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A Hybrid Classical-Quantum Computing Framework for RIS-assisted Wireless Network

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***Abstract*—Recently, there has been a growing interest in employing reconfigurable intelligent surfaces (RISs) to improve the spectrum and energy efficiency of wireless networks. In RIS-assisted wireless networks, channel estimation and optimization is a difficult task, particularly for nearly passive RIS devices with low-complexity hardware design. We have proposed a hybrid classical-quantum computing framework that allows for ultra-fast optimization adapting to multipath wireless environments. The onsite optimization of RIS configuration can be performed almost instantaneously using only feedback (received power) at wireless endpoints. The performance of the proposed work is demonstrated in representative wireless propagation scenarios.**

***Index Terms*—Electromagnetic metamaterials, Ising model, reconfigurable intelligent surface, quantum annealing, wireless communication, 6G.**

I. Motivation

The reconfigurable intelligent surfaces (RISs) are software-controlled large engineered surfaces with many low-cost passive reflecting elements, where the desired reflective wavefront may be achieved by tuning the local reflection phase and/or amplitude of individual elements. Going beyond 5G and entering 6G, it is envisioned that large-scale, distributed RIS devices will be deployed at the surface of interacting objects, e.g. walls, windows, and furniture, in the propagation channel [1]. The overall goal is to transform the radio environment into a smart and reconfigurable space that provides enhanced coverage with high energy efficiency and supports ultra-fast and seamless connectivity [2].

Despite its great potential, there are also pressing challenges needed to be addressed in RIS-empowered smart radio environments [3], [4]. Due to the constraint of channel coherence time, one needs to rapidly optimize the states of RIS with prescribed objective functions, e.g., multi-beamforming, localization/focusing, and channel spatial diversity. This constitutes a heavy computational burden in the physical layer of the wireless network. Furthermore, to meet the requirement of green communications, the RISs are designed to be nearly passive with low-cost hardware and low power requirements. Since the RIS does not possess sensing capability, the channel estimation has to be implemented at wireless endpoints of the communication link. This makes the channel optimization of RIS-assisted networks very challenging [5], [6].

The scientific contribution in this paper is a physics-based, mathematically tractable computational framework for optimizing RIS configuration in complex radio environments. Such optimization is performed without the need to estimate the cascaded channels [7] that link the transmitter to the RIS and the RIS to the receiver. The idea starts with expressing the power of end-to-end channel transfer function as an Ising Hamiltonian model [8]. A hybrid classical-quantum computing model is proposed next to navigate the RIS configuration space and to rapidly optimize the RIS state in a multipath radio environment. Compared to the state-of-the-art solutions, we show that the Ising Hamiltonian model serves as a unified mathematical framework describing wave physics in the RIS-assisted wireless network. By leveraging the computing power of quantum adiabatic evolution and mathematics of tensor contraction, the channel estimation and optimization can be completed in the order of milliseconds. The outcomes enable the possibility of ultrafast optimization adapting to dynamic wireless environments.

II. Ising Model for RIS-aided Wireless Channel

We consider the basic problem statement of a RIS-assisted wireless network as illustrated in Fig. 1, including a user's equipment (UE), a base station (BS), and a passive RIS array. One can tune the reflection phase of each RIS unit cell from a finite set of phase states, e.g., 1-bit (binary) RIS can be tuned with a reflection phase of 0^o or 180^o, and a 2-bit RIS unit cell exhibits four reflection phase states. As such, we can view the RIS optimization as an integer programming model, which searches for an optimal solution over all the combinatorial states of RIS elements.

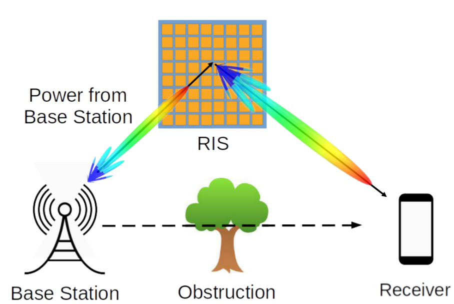


Fig. 1: A RIS-assisted wireless network for creating a virtual line-of-sight between BS and UE.

In [9], we developed an Ising model for the RISs with beamforming/nullforming applications. By designing the Ising Hamiltonian to mimic EM scattered power, the optimal

RIS configuration is encoded in the ground state solution of the Ising spin system, which can be effectively found by heuristic quantum optimization algorithms.

To briefly demonstrate the method, we consider an M by N element RIS array with the desired signal maximization towards the elevation angle of θ^s and azimuthal angle of ϕ^s. The scattered EM field can be written in the Dirac notation as: $|\mathbf{E}(\theta,\phi)\rangle = \sum_{m=1}^{M}\sum_{n=1}^{N}\mathbf{G}_{mn}(\theta,\phi)\,|s_{mn}\rangle$, where the RIS basis state s_{mn} represents the element phase modulation, e.g. ± 1 corresponding to the $0/\pi$ phase response, and the $\mathbf{G}_{mn}(\theta,\phi)$ is the element-wise scattering vector. We can then express the EM scattered power as a quadratic model:

$$\begin{aligned} P(\theta,\phi) &= \langle \mathbf{E}(\theta,\phi)|\mathbf{E}(\theta,\phi)\rangle \\ &= \sum_{m_1=1}^{M}\sum_{n_1=1}^{N}\sum_{m_2=1}^{M}\sum_{n_2=1}^{N}\langle s_{m_1n_1}|\,\mathbf{G}^*_{m_1n_1}\mathbf{G}_{m_2n_2}\,|s_{m_2n_2}\rangle \end{aligned} \tag{1}$$

From this, we can construct an energy maximization Hamiltonian with an order 2 polynomial. By using symmetry in the scattering vector, the effective Hamiltonian can be constructed as an Ising spin-glass model:

$$\begin{aligned} H(\theta^s,\phi^s) = -\,P(\theta^s,\phi^s) &= \sum_{m=1}^{M} w_m s_m \\ &+ \sum_{m=1}^{M}\sum_{n=m+1}^{M} s_m s_n J_{mn}(\theta^s,\phi^s) \end{aligned} \tag{2}$$

in which the desired scattering direction is denoted by θ^s and ϕ^s. The computation of spin bias w_m and spin-spin interaction strength, J_{mn}, is detailed in [9] and skipped here for brevity. The solution to the beamforming problem can then be found by finding the ground state of the Ising Hamiltonian:

$$\hat{s}_1,\cdots,\hat{s}_M = \underset{s_1,\cdots,s_M}{\operatorname{argmin}}\, H(\theta^s,\phi^s) \tag{3}$$

III. Onsite Learning and Optimization

In the previous study [9], the locations of the transmitter and receiver are assumed to be known to the RISs. Thereby the Ising model can be computed by the semi-analytical formula. Due to low hardware complexity and power constraints, the RIS considered in this work is a nearly passive device that does not possess sensing capabilities. Since the RIS cannot estimate the direction of arrival/departure (DOA/DOD) nor the locations of Tx and Rx, it completely relies on the BS to (***i***) estimate the channel of the propagation environment, (***ii***) learn the perturbative space that RIS could offer, and (***iii***) find the optimal RIS configuration to achieve the maximum channel gain. It is clearly a very challenging computational task, which motivates this study.

We propose a hybrid classical-quantum computing model for ultrafast channel estimation and optimization at wireless endpoints. The classical part of the hybrid model includes a tensor contraction and linear regression algorithm, which approximates the dense spin-spin interaction matrix with a tensorial representation. The ground state solution of the approximate Ising model is computed with a quantum annealing algorithm on physical quantum computing hardware. An overview of the proposed work is given in Fig. 2.

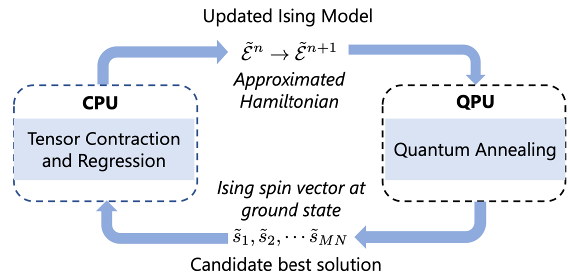


Fig. 2: A hybrid classical-quantum computing model.

1) Tensor contraction and regression (TCR): It is important to recognize that the Ising model in (2) exhibits strong structural and low-rankness properties. For instance, the spin-spin interaction strength between two Ising variables is determined by the displacement vector in the Cartesian product. In this regard, we can first construct a tensor $\mathcal{T}^{ijk} \in \mathcal{R}^{MN\times MN\times(2MN-M)}$. Each mode 3 $MN \times MN$ slice of $\mathcal{T}^{ijk}$ corresponds to a displacement vector, and therefore a unique value in the spin-spin interaction. For a training set of n_s samples with known Ising spin values and Hamiltonian y^s, the Ising spin states of the RIS are put into a matrix $\sigma \in \mathcal{R}^{MN\times n_s}$. The tensor contraction is calculated as: $\sum_{ij}\sigma^{si}\mathcal{T}^{ijk}\sigma^{sj} = x^{sk}$. Next, the spin bias and coupling terms in (2) can be approximated with linear regression $[w, J] = ((x^{sk})^T x^{sk})^{-1}(x^{sk})^T y^s$.

