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Distributed CSMA/CA MAC Protocol for RIS-Assisted Networks

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Abstract—This paper focuses on achieving optimal multi-user channel access in distributed networks using a reconfigurable intelligent surface (RIS). The network includes wireless channels with direct links between users and RIS links connecting users to the RIS. To maximize average system throughput, an optimal channel access strategy is proposed, considering the trade-off between exploiting spatial diversity gain with RIS assistance and the overhead of channel probing. The paper proposes an optimal distributed Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA) strategy with opportunistic RIS assistance, based on statistics theory of optimal sequential observation planned decision. Each source-destination pair makes decisions regarding the use of direct links and/or probing source-RIS-destination links. Channel access occurs in a distributed manner after successful channel contention. The optimality of the strategy is rigorously derived using multiple-level pure thresholds. A distributed algorithm, which achieves significantly lower online complexity at $O(1)$, is developed to implement the proposed strategy. Numerical simulations verify the theoretical results and demonstrate the superior performance compared to existing approaches.

Index Terms—Carrier Sense Multiple Access (CSMA), Collision Avoidance (CA), Multi-user communications, Reconfigurable intelligent surface (RIS), Sequential analysis, Statistics theory.

I. INTRODUCTION

The emerging technology of reconfigurable intelligent surfaces (RIS) has the potential to boost wireless network throughput and spectral efficiency [1]. RISs offer costeffective and energy-efficient advantages over active relays for facilitating efficient transmission among multiple users. However, integrating RISs into multiple user and RIS medium access control (MAC) layer designs faces challenges due to network decentralization and changing channel conditions. This paper focuses on designing reliable and efficient strategies that incorporate RISs to enhance transmission robustness and spectrum utilization efficiency, especially for high-rate data exchange in next-generation smart communications. Extensive research has explored RIS-assisted wireless channel access, primarily focusing on single-RIS system's physical layer design to adjust electromagnetic wave phases for improved communication [2]–[4]. RIS integration extended to MIMO systems in [2], [5], demonstrating advantages over traditional relaying methods in [6]. RIS has also been integrated into wireless network MAC design, especially in multi-antenna base station cellular networks as seen in [7], [8]. The impact of limited RIS phase shifts and size on system performance was analyzed in [9]. Further, the transmit powers and the

phase shift at each element of the RIS were optimized to maximize the sum-secrecy rate in [10].

Current research in this field often assumes the presence of global channel state information (CSI), overlooking the time needed for CSI acquisition. The emerging area of distributed RIS-assisted MAC faces three key challenges: (i) Joint scheme for channel contention, CSI acquisition, and RIS-assisted channel access for multiple users. (ii) Tradeoff between RIS channel acquisition overhead, effective data transmission, channel contention time, and diversity. (iii) Requirement for low-complexity distributed network operations enabling feasible strategies based on local observations for each user. *This work pioneers the solution to the distributed MAC problem with the assistance of RIS and introduces a robust statistical optimization framework*. It significantly contributes to the existing body of research by addressing the following gaps:

- 1) Distributed Network Design: Our novel approach integrates multi-user opportunistic RIS CSI acquisition and assisted access, utilizing optimal sequential observation planned decision theory. This robust framework addresses the MAC problem effectively.
- 2) Optimal RIS-Assisted MAC Strategy: We have developed an optimal MAC strategy that maximizes average throughput by jointly optimizing direct link transmission, opportunistic RIS probing, and RISassisted transmission. This statistically proven strategy is practical, supported by closed-form thresholds and a distributed channel access algorithm.
- 3) Superior Performance: Comprehensive evaluations and comparisons confirm the superiority of our proposed strategy. It significantly enhances network performance, underlining its potential for improving wireless communication systems.

Notations: Throughout this paper, numbers, vectors, and matrices are denoted by lower-case, bold-face lower-case, and bold-face upper-case letters, respectively. The superscript $(\cdot)^T$ stands for the transpose. x⊙y denotes the Hadamard product operator. $\mathbb{E}[\cdot]$ represents the expectation operator. Moreover, $CN(\cdot,\cdot)$ is a circularly symmetric complex Gaussian distribution. For a set S , $|S|$ denotes set cardinality.

Fig. 1. A cooperative network with multiple-user pairs and single RIS.

II. SYSTEM MODEL

A. Network Model

We examine a wireless network comprising a RIS with M passive reflecting elements (REs), as illustrated in Fig. 1. The network comprises K source-destination pairs denoted as S_k , D_k , and $S_k - D_k$, respectively, for $k = 1, \dots, K$. The RIS has its own controller for phase adjustment, and we focus on the transmission of $S_k - D_k$ using the mth element of the RIS, where $m = 1, \dots, M$. The power budget for each source is P_t . We denote the fading coefficients of $S_k - D_k$ link as h_k , the first-hop of the RIS link as $f_{k,m}$, and the second-hop of the RIS link as $g_{k,m}$. We assume independent multipath complex Gaussian fading for all the links, along with large-scale pathloss. We denote the distances associated with the direct link of S_k-D_k as d_k , the first hop and the second hop via the RIS as $d_{k,1}$ and $d_{k,2}$, respectively. Thus, we have $\mathbf{f}_k = [f_{k,m}] \in \mathbb{C}^{M \times 1}$, $\mathbf{g}_k = [g_{k,m}] \in \mathbb{C}^{\bar{M} \times 1}, \ h_k \sim \mathcal{CN}(0, d_k^{-\alpha_1}), \ f_{k,m} \sim \mathcal{CN}(0, d_{k,1}^{-\alpha_2}),$ and $g_{k,m} \sim \mathcal{CN}(0, d_{k,2}^{-\alpha_2})$, where α_1 and α_2 denote the path-loss exponents for the direct link and the RIS link, respectively. The statistical information of the network, i.e., distances $d_k, d_{k,1}, d_{k,2}, \forall k$, is available at the D_k s. The additive white Gaussian noise (AWGN) at the RIS and D_k s has noise power N_0 . For path loss, we denote the antenna gains at each S_k and D_k as G_t and G_r , respectively, and the reference path loss at 1 m distance as β_0 . Channels' coherence time is τ_d .

B. Framework of the CSMA/CA Protocol

We use the CSMA/CA protocol for channel access in our RIS-assisted multi-user network [11]–[14]. The protocol includes request-to-send (RTS) and clear-to-send (CTS), each with time durations τ_R and τ_C , respectively. It enables users to initiate transmissions without admission and guarantees that only one user-pair can communicate at a time.

In the first stage, $S_k - D_k$ pairs contend for channel access over slots with minimum duration δ using the CSMA/CA protocol. S_k sends an RTS packet with probability p_k and the MAC protocol proceeds only if a winner is determined, denoted $S_w - D_w$. The winner decides to communicate through the direct link, both the direct and RIS links, or not communicate, based on the achievable rate of the direct link, calculated using the direct channel gain h_w , and the achievable rate of both links, calculated using the direct channel gain h_w and RIS links' statistics. The direct channel gain h_w is estimated at D_w upon receiving the RTS, and RIS links' statistical knowledge is assumed to be available at D_w . The destination D_w then makes the decision by comparing the achievable rates as follows:

- 1) stop: If the achievable rate of the direct link is high enough, D_w selects to use only the direct link, and broadcasts a CTS to all nodes. S_w then transmits data to D_w during the period ($\tau_d-\tau_{M,1}$), while all other sources remain silent within the same period. The total time for message exchange is denoted as $\tau_{M,1} = \tau_R + \tau_C$.
- 2) continue: If both rates are low, D_w decides not to transmit and broadcasts a CTS to all nodes. This prompts all S_k s to restart channel contention in the next time slot.
- 3) assist RIS: If the achievable rate of the direct link is low but the expected achievable rate of RISassisted links is sufficiently high, D_w delays its decision of whether to stop or continue until it obtains instantaneous channel knowledge of the RIS link. In particular, D_w sends a CTS to the controller of the RIS. After receiving the CTS, the RIS controller activates (or switch-on) the RIS. Then S_w sends RIS training pilots to estimate the instantaneous cascaded channel gain, i.e., $f_k \odot g_k$ within a time period of τ_p , where τ_p denotes the pilot time period [15]. This allows D_w to calculate the instantaneous achievable rate of the direct and RISassisted communications. Based on this achievable rate, D_w makes one of the following decisions:
	- a) stop: If the achievable rate is sufficiently high, D_w uses RIS-assisted communications and broadcasts a CTS to all nodes. Then S_w transmits data assisted by the RIS within $(\tau_d - \tau_{M,2})$ time, here $\tau_{M,2} = \tau_{M,1} + \tau_p + \tau_C$ denotes the total time for pilot and message exchange.
	- b) continue: If the achievable rate is low, D_w abandons communications and broadcasts a CTS, prompting all S_k s to contend for the channel in the next time slot.

After a successful channel access by stop, the next round of channel access among all user pairs initiates the next possible data transmission. The system has two decision levels: the winner source's destination decides to stop, continue, or assist RIS based on direct link rate. If assist RIS, the destination evaluates RIS-assisted channels to decide to stop or continue.

