |x_n| = 1, \ \forall n \right\}. \tag{34}$$

To ensure that the update direction remains feasible, the Euclidean gradient in (33) is projected onto the tangent space of $\mathcal{M}$ at $\mathbf{x}$, yielding the Riemannian gradient

$$\text{grad}_R\, f(\mathbf{x}) = \nabla f(\mathbf{x}) - \Re\{\nabla f(\mathbf{x}) \odot \mathbf{x}^*\} \odot \mathbf{x}, \tag{35}$$

where $\odot$ denotes element-wise multiplication. Starting from an initial feasible point $\mathbf{x}^{(0)} \in \mathcal{M}$, the IRS reflection coefficient vector is updated iteratively as

$$\tilde{\mathbf{x}}^{(t+1)} = \mathbf{x}^{(t)} + \mu_t\, \text{grad}_R\, f(\mathbf{x}^{(t)}), \tag{36}$$

where μ_t is a suitable step size. Since $\tilde{\mathbf{x}}^{(t+1)}$ may violate the constraint in (29), a retraction step is applied to project it back onto $\mathcal{M}$:

$$x_n^{(t+1)} = \tilde{x}_n^{(t+1)}/|\tilde{x}_n^{(t+1)}|, \quad \forall n = 1,\ldots,N. \tag{37}$$

The above iterative procedure produces a sequence $\{\mathbf{x}^{(t)}\}$ with non-decreasing objective values in (31). Since the objective in (28) is upper bounded under the constraint in (29), the algorithm converges to a stationary point of P_6.

C. Proposed Subset Selection Algorithm

We now present the complete algorithm combining the solutions obtained for the sub-problems considered above. For each Rx antenna $r \in \{1,2,\ldots,N_r\}$, we first initialize a random IRS reflection coefficient vector $\mathbf{x}$. Following that, we construct the QUBO matrix $\mathbf{Q}$ using (23) and (24). We then solve the formulated QUBO using SA or QISB described above to obtain the corresponding subset $\mathcal{S}(\mathbf{z})$. For the obtained subset, we then solve the optimization problem

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TABLE I
RUNTIME IN SECONDS PER CHANNEL REALIZATION ($N_{\mathrm{t}} = 4, N_{\mathrm{RF}} = 2$)

N	MOBSS	QISB	SA
50	0.19259	0.22153	0.03236
100	0.30779	0.43140	0.05300
150	0.49331	0.51795	0.08385

$\mathcal{P}_6$ in (28) using the manifold optimization techniques to obtain the local optimal IRS reflection coefficient vector.

After obtaining the Tx antenna subset and IRS reflection coefficient vector for each Rx antenna, we select the optimal Rx antenna r_{opt} and the subset $\mathcal{S}_{\mathrm{opt}}$ that maximizes the SNR in (2). Configure the corresponding reflection coefficient vector at the IRS and beamforming vector $\mathbf{w}_{\mathrm{MRT}}$ from (7) at the Tx. The complete procedure is described in Algorithm 1.

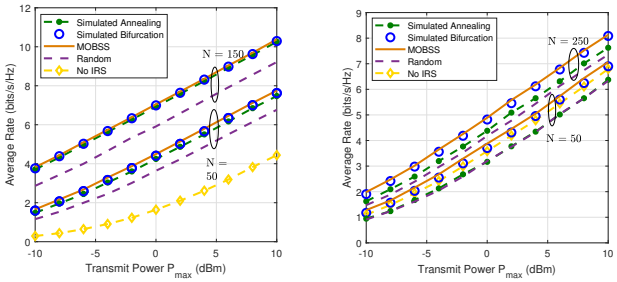
Algorithm 1 Subset Selection Algorithm

1: **Input**: Channel gains.
2: **for** $r = 1$ to N_r **do**
3: Initialize IRS phase vector $\mathbf{x}$.
4: Construct QUBO matrix $\mathbf{Q}$.
5: Solve QUBO problem using SA or QISB to get $\mathcal{S}(\mathbf{z})$.
6: Use manifold optimization to get optimal $\mathbf{x}$
7: **end for**
8: Select $(r_{\mathrm{opt}}, \mathcal{S}_{\mathrm{opt}})$ that maximizes the SNR.
9: Compute optimal beamforming vector $\mathbf{w}_{\mathrm{MRT}}$ using (7).
10: **return** $\mathcal{S}_{\mathrm{opt}}, r_{\mathrm{opt}}, \mathbf{w}_{\mathrm{MRT}}, \mathbf{x}_{\mathrm{opt}}$.

Complexity Analysis The proposed algorithm replaces exhaustive subset enumeration with a QUBO solver while using the manifold optimization for IRS phase design. For each Rx antenna, number of computations required to obtain $c_1, c_2, \ldots, c_{N_t}$ in (15) is $\mathcal{O}(NN_{\mathrm{t}})$ and for obtaining QUBO matrix is $\mathcal{O}\left(N_{\mathrm{t}}^2\right)$. The complexity of solving P_5 depends on the adopted solver. For I_{Q} iterations, the complexity is $\mathcal{O}(I_{\mathrm{Q}}{N_{\mathrm{t}}}^2)$. For each Rx antenna, proposed algorithm solves manifold optimization once with complexity $\mathcal{O}\left(N^{1.5}\right)$, when conjugate-gradient algorithm is employed [1]. For N_r antennas, the overall complexity of the proposed subset selection is $\mathcal{O}\big(N_r\left(NN_{\mathrm{t}} + I_{\mathrm{Q}}{N_{\mathrm{t}}}^2 + N^{1.5}\right)\big)$, which is independent of N_{RF}. The MOBSS algorithm solves manifold optimization for each Tx subset and for each Rx antenna. Hence, its complexity of is given by $\mathcal{O}\left(N_r N_{\mathrm{t}}^{N_{\mathrm{RF}}} N^{1.5}\right)$, which grows exponentially with the number of RF chains [1].

IV. Numerical Results

We now evaluate the performance of the proposed quantum-inspired subset selection algorithms under various system parameters and compare them with the MOBSS algorithm proposed in [1]. Half-wavelength spacing is considered for the antennas. A uniform planar array (UPA) is considered for the IRS. The Rician factor is set to 10. The distance between the Tx and IRS is fixed at $d_{TI} = 40$ m. The Rx moves along a line parallel to the Tx–IRS axis, with a fixed offset of 2 m.



(a) $d = 35$ m (b) $d = 20$ m

Fig. 2. Average received rate as a function of P_t for different N ($N_{\mathrm{t}} = 4$, $N_{\mathrm{RF}} = 2$, $N_r = 1$).

The horizontal distance between the Tx and Rx measured along a line parallel to the Tx–IRS axis is denoted by d. The large-scale fading is modeled using the path-loss expression $10\log_{10}\left(\frac{1}{10^3 d^\eta}\right)$, where the path-loss exponent η is set to 3.6 for Rayleigh fading and 2.2 for Rician fading links.

For the SA solver, the initial temperature T_0 is set to 100 and is gradually reduced according to a geometric cooling schedule with factor $\alpha = 0.95$ until $T_{\min} = 10^{-5}$ is reached. A relatively high T_0 enables occasional acceptance of higher-energy solutions with probability $\exp(-\Delta E/T_t)$, promoting exploration and avoiding poor local minima. The choice of $\alpha = 0.95$ allows sufficient exploration, while $T_{\min} = 10^{-5}$ avoids excessive computation after convergence. The penalty parameter is chosen as $\lambda = 5\max_k(|c_k|^4)$, where c_k denotes the effective channel gain of the k^{th} transmit antenna. This value was selected empirically, as smaller λ values failed to enforce the subset cardinality constraint, whereas larger values overemphasized constraint satisfaction at the expense of SNR maximization. QISB is implemented using 100 agents, ensuring a good balance between exploration and computational cost and 10000 iterations in discrete spin mode, allowing reliable convergence to near-optimal solutions in the discrete search space. The reported results are averaged over 500 (MOBSS, SA) and 100 (QISB) independent channel realizations.

Fig. 2a plots the average rate as a function of the peak transmit power $P_{\max}$ for different values of N and fixed Tx-Rx distance of $d = 35$ m. The performance of the SA and QISB algorithms is compared with benchmark schemes MOBSS in [1], random antenna selection, and the case without IRS. The average rate increases as $P_{\max}$ increases. It also increases as the number of IRS elements increases due to improved array and aperture gains. The performance of QISB closely matches that of the MOBS scheme for both values of N. SA performs close to the MOBSS schemes for $N = 50$ and matches for $N = 150$. The random selection performs worse for both values of N, and the gap increases as N increases. Furthermore, the no-IRS case has the lowest achievable rate, demonstrating the benefit of the IRS.

Fig. 2b plots the average rate as a function of the peak transmit power $P_{\max}$ for $d = 20$ m. Now, the increase in N from 50 to 250 yields a lower gain as the Rx moved closer to the

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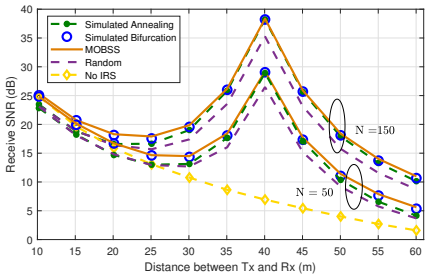


Fig. 3. SNR as a function of d for different N ($N_{\mathrm{t}} = 4$, $N_{\mathrm{RF}} = 2$, $N_r = 1$, and $P_{\max} = 5$ dBm).

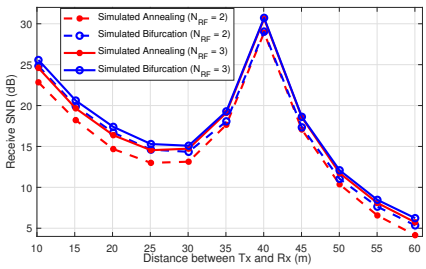


Fig. 4. SNR for SA and QISB as a function of d for different N_{RF} ($N = 50$, $N_{\mathrm{t}} = 4$, $N_r = 1$ and $P_{\max} = 5$ dBm).

Tx and away from the IRS. As earlier, the performance of the QISB matches that of the MOBSS. However, the performance of the SA is lower due to a weaker IRS link. For $N = 50$, the no-IRS case performs better than the SA and random schemes as the direct link is strong. However, with more IRS elements, i.e., $N = 250$, SA and random schemes perform better than a no-IRS system due to a stronger link through IRS. We also see that the QISB consistently outperforms SA. The random antenna selection scheme performs worse than the optimized methods, as expected, due to its inability to adapt to instantaneous channel conditions. Here, the performance gain with N is less compared to Fig. 2a, where Rx is closer to the IRS.

Fig. 3 plots the average SNR as a function of the distance d between the Tx and Rx for different values of N. Initially, as the d increases, the Rx moves away from the Tx and the SNR decreases. With further movement the SNR increases though direct Tx-Rx link weakens. This happens as the Rx moves closer to the IRS. It peaks around $d = 40$ m, where the Rx is closest to the IRS. After that it starts to decrease as the Rx moves away from both Tx and IRS. In contrast, the SNR due to no IRS case monotonically decreases with d as it relies only on the direct Tx-Rx link. QISB matches the MOBSS scheme for all distances. For small d, the SNR of the SA is lower than the QISB and MOBSS. However, as d increases this gap decreases and SA matches with them. At $d = 40$ m, all schemes exhibit similar performance. The average SNR increases significantly as N increases from 50 to 150. The random selection scheme has lower SNR for all values of d.

Fig. 4 plots the average SNR as a function of the distance d for SA and QISB algorithms for $N_{\mathrm{RF}} = 2$ and $N_{\mathrm{RF}} = 3$. For a given N_{RF}, the behavior as a function of d is similar to the Fig. 3. For this reason other schemes are not shown to keep the figure clean. For a given d, for both schemes, we see that the SNR increases as N_{RF} increases. This happens for all values of d due to the increased array gain due to increase in the number of RF chains allowing the Tx to activate more antennas simultaneously.

V. Conclusion

We revisited the antenna subset selection problem for IRS-assisted systems from a different perspective. We decomposed the problem into two stages and reformulated the subset selection problem in terms of the QUBO problem, allowing the use of SA and quantum-inspired QISB solvers. For the selected subset, we employed manifold optimization to obtain a local optimal IRS reflection coefficient vector. Through numerical results, we showed that the proposed algorithms achieved the performance of the conventional MOBSS while avoiding its exponential complexity in terms of number of RF chains. Several directions remain open for further study, including extensions to imperfect CSI and more general multi-user settings.

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