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Performance Analysis of Wireless Powered Communications With Multiple Antennas

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ABSTRACT This paper analytically investigates the performance of a wireless powered communication system, where a source powered by multiple dedicated power beacons communicates with a destination. Specifically, we consider a harvest-then-transmit multiple-input multiple-output communication system, where the source uses all harvested energy for information transmission in each time block. The random placement of terminals is characterized by stochastic geometry tools. Taking into account the effects of imperfect channel state information in wireless energy transfer and wireless information transmission, the ergodic achievable rate of information transmission is derived analytically by considering co-channel interference (CCI) and the noise. In addition, assuming the CCI can be accurately approximated by a Gamma distributed variable, the outage probability of information transmission is investigated. Numerical results validate the analytical results and show the impacts of the antenna number, distribution density, estimation error, and the transmit power of terminals on the system performance.

INDEX TERMS Wireless powered communications, Poisson point process, imperfect channel estimation, ergodic achievable rate, outage probability.

I. INTRODUCTION

In order to reap the benefits of energy harvesting in long-distance transmission, a practical transmission architecture is proposed by deploying the dedicated power beacons (PBs) in the network [1], [2]. It is also verified experimentally that the harvested energy from multiple PBs can be additive [3]. Hence multiple PBs can be located relatively closed to the energy harvester and the wireless devices are able to use the harvested energy to transmit information. Such scheme is also known as the wireless powered communications (WPC).

In the harvest-then-transmit WPC model, each time block is partitioned into two phases for energy harvesting and information transmission. Depending on whether the wireless node deploys a rechargeable battery or supercapacitor, and whether there exists a transmit power constraint, several transmission policies for utilizing the harvested energy exist in literatures: 1) battery-equipped wireless node [2], [4], 2) supercapacitor-equipped with power constraint [5], [6], and 3) supercapacitor-equipped without power constraint [7], [8]. A sensor with supercapacitor is widely applied in wireless networks where the wireless device is able to quickly store and release energy from ambient sources. Without considering the power constraint, the power of the received information signal can be characterized by exploiting the product distribution of channel gains belonging to energy harvesting and information transmission channels, if the geometric location of all nodes are fixed and known. Within this derived closed-form distributions, the network performance is analyzed in terms of the ergodic capacity and the outage probability [7], [9].

Considering multiple PBs are randomly distributed in a large-scale communication scenario, stochastic geometry tools can be applied to characterize the location of the randomly distributed wireless nodes. Among multiple models, Poisson Point Process (PPP) is considered as the most tractable and appropriate model that can be applied to analytically investigate the performance of cellular networks [2], relay networks [10], and cognitive networks [11]. Since numerous PBs are deployed randomly in the wireless powered communication networks, the locations of PBs can be modeled as a homogeneous PPP. Several research in wireless powered communication networks have already applied

PPP to characterize the randomly distributed wireless nodes. Lu *et al.* [12] study a cognitive D2D communication underlying a cellular network where the D2D transmitters first harvest energy from the ambient energy sources and then use the energy for further transmission, and the locations of wireless terminals are modeled by PPP. Flint *et al.* [8] consider a point-to-point network, where a wireless sensor harvests the energy from the randomly distributed PBs modeled by PPP, then transmits information to a data sink using the harvested energy.

Meanwhile, the utilization of multiple-antenna can substantially improve the achievable transmission rate and the reliability in WPC network. Zhong *et al.* [7] discuss the average throughput of a wireless powered network considering only one multiple-antenna equipped PB in the network. In [9], it is assumed that a multiple-antenna access point first sends the energy to a single-antenna user with energy beamforming and the user then use the harvested energy for further transmission. In our previous work [13], the expected energy harvesting rate and a tight bound of the information transmission rate are analytically investigated in a WPC model. However, most of the literatures that focus on the performance analysis assume that perfect channel state information (CSI) of multiple-input multiple-output (MIMO) channels can be obtained, which is obviously infeasible in practice, due to the inevitable feedback delays and unknown channel noise component. Although the effects of imperfect CSI on wireless energy transfer have been investigated [14], [15], to the best of our knowledge, when the energy-constrained terminal is supercapacitor-equipped, the combined effect of the randomly distributed PBs, imperfect CSI and the MIMO setting on WPC performance has yet to be analytically explored, due to the prohibited analysis complexity.

In order to address the above issue, we consider a WPC MIMO communication system where a supercapacitor equipped sensor communicates with a data sink.[1] The sensor entirely relies on the energy harvested from the surrounding dedicated PBs. The location of PBs and interferers are modeled by stochastic geometry tools. First, a WPC MIMO communication model is constructed by incorporating the effects of imperfect CSI in MIMO transmission. Based on this model, the performance of information transmission is evaluated analytically. By using moment generating function (MGF) approach, we provide a semi-analytical expression of the ergodic achievable rate of information transmission. In addition, we investigate the approximation of co-channel interference (CCI) in such network model. Within the verified approximation result, the outage probability of information transmission is derived. Both expressions of network performance are simplified in the special case where the channel training is perfect and the communication is interference limited. The derived semi-analytical results can be computed efficiently through numerical integration. Furthermore, by numerical simulations, we investigate the network performance as the PB density, the PB transmit power, the number of sensor antennas and the channel estimation error vary.

[1] In practical multi-sensor systems, multiple sensors need to be simultaneously served by PBs and several network architectures are proposed in [16]. In this work we only focus on the scenario where a cluster of PBs serve only one sensor in each block time.

II. NOTATION AND DEFINITION

Throughout the paper, matrices and vectors are denoted by uppercase and lowercase boldface letters, respectively. $\mathbb{E}[\cdot]$ denotes statistical expectation, and $\mathcal{M}_x(s) = \mathbb{E}[e^{-sx}]$ indicates the MGF of variable x. $\Gamma(\cdot)$ indicates the standard gamma function, and $\Gamma(\cdot,\cdot)$ represents the upper incomplete Gamma function. The Gaussian hypergeometric function is defined as ${}_2F_1(a_1, a_2; b_1; x)$, and can be expanded as

$$ {}_2F_1(a_1, a_2; b_1; x) = \sum_{k=0}^{\infty} \frac{(a_1)_k (a_2)_k}{(b_1)_k} \frac{x^k}{k!} $$

where $(a)_k = \Gamma(a+k)/\Gamma(a)$ denotes the Pochhammer symbol.