III. PROBLEM FORMULATION

To maximize system throughput, we formulate the problem for RIS-assisted channel access. Using the distributed MAC protocol from Section II-B, we use $w(n) \in 1,...,K$ to represent the source index of the winning pair after *th successful* channel contention within one data transmission round. We examine both direct and RIS-assisted links for the winner pair $S_{w(n)}$ – $D_{w(n)}$, with the achievable rate of the direct link given as

$$
R_{w(n),d} = \log_2(1 + \gamma_{w(n),d})
$$
 (1)

where $\gamma_{w(n),d} = \bar{\rho} |h_{w(n)}(n)|^2$, $\bar{\rho} = P_t G_t G_r \beta_0 / N_0$ and $h_{w(n)}(n)$ represents its direct link instantaneous CSI.

The matrix that includes the reflecting coefficients of RIS is denoted as $\Phi_{w(n)} = \text{diag}([e^{j\phi_{w(n),1}},...,e^{j\phi_{w(n),M}}]) \in \mathbb{C}^{M \times M},$ where $\phi_{w(n),m} \in [0, 2\pi)$ represents the adjustable angle of the mth element of the RIS. To maximize throughput, the optimal reflecting coefficients are given by $\Phi^*_{w(n)}$ with $\phi^*_{w(n),m} \ = \ \arg(h_{w(n)}(n)) \ - \ \arg(f_{w(n),m}(n) \ \cdot \ g_{w(n),m}(n)),$ and $f_{w(n),m}(n) \cdot g_{w(n),m}(n)$ represents RIS cascaded link instantaneous CSI for $m = 1, \dots, M$. The achievable rate of the winner pair is then

$$
R_{w(n),r} = \log_2(1 + \gamma_{w(n),r}(n))
$$
 (2)

where $\gamma_{w(n),r}(n) = \overline{\rho}(|h_{w(n)}(n)| + |\mathbf{f}_{w(n)}(n)|^T |\mathbf{g}_{w(n)}(n)|)^2$. *A. Sequential observation process*

When a source wins a channel contention and the winning destination estimates its CSI, an *observation* (Obs.) occurs. The achievable rate in the first-stage Obs. requires direct link CSI, while the achievable rate in the secondstage Obs. can only be calculated with optimal reflecting coefficients obtained from cascaded CSI. The first-stage Obs. is always performed, while the second-stage Obs. may not be done every time, as discussed in Section II-B. To differentiate between them, odd numbers are used to index the first-stage Obs., and even numbers are used to index the second-stage Obs. Therefore, for the *nth* successful channel contention, two observations are available: Obs. $(2n - 1)$ and Obs. (2n). For Obs. (2n – 1), D_{w(n)} observes $h_{w(n)}(n)$ and the time spent for the nth successful channel contention $t_{w(n)}(n), n = 1, \dots, \infty$. The number of time slots for a successful channel contention is an i.i.d. geometric random variable [16]. For Obs. (2n), $D_{w(n)}$ observes $f_{w(n)}(n)$ ⊙ $g_{w(n)}(n)$. The observed information at Obs. $(2n - 1)$ and Obs. $(2n)$ are denoted as $\mathscr{F}_n = \{w(n), t_{w(n)}(n), h_{w(n)}(n)\}\$ and $\mathscr{G}_n = \{ \mathbf{f}_{w(n)}(n) \odot \mathbf{g}_{w(n)}(n) \}$, respectively. *B. Observation path*

The *observation path* a is the sequence of states for all observations from the first to the nth successful channel contention. The path is denoted by odd and even indices, where odd index is always 1 representing direct-link CSI, and even index represents RIS assist with $a_l = 1$ indicating RIS link is estimated and $a_l = 0$ otherwise. The observation path a can be expressed as a vector:

$$
\mathbf{a} = \begin{cases} (1, a_1, \cdots, 1, a_l, \dots, 1), & \text{Obs.}(2n-1) \\ (1, a_1, 1, \cdots, 1, a_l, \dots, 1, a_n), & \text{Obs.}(2n) \end{cases}
$$

C. Instantaneous rewards

For observation path a, we define the reward function Y_a as the transmitted data in *bits* by stop. For Obs. $(2n - 1)$ and Obs. $(2n)$, we have instantaneous rewards

$$
Y_{\mathbf{a}} = \begin{cases} (\tau_d - \tau_{M,1}) R_{w(n),d}, & \text{Obs.}(2n-1) \\ (\tau_d - \tau_{M,2}) R_{w(n),r}, & \text{Obs.}(2n) \text{ and } a_n \neq 0 \\ -\infty, & \text{Obs. } (2n) \text{ and } a_n = 0 \end{cases}
$$
(3)

