MIMO Assisted Networks Relying on Large Intelligent Surfaces: A Stochastic Geometry Model

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Abstract—Large intelligent surfaces (LISs) constitute a promising performance enhancement for next-generation (NG) wireless networks in terms of enhancing both their spectrum efficiency (SE) and energy efficiency (EE). Hence we conceive a LIS-aided multiple-input multiple-output framework for providing wireless services to randomly roaming users and analyze its performance by utilizing stochastic geometry tools. As such, each user receives the superseded signals reflected by multiple LISs. We aim for serving multiple users by jointly designing the passive beamforming weight at the LISs and detection weight vectors at the users. As a benefit, the intra-cell interference imposed by the LISs can be suppressed. In an effort to evaluate the performance of the proposed framework, we first derive new channel statistics for characterizing the effective channel gains. Then, we derive closed-form expressions both for the outage probability and for the ergodic rate of users. For gaining further insights, we investigate both the diversity orders of outage probability and the high signal-to-noise (SNR) slopes of ergodic rate. We also derive the SE and EE of the proposed framework. Our analytical results demonstrate that the specific fading environments encountered between the LISs and users have almost no impact on the diversity orders attained. Numerical results are provided to confirm that: i) the high-SNR slope of the proposed framework is one; and ii) the SE and EE can be significantly enhanced by increasing the number of LISs.

Index Terms—Large intelligent surface, multiple-input multiple-output, passive beamforming, stochastic geometry.

I. INTRODUCTION

A variety of sophisticated wireless technologies have been proposed for next-generation (NG) networks, including massive multiple-input multiple-output (MIMO) and millimeter wave (mmWave) communications. In the 5G new radio (NR) standard, reaching out beyond 6GHz, the coverage area is significantly reduced [1], [2]. Since high-frequency signals are sensitive to blockage effects [3] of trees and buildings. In order to circumvent the above limitations, the cost-effective technique of large intelligent surface (LIS) assisted wireless networks has been proposed [4], [5].

A LIS system relies on a large number of reflective surface arrays, where each surface can adjust the phase shifts and amplitude reflection coefficients of the incident signals. Hence the concept of LIS networks relies on electromagnetically controllable surfaces, which can be intelligently integrated into the existing infrastructure by beneficially exploiting the channel state information (CSI) [6], [7]. For example, by conceiving a sophisticated signal alignment technique for employment at the LISs, the signal received by the users can be constructively boosted by controlling the phase shifts reflected by LISs. On the other hand, the LISs are also capable of mitigating both the intra-cell and inter-cell interferences, by appropriately adjusting the global CSI properly for enhancing the network’s performance [8]–[11]. Hence, LIS aided networks have received considerable attention as a benefit of their high energy efficiency (EE).

Based on the revolutionary concept of LIS networks [12], numerous future issues were addressed, such as physical layer security [13], cell edge enhancement [14], device-to-device (D2D) communications, and LIS assisted simultaneous wireless information and power transfer (SWIPT) [15]. The performance of LIS-aided and relay-aided networks were compared in [4], which indicates that LIS-aided networks are capable of providing better network performances while the number of LISs is high enough. In order to minimize the total transmit power, the active beamforming employed at the BS and passive beamforming used at the LISs were jointly optimized in a multiple-input single-output (MISO) LIS-aided network [16]. The signal-to-interference-plus-noise ratio (SINR) was optimized in a LIS-aided network for infinite-resolution phase shifters [17], where multiple users have been supported simultaneously by the BS. However, in practice, the phase shifts of LISs may not be continuous, thus discrete phase shifts was considered in [18] for a MISO assisted LIS network. The associated energy consumption model was proposed in [19], [20], where the EE of the proposed networks was optimized. Naturally, the link quality between the BS and users plays a key role in [21]. The impact of fading environments on LIS networks was also attracted considerable attention. The associated bit error ratio was evaluated in [22] in the case of Rayleigh fading. The existence of line-of-sight (LoS) links between the BS and LISs is quite likely in NG networks. Therefore, Rician fading channels were considered in [23], and the lower bound of the associated ergodic rate was evaluated. The asymptotic transmission rate of LIS networks was evaluated in [24], where the impact of LISs on the channel hardening was considered in Rice fading channels.

However, there is a paucity of literature on the impact of user-locations on the attainable performance. Stochastic geometry (SG) constitutes an efficient mathematical tool for

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capturing the topological randomness of networks [25], [26]. The users were assumed to be randomly located according to a homogeneous Poisson point process (HPPP) in [21], and the impact of location randomness in cellular networks was evaluated in [28]. The analytical results indicated that the system performance trends were not greatly affected by shadowing. However, in order to conceive a practical LIS framework, the user-positions have to be taken into account using SG, which is the objective of this treatise.

A. Motivations and Contributions

On the one hand, the previous contributions [14], [16]–[18], [20]–[24] have mainly been focussed on MISO assisted LIS networks, where only a single antenna is employed by the users. On the other hand, there is a lack of literature on the impact of the locations of multiple users. Motivated by the potential benefits of the LIS-aided networks, in this article we will develop the first comprehensive downlink (DL) analysis of a MIMO-LIS framework using tools from SG, which is capable of providing the first mathematical model of the spatial randomness of multiple users. The proposed MIMO-LIS framework design has to tackle three additional challenges: i) Having multiple antennas and multiple LISs impose additional intra-cell interference on the users; ii) The LIS framework has to consider different fading channels between the BS and LISs; iii) The passive beamforming technique used at the multiple LISs also has to be reconsidered. In contrast to previous contributions, we will show that the active beamforming used at the BS combined with appropriately chosen detection vectors at the users perform well both in LIS and non-LIS scenarios.

Against to above background, our contributions can be summarized as follows:

- We propose a novel LIS framework, where SG is invoked for modelling the location of users. We also conceive a new general detection vector design for the users combined with passive beamforming at the LISs. The proposed MIMO-LIS framework design has to tackle three additional challenges: i) having multiple antennas and multiple LISs impose additional intra-cell interference on the users; ii) The LIS framework has to consider different fading channels between the BS and LISs; iii) The passive beamforming technique used at the multiple LISs also has to be reconsidered. In contrast to previous contributions, we will show that the active beamforming used at the BS combined with appropriately chosen detection vectors at the users perform well both in LIS and non-LIS scenarios.

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- Explicitly, we derive closed-form expressions of both the outage probability (OP) and ergodic rate for the proposed MIMO-LIS framework. Both analytical and asymptotic results are derived. Furthermore, diversity orders and high-SNR slopes are obtained based on the OP and ergodic rate developed. The results confirm that the diversity order of the proposed framework mainly depends on the distribution of the fading between the BS and LISs.

- The simulation results confirm our analysis, illustrating that: 1) the antenna gain improves the system performance; 2) the distribution of the fading between the LISs and users only have a modest impact on the network performance; 3) the SE and EE of the proposed MIMO-LIS framework can be significantly enhanced by increasing the number of antennas at the BS or increasing the number of LISs.

B. Organization and Notations

The rest of the paper is organized as follows. In Section II, our MIMO-LIS frameworks is discussed. Our analytical results are presented in Section III to quantify the performance attained. Our numerical results in Section IV verify the accuracy of our analysis, which is followed by conclusions in Section V. Table I lists some of the critical notations used in this article. \( H^T \), \( H^H \), \( \text{rank}(H) \) and \( tr(H) \) denote the transpose, conjugate transpose, rank and trace of the matrix \( H \). \( \| \cdot \|_2 \) denotes the Frobenius norm. \( \mathbb{P}(\cdot) \) and \( \mathbb{E}(\cdot) \) denotes the probability and expectation, respectively. The distribution of a circularly symmetric complex Gaussian (CSCG) random variable with mean \( x \) and covariance matrix \( k \) is denoted by \( \mathcal{CN}(x, k) \); and \( \sim \) stands for distributed as.

### II. System Model

Let us consider the MIMO-LIS DL, where a BS equipped with \( M \) transmit antennas (TAs) is communicating with \( M \) users each equipped with \( K \) receive antennas (RAs). We have \( MN \) intelligent surfaces between the BS and users. It is assumed that \( N \geq K \geq M \), where the \( MN \) surfaces serve \( M \) users simultaneously. By appropriately adjusting the reflection angles and amplitude coefficients of the LIS elements, the
electromagnetic signal can be beneficially manipulated. Fig. 1 illustrates the wireless communication model for a single BS.

### A. System Description

The locations of the BS and LISs are fixed in practice, hence we assume that the distance between the BS and LISs is $d_1$, which can be any arbitrary value, while the distances between the LISs and users are random, denoted by $d_2$. Without loss of generality, we focus our attention on the $m$-th user, where the distance between the LISs and user $m$ is denoted by $d_{2,m}$. The users are located on a disc $R^2$ with the radius $R$ according to a HPPP $\Psi$ with density $\lambda$. We assume that in NG mmWave communications, the direct transmission link between the BS and users may be blocked by trees or buildings.

Let us consider a composite channel model of large-scale and small-scale fading. It is assumed that the distance $d_1$ and the distance $d_2$ are independently and identically distributed (i.i.d.), and the large-scale fading is represented by the path loss. Furthermore, it is assumed that the distances $d_1$ and $d_2$ are higher than $r_m$ for simplifying the analytical results. Therefore, the large-scale fading between the BS and user $m$ can be expressed as

$$L_m = (d_1d_{2,m})^{-\alpha},$$

where $\alpha$ denotes the path loss exponent.

In order to illustrate the LoS links between the BS and LISs, the small-scale fading matrix is defined as

$$H = \begin{bmatrix} h_{1,1} & \cdots & h_{1,M} \\ \vdots & \ddots & \vdots \\ h_{M,N,1} & \cdots & h_{M,N,M} \end{bmatrix},$$

where $H_1$ is a $M \times M$ matrix whose elements represent Nakagami fading channel gains. The probability density function (PDF) of the elements can be expressed as

$$f_1(x) = \frac{m_1^{m_1}x^{m_1-1}}{\Gamma(m_1)}e^{-m_1x},$$

where $m_1$ denotes the fading parameter, and $\Gamma(\cdot)$ represents the Gamma function. Note that $\Gamma(m_1) = (m_1-1)!$ when $m_1$ is an integer.

The small-scale fading matrix between the LISs and user $m$ is defined as

$$G_m = \begin{bmatrix} m_1g_{1,1} & \cdots & m_1g_{1,MN} \\ \vdots & \ddots & \vdots \\ m_{K,1} & \cdots & m_{K,MN} \end{bmatrix},$$

where $G_m$ is a $K \times MN$ matrix whose elements represent Nakagami fading channel gains with the fading parameter $m_2$.

In order to simultaneously control multiple LISs, the global CSI is assumed to be perfectly known at both the LISs and the users. In the DL transmission, the BS sends the following $M \times 1$ information bearing vector:

$$s = [s_1 \cdots s_M]^T,$$

where $s_m$ denotes the signal intended for user $m$.

Thus, the signal received from the BS through LISs for user $m$ is given by

$$y_m = G_m \Phi H \Psi \sqrt{L_m} + N_0,$$

where $\Phi \triangleq \text{diag}[\beta_1, \beta_2, \cdots, \beta_{MN}]$ is a diagonal matrix, which accounts for the effective phase shift applied by all intelligent surfaces, $\beta_n \in (0, 1]$ represents the amplitude reflection coefficient of LISs, $\phi_n = \exp(j\theta_n)$, $j = \sqrt{-1}$, $v_n = 1, 2, \cdots, MN$. $\theta_n \in [0, 2\pi)$ denotes the phase shift introduced by the $n$-th intelligent surface. It is also assumed that the effective phase shifts and amplitude reflection coefficients are perfectly known at the users. Finally, $N_0$ denotes the additive white Gaussian noise (AWGN), which is modeled as a realization of a zero-mean complex circularly symmetric Gaussian variable with variance $\sigma^2$.

### B. Design of Passive Beamforming

The active beamforming weight at the BS are denoted by $P \triangleq [p_1, p_2, \cdots, p_M]$. The receiver of user $m$ applies a detection vector $\nu_m$ to its observation, therefore the users’ observations can be written as follows:

$$\tilde{y}_m = y_m^H G_m \Phi H \Psi \sqrt{L_m} p_m s_m + \nu_m^H N_0,$$

where $\nu_m$ is a $1 \times K$ vector.

In order to provide a general framework, where the DL reception can succeed both with and without LISs, we assume that the active beamformer weights obey:

$$P = I_M,$$

where $I_M$ represents a $M \times M$ identity matrix.

For simplicity, we define the effective channel gain of user $m$ as follows:

$$H_m = G_m \Phi H,$$

where $H_m$ is a $K \times MN$ matrix. Note that the element located at the $k$-th row and $m$-th column of $H_m$ represents the signal received at the $k$-th antenna via $MN$ LISs from the $m$-th antenna of the BS.

We then turn our attention to the design of the passive beamformer at the LISs, and assume that the $MN$ surfaces simultaneously serve all $M$ users. In order to maximize the signal simultaneously transmitted by the LISs for all $M$ users, we first define matrix $\tilde{H}_m$ as follows:

$$\tilde{H}_m = \begin{bmatrix} m_{1,1}h_1,1,1 & \cdots & m_{1,1}h_{1,N,1} & m_{1,1}h_{1,MN,1} \\ \vdots & \ddots & \vdots & \vdots \\ m_{1,1}h_1,1,1 & \cdots & m_{1,1}h_{1,N,1} & m_{1,1}h_{1,MN,1} \end{bmatrix},$$

where $\tilde{H}_m$ contains $K \times MN$ complex-valued Gaussian elements. It is worth noting that the effective channel vector...
of user $m$ can be expressed by $h_m = \text{sum}\left(\bar{H}_m\right)_{row}$, where $\text{sum}(\cdot)_{row}$ denotes the row summation of the matrix. In this article, each element in $h_m$ is a summation of $MN$ complex-valued elements.

As seen in (10), the messages attained for user $m$ are superimposed, which causes strong interference at the user side. The objective of designing the passive beamformer, both the phase shifts and amplitude coefficients at the LISs is to ensure that user $m$ can receive the signal from the $m$-th antenna only without contaminated by any interference. To achieve the ambitions design objective, we first define a matrix $\bar{H}$ by stacking $\bar{H}_1$ to $\bar{H}_M$ as follows:

$$\bar{H} = \begin{bmatrix}
1g_{1,1}h_{1,1} & \cdots & 1g_{1,MN}h_{MN,1} \\
\vdots & & \vdots \\
1g_{K,1}h_{1,1} & \cdots & 1g_{K,MN}h_{MN,1} \\
2g_{1,1}h_{1,2} & \cdots & 2g_{1,MN}h_{MN,2} \\
\vdots & & \vdots \\
Mg_{1,1}h_{1,M} & \cdots & Mg_{K,MN}h_{MN,M}
\end{bmatrix},$$ (11)

where $\bar{H}$ is a $M K \times MN$ matrix. For simplicity, we denote the effective passive beamforming vectors by $\Phi_v = [\bar{\beta}_1\bar{\phi}_1, \cdots, \bar{\beta}_{MN}\Phi_{MN}]^T$.

In order to obtain the global solution of the proposed framework, we first define the maximum channel gain vector as follows:

$$X = [x_{1,1}, x_{1,2}, \cdots, x_{M,K}]^T,$$ (12)

where $X$ denotes a $MK \times 1$ complex-valued vector. The elements of $X$ can be obtained by the row summation of the maximum achievable channel gain of each antenna. Hence the maximum achievable channel gain for the 1-st antenna at user $m$ can be written as:

$$x_{m,1} = \sum_{n=1}^{MN} mg_{1,n}h_{n,m}\beta_n \leq \sum_{n=1}^{MN} mg_{1,n}h_{n,m}\beta_n.$$ (13)

Since $\beta_n \leq 1$, the maximum achievable channel gain can be expressed as

$$x_{m,1} = \sum_{n=1}^{MN} \left| mg_{1,n}\right| |h_{n,m}|.$$ (14)

Thus, the objective of passive beamforming is to find:

$$\Phi_v = \bar{H}^{-1}X$$

subject to $\theta_1 \cdots \theta_{MN} \in [0, 2\pi).$ (15)

Based on the constraint $\beta_1 \cdots \beta_{MN} \in (0, 1]$, the amplitude coefficients should be normalized as follows

$$\beta_n = \frac{\bar{\beta}_n}{\bar{\beta}_{\text{max}}},$$ (16)

where $\beta_{\text{max}}$ is obtained by finding the maximum amplitude coefficient of $\beta_n$.

Note that we have $\text{rank}(\bar{H}) \leq MK$, thus for the case of $N \geq K$, there exists infinite number of homogeneous solutions for passive beamforming at the LISs, which satisfy the constraints of $\theta_n \in [0, 2\pi)$ and $\beta_n \in (0, 1]$, $\forall n = 1 \cdots MN$.

By applying the proposed design of passive beamforming at the LISs, the $m$-th column of $\bar{H}_m$, which contains all effective channel gains for user $m$, can be rewritten as

$$h_m = \begin{bmatrix}
\frac{1}{\beta_{\text{max}}} \sum_{n=1}^{MN} |mg_{1,n}| h_{n,m} \\
\vdots \\
\frac{1}{\beta_{\text{max}}} \sum_{n=1}^{MN} |mg_{K,n}| h_{n,m}
\end{bmatrix}. (17)$$

### C. Design of the User’s DL Detection Vector

We then focus on designing detection vectors at users. In order to eliminate the intra-cell interference, the following constraint has to be met:

$$v_{m,h}^H h_m p_i = 0,$$ (18)

for any $i \neq m$.