III. SYSTEM MODEL

We consider a WPC MIMO network as depicted in Fig. 1, where a RF-powered sensor (S) delivers information signal to the data sink (D), and the information transmission is impaired by the co-channel interferers (I). All wireless terminals, including S, D, PB and I in the network are considered to be equipped with multiple antennas. N_s, N_d, N_p and N_i are used to denote the number of antennas on S, D, PB and I, respectively. The location of D is fixed and its Euclidean distance to S is known and denoted by r_0. PBs are located according to PPP Ψ with density ρ in such plane, and the Euclidean distance between the i-th PB and S is denoted by $r_i, i \in \Psi$. Similarly, we assume the randomly distributed interferers are located according to another independent PPP Φ with density ρ', and the Euclidean distance between the j-th I and D is denoted by $r_j, j \in \Phi$. By Slivnyak's theorem and due to the stationary of Ψ, we focus on the scenario where S is located at the origin of the Euclidean plane.

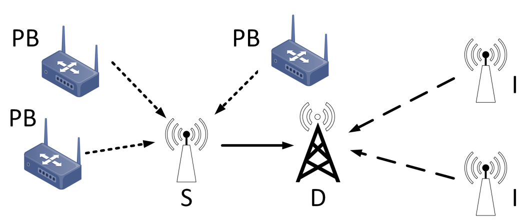

FIGURE 1. A network model of WPC MIMO communications.

Assuming a block time of T symbols, during the first phase of the duration τT, where $0 < \tau < 1$, S harvests energy from multiple PBs. The wireless power transfer between PBs and S can be characterized as

$$ \mathbf{y}_s = \sum_{i \in \Psi} \mathbf{G}_i \mathbf{s}_i + \mathbf{n}_s \tag{1} $$

where $\mathbf{s}_i$ represents the energy signal vector at the i-th PB, $\mathbf{n}_s$ is the AWGN noise, and $\mathbf{G}_i$ denotes a $N_s \times N_p$ true channel matrix, whose (m, n)-th element $g_{mn} = h_{mn} r_i^{-\frac{\alpha}{2}}$ is the channel coefficient incorporating the small scale Rayleigh fading h_{mn} and the path-loss effect with r_i standing for the distance and α is the path-loss exponent of the channel. Due to the existance of the operational sensitivity level of the energy harvester, it is only feasible for the PBs to tranfer energy signal to S within a maximum distance [1]. In this work we assume the maximum distance between PB and S is L.

It is known that the maximization of the power transfer efficiency can be achieved by beamforming the signal along the strongest eigenmode of the corresponding MIMO channel [16]. Different to the MIMO transmission of information signals, the energy beamforming transmission only depends on the acquisition of the CSI of PB-S link at PBs. The channel training approach adopted in this work is reverse-link training by exploiting the channel reciprocity, which is accomplished by first sending pilot signals from S to PBs. We here consider the time allocated for channel training is $\tau_t T$ and the time left for the energy transfer is $(\tau - \tau_t)T$. We neglect the noise effect during energy beamforming since the power of noise introduced by the receiver antenna is much smaller than that of the received energy signal in practice [17]. In order to analytically explore the effects of imperfect CSI on the network performance, we use channel estimation error model in [18] and [19] rather than the actual MIMO channel estimation model [15]. Within the above channel training scheme, the actual channel matrix between the i-th PB and S is decomposed as:

$$\mathbf{G}_i = \hat{\mathbf{G}}_i + \tilde{\mathbf{E}}_i = r_i^{-\frac{\alpha}{2}} \hat{\mathbf{H}}_i + r_i^{-\frac{\alpha}{2}} \mathbf{E}_i \tag{2}$$

where $\hat{\mathbf{G}}_i$ denotes the MMSE estimate of the channel known at PB and $\tilde{\mathbf{E}}_i$ represents the estimation error matrix. According to the orthogonal property of the MMSE estimation for Gaussian random variables, $\hat{\mathbf{H}}_i$ and $\mathbf{E}_i$ are independent and they have independent and identically distributed (i.i.d.) zero-mean circularly symmetric complex Gaussian (CSCG) entries with variances $\sigma_H^2 = \frac{1}{1+\sigma_\epsilon^2}$ and $\sigma_E^2 = \frac{\sigma_\epsilon^2}{1+\sigma_\epsilon^2}$, respectively. $\sigma_\epsilon^2 = \sigma_u^2 + \frac{\sigma_n^2}{P_t}$ is used in this model to characterize the effects of the estimation error as in [18], where σ_u^2 stands for the prediction error due to time variability of the channel, σ_n^2 is the measurement discrepancy caused by AWGN noise, and P_t represents the transmit power used for channel training.

Based on the imperfect CSI, the amount of the energy, (also known as energy harvesting rate) collected at S in one block time can be expressed as

$$E_h = \sum_{i \in \Psi} \mu(\tau - \tau_t) T \operatorname{tr}\left(\mathbf{G}_i^\dagger \mathbf{G}_i \mathbf{S}_i\right) - P_t \tau_t T \tag{3}$$

where $0 < \mu < 1$ is the energy conversion efficiency, $\mathbf{S}_i = \mathbf{s}_i \mathbf{s}_i^\dagger$ stands for the transmit covariance matrix conditioned on the imperfect CSI on the i-th PB. By using the above energy beamforming tecnique, $\mathbf{S}_i$ is designed to be

$$\mathbf{S}_i = P_e \mathbf{v}_i \mathbf{v}_i^\dagger \tag{4}$$

where P_e is the transmit power of the energy signal, and $\mathbf{v}_i = \mathbf{v}_{\max}(\hat{\mathbf{G}}_i^\dagger \hat{\mathbf{G}}_i)$ denotes the eigenvector corresponding to the dominant eigenvalue of $\hat{\mathbf{G}}_i^\dagger \hat{\mathbf{G}}_i$.