Additionally, to prevent the winning pair from ending with a decision of continue, $Y_{\mathbf{a}} = -\infty$ is defined without any restrictions on feasible MAC strategies. Obs. $(2n - 1)$ and Obs. (2n) are associated with the time cost function T_a , which calculates the overall time spent waiting from Obs. (1) to Obs. $(2n - 1)$ or Obs. $(2n)$, including data transmission time. Therefore, the function can be formulated as

$$
T_{\mathbf{a}} = \sum_{l=1}^{n} t_{w(l)}(l) + \sum_{l=1}^{n-1} \mathbb{I}[a_l \neq 0] (\tau_C + \tau_p) + \tau_d - \tau_{M,1}.
$$
 (4)

D. Optimization goal

We define a_s as the observation path leading to a stop decision in the sequential decision-making process of the distributed MAC strategy described in Section II-B. The transmitted data in *bits* and the time cost of strategy a^s are denoted as $Y_{\mathbf{a}_s}$ and $T_{\mathbf{a}_s}$, respectively, both of which are random variables due to the stochastic nature of the sequential observation process. By repeating strategy a_s over sufficient rounds of data transmission, the sample average system throughput approaches the average system throughput expressed as $\mathbb{E}[Y_{\mathbf{a}_s}]/\mathbb{E}[T_{\mathbf{a}_s}]$. Our objective is to maximize the average system throughput by identifying the optimal strategy a_s^* among all feasible channel access strategies a_s and the maximal average system throughput, which can be evaluated, respectively, as

$$
\mathbf{a}_s^* = \arg\sup_{\mathbf{a}_s > 0} \frac{\mathbb{E}[Y_{\mathbf{a}_s}]}{\mathbb{E}[T_{\mathbf{a}_s}]} \text{ and } \lambda^* = \frac{\mathbb{E}[Y_{\mathbf{a}_s^*}]}{\mathbb{E}[T_{\mathbf{a}_s^*}]}.
$$
 (5)

IV. OPTIMAL MAC STRATEGY AND ALGORITHM

In this section, our objective is to determine the optimal MAC strategy a_s^* that maximizes the average system throughput λ^* as in (5).

A. Optimal Strategy

Using equivalent transformation and optimal sequential observation planned decision theory, we obtain the optimal MAC strategy a_s^* , which maximizes system throughput $\sup_{\mathbf{a}_s>0}$ $\mathbb{E}[Y_{\mathbf{a}_s}]/\mathbb{E}[T_{\mathbf{a}_s}]$. The optimal MAC strategy, as described in Theorem 1, is presented below.

Theorem 1. *For a round of successful data transmission, an optimal RIS-aided MAC strategy* a ∗ s *is in the form that: beginning from* n= 1*, after* n*th successful channel contention, the* w(n)*-th source-destination pair wins the channel and* $D_{w(n)}$ *obtains CSI* $h_{w(n)}(n)$ *.*

1) *if* $(\tau_d - \tau_{M,1})(R_{w(n),d}(n) \lambda^*$) ≥ $\max\{\Lambda_{w(n)}(\lambda^*,~|h_{w(n)}(n)|),~0\},~~D_{w(n)}$ stop, and $S_{w(n)}$ *transmits data to* $D_{w(n)}$ *in direct link. Function* $\Lambda_{w(n)}(\lambda^*,\;\;|h_{w(n)}(n)|)$ representing the expected *maximal reward if RIS link is estimated after the* n*th successful channel contention, is expressed as*

$$
\Lambda_{w(n)}(\lambda^*, |h_{w(n)}(n)|) = \mathbb{E}[\max\{(\tau_d - \tau_{M,2})\} R_{w(n),r}(n) - \lambda^*(\tau_d - \tau_{M,1}), -\lambda^*(\tau_p + \tau_C)\}].
$$
 (6)