2) Quantum Annealing (QA): Generally speaking, finding the ground state of an Ising model is a NP-hard (non-deterministic polynomial-time hard) problem due to the exponentially large solution space, i.e. $O(2^{MN})$ for 1-bit RIS and $O(4^{MN})$ for 2-bit RIS. Classical optimization algorithms do not scale well with a large number of RIS elements. In this work, we leverage recent advances in the adiabatic quantum computing (QC) hardware, so-called quantum annealer (QA) [10], to find the ground-state solution of the Ising Hamiltonian. The particular physical QA hardware considered in this work is the D-Wave Advantage 4.1 QPU [11], which received considerable interest lately due to the number of available qubits and programmability.

3) System Model Overview: We consider a RIS-assisted wireless network involving a BS and a UE. The BS controls the RIS configurations through an out-of-band control channel to the RIS controller. The communication protocol consists of a training phase and an access phase. During the training phase, the UE repeats a known pilot signal. The BS starts by selecting a finite set of RIS configurations as an initial training set. Each RIS configuration is denoted by a binary Ising spin vector $\mathbf{s} = [s_{11}, s_{12}, \ldots, s_{MN}]$. The corresponding received signal power y^s at the BS is recorded as figures of merit (FOM). These initial training data samples are inputs to the TCR such that an approximate Ising model is constructed.

Next, the trained Ising model is compiled into the D-Wave QA hardware through a process of embedding and de-embedding. The Ising spin vectors of low-energy stages are collected from the outcome of QA sampling. These candidate solutions are appended to the training set, and their respective FOMs are measured at the BS. Based on the initial and newly collected data samples, the TCR-trained Ising model is updated. This concludes one iteration of the learning phase. The iterative process of sampling by the QA and retraining by the TCR is repeated until some desired stopping condition or a maximum number of iterations is achieved. After the training phase, the optimized RIS configuration is found for the BS-UE link and can be used in the access phase.

IV. Numerical Experiments

A. Test Problem Setup

Consider a RIS-aided narrowband communication system depicted in Fig. 3. The UE and BS antennas are in non-line-of-sight (NLOS) between each other while they both are in LOS with the RIS. The carrier frequency of the passband signal is 2.4 GHz. Both antennas are half-wavelength electric dipoles. The distance between UE and RIS is 2.5 m, and the distance between RIS and BS is 3.75 m. A planar 10 by 10 RIS array resides in the xy plane. The size of the array element is $d = 1\lambda$. The incident angle from the UE to the RIS is $\theta^i = 15°$ and $\phi^i = 270°$.

In addition, we include a reflective scatterer that is close to the transmitter. Therefore a second ray trajectory with $\theta^i = 30°$ and $\phi^i = 270°$ is created between the scatterer and RIS. Finally, there is a direct reflection ray path between the UE and the BS, which is not affected by the RIS configuration. The goal is to optimize the channel gain at the BS in the direction of $\theta^s = 20°$ and $\phi^s = 90°$. We remark that it is a rather difficult scenario as the channel transfer function will include a perturbative component as well as a non-perturbative, static component. Besides the beamforming at the BS, the optimal RIS configuration has to ensure that perturbative and static components are added up constructively.

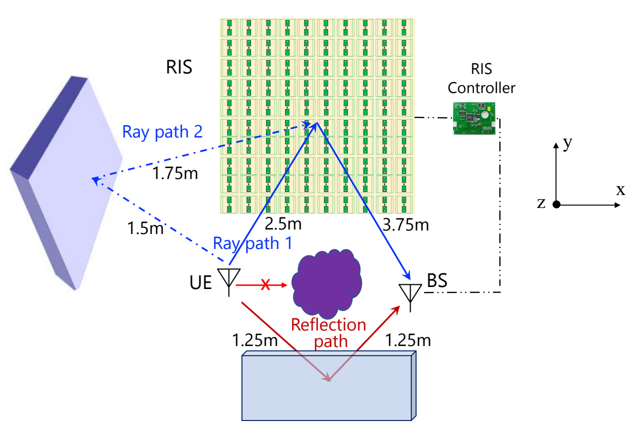


Fig. 3: The case of two ray-trajectory between UE-RIS-BS and a direct reflected path between UE and BS.

The BS controls the operation of the RIS through an out-of-band (wireless) control channel to the RIS controller. The RIS unit cells are individually connected to the RIS controller that implements tunability of local reflection phases to incoming waves. We will consider both 1-bit binary array and 2-bit quadriphase array in this study. For the 2-bit array, two Ising spin variables per element are used to represent four phase states, following the procedure introduced in [9].

B. Profiling of the Hybrid Computing Model

In this study, we will evaluate the performance of the hybrid classical (TCR) - quantum (QA) computing model to learn the Ising model and optimize the channel gain at the receiver. The TCR is utilized to predict the Ising model in which the spin-spin interactions are approximated by a tensorial representation. The QA is utilized to find the ground-state solution of the TCR-based Ising model.