Based on the design of the active beamformer $P$, the above constraint in (18) can be transformed into

$$v_{m}^H h_i = 0,$$ (19)

where $h_i$ denotes the $i$-th column of the effective channel matrix $H_m$. Thus, by removing the $m$-th column of the effective channel matrix $H_m$, we define

$$\bar{H}_m = \begin{bmatrix}
h_1 & \cdots & h_{m-1} & h_{m+1} & \cdots & h_M
\end{bmatrix}. (20)$$

Thus, the constraint in (19) can be rewritten as follows:

$$v_{m}^H \bar{H}_m = 0,$$ (21)

where $\bar{H}_m$ is a $K \times (M-1)$ matrix.

As a result, the DL detection vector of user $m$ can be obtained from the null space of $\bar{H}_m$, which can be written as

$$v_m = T_m x_m,$$ (22)

where $T_m$ contains all the left singular vectors of $\bar{H}$ corresponding to zero singular values. By utilizing the classic maximal ratio combining (MRC) technique, $x_m$ is given by

$$x_m = \frac{T_m^H h_m}{|T_m^H h_m|}.$$ (23)

It is worth mentioning that the number of DL RAs has to be higher than or equal to that of the BS, in order to ensure the existence of a solution in (20), i.e., $K \geq M$.

By using the above active beamforming and DL user-detection vectors, the expectation of the transmit signal power from the BS obeys the maximum transmit power constraint:

$$\mathbb{E}\left\{|P_s|^2\right\} = \text{tr}(P^HP)p_b,$$ (24)

where $p_b$ denotes the transmit power of the BS for user $m$.

Based on the active beamforming and DL user-detection vectors designed, the SINR for user $m$ after detection can be written as:

$$\text{SINR}_m = \frac{|v_m^H h_m|^2(d_1d_2m)^{-\alpha} p_b}{|v_m^H|^2 \sigma^2},$$ (25)
where $\sigma^2$ denotes the AWGN power. The DL user-detection vector is normalized, and thereby some further relevant observations can be formulated as follows:

$$|y_m^H|^2 = \left( \frac{T_m^H T_m^H}{|T_m^H|^2} \right)^2 = |T_m^H|^2,$$  \hspace{1cm} (26)

and

$$|y_m^H h_m|^2 = \left( \frac{T_m^H T_m^H h_m^2}{|T_m^H|^2} \right)^2 = |T_m^H h_m|^2.$$  \hspace{1cm} (27)

Based on the effective channel gain given by (26) and noting that $T_m^H T_m = I_Q$ along with the effective antenna gain $Q = K - M + 1$, the channel gain of user $m$ can be transformed into

$$\hat{\mathbf{h}}_m = \frac{1}{\beta_{\text{max}}} \left[ \sum_{n=1}^{MN} |m g_{1,n}| |h_{n,m}| : \ldots : \sum_{n=1}^{MN} |m g_{N,n}| |h_{n,m}| \right].$$  \hspace{1cm} (28)

Thus, the SINR for user $m$ can be expressed as

$$\text{SINR}_m = \frac{|\hat{\mathbf{h}}_m|^2}{\sum_{n=1}^{MN} \left( \alpha_d d_{2,m} \right)^{-\alpha_p} \beta_{\text{max}}^2 \|I_Q\|_2^2 2^{\gamma^2}}.$$  \hspace{1cm} (29)

III. PERFORMANCE ANALYSIS OF MIMO-LIS FRAMEWORK

In this section, we discuss the performance of the proposed MIMO-LIS framework. Our new channel statistics, outage probabilities, ergodic rates, SE and EE expressions are illustrated in the following subsections.

A. New Channel Statistics

In this subsection, we derive new channel statistics for the proposed MIMO-LIS framework, which will be used for evaluating the outage probabilities and ergodic rates in the following subsections.

**Lemma 1.** Assuming that the users are located according to a HPPP within the disc of Fig. 7 the probability density functions (PDFs) of the user locations are given by

$$f_d (r) = \frac{2r}{(R^2 - r_0^2)}, \quad r_0 < r < R.$$  \hspace{1cm} (30)

**Proof:** According to the HPPP, the PDF of users can be expressed as:

$$f_d (r) = \frac{\lambda \Psi 2 \pi r}{\lambda \Psi (\pi R^2 - \pi r_0^2)},$$  \hspace{1cm} (31)

After some algebraic manipulations, Lemma 7 can be readily proved.

The effective channel gain $\hat{\mathbf{h}}_m$ of our MIMO-LIS framework is evaluated in the following Lemma.

**Lemma 2.** Let us assume that the elements in $\mathbf{H}$ and $\mathbf{G}_m$ are i.i.d. along with fading parameters $m_1$ and $m_2$, respectively. In the proposed MIMO-LIS framework, $NM$ LISs simultaneously serve $M$ users, where $N \geq K \geq M$. The distribution of the effective channel gain at user $m$ is given by

$$\|\hat{\mathbf{h}}_m\|_2^2 \sim \Gamma \left( \frac{MNQ \alpha}{m_h}, m_h \right),$$  \hspace{1cm} (32)

where $\Gamma (., .)$ represents the Gamma distribution, and $m_h = (1 + m_1 + m_2)$.

**Proof:** Please refer to Appendix A.

B. Outage Probability

In this article, the OP of user $m$ is defined by

$$P_m = \mathbb{P} \left( \log_2 (1 + \text{SINR}_m) < R_m \right),$$  \hspace{1cm} (33)

where $R_m$ denotes the target rate of user $m$. Then we turn our attention to calculating the OP of user $m$, which is given by the following Theorem.

**Theorem 1.** Assuming that $NM$ LISs simultaneously serve $M$ users with $N \geq K \geq M$, the closed-form OP expression of user $m$ can be expressed as

$$P_{m,l,t} = \tau_{1,t} R_0 \alpha + 2 F_2 (\alpha, a + \delta_2; a + 1, a + \delta_2 + 1; -b_l R_0^\alpha)$$

$$- \tau_{1,t} R_0 \alpha + 2 F_2 (\alpha, a + \delta_2; a + 1, a + \delta_2 + 1; -b_l R_0^\alpha),$$  \hspace{1cm} (34)

where we have $\delta_{m,l} = \frac{\varepsilon_m \beta_{\text{max}} \sigma^2}{\bar{b}}$, $\varepsilon_m = 2 R_m - 1$, $a = \frac{MNQ}{m_h}$, $b_l = \frac{\bar{b}_l d_{l,m}^2}{m_h}$, $\delta_2 = \frac{4}{\alpha}$, $\varphi = \frac{2}{\Gamma (\alpha) (R_0^\alpha - R_0^\alpha)}$, and $\tau_{1,t} = \frac{\phi_{\beta}}{a (\alpha \alpha + 2)}$.

$$2 F_2 (\cdot; \cdot; \cdot; \cdot; \cdot)$$

denotes Gauss hypergeometric function \cite{29}. \hspace{1cm} (9.142)

**Proof:** Please refer to Appendix B.

Since $\delta_m$ is a function of the maximum amplitude coefficients, which is not tractable, it is hard to obtain analytical insights from (34). Thus, we turn our attention to finding the optimized solutions. It is worth noting that for the case of $K = M = 1$, the amplitude coefficients $\beta_{\text{max}}$ can all be considered to one, and the maximum signal power can be obtained by appropriately adjusting the phase shifts. However, for the case of $K > 1$, no optimized solution exists which satisfies the constraint $\beta_{\text{max}} = 1$.

Based on our passive beamforming design, the solution can only be obtained when $N \geq K$. Thus, we analyze $\beta_{\text{max}}$ as the number of LISs tends to infinity. On the one hand, as $N$ increases, the increased spatial diversity enhances the received power of the users, while the value of $\beta_{\text{max}}$ does not change substantially. On the other hand, as $N$ increases, more potential solutions can be obtained for passive beamforming at the LISs. Thus, the optimal solution, where all the amplitude coefficients $\beta_{\text{max}} \approx 1$, $\forall n = 1 \cdots MN$ can be found.

In order to provide some fundamental engineering insights, we mainly focus our attention on the optimized scenario in the rest of this article, where $\beta_{\text{max}} = 1$. Thus, we derive the minimum achievable OP in the following Theorem.

**Theorem 2.** Assuming that $NM$ LISs simultaneously serve $M$ users with $N \geq K \geq M$, the approximated OP of user $m$
can be expressed as
\[ P_m = \tau_1 \Gamma(a + \delta_2 + \frac{2}{a} + \frac{2}{\alpha a + 2} - \frac{2}{\alpha a + 2} + 1, a + \delta_2 + 1; -bR^\alpha) \]
where we have \( \delta_m = \frac{mQ_\alpha^2}{p_b}, b = \frac{\delta_m}{\max}, \) and \( \tau_1 = e^{b^\alpha}. \)

Proof: Similar to Appendix B, the results in (35) can be readily proved.

Remark 1. The results in (35) indicate that the diversity order is \( N \) in the case of the proposed MIMO-LIS framework for \( M = K = m_2 = 1, m_1 \to \infty. \)

Remark 2. For the case of \( m_2 = 1, \) the diversity order of the proposed framework approaches \( m_1 N. \)

Remark 3. The results in (37) demonstrate that multiple LISs provide increased spatial diversity gains, and hence reducing OP. It is also worth noting that the minimum diversity order of the proposed MIMO-LIS framework is \( \frac{1}{3}, \) in the case of \( m_1 = m_2 = M = K = 1 \) and \( N = 1, \) i.e., \( \min(d_m) = \frac{1}{3}. \)

Remark 5. The results in (38) illustrate that the OP is a monotonically increasing function of the serving distances \( d_1 \) and \( R. \)

Remark 6. We also provide a basic engineering insight relying on the proposed framework, where a BS equipped with a single TA is communicating with a user equipped with a single RA. It is reasonable to assume that no LoS link exists between the LISs and the user, where the Nakagami fading parameter is \( m_2 = 1. \) Thus, based on the results in (37), we can readily infer that the diversity order approaches \( d_m = \frac{\Sigma m}{m_1 + 2}. \)

C. Ergodic Rate

The ergodic rate is another salient performance metric related to the SE and EE. Therefore, we focus our attention on analyzing the ergodic rate of user \( m, \) which is determined by its channel conditions and SG parameters. The analytical ergodic rate expressions for user \( m \) are given in the following Theorem.

Theorem 3. Assuming that \( MN \) LISs simultaneously serve \( M \) users with \( N \geq K \geq M, \) the maximum achievable ergodic rate of user \( m \) can be expressed in the closed-form as follows:
\[ R_{m,e} = \frac{2\Omega}{2\ln(2)} \left[ \begin{array}{c} G_{3,1}^{1,3} \left( \begin{array}{c} 0, 1 \\ 0, 0, a \end{array} \right) cR^\alpha \\ G_{3,1}^{2,3} \left( \begin{array}{c} 0, 1 \\ 0, 0, a \end{array} \right) cR^\alpha \\ G_{3,1}^{1,3} \left( \begin{array}{c} 0, 1 \\ 0, 0, a \end{array} \right) cR^\alpha \\ 0 \end{array} \right] \]
where \( c = \frac{Q_\alpha^2}{p_b}. \)

Proof: Please refer to Appendix D.

To gain deep insights into the system’s performance, the high SNR slope, as the key parameter determining the ergodic rate in the high-SNR regime, is worth estimating. Therefore, we first express the high SNR slope as
\[ S_m^\infty = -\lim_{s \to \infty} \frac{R_{m,e}}{\log_2(1 + \frac{\sigma}{P})}. \]

Proposition 2. By substituting (39) into (40), the high-SNR slope of user \( m \) in the proposed MIMO-LIS framework is given by
\[ S_m^\infty = 1. \]


**Remark 7.** The results in (41) illustrate that the slope of the proposed MIMO-LIS framework is one, which is not affected by the number of LISs.

**Remark 8.** The results in (41) demonstrate that the slope of the ergodic rate is not impacted by the fading environments and the number of TAs/RA.

**D. Spectrum Efficiency**

Based on the analysis of the last two subsections, a tractable SE can be formulated in the following Proposition.

**Proposition 3.** The SE of the proposed MIMO-LIS framework is given by

\[ S = \sum_{m=1}^{M} R_{m,e}. \]  

(42)

**E. Energy Efficiency**

In NG networks, EE is an important performance metric. Thus, based on insights gleaned from [30], we first model the total dissipation power of the proposed MIMO-LIS framework as

\[ P_e = P_{B,s} + M P_U + M p_b \varepsilon_b + M N P_L, \]  

(43)

where \( P_{B,s} \) is the static hardware power consumption of the BS, \( \varepsilon_b \) denotes the efficiency of the power amplifier at the BS, \( P_U \) is the power consumption of each user, and \( P_L \) represents the power consumption of each LIS. Thus, the EE of the proposed framework is given by the following Proposition.

**Proposition 4.** The EE of the proposed MIMO-LIS framework is

\[ \Theta_{EE} = \frac{S}{P_e}, \]  

(44)

where \( S \) and \( P_e \) are obtained from (42) and (44), respectively.

**IV. Numerical Studies**

In this section, numerical results are provided for the performance evaluation of the proposed framework. Monte Carlo simulations are conducted to verify the accuracy of our analytical results. The path loss exponent is set to \( \alpha = 3 \). The bandwidth of the DL transmission is set to \( BW = 300 \text{ kHz} \), and the power of the AWGN is set to \( \sigma^2 = -174 + 10\log_{10}(BW) \) dBm. Note that LoS and NLoS links are indicated by the Nakagami fading parameter, i.e., \( m_1 = 1 \) and \( m_1 > 1 \) are for NLoS link and for LoS link, respectively. The minimum distance is \( r_0 = 1 \text{m} \), and the disc radius is \( R = 100 \text{m} \). The target rate is \( R_m = 1.5 \text{bps per channel use (BPCU)}. \)

1) **Impact of the Number of LISs:** In Fig. 2 we focus our attention on the OP of the MIMO-LIS framework. The solid curves and dashed curves represent the analytical results and asymptotic results, respectively. The close agreement between the simulation, and analytical results, as well as asymptotic results in the high-SNR regime, verifies the accuracy of results. We can see that as the number of LISs serving user \( m \) increases, the OP decreases. This is due to the fact that, as more LISs are employed, the received signal power can be increased by the increased diversity order. For example, as shown by the blue curve and green curve, as well as by the results in (37), the diversity orders are \( \frac{2}{3} \) and 1 for the cases of \( m_1 = m_1 = 1, N = 2 \) and \( m_1 = 1, m_2 = 1, N = 3 \), respectively. We can also observe that stronger LoS environments typically decrease the OP. Observe that the slope of curves increases with the number of LISs, which validates our Remark 2 and Remark 3.

2) **Impact of Fading Environments:** In Fig. 3 we evaluate the OP of user \( m \) in different fading environments. We can see that as the transmit power increases, the OP decreases. Observe that the fading parameter of LISs-user link has almost no effect on the OP, which mainly depends on that of the BS-LISs link. This phenomenon verifies the insights gleaned from Remark 1. Note that the slope of the curves is governed by \( m_1 \), which verifies that the diversity orders of the schemes mainly depend on \( m_1 \), when the effective channel gain is high.
respectively. and asymptotic results are calculated from (34) and (36), respectively.

Remark 2. From (39), (45) and (48), respectively.

Fig. 4: OP of the MIMO-LIS framework versus the transmit power, where the number of LISs is given by $N = 5$. The fading parameters are $m_1 = 1$, $m_2 = 1$. The analytical results and asymptotic results are calculated from (34) and (36), respectively.

3) Impact of the Number of RAs: We study the impact of the number of RAs $K$ on OP in Fig. 4. Observe that the OP decreases upon increasing the number of RAs, because the effective antenna gain increases with the number of RAs. Based on the results in the high-SNR regime, the diversity order is seen to be significantly enhanced by increasing the number of TAs. This is due to the fact that the number of LISs is a function of the number of TAs. It is also worth noting that in Fig. 4, the diversity order of the schemes is $m_1$ in the case of large $K$, which validates the insights gained from Remark 2.

4) Ergodic Rate: Fig. 5 compares the ergodic rate of user $m$ versus the transmit power for different fading parameters and different number of RAs. Several observations can be drawn as follows: 1) Based on the black curve and cyan curve, the LoS links between the LISs and users have nearly no effect on ergodic rate of user $m$, whereas the LoS links between the BS and LISs improve the ergodic rate, which also verifies Remark 2. 2) The solid curves and dotted curves show a close agreement between the analytical results and simulations, which verify the accuracy of our results. 3) As seen from the figure, the high SNR slope of user $m$ is one, which also verifies Remark 3. 4) The ergodic rate can be significantly increased by employing more LISs, which is because that the spatial diversity gain can be significantly increased upon increasing the number of LISs.

5) Comparing the AF-relay and DF-relay setup:

In order to provide further engineering insights, combined with the insights from [31], the achievable rate of two alternative half-duplex relay setups, namely of amplify-then-forward (AF) relay and of decode-then-forward (DF) relay setup are evaluated. We consider the classic relaying protocols where the transmission is divided into two equal-duration phases. It is assumed that the BS, relay and user are equipped with a single antenna in both the AF-relay and DF-relay setup. We first evaluate the achievable rate of the AF-relay setup, where the AF-relay simply amplifies the received signal without decoding. Therefore, on the one hand, the achievable rate of the AF-relay setup can be written as

$$R_{AF} = \mathbb{E} \left\{ \frac{1}{2} \log_2 (1 + SINR_{AF}) \right\},$$

where $p_d$ denotes the transmit power of the relay, $SINR_{AF} = \frac{\varepsilon_a (d_1^2 d_2^2 \frac{|h_1|^2}{m} |h_2|^2)^2}{\sigma^2 (1 + \frac{\varepsilon_a (d_1^2 d_2^2 \frac{|h_1|^2}{m} |h_2|^2)^2}{p_d})}$, and $\varepsilon_a$ denotes the amplification coefficient of the AF-relay with $\varepsilon_a = \frac{p_d d_1^2 |h_1|^2}{p_d}$. Note that the AWGN between the BS to LISs is also amplified by the AF-relay.

On the other hand, the achievable rate expression of the DF-relay setup is more complicated. The DF-relay has to decode the signal from the BS, and the achievable rate can be written as follows:

$$R_{DF,1} = \mathbb{E} \left\{ \frac{1}{2} \log_2 (1 + SNR_{DF1}) \right\},$$

Fig. 6: Ergodic rates of the MIMO-LIS framework, AF-relay and DF-relay setup versus the number of LISs and the disc radius, where the number of TAs/RAs are $M = 1$, $K = 1$. The fading parameters are $m_1 = 3$, $m_2 = 1$. The analytical results are calculated from (39), (45) and (48), respectively.
Fig. 7: SE of the proposed MIMO-LIS framework versus the number of TAs and the number of LISs, where the fading parameters are $m_1 = m_2 = 2$. 

where $SNR_{DF1} = \frac{p_1 d_1^{-\alpha} |h_1|^2}{\sigma^2}$. Then, the user decodes the signal retransmitted by the DF-relay as follows:

$$R_{DF,1} = \frac{1}{2} \log_2 (1 + SNR_{DF2})$$

(47)

where $SNR_{DF2} = \frac{p_2 d_2^{-\alpha} |h_2|^2}{\sigma^2}$. Thus, the achievable rate of the DF-relay setup can be rewritten as

$$R_{DF} = \min \{ R_{DF,1}, R_{DF,2} \}$$

(48)

Here, we evaluate the channel capacity of our LIS framework, as well as of the AF-relay and DF-relay setup in Fig. 6. The results of the AF-relay and DF-relay setup are derived from (45) and (48), respectively. The fading parameters of both the AF-relay and DF-relay setup are set to $m_1 = 3, m_2 = 1$, while the transmit powers of both are set to $p_2 = (p_1 - 10)\text{dBm}$. We can see that the achievable rate gap between the MIMO-LIS framework, AF-relay and DF-relay setup becomes smaller, when the number of LISs is increased. Observe that for the case of $N = 30$, the proposed MIMO-LIS framework is capable of outperforming the AF-relay and DF-relay setup, which indicates that the MIMO-LIS framework become more competitive, when the number of LISs is high enough.

6) Spectrum Efficiency: Fig. 7 plots the SE of the proposed MIMO-LIS framework versus the number of TAs and the number of LISs. Observe that the SE of the proposed framework improves with the number of TAs, because the BS can simultaneously serve more users, hence providing a higher SE. It is also worth noting that the SE is a monotonically increasing function on the number of TAs and the number of LISs. Furthermore, for the case of $MN < MK$, there is no solution for passive beamforming at the LISs, which indicates that the DL transmission will fail.

7) Energy Efficiency: Fig. 8 evaluates the EE of the proposed LIS framework versus the transmit power, where the fading parameters are set to $m_1 = 5, m_2 = 1$. The amplifier efficiency at the BS is set to $\varepsilon_b = 1.2$. The static power at the BS and users are set to $P_{b,s} = 9 \text{ dBW}$ and $P_f = 10 \text{ dBm}$, respectively. The power consumption for a single LIS is set to $P_L = 10 \text{ dBm}$.

On the other hand, the EE can be enhanced by increasing the number of serving LISs. Moreover, the EE slope of the proposed MIMO-LIS framework can be enhanced by increasing the number of TAs and the number of LISs, which indicates that the EE of the MIMO-LIS framework mainly depends on the number of LISs.

V. Conclusions

In this article, we first reviewed the recent advances in the MIMO-LIS framework. The detection vectors of the users and the passive beamforming at the LISs were designed for the proposed framework. New channel characteristics, outage probabilities, ergodic rates, SEs and EEs were derived in closed-form for evaluating the system performance. The results derived provide the first benchmark for the LIS related framework. In NG communications, multiple LISs can be employed attached to the building surfaces, cloths and other local paraphernalia. Thus, an important future direction is to extend the proposed model to a distributed LIS framework, where multiple LISs are beneficially distributed in the coverage area.

Appendix A: Proof of Lemma 2

Based on the result derived in (23), and exploiting the fact that the elements of $|G_m|$ and $|H|$ are i.i.d., the effective channel gain vector of user $m$ can be transformed into

$$\left| \hat{h}_m \right|^2 = \sum_{q=1}^{Q} \sum_{n=1}^{MN} |m g_{q,n} h_{n,m}|^2$$

(4.1)

$$= \sum_{q=1}^{Q} \sum_{n=1}^{MN} |m g_{q,n}|^2 |h_{n,m}|^2 .$$

Note that the elements of the channel matrix $|H|^2$ and $|G_m|^2$ obey the Nakagami distribution with fading parameters.
of $m_1$ and $m_2$, respectively. By exploiting the properties of random variables, we have:

$$
\left( \sum_{q=1}^{Q} |m_{g,n}|^2 \right) \sim \mathcal{CN} \left( Q, \frac{Q}{m_2} \right), \tag{A.2}
$$

where $|m_{g,n}|^2 \sim \mathcal{CN} \left( 1, \frac{1}{m_2} \right)$. Then the mean and variance of the effective channel gain can be expressed as

$$
E_1 = E \left( \sum_{q=1}^{Q} |m_{g,n}|^2 \right) \quad \text{and} \quad \text{Var} \left( \sum_{q=1}^{Q} |m_{g,n}|^2 \right) = Q, \tag{A.3}
$$

and

$$
V_1 = \left( E \left( \sum_{q=1}^{Q} |m_{g,n}|^2 \right) \right)^2 \quad \text{and} \quad \text{Var} \left( \sum_{q=1}^{Q} |m_{g,n}|^2 \right) = Q \left( 1 + m_1 + Qm_2 \right) \frac{m_1 m_2}{m_{1+m_2}}, \tag{A.4}
$$

where $\text{Var} \cdot (\cdot)$ denotes the variance of random variables. Thus, the mean and variance of the effective channel gain is given by

$$
\| \hat{h}_m \|_2^2 \sim \mathcal{CN} \left( MNQ, MNQm_h \right), \tag{A.5}
$$

where $m_h = \frac{1}{4} \left( 1 + m_1 + Qm_2 \right)$. After some algebraic manipulations, we obtain the effective channel gain in a more elegant form in (32). The proof is complete.

**APPENDIX B: PROOF OF THEOREM**

We first handle the OP defined of user $m$ in (33), which can be rewritten as

$$
P_{m,t} = P \left( \| \hat{h}_m \|_2^2 < \delta_{m,t}(d_1 d_2, m)^\alpha \right). \tag{B.1}
$$

Then, based on the new channel statistics derived in (32) and the distance distribution in (30), the OP can be transformed into

$$
P_{m,t} = \frac{2}{G(MNQ, MNQm_h)} \int_0^{R} \gamma \left( \frac{MNQ}{m_h}, \frac{\delta_{m,t} d_1^\alpha}{m_h} \right) r dr, \tag{B.2}
$$

where $\gamma \cdot (\cdot)$ represents the lower incomplete Gamma function. By some further algebraic manipulations, we arrive at:

$$
P_{m,t} = \frac{\varphi}{\alpha b_{1}^{\alpha}} \int_0^{R} \gamma \left( a, x \right) x^{\delta_2 - 1} dx, \tag{B.3}
$$

where $\left( \cdot \right)$ is obtained by substituting $x = b_{1}^{\alpha} R_{m}^\alpha$.

Then, based on (29), the OP can be calculated as

$$
P_{m,t} = \frac{\varphi b_{1}^{\alpha} R_{m}^{\alpha+2}}{a_{1}(a + 2)} 2 F_2 \left( a, a + \delta_2; a + 1, a + \delta_2 + 1; -b_{1}R_{m}^{\alpha} \right) \tag{B.4}
$$

Thus, the closed-form OP expression can be obtained as in (34), and the proof is complete.

**APPENDIX C: PROOF OF COROLLARY**

For the case of $bR_{m}^\alpha < 1$, the hypergeometric function can be expanded to

$$
2 F_2 \left( a, a + \delta_2; a + 1, a + \delta_2 + 1; -b_{1}R_{m}^{\alpha} \right)
= \sum_{n=0}^{\infty} \left( \binom{a}{n} \binom{a + \delta_2}{n} \right) b_{1}^{n} R_{m}^{\alpha n}. \tag{C.1}
$$

Thus, we can readily arrive at the asymptotic result of

$$
P_{m} = \frac{\varphi}{a_{1}(a + 2)} \sum_{n=0}^{\infty} n! \alpha a^{n+2} \left( R_{m}^{\alpha a + \alpha n+2} - \bar{r}_{0}^{\alpha a + \alpha n+2} \right). \tag{C.2}
$$

After some further algebraic manipulations, we can derive the desired result in (36). The proof is complete.

**APPENDIX D: PROOF OF THEOREM**

Let us commence by expressing the ergodic rate of user $m$ as follows:

$$
R_{m,e} = E \left\{ \log_2 \left( 1 + SINR_m(x) \right) \right\}
= \int_0^{\infty} \log_2(1 + x) d \left( 1 - F(x) \right), \tag{D.1}
$$

The cumulative distribution function (CDF) of user $m$ can be calculated as

$$
F(x) = 1 - F(x) = \varphi \int_{0}^{x} \Gamma_r \left( a, c x^\alpha \right) r dr, \tag{D.2}
$$

where $\Gamma_r \cdot (\cdot)$ represents the upper incomplete Gamma function. By substituting $t = c x^\alpha$ into (D.2), the ergodic rate can be transformed into

$$
\tilde{F}(x) = \frac{\varphi }{\alpha b_{1}^{\alpha}} \int_{0}^{\delta_2} \Gamma_r \left( a, c x^\alpha \right) t^{\delta_2 - 1} dt. \tag{D.3}
$$

After some algebraic manipulations, $\tilde{F}(x)$ can be further transformed into

$$
\tilde{F}(x) = \frac{\varphi}{2} R^2 \Gamma_r \left( a, c R^\alpha x \right) - \frac{\varphi}{2} (c x)^{-\delta_2} \Gamma_u \left( a + \delta_2, c R^\alpha x \right)
- \frac{\varphi}{2} \bar{r}_{0}^{\alpha} \Gamma_r \left( a, c R^\alpha x \right) + \frac{\varphi}{2} (c x)^{-\delta_2} \Gamma_u \left( a + \delta_2, c R^\alpha x \right). \tag{D.4}
$$
In order to derive tractable analytical results, we first expand the upper incomplete Gamma function to the Meijer-G function \([29]\) as

\[
\Gamma_n(a, cR^\alpha x) = G_{2,0}^{1,2} \left( \begin{array}{c} \frac{1}{cR^\alpha x} \\ \frac{cR^\alpha x}{} \end{array} \right)
\]

Then, based on \([29]\), the ergodic rate of user \(m\) can be expressed as

\[
\int_0^\infty \frac{\tilde{F}(x)}{1+x} dx = \frac{\varphi^2}{2} R^2 G_{3,1}^{3,2} \left( \begin{array}{c} 0, 1 \\ 0, 0, a \end{array} \right)_{cR^\alpha x} - \frac{\varphi^2}{2} e^{-\delta_2} G_{3,2}^{3,2} \left( \begin{array}{c} \delta_2, 1 \\ \delta_2, 0, a + \delta_2 \end{array} \right)_{cR^\alpha x} - \frac{\varphi^2}{2} e^{-\delta_2} R^2 G_{3,2}^{3,2} \left( \begin{array}{c} 0, 1 \\ 0, 0, a \end{array} \right)_{cr_0^\alpha} + \frac{\varphi^2}{2} e^{-\delta_2} G_{3,2}^{3,2} \left( \begin{array}{c} \delta_2, 1 \\ \delta_2, 0, a + \delta_2 \end{array} \right)_{cr_0^\alpha}.
\]

Thus, the ergodic rate of user \(m\) is obtained in \([39]\), and the proof is complete.

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