The maximal average system throughput λ ∗ *can be uniquely solved by equation*

$$
\frac{1}{K} \sum_{k=1}^{K} \int_{0}^{+\infty} \max \Biggl\{ (\log_2(1+\overline{\rho}h_s^2) - \lambda^*)(\tau_d - \tau_{M,1}),
$$

$$
\Lambda_k(\lambda^*, h_s), 0 \Biggr\} dF_{|h_k|}(h_s) = \lambda^* \tau_o \quad (7)
$$

where $F_{|h_k|}(h_s)$ *denotes the c.d.f. of* $|h_k|$ *which is Rayleigh distributed, and* τ_o *denotes the average duration of a successful channel contention* $t_w(n)$ *, expressed*

as
$$
\tau_o = \tau_{M,1} + \prod_{k=1}^K (1 - p_k) \frac{\delta}{p_s} + (1 - \prod_{k=1}^K (1 - p_k) - p_s) \frac{\tau_R}{p_s},
$$

with $p_s = \sum_{k=1}^K p_k \prod_{i \neq k} (1 - p_i).$

- 2) *if* max $(\tau_d \quad - \quad \tau_{M,1})(R_{w(n),d}(n) \quad \lambda^*$), $\Lambda_{w(n)}(\lambda^*, |h_{w(n)}(n)|)\}<0$, $D_{w(n)}$ continue, *gives up transmission and then all sources re-contend the channel.*
- 3) *otherwise*, $D_{w(n)}$ assist RIS, and then estimates *cascaded RIS channel gains* $f_{w(n)}(n)$ \odot $g_{w(n)}(n)$ *.*
	- a) *if reward* $R_{w(n),r}(n) \geq \lambda^*,$ $D_{w(n)}$ stop, and *S*w(n) *transmits data assisted by the RIS with* reflecting coefficients matrix $\boldsymbol{\Phi}^*_{w(n)}$.
	- b) *otherwise*, $D_{w(n)}$ continue, gives up transmis*sion and then all sources re-contend the channel.*

Proof. Let $Z_{\mathbf{a}}(\lambda) = Y_{\mathbf{a}} - \lambda T_{\mathbf{a}}$, where λ is the price charged for time spent. A strategy that achieves $\sup_{\mathbf{a}_s>0} \mathbb{E}[Z_{\mathbf{a}_s}(\lambda)]$ for a given $\lambda > 0$ is denoted as $a_s(\lambda)$, and the corresponding optimal strategy is denoted as $a_s^*(\lambda)$, which is expressed as

$$
\mathbf{a}_{s}^{*}(\lambda) = \arg \sup_{\mathbf{a}_{s} > 0} Z_{\mathbf{a}_{s}}(\lambda) = \arg \sup_{\mathbf{a}_{s} > 0} \{ Y_{\mathbf{a}_{s}} - \lambda T_{\mathbf{a}_{s}} \}.
$$
 (8)

As problem (8) is the alternative problem which is equivalent to (5) when $\lambda = \lambda^*$ according to Theorem 1 in [17], the optimal strategy a_s^* is $a_s^*(\lambda^*)$, and is solved by following steps.

1) Find the optimal strategy $\mathbf{a}_s^*(\lambda)$ for price $\lambda > 0$: Based on Theorem 2.14 in [18], for any price $\lambda > 0$, an optimal strategy $a_s^*(\lambda)$ is that: Starting from $n = 1$, it takes the following procedure until stop. In particular,

- at Obs. $(2n-1)$, it is optimal to stop with $\mathbf{a}_{s}^{*}(\lambda) = \mathbf{a}$ if $Z_{\mathbf{a}} \geq V_{\mathbf{a}}^1$, and continue observation otherwise. If continue is optimal, we update the observation path by appending the action as $a = (a, a_n^*)$ where $\mathbb{E}[U_{(\mathbf{a},a_n^*)}|\mathscr{B}_{\mathbf{a}}] = V_{\mathbf{a}}^1$, $a_n^* \in \{0,1\}$, and the observed information for the observation path a is denoted as \mathscr{B}_a ;
- at Obs. (2n), it is optimal to stop with $\mathbf{a}_{s}^{*}(\lambda) = \mathbf{a}$ if $Z_{\mathbf{a}} \geq V_{\mathbf{a}}^2$, and continue observation otherwise. If continue, update observation path by adding 1, i.e., $\mathbf{a} = (\mathbf{a},1).$

For the strategy, the reward function for observation path a is defined as $U_{\mathbf{a}} = \sup$ ^b≥^a $\mathbb{E}[Y_{\mathbf{b}} - \lambda T_{\mathbf{b}} | \mathscr{B}_{\mathbf{a}}]^1$, which represents the expected maximal reward based on the observed information \mathscr{B}_a so far. For Obs. (2n−1), we define the reward function $V_{\mathbf{a}}^1 = \max_{j=0,1} \mathbb{E}[U_{(\mathbf{a},j)}|\mathcal{B}_{\mathbf{a}}]$, which represents the expected $j=0,1$ maximal rewards if stop is not made at Obs. $(2n-1)$. For Obs. (2n), we define the reward function $V_{\mathbf{a}}^2 = \mathbb{E}\left[U_{(\mathbf{a},1)}\middle|\mathcal{B}_{\mathbf{a}}\right]$, which represents the expected maximal rewards if stop is not made at Obs. (2n). If $|\mathbf{a}| = 0$ (i.e., no observation has been made yet), we calculate $U_{\mathbf{a}}$ as $U_0 = \sup \mathbb{E}[Z_{\mathbf{a}_s}(\lambda)].$