As illustrated in Sec. III, the hybrid computing model consists of an iterative process of QA sampling and TCR training. The inputs to the TCR training include the dimension of the Ising variables $M \times N$, Ising spin vectors $\mathbf{s} = [s_{11}, s_{12}, \ldots, s_{MN}]$, and the received power at the BS as FOMs. We start by selecting five orthogonal RIS configurations (i.e. Ising spin vectors) as an initial training set. An approximate Ising model is constructed by the TCR. Next, the QA algorithm is used to select Ising spin vectors of the lowest energy candidate based on the currently trained Ising model. The candidate best solution is then used to update the TCR parameters. Throughout this iterative process, the Ising model is updated until the FOM reaches saturation or a maximum number of iterations is achieved.

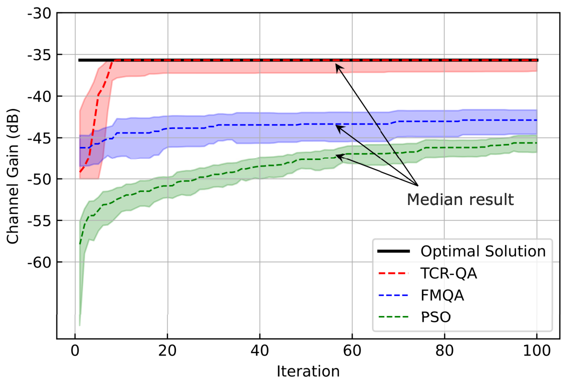
To profile the performance of the proposed work, we considered two other metaheuristic algorithms for comparison. One is the well-known particle swarm optimization (PSO) algorithm [12]. The other one is the factorization machine with quantum annealing (FMQA) [13]. The factorization machine is a supervised learning model [14], which uses factorized parameters to model the spin bias and spin-spin interactions.

Given the probabilistic nature of metaheuristic optimization, we repeat 100 runs for each of the three algorithms. The convergence histories in terms of channel gain using TCR-QA, PSO, and FMQA are presented in Fig. 4. The optimal solution is obtained by the brute force search and is used as the reference. By comparing the channel gains obtained from three algorithms, it is shown that the other two algorithms may be trapped in local optimal values easily. For both 1-bit and 2-bit RIS array studies, the TCR-QA offers ultrafast convergence. The results demonstrate the effectiveness of the proposed work in channel estimation (onsite learning of the Ising model) and optimization (finding a global-optimal solution) of RIS-assisted wireless networks.

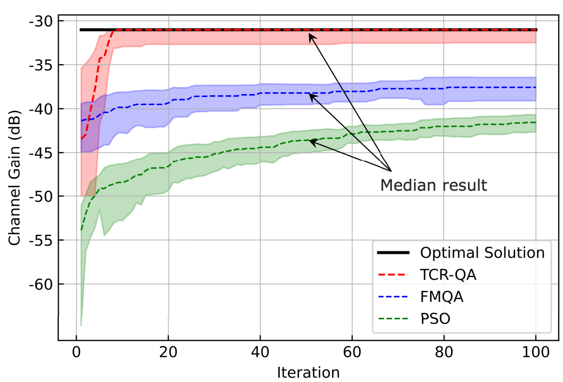
Table I gives the median wall-clock time (CPU portion plus QPU portion) over 100 runs for the three methods. For TCR-QA, it is the time taken to find the optimal solution within 100 iterations. Since FMQA and PSO didn't find the best solution, the time is calculated for a maximum number (i.e. 100) iterations. As is evident, the proposed work achieves a significant speed-up with respect to other algorithms. The median wall-clock time including learning and optimization for the 10 by 10 2-bit RIS array only takes 0.158 s.

TABLE I: The wall clock time for three algorithms

RIS panel	TCR-QA	PSO	FMQA
1 bit array	0.074 s	13.29 s	21.82 s
2 bit array	0.158 s	25.40 s	97.95 s



(a) 1-bit square RIS array



(b) 2-bit square RIS array

Fig. 4: Numerical experiment for a 10 by 10 RIS array with two ray-trajectories between UE-RIS-BS and a direct reflected path between UE-BS.

V. Conclusion

Efficient channel estimation and optimization of smart radio environments is a challenging task, especially for nearly passive RIS devices with no sensing capabilities. We have demonstrated the great potential of a hybrid classical-quantum computing framework for RIS-assisted wireless networks. Such a framework allows for simultaneous channel estimation and RIS configuration optimization. The onsite optimization of RIS configuration can be done almost instantaneously using only feedback (received power) at wireless endpoints.

We remark that the work can be naturally extended to higher-order spin-spin interactions resulting from complex objective functions, e.g. multiple access points multiuser maximum signal deposition. Additionally, it is assumed the base station has access to a quantum backbone computing network. Nonetheless, quantum-inspired metaheuristic algorithms or specialized Ising machine hardware may be used at the base station instead of a quantum annealing sampler.

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