In the information transmission phase, the harvested energy is utilized by S to transmit information to D during the time $(1 - \tau - \tau_t)T$, where the remaining time $\tau_t T$ is used for the channel estimation of the S-D link. Hence the transmission power at S is expressed as $P_s = E_h/((1 - \tau - \tau_t)T)$. We target to design a scheme that is robust against severe effects of fading in order to acheive the maximum diversity gain in the MIMO model rather than multiplexing gain. Hence we consider the single-datastream beamforming transmission scheme is implemented between S and D. In this time division duplex (TDD) transmission scheme, by exploiting the channel reciprocity, we also assume imperfect CSI of the S-D channel is known to S and D, written as

$$\mathbf{G}_0 = \hat{\mathbf{G}}_0 + \tilde{\mathbf{E}}_0 = r_0^{-\frac{\alpha}{2}} \hat{\mathbf{H}}_0 + r_0^{-\frac{\alpha}{2}} \mathbf{E}_0 \tag{5}$$

where $\mathbf{G}_0$ denotes a $N_d \times N_s$ true channel matrix, $\hat{\mathbf{G}}_0$ is the MMSE estimate of the S-D channel and $\tilde{\mathbf{E}}_0$ represents the estimation error matrix. $\hat{\mathbf{H}}_0$ and $\mathbf{E}_0$ are independent and they have i.i.d. zero-mean CSCG entries with variances $\sigma_{H_0}^2 = \frac{1}{1+\tilde{\sigma}_\epsilon^2}$, and $\sigma_{E_0}^2 = \frac{\tilde{\sigma}_\epsilon^2}{1+\tilde{\sigma}_\epsilon^2}$. For the simplification of the expression, we assume $\sigma_\epsilon^2 = \sigma_\epsilon^2$ and $\sigma_{H_0}^2 = \sigma_H^2, \sigma_{E_0}^2 = \sigma_E^2$. Then, S is able to precode the information signal by beamforming the signal along the the right eigenvector corresponding to the dominant singular value of the MIMO channel $\hat{\mathbf{G}}_0$, say $\hat{\mathbf{v}}_0$, and D will project the signal along the left eigenvector $\hat{\mathbf{u}}_0$.

We consider the received information signal at D is impaired by CCI and AWGN noise. Assuming both the desired information signal x and the interfering signal $\tilde{x}_j$ of the j-th interferer are zero mean and unit variance, the received signal at D can be written as

$$\begin{aligned} y_D = & \ \hat{\mathbf{u}}_0^\dagger \Big(\sqrt{P_s}(\hat{\mathbf{G}}_0 + \tilde{\mathbf{E}}_0)\hat{\mathbf{v}}_0 x + \sum_{j \in \Phi} \sqrt{\tilde{P}_j} \tilde{\mathbf{G}}_j \mathbf{v}_j \tilde{x}_j\Big) + n_D \\ = & \sqrt{P_s r_0^{-\alpha}} \hat{\mathbf{u}}_0^\dagger \hat{\mathbf{H}}_0 \hat{\mathbf{v}}_0 x + \sum_{j \in \Phi} \sqrt{\tilde{P}_j r_j^{-\alpha}} \hat{\mathbf{u}}_0^\dagger \tilde{\mathbf{H}}_j \mathbf{v}_j \tilde{x}_j \\ & + \sqrt{P_s r_0^{-\alpha}} \hat{\mathbf{u}}_0^\dagger \mathbf{E}_0 \hat{\mathbf{v}}_0 x + n_D \\ = & \sqrt{P_s r_0^{-\alpha}} \hat{\lambda}_0 x + \sum_{j \in \Phi} \sqrt{\tilde{P}_j r_j^{-\alpha}} \tilde{h}_j \tilde{x}_j + n_e \end{aligned} \tag{6}$$

where $\tilde{P}_j$ represents the transmit power of the j-th I, $\tilde{\mathbf{H}}_j$ represents the MIMO channel of the j-th CCI link. We express $\hat{\mathbf{u}}_0^\dagger \hat{\mathbf{H}}_0 \hat{\mathbf{v}}_0 = \hat{\lambda}_0^{\frac{1}{2}}$ where $\hat{\lambda}_0$ follows the law of the dominant eigenvalue of the Gramian matrix $\hat{\mathbf{H}}_0 \hat{\mathbf{H}}_0^\dagger$. The square root of the channel gain of the j-th CCI link is denoted as $\tilde{h}_j = \mathbf{u}_{H_0}^\dagger \tilde{\mathbf{H}}_j \mathbf{v}_{\tilde{H}_j}$. It is pointed out that $\tilde{h}_j$ is a zero-mean complex Gaussian variable [20]. CCI interferers locate outside an exclusion area centered at D with radius r_c in cell association scheme. For the sake of simplicity, in the following, we assume the transmit power of I is identical (i.e. $\tilde{P}_j = \tilde{P},\ j \in \Phi$). Furthermore, n_e represents the effective noise component with mean zero and variance $\sigma_e^2 = P_s r_0^{-\alpha}\sigma_E^2 + \sigma_D^2$.

As such, the resulting instantaneous SINR at D can be expressed as

$$\gamma_D = \frac{P_s \hat{\lambda}_0 r_0^{-\alpha}}{I + \sigma_e^2} \tag{7}$$

where $I = \sum_{j\in\Phi} \tilde{P}|\tilde{h}_j|^2\ r_j^{-\alpha}$ denotes the contribution of I at D.

IV. PERFORMANCE ANALYSIS

We evaluate the performance of WPC MIMO system in terms of the ergodic achievable rate and the outage probability. The ergodic achievable rate can be mathematically defined as the expected value of the instantaneous mutual information, which is $\mathcal{R} = \mathbb{E}[\ln(1+\gamma_D)]$, and the outage probability is defined as the probability that SIR at D is lower than a threshold, written as $\mathcal{P} = P(\gamma_D < \gamma_{th})$.

A. ERGODIC ACHIEVABLE RATE

By using MGF-based approach, the ergodic achievable rate can be expressed by the proposed lemma in [21] in terms of the MGFs of the nominator and denominator of SINR. For the sake of brevity, we first define p and q as $p = \min(N_s, N_d)$ and $q = \max(N_s, N_d)$. Similarly, v and t are defined as $v = \min(N_p, N_s)$ and $t = \max(N_p, N_s)$, respectively.

Proposition 1: The ergodic achievable rate of WPC MIMO system can be characterized as

$$\mathcal{R} = \int_0^\infty \frac{1}{s}(1 - \mathcal{M}_s(s))\mathcal{M}_i(s)\mathcal{M}_n(s)\, ds \tag{8}$$

where $\mathcal{M}_s(s)$ denotes the MGF of $P_s\hat{\lambda}_0\ r_0^{-\alpha}$ as follows

$$\mathcal{M}_s(s) = \sum_{b'=1}^{p} \sum_{c'=q-p}^{(q+p)b'-2b'^2} \frac{b'^{c'+1} d_{b',c'}}{c'!} \cdot \int_0^\infty \lambda_0^{c'} e^{2\pi\rho(C_{b,c} - L^2/2)} \cdot e^{s\frac{\sigma_H^2\lambda_0 r_0^{-\alpha} P_t\tau_t}{1-\tau-\tau_t} - b'\lambda_0}\, d\lambda_0, \tag{9}$$

$$C_{b,c} = \sum_{b=1}^{v} \sum_{c=t-v}^{(t+v)b-2b^2} \int_0^L \frac{d_{b,c} e^{-s\mu\lambda_0\phi P_e N_s \sigma_H^2\sigma_E^2 r^{-\alpha} r_0^{-\alpha}}\, r\, dr}{(s\mu\lambda_0\sigma_H^4\phi P_e/(r^\alpha r_0^\alpha b) + 1)^{c+1}}, \tag{10}$$

the MGF of I is written by

$$\mathcal{M}_i(s) = \exp(-\frac{2\pi\rho' s\tilde{P}{}_2F_1(1, 1-\frac{2}{\alpha}; 2-\frac{2}{\alpha}; -\frac{s\tilde{P}}{r_c^\alpha}))}{(\alpha-2)r_c^{\alpha-2}}, \tag{11}$$

and $\mathcal{M}_n(s) = \exp(-s(P_s r_0^{-\alpha}\sigma_E^2 + \sigma_D^2))$ is evaluated as

$$\mathcal{M}_n(s) = e^{2\pi\rho\tilde{C}_{b,c} - \pi\rho L^2} e^{-s(\frac{\sigma_E^2 r_0^{-\alpha} P_t\tau_t}{1-\tau-\tau_t} - \sigma_D^2)}, \tag{12}$$

$$\tilde{C}_{b,c} = \sum_{b=1}^{v} \sum_{c=t-v}^{(t+v)b-2b^2} \int_0^L \frac{d_{b,c} e^{-s\mu\phi r_0^{-\alpha} P_e r^{-\alpha} N_s \sigma_E^4}\, r\, dr}{(s\mu\phi\sigma_H^2\sigma_E^2 P_e/(r_0^\alpha r^\alpha b) + 1)^{c+1}}. \tag{13}$$

ϕ is defined as $\phi = (\tau - \tau_t)/(1 - \tau - \tau_t)$. The coefficients $d(a, b)$ in (9) and (10) depend on a and b, their sum equals to 1, and they can be computed by using the efficient algorithm proposed in [22].

Proof: The proof is given in Appendix. ■

It is worth to point out that the integrals with respect to s and λ_0 in (8) and (9) can be efficiently computed by Gauss-Laguerre quadrature, and the integral with respect to r in (11) and (12) can be computed by Gauss-Legendre quadrature. Nevertheless, the derived ergodic achievable rate in (8) is not in a simple form since it requires a multi-fold integration. As such we consider a special case where both expressions of $\mathcal{M}_s(s)$ can be simplified, leading to a more compact form in the following corollary,

Corollary 1: When the acquired CSI at PB and S are perfect, considering the interference limited case, the ergodic achievable rate of WPC MIMO system can be characterized as

$$\mathcal{R} = \int_0^\infty \frac{1}{s}(1 - \mathcal{M}_s(s))\mathcal{M}_i(s)\, ds \tag{14}$$

where $\mathcal{M}_s(s)$ is given in (9). As such, $C_{b,c}$ is simplified as

$$C_{b,c} = \sum_{b=1}^{v} \sum_{c=t-v}^{(t+v)b-2b^2} \frac{d_{b,c}(s\mu\lambda_0\sigma_H^4\phi r_0^{-\alpha} P_e/b)^{-c-1}}{L^{-(\alpha\alpha')}\alpha\alpha'} \cdot {}_2F_1(c+1, \alpha'; \alpha'+1; -\frac{L^\alpha b r_0^\alpha}{s\mu\lambda_0\sigma_H^4\phi P_e}) \tag{15}$$

where $\alpha' = c + 1 + 2/\alpha$. $\mathcal{M}_i(s)$ is provided in (11)

Proof: When $\sigma_H^2 = 1$ and $\sigma_E^2 = 0$, $C_{b,c}$ can be simplified into a closed-form following from [23, eq. (3.194.2)]. ■

B. OUTAGE PROBABILITY

The distribution of SINR can be used to characterize the outage probability of information transmission in WPC system. However, the closed-form expressions of $\mathcal{P}$ in MIMO WPC systems are still open problems, since the contributions of PBs and CCI are both modeled by PPPs. In this work, we circumvent this difficulty by approximating the I in (7) using Gamma distribution.

It has been declared that the Gamma distribution can provide a satisfactory tight fit to the statistics of Poisson interference [24] considering an exclusion area. The CCI in the considering WPC networks can be characterized in the following proposition.

Proposition 2: The interference I can be approximated by a Gamma distributed variable $\tilde{I}$ with distribution $\mathbb{P}(\tilde{I} < z) = 1 - \Gamma(k, z/\theta)/\Gamma(k)$, where k and θ are

$$k = 2\pi\rho' r_c^2(\alpha-1)/(\alpha-2)^2 \tag{16}$$

$$\theta = \tilde{P}_j r_c^{-\alpha}(\alpha-2)/(\alpha-1) \tag{17}$$

Proof: The mean value and the variance of the interference are computed by exploiting the exponential distributed channel gain and Campbell's theorem [25],

$$\mathbb{E}[I] = 2\pi\rho'\tilde{P}r_c^{2-\alpha}/(\alpha-2)$$
$$\mathrm{Var}[I] = 2\pi\rho'\tilde{P}^2 r_c^{2-2\alpha}/(\alpha-1)$$

Through second-moment matching, the parameters of Gamma distribution, k and θ can be obtained by using the relations $\mathbb{E}[\tilde{I}] = k\theta$ and $\mathrm{Var}[\tilde{I}] = k\theta^2$. ■

After replacing I with $\tilde{I}$, the MGF of the interference can be computed by leveraging the interference approximation result.

$$\tilde{\mathcal{M}}_i(s) = \mathbb{E}[\exp(-\tilde{I}s)] = \left(1+\theta s\right)^{-k} \tag{18}$$

In order to validate the approximation of CCI in the considering network model, the results of $\tilde{\mathcal{M}}_i(s)$ will be compare with that of $\mathcal{M}_i(s)$ in next section.

Since $\tilde{I}$ is Gamma distributed and the shape parameter k given in (16) is usually not an integer, for $k>1$, the pdf of $\tilde{I}$ can be expressed as a weighted sum of Erlang PDF (as the shape parameter is an integer),

$$f_{\tilde{I}}(w) = \sum_{\beta=0}^{\infty} A_\beta \frac{e^{-w\frac{K}{\Omega}}w^\beta}{\Gamma(\beta+1)}(\frac{K}{\Omega})^{\beta+1} \tag{19}$$

where $A_\beta = e^{-(K-1)}(K-1)^\beta/\beta!$, $\Omega = k\theta$, and $K = k+\sqrt{k(k-1)}$. Then, based on the SINR expression given in (7), the outage probability equals to

$$\begin{aligned}
\mathcal{P} &= P\big(\tilde{I} > P_s r_0^{-\alpha}(\frac{\hat{\lambda}_0}{\gamma_{th}} - \sigma_E^2) - \sigma_D^2\big)\\
&= \mathbb{E}[\sum_{\beta=0}^{\infty}\frac{A_\beta\Gamma(\beta+1, \frac{K}{\Omega}(P_s r_0^{-\alpha}(\frac{\hat{\lambda}_0}{\gamma_{th}}-\sigma_E^2)-\sigma_D^2))}{\Gamma(\beta+1)}]\\
&\overset{(a)}{=} \mathbb{E}[\sum_{\beta=0}^{\infty}\frac{A_\beta}{\Gamma(\beta+1)}e^{-\frac{K}{\Omega}(P_s r_0^{-\alpha}(\frac{\hat{\lambda}_0}{\gamma_{th}}-\sigma_E^2)-\sigma_D^2)}\\
&\quad\times\int_0^\infty e^{-u}(u+\frac{K}{\Omega}(P_s r_0^{-\alpha}(\frac{\hat{\lambda}_0}{\gamma_{th}}-\sigma_E^2)-\sigma_D^2))^\beta\,du]\\
&= \mathbb{E}[\sum_{\beta=0}^{\infty}\sum_{\eta=0}^{\beta}\frac{A_\beta e^{-\frac{K}{\Omega}P_s r_0^{-\alpha}(\frac{\hat{\lambda}_0}{\gamma_{th}}-\sigma_E^2)}}{\Gamma(\beta+1)}C_\beta^\eta\\
&\quad\times(\frac{KP_s}{\Omega r_0^\alpha}(\frac{\hat{\lambda}_0}{\gamma_{th}}-\sigma_E^2))^\eta\Gamma(\beta-\eta+1,-\frac{K}{\Omega}\sigma_D^2)]
\end{aligned} \tag{20}$$

where (a) is obtained by employing Kummer's identity on incomplete Gamma function. Next, the evaluation has to be performed by taking the expectation with respect to λ_0 and E_h. We have

$$\begin{aligned}
&\mathbb{E}[e^{-\frac{K}{\Omega}P_s r_0^{-\alpha}(\frac{\hat{\lambda}_0}{\gamma_{th}}-\sigma_E^2)}(\frac{K}{\Omega}P_s r_0^{-\alpha}(\frac{\hat{\lambda}_0}{\gamma_{th}}-\sigma_E^2))^\eta]\\
&= \sum_{b'=1}^{p}\sum_{c'=q-p}^{(q+p)b'-2b'^2}\sum_{w=0}^{\eta}\frac{b'^{c'+1}d_{b',c'}}{c'!}C_\eta^w\frac{(-\sigma_E^2)^{\eta-w}(w+c')!}{(\gamma_{th}(1+\sigma_\epsilon^2))^w}\\
&\quad\cdot\mathbb{E}_{P_s}[e^{\frac{KP_s\sigma_E^2}{\Omega r_0^\alpha}}(\frac{KP_s}{\Omega r_0^\alpha})^\eta(\frac{KP_s\sigma_H^2}{\Omega\gamma_{th}r_0^\alpha}+b')^{-(w+c'+1)}]
\end{aligned} \tag{21}$$

By applying the identity for the negative power of $(\frac{Kr_0^{-\alpha}\sigma_H^2}{\Omega\gamma_{th}}P_s+b')$ [23, eq. (3.381.4)], we have:

$$\begin{aligned}
&\mathbb{E}_{P_s}[e^{\frac{KP_s\sigma_E^2}{\Omega r_0^\alpha}}(\frac{KP_s}{\Omega r_0^\alpha})^\eta(\frac{Kr_0^{-\alpha}\sigma_H^2}{\Omega\gamma_{th}}P_s+b')^{-(w+c'+1)}]\\
&= \int_0^\infty\frac{b'^{-(w+c'+1)}z^{w+c'}e^{-z}}{\Gamma(w+c'+1)}\\
&\quad\cdot\int_0^\infty(\frac{KP_s}{\Omega r_0^\alpha})^\eta e^{-z\frac{KP_s}{\Omega r_0^\alpha}(\frac{\sigma_H^2}{b'\gamma_{th}}-\sigma_E^2)}f_{P_s}(P_s)\,dP_s\,dz\\
&= \int_0^\infty\frac{b'^{-(w+c'+1)}z^{w+c'}e^{-z}}{\Gamma(w+c'+1)(\sigma_E^2-\frac{z\sigma_H^2}{b'\gamma_{th}})^\eta}[\frac{d^\eta\mathcal{M}_\epsilon(s)}{ds^\eta}]_{s=1}\,dz
\end{aligned} \tag{22}$$

where $\epsilon = \frac{KP_s}{\Omega r_0^\alpha}(\frac{z\sigma_H^2}{b'\gamma_{th}}-\sigma_E^2)$. Then, the outage probability can be computed.

Proposition 3: The outage probability of WPC MIMO system can be characterized as

$$\begin{aligned}
\mathcal{P} = &\sum_{\beta=0}^{\infty}\sum_{\eta=0}^{\beta}\sum_{b'=1}^{p}\sum_{c'=q-p}^{(q+p)b'-2b'^2}\sum_{w=0}^{\eta}\frac{A_\beta C_\beta^\eta\Gamma(\beta-\eta+1,-\frac{K}{\Omega}\sigma_D^2)}{\Gamma(\beta+1)c'!(\gamma_{th}b')^w}\\
&\cdot\int_0^\infty\frac{z^{w+c'}e^{-z}d_{b',c'}C_\eta^w}{(\sigma_\epsilon^2-\frac{z}{b'\gamma_{th}})^\eta(-\sigma_\epsilon^2)^{\eta-w}}[\frac{d^\eta\mathcal{M}_\epsilon(s)}{ds^\eta}]_{s=1}\,dz
\end{aligned} \tag{23}$$

where $\mathcal{M}_\epsilon(s)$ is written as

$$\mathcal{M}_\epsilon(s) = e^{2\pi\rho(\bar{C}_{b,c}-L^2/2)}\cdot\exp(s\frac{\frac{KP_t\tau_t}{\Omega r_0^\alpha}(\frac{z\sigma_H^2}{b'\gamma_{th}}-\sigma_E^2)}{1-\tau-\tau_t}), \tag{24}$$

$$\begin{aligned}
\bar{C}_{b,c} = &\sum_{b=1}^{v}\sum_{c=t-v}^{(t+v)b-2b^2}\\
&\cdot\int_0^L\frac{d_{b,c}\exp(-s\frac{\mu\phi P_e N_s\sigma_E^2}{r_0^\alpha r^\alpha}\frac{K}{\Omega}(\frac{z\sigma_H^2}{b'\gamma_{th}}-\sigma_E^2))}{(s\frac{\mu\phi\sigma_H^2 P_e}{br_0^\alpha r^\alpha}\frac{K}{\Omega}(\frac{z\sigma_H^2}{b'\gamma_{th}}-\sigma_E^2)+1)^{c+1}}r\,dr
\end{aligned} \tag{25}$$

Note that the high-order derivatives in (23) can be evaluated using Faà di Bruno's formula, written as

$$\begin{aligned}
\frac{d^{\beta+1}}{d\epsilon^{\beta+1}}\mathcal{M}_\epsilon(s) &= \frac{d^{\beta+1}}{d\epsilon^{\beta+1}}f(g(s)) = \sum_{i=1}^{\beta+1}f^i(g(s))\\
&\quad\cdot B_{(\beta+1,i)}(g^1(s), g^2(s),\ldots,g^{\beta+2-i}(s))
\end{aligned}$$

where $f(g(s)) = \exp(g(s))$ and $g(s)$ is the term inside the exponential function of (24). $f^i(\cdot)$ and $g^i(\cdot)$ denote the i-th order derivatives of the corresponding function.

$B_{(a,b)}(x_1, \ldots, x_{a-b+1})$ denotes the incomplete Bell polynomials. In addition, we have to clarify that although the upperbound of the sum over β in (23) is infinity, the analytical result, whose accuracy reaches approximately 1×10^{-10}, can be obtained by updating the upperbound of β to 30 in the network models specified in next section. We also point out that the integrals with respect to z in (23) can be efficiently computed by Gauss-Laguerre quadrature, and the integral with respect to r in (25) can be computed by Gauss-Legendre quadrature.

Similar to the investigation of the ergodic achievable rate, if perfect CSI of channels can be obtained at PBs and S, i.e., $\sigma_H^2 = 1$ and $\sigma_E^2 = 0$, the outage probability of information transmission can be simplified.

Corollary 2: When the acquired CSI at PB and S are perfect, considering the interference limited case, the outage probability of WPC MIMO system can be expressed as

$$\mathcal{P} = \sum_{\beta=0}^{\infty}\sum_{\eta=0}^{\beta}\sum_{b'=1}^{p}\sum_{c'=q-p}^{(q+p)b'-2b'^2} \frac{A_\beta C_\beta^\eta(\beta-\eta)!)d_{b',c'}}{\Gamma(\beta+1)c'!(\gamma_{th}b')^w} \cdot \int_0^\infty z^{\eta+c'} e^{-z}(-\frac{z}{b'\gamma_{th}})^{-\eta}[\frac{d^\eta \mathcal{M}_\epsilon(s)}{ds^\eta}]_{s=1}\, dz \quad (26)$$

where $\mathcal{M}_\epsilon(s)$ is written as

$$\mathcal{M}_\epsilon(s) = e^{2\pi\rho(\bar{C}_{b,c}-L^2/2)} \cdot \exp(s\frac{Kr_0^{-\alpha}zP_t\tau_t}{\Omega b'\gamma_{th}(1-\tau-\tau_t)}),$$

$$\bar{C}_{b,c} = \sum_{b=1}^{v}\sum_{c=t-v}^{(t+v)b-2b^2} \frac{d_{b,c}L^{\alpha\alpha'}}{(s\frac{\mu r_0^{-\alpha}\phi Kz}{b\Omega b'\gamma_{th}}P_e)^{c+1}\alpha\alpha'} \cdot {}_2F_1(c+1,\alpha';\alpha'+1;-\frac{L^\alpha b\Omega b'\gamma_{th}}{s\mu r_0^{-\alpha}\phi KzP_e}) \quad (27)$$

V. NUMERICAL RESULTS

In this section, the performance of Gamma approximation of CCI is first presented, through the comparison between the MGF of I and $\tilde{I}$. Then, in order to compare the network performance results with Monte-Carlo simulations, the numerical examples for the ergodic achievable rate and outage probability expressions are presented. We further aim to quantify the effects of the transmit power, deployment density of PBs, and the channel estimation error on the system performances which could shed some light on the system design.

Throughout this section, the number of antennas on PBs and D is equal to 2, while the number of antennas on S and interferers could be set as 2 or 4. The RF-to-DC power conversion efficiency is considered as $\mu = 60\%$. The distance between S and D is known as $r_0 = 20$m and the maximum distance between PB ans S is set as $L = 200$m. We also assume the exclusion distance as $r_c = 200$m, and the path-loss exponents of links as $\alpha = 3.5$, except otherwise stated. During one block time, $\tau = 30\%$ time slots are allocated for the energy harvesting, while the rest of the time slots are reserved for the information transmission. The time left for channel training in both phases is set as $\tau_t = 0.01\%$ and the

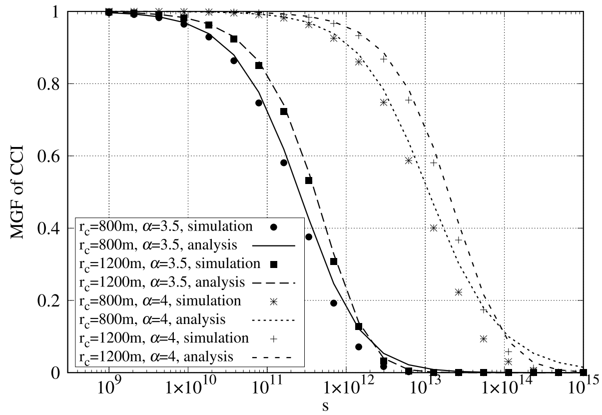

FIGURE 2. Comparison of MGF of CCI I and the Gamma approximation $\tilde{I}$.

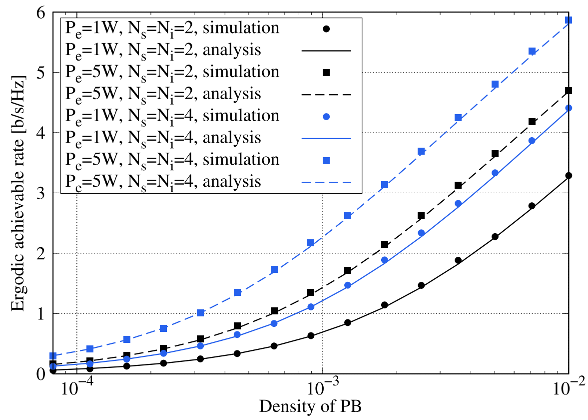

FIGURE 3. Achievable data rate versus density of PB with different N_s and P_e.

power for pilot sigals is set as $P_t = 0.01$W. The density of the interferers is set as $\rho' = 2 \times 10^{-5}\text{m}^{-2}$ and the transmit power of I is set as $\tilde{P} = 1$W. In the following figures, we use lines to represent the analytical results and points to denote the corresponding Monte-Carlo simulation results.

Fig. 2 exhibits the comparison between MGF of I and $\tilde{I}$, by setting the the exclusion distance r_c as 800m and 1200m, and α as 3.5 and 4. We observe that the Gamma approxiamtion can provides an acceptable fit to the true MGF of CCI for a wide range of variable values.

Fig. 3 shows the ergodic achievable rate of the information transmission versus PB density when the channel estimation error $\sigma_\epsilon^2 = 0.001$. The simulation is carried out by setting different values of the transmit power on PB, as $P_e = 1$W and 5W. By setting different values of N_s and N_i, the analytical results obtained from (8) match the simulation results accurately over a wide range of the PB density ρ. It could be readily observed that the ergodic achievable rate can be substantially improved by implementing more PBs or increasing the transmit power of PB.

Similarly, Fig. 4 presents the outage probability of the information transmission versus PB density with different value of N_s and N_i. Acceptable match is shown between the analytical results based on (23) and the simulation results,

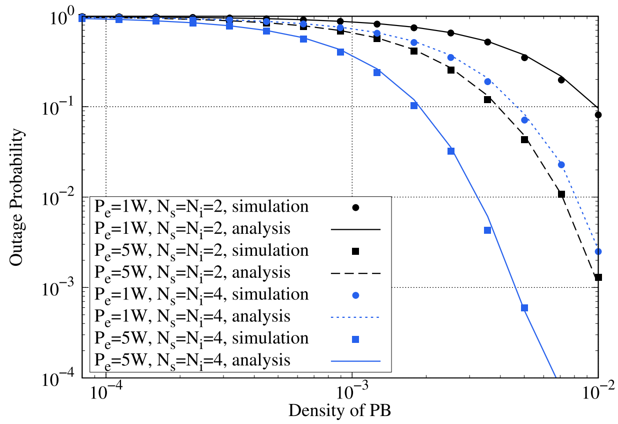

FIGURE 4. **Outage probability versus density of PB with different N_s and P_e.**

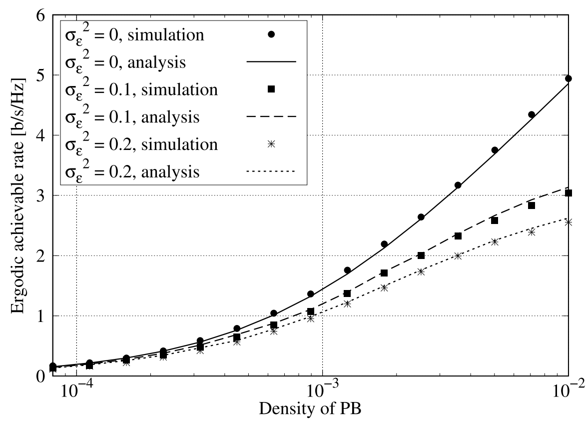

FIGURE 5. **Achievable data rate versus density of PB with different channel estimation errors.**

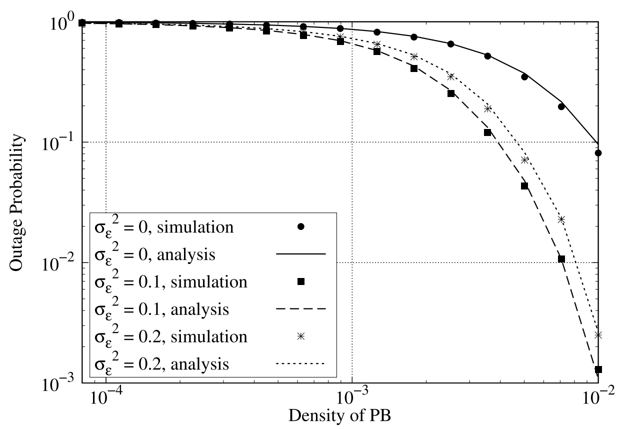

FIGURE 6. **Outage probability versus density of PB with different channel estimation errors.**

especially for the cases where the value of PB density is low or moderate. Since the CCI is approximated by a Gamma distributed variable, the analytical results of the outage probability deviate from the simulation results when the PB density is large.

Fig. 5 and Fig. 6 presents the influence of the channel estimation error on the ergodic achievable rate and the outage probability, respectively, when $P_e = 5$W and $N_s = N_i = 2$. The analytical results for $\sigma_\epsilon^2 = 0$ is obtained through (14) and (26). The performance degradation of the information transmission are presented with the increase of the channel estimation error in both figures.

VI. CONCLUSION

We have analytically investigated the network performance of WPC MIMO system. To this end, the ergodic achievable rate and the outage probability for information transmission were derived. The performance impact of the PB distribution density, PB transmit power, channel estimation errors and number of antennas was characterized by the obtained analytical results. Specifically, a semi-analytical expression for the ergodic achievable rate was derived by using MGF approaches. By approxiamting the interference by a Gamma distributed variable, the expression of outage probability for information transmission was obtained. The expression of performance can be further simplified in a special scenario. All analytical results were presented in compact semi-analytical forms and can be computed efficiently. Our analysis was validated by showing the excellent match between the results obtained through our exact expressions and those obtained via Monte Carlo simulations. The derived results could provide valuable insights for designing the practice WPC systems.

APPENDIX

PROOF OF PROPOSITION 1

Based on the useful lemma to computing the capacity of fading interference channel in [21], the ergodic achievable rate can be expressed by deriving both MGFs of signal term and interference term of γ_D. First of all, the MGF of the signal term $P_s\hat{\lambda}_0\, r_0^{-\alpha}$ can be evaluated as

$$
\begin{aligned}
\mathcal{M}_s(s) &= \mathbb{E}\Big[\exp\Big(-s\frac{\hat{\lambda}_0\, r_0^{-\alpha}}{(1-\tau-\tau_t)T} \\
&\quad\cdot\Big(\sum_{i\in\Psi}\mu(\tau-\tau_t)T\,\mathrm{tr}(\mathbf{G}_i^\dagger\mathbf{G}_i\mathbf{S}_i) - P_t\tau_t T\Big)\Big)\Big] \\
&= \mathbb{E}\Big[\exp\Big(-s\mu\hat{\lambda}_0\, r_0^{-\alpha}\phi\sum_{i\in\Psi}\mathrm{tr}((\hat{\mathbf{G}}_i^\dagger\hat{\mathbf{G}}_i \\
&\quad + r_i^{-\alpha}N_s\sigma_E^2\mathbf{I}_{N_p})\mathbf{S}_i)\Big)\cdot\exp(s\frac{\hat{\lambda}_0 r_0^{-\alpha}P_t\tau_t}{1-\tau-\tau_t})\Big] \\
&= \mathbb{E}\Big[\exp\Big(-s\mu\hat{\lambda}_0 r_0^{-\alpha}\phi\sum_{i\in\Psi}P_e r_i^{-\alpha}(\hat{\lambda}_i + N_s\sigma_E^2)\Big) \\
&\quad\cdot\exp(s\frac{\hat{\lambda}_0 r_0^{-\alpha}P_t\tau_t}{1-\tau-\tau_t})\Big] \\
&= \mathbb{E}\Big[\exp\Big(-s\mu\hat{\lambda}_0 r_0^{-\alpha}\phi\sum_{i\in\Psi}P_e r_i^{-\alpha}(\hat{\lambda}_i + N_s\sigma_E^2)\Big)\Big] \\
&\quad\cdot\mathbb{E}\Big[\exp(s\frac{\hat{\lambda}_0 r_0^{-\alpha}P_t\tau_t}{1-\tau-\tau_t})\Big]
\end{aligned}
\tag{28}
$$

By applying the pdf of λ_i and stochastic geometry tools, $\mathcal{M}_s(s)$ can be developed as

$$\begin{aligned}
&\mathbb{E}\Big[\exp\big(-s\mu\hat{\lambda}_0 r_0^{-\alpha}\phi\sum_{i\in\Psi}P_e r_i^{-\alpha}(\hat{\lambda}_i+N_s\sigma_E^2)\big)\Big]\\
&\overset{(a)}{=}\mathbb{E}_{\Psi,\hat{\lambda}_0}\Big[\prod_{i\in\Psi}\int_0^\infty \exp(-s\mu\hat{\lambda}_0 r_0^{-\alpha}\phi\frac{P_e}{r_i^\alpha}(\sigma_H^2 g+N_s\sigma_E^2))\\
&\quad\cdot\sum_{b=1}^{v}\sum_{c=t-v}^{(t+v)b-2b^2}\frac{b^{c+1}d_{b,c}}{c!}g^c\exp(-bg)\,dg\Big]\\
&\overset{(b)}{=}\mathbb{E}_{\hat{\lambda}_0}\Big[\exp\Big(-2\pi\rho\int_0^L\Big(1-\\
&\quad\sum_{b=1}^{v}\sum_{c=t-v}^{(t+v)b-2b^2}\frac{d_{b,c}\exp(-s\mu\hat{\lambda}_0 r_0^{-\alpha}\phi P_e r^{-\alpha}N_s\sigma_E^2)}{b^{-c-1}(s\mu\hat{\lambda}_0 r_0^{-\alpha}\phi P_e r^{-\alpha}\sigma_H^2+b)^{c+1}}\Big)r\,dr\Big)\Big]\\
&=\mathbb{E}_{\hat{\lambda}_0}\Big[\exp\Big(-2\pi\rho\big(L^2/2-C_{b,c}\big)\Big)\Big] \qquad (29)
\end{aligned}$$

where

$$\begin{aligned}
&C_{b,c}\\
&=\sum_{b=1}^{v}\sum_{c=t-v}^{(t+v)b-2b^2}\int_0^L\frac{d_{b,c}\exp(-s\mu\hat{\lambda}_0 r_0^{-\alpha}\phi P_e r^{-\alpha}N_s\sigma_E^2)}{(s\frac{\mu\hat{\lambda}_0 r_0^{-\alpha}\phi\sigma_H^2}{b}P_e r^{-\alpha}+1)^{c+1}}r\,dr
\end{aligned} \qquad (30)$$

In (29), (a) is obtained by incorporating the pdf of λ_i, (b) follows from the probability generating function (PGFL) for PPP, and $C_{b,c}$ is used to denote the summation in (c) for the sake of brevity. Then, the MGF of $\mathcal{M}_s(s)$ can be expressed by incorporating the pdf of $\hat{\lambda}_0$, written as

$$\begin{aligned}
&\mathcal{M}_s(s)\\
&=\sum_{b'=1}^{p}\sum_{c'=q-p}^{(q+p)b'-2b'^2}\frac{b'^{c'+1}d_{b',c'}}{c'!}\int_0^\infty\lambda_0^{c'}\\
&\quad\cdot\exp\big(2\pi\rho(C_{b,c}-\frac{L^2}{2})-b'\lambda_0\big)\cdot\exp(s\frac{\sigma_H^2\lambda_0 r_0^{-\alpha}P_t\tau_t}{1-\tau-\tau_t})\,d\lambda_0
\end{aligned} \qquad (31)$$

where $\hat{\lambda}_0$ in (30) is replaced by $\sigma_H^2\lambda_0$.

Similarly, the MGF of the interference term of γ_D is given by

$$\begin{aligned}
&\mathcal{M}_i(s)\\
&=\mathbb{E}[\exp(-s\sum_{j\in\Theta}\tilde{P}_j|\tilde{h}_j|^2 r_j^{-\alpha})]\\
&\overset{(a)}{=}\mathbb{E}_\Theta[\prod_{j\in\Theta}(1+s\tilde{P}r_j^{-\alpha})^{-1}]\\
&=\exp\Big(-2\pi\rho'\int_{r_c}^\infty\frac{s\tilde{P}r^{-\alpha}r}{1+s\tilde{P}r^{-\alpha}}dr\Big)\\
&\overset{(b)}{=}\exp\big(-\frac{2\pi\rho' s\tilde{P}}{(\alpha-2)r_c^{\alpha-2}}\,{}_2F_1(1,1-\frac{2}{\alpha};2-\frac{2}{\alpha};-\frac{s\tilde{P}}{r_c^\alpha})\big)
\end{aligned} \qquad (32)$$

where (a) is obtained by incorporating the exponential distribution of $|\tilde{h}_j|^2$, and (b) follows from [23, eq. (3.194.1)]. ■

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