 \mathbf{a}_s >0 2) *Replace* λ *with* λ^* : By replacing λ with λ^* , to implement the optimal strategy $\mathbf{a}_{s}^{*}(\lambda^{*})$, we calculate $U_{\mathbf{a}}, V_{\mathbf{a}}^{1}$ and V_a^2 using the Bellman equation in Lemma 2.8 in [18] as:

$$
U_{\mathbf{a}} = \max\{ (\tau_d - \tau_{M,1})(R_{w(n),d}(n) - \lambda^*), \Lambda_{w(n)}(\lambda^*, |h_{w(n)}(n)|), 0 \} - \lambda^* T_c(n)
$$
\n(9)

$$
V_{\mathbf{a}}^1 = \max\left\{\Lambda_{w(n)}(\lambda^*, |h_{w(n)}(n)|), 0\right\} - \lambda^* T_c(n) \tag{10}
$$

$$
V_{\mathbf{a}}^2 = -\lambda^* T_c(n) - \lambda^* \mathbb{I}[|a_n| > 0](\tau_p + \tau_C)
$$
\n(11)

where $T_c(n) = \sum_{l=1}^{n} t_{w(l)}(l) + \sum_{l=1}^{n-1}$ $\sum_{l=1}^{\infty} \mathbb{I}[a_l > 0](\tau_p + \tau_C).$

By making expectation on both sides of (9) with $|\mathbf{a}| = 0$, we can solve λ^* using the equation $\mathbb{E} \left[\max \{ (\tau_d - \tau) \right]$ $(\tau_{M,1})(R_{w(n),d}(n)-\lambda^*), \Lambda_{w(n)}(\lambda^*, |h_{w(n)}(n)|), 0 \}] = \lambda^* \tau_o.$ This can be rewritten as (7), and the uniqueness of λ^* follows from the monotonicity of its both sides.

3) Solution a_s^* *and decision conditions:* Since the optimal solution to the original problem is $\mathbf{a}_s^* = \mathbf{a}_s^*(\lambda^*)$, we analyze the optimal decision after each observation under the MAC framework in Section II-B. First, we consider the case at Obs. $(2n-1)$. By definitions in (3), (4) and (10), the condition to stop is rewritten as $(\tau_d - \tau_{M,1})(R_{w(n),d}(n) - \lambda^*) \ge$ $\max\left\{\Lambda_{w(n)}(\lambda^*, |h_{w(n)}(n)|), 0\right\}$. Similarly, the condition to continue is rewritten as $\max \left\{ (\tau_d - \tau_{M,1})(R_{w(n),d}(n) \lambda^*$), $\Lambda_{w(n)}(\lambda^*, |h_{w(n)}(n)|)$ < 0. Then the condition to assist RIS can be derived. Secondly, we consider the case at Obs. $(2n)$. By definition in (11), the condition for stop is rewritten as $R_{w(n),r}(n) \geq \lambda^*$. Finally, following the MAC framework in Section II-B, by substituting above conditions into strategy a_s^* , the optimal MAC strategy is derived.

 \Box

Theorem 1 provides an optimal MAC strategy for the network, requiring efficient calculation of λ^* and $\Lambda_{w(n)}(\lambda, |h_{w(n)}(n)|)$ in (7) and (6), respectively. The former can be calculated offline by solving (7), while the latter requires online computation for each instantaneous CSI. We next propose a closed-form solution for the threshold function, enabling efficient calculation for the optimal strategy.

B. A close-form expression for $\Lambda_k(\lambda, h_s)$

For winner pair $w(n)=k$, by using (2) and (6), we have

$$
\Lambda_k(\lambda, h_s) \stackrel{\text{(a)}}{\approx} (\tau_d - \tau_{M,2}) \log_2 \left(1 + \mathbb{E} \left[\max \{ \overline{\rho} \left(h_s + |\mathbf{f}_k(n)|^T | \mathbf{g}_k(n) | \right)^2, 2^{\lambda} - 1 \} \right] \right) - \lambda (\tau_d - \tau_{M,1})
$$
\n
$$
\stackrel{\text{(b)}}{\approx} (\tau_d - \tau_{M,2}) \log_2 \left(1 + \Omega(\lambda, h_s, \mu_k, \sigma_k) \right) - \lambda (\tau_d - \tau_{M,1})
$$
\n
$$
\stackrel{\text{(12)}}{=} \overline{\Lambda}_k(\lambda, h_s)
$$

¹For paths **a** and **b**, **b** \geq **a** if and only if $|$ **b** $|\geq$ $|$ **a** $|$ and path **a** is the initial segment of path **b**. Here $\overline{|\cdot|}$ represents the cardinality.

where (a) is derived by applying the Taylor series, while (b) is obtained by taking the expectation utilizing the Central Limit Theorem (CLT), i.e., $|\mathbf{f}_k(n)|^T |\mathbf{g}_k(n)| \sim \mathcal{N}(\mu_k, \sigma_k^2)$ with $\mu_k = \frac{M\pi}{4} d_{k,1}^{-\alpha_2/2} d_{k,2}^{-\alpha_2/2}$ and $\sigma_k^2 = M(1 - \frac{\pi^2}{16}) d_{k,1}^{-\alpha_2} d_{k,2}^{-\alpha_2}$, and

$$
\Omega(\lambda, h_s, \mu, \sigma) = \frac{(2^{\lambda} - 1) \left(erf\left(\frac{\mu}{\sqrt{2}\sigma}\right) - erf\left(\frac{-\sqrt{\frac{2^{\lambda} - 1}{\overline{\rho}}} + h_s + \mu}{\sqrt{2}\sigma}\right)\right)}{2} + \frac{\left(\overline{\rho}\sigma(h_s + \mu) + \sqrt{\overline{\rho}(2^{\lambda} - 1)}\sigma\right)e^{-\frac{\left(\sqrt{2^{\lambda} - 1} - \sqrt{\overline{\rho}}(h_s + \mu)\right)^2}{2\overline{\rho}\sigma^2}}}{\sqrt{2\pi}} + \frac{\overline{\rho}((h_s + \mu)^2 + \sigma^2)erfc\left(\frac{\sqrt{2^{\lambda} - 1} - \sqrt{\overline{\rho}}(h_s + \mu)}{\sqrt{2\overline{\rho}}\sigma}\right)}{2}.
$$
\n(13)

Here, $\text{erf}(x) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2} dt$ and $\text{erfc}(x) = 1 - \text{erf}(x)$.

We can use the closed-form expression to design an iterative algorithm for calculating the average throughput λ^* , where ϵ denotes numerical accuracy. This is outlined in Theorem 2:

Theorem 2. *The sequence* $\{\lambda_l\}, l = 1, 2, ..., \infty$ *generated* by $\lambda_{l+1} = \lambda_l + \alpha \left(\frac{1}{K} \sum_{i=1}^K \right)$ $k=1$ $+∞$ 0 $\max\left\{(\log_2(1+\overline{\rho}h_s^2)-\lambda^*)(\tau_d-\right\}$ $(\tau_{M,1}),\, 0,\, \overline{\Lambda}_k(\lambda^*,\,h_s)\big\}dF_{\lfloor h_k\rfloor}(h_s)\,-\,\lambda_l\tau_o)\,$ with step-size α satisfying $\epsilon \leq \alpha \leq \frac{2-\epsilon}{\tau_0+\tau_d-\tau_{M,1}}$, converges to the maximal *average throughput* λ ∗ *.*

Proof: The convergence of $\{\lambda_l\}, l = 1, \dots, \infty$ to λ^* can be directly proven based on the Lipschitz continuity condition presented in Proposition 1.2.3 in [19]. *C. Distributed Algorithm in Low Complexity*

Using Theorem 1, we can calculate the function $\Lambda_{w(n)}(\lambda^*, |h_{w(n)}(n)|)$ based on the instantaneous channel gain $h_{w(n)}(n)$ and make decisions. To reduce calculation complexity further, we derive a decision criteria under a loose condition for the maximal average throughput $\lambda^* \geq 1$.

Lemma 1. For each pair S_k - D_k , it never opts for the assist RIS *decision if* $\overline{\Lambda}_k(\lambda^*, \sqrt{2^{\lambda^*}-1}) \leq 0$. Otherwise, *the decision to* assist RIS *can be optimal.*

Proof. It is proved by monotonicity of $\Lambda_k(\lambda^*,h_s)$ over h_s .

Then, we define source-destination pairs set as $\mathscr{K}^* = \{k \in \{1, ..., K\} : \overline{\Lambda}_k(\lambda^*, \sqrt{2^{\lambda^*}-1}) > 0\}.$ Using $\overline{\Lambda}_k(\lambda^*,h_s)$ and λ^* , we can calculate the set \mathscr{K}^* offline.

Moreover, for all pair $k \in \mathcal{K}^*$, we define ζ_k as the solution to $\overline{\Lambda}_k(\lambda^*,h_s) = 0$, and η_k as the solution to $(\log_2(1+\overline{\rho}h_s^2))$ $(\lambda^*)(\tau_d-\tau_{M,1})=\overline{\Lambda}_k(\lambda^*,h_s)$. And they exist uniquely.

Furthermore, we are now designing a network implementation algorithm based on the proposed MAC strategies to enable distributed network operation. The algorithm follows the channel access procedure outlined in Section II-B. The algorithm operates for each source-destination pair, utilizing \mathcal{K}^* and offline-obtained parameters $\zeta_k, \eta_k, k \in \mathcal{K}^*$. With its purethreshold structure, the proposed algorithm achieves significantly lower online complexity at $O(1)$, in contrast to the strategy outlined in Theorem 1, which ensures efficient decision.

V. NUMERICAL RESULTS

In this section, we numerically evaluate the performance. The network consists of $K = 8$ with a central frequency of $f_c = 2 \text{ GHz}$, antenna gains $G_t = G_r = 0 \text{ dBi}$, $\beta_0 = -30 \text{ dB}$, $P_t = 30$ dBm, and $N_0 = -80$ dBm. The channel contention parameters are $p_0 = 0.3$, $\delta = 25 \mu s$, $\tau_R = \tau_C = 50 \mu s$, and $\tau_p = 500 \mu s$. The path loss exponents are $\alpha_1 = 3$ and $\alpha_2 = 2.5$. Locations in 2D plane of S_k and D_k are represented by $S = [(0, 0), (0, 10), ..., (0, (K - 1)10)]$ and $\mathbf{D} = [(150,0), (150,10), ..., (150, (K-1)10)]$, respectively. The RIS is located at $(75,100)$ with $M = 32$. In Fig. 2 and Fig. 3, the results, marked as "Analytical", and the approximated results, marked as "Approximation", are calculated based on the proposed iterative algorithm with Monte-Carlo calculated functions in (6) and the closed-form expression in (12), respectively. The simulation results, marked as "Simulation", are calculated from the sample average of transmitted traffic and time spent in the trails of data transmissions using Algorithm 1. In all figures, we observe that the approximation, analytical, and simulation results are well-matched, which validates the accuracy of the analysis for our proposed strategy.

We compare our proposed strategy with three benchmark strategies: (i) "No-wait-direct": a winner pair has the direct link CSI and always transmits via the direct link; (ii) "No-

Fig. 2. Average throughput vs P_t for $K = 8$ and $\tau_d = 15$ ms.

wait-RIS": a winner pair has both direct and RIS link CSI, and always transmits via RIS assisted strategy, and (iii) "Optimal-RIS-stop": a winner pair has both direct and RIS link CSI, and an optimal stopping strategy is used as in [16]. Fig. 2 shows the average throughput vs transmit power P_t for $\tau_d = 15$ ms. Our proposed strategy outperforms all other strategies achieving over 8% average throughput gain over the best alternative strategy (optimal-RIS-stop) and over 66% and 27% throughput advantage over the no-wait-direct and no-wait-RIS strategies, respectively. Fig. 3 plots the average throughput versus channel coherence time for the proposed and alternative strategies. The proposed strategy consistently outperforms all other strategies, with throughput advantages of more than 10%, 31%, and 13% over the optimal-RIS-stop, no-wait-direct, and no-wait-RIS strategies, respectively, at $\tau_d = 5$ ms. The proposed strategy exploits varying channel conditions of different user pairs and the RIS, resulting in better channel access decisions and higher average throughput gain compared to all no-wait strategies.

VI. CONCLUSION

This research presents an optimal RIS-assisted channel access strategy for a distributed cooperative network involving multiple source-destination pairs and a single RIS. We use CSMA/CA strategy designed through sequential planned decision theory in a distributed manner to maximize average system throughput, rigorously proving its optimality. We achieve low online-complexity at $O(1)$ and develop a purethreshold algorithm for distributed strategy implementation. Our proposed strategy surpasses existing ones in terms of system throughput. These findings have wide applicability in developing innovative RIS-integrated designs for opportunistic access across various networks like cellular networks and IoT networks. Future work will extend this strategy to distributed cooperative networks with multiple source-destination pairs and multiple RISs, allowing us to select a set of RISs as an additional design parameter.

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Fig. 3. Average throughput vs τ_d for $K = 8$ and $P_t = 26$ dBm.

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