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IRS-Assisted RF-Powered IoT Networks: System Modeling and Performance Analysis

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Abstract—Emerged as a promising solution for future wireless communication systems, intelligent reflecting surface (IRS) is capable of reconfiguring the wireless propagation environment by adjusting the phase-shift of a large number of reflecting elements. To quantify the gain achieved by IRSs in the radio frequency (RF) powered Internet of Things (IoT) networks, in this work, we consider an IRS-assisted cellular-based RF-powered IoT network, where the cellular base stations (BSs) broadcast energy signal to IoT devices for energy harvesting (EH) in the charging stage, which is utilized to support the uplink (UL) transmissions in the subsequent UL stage. With tools from stochastic geometry, we first derive the distributions of the average signal power and interference power which are then used to obtain the energy coverage probability, UL coverage probability, overall coverage probability, spatial throughput and power efficiency, respectively. With the proposed analytical framework, we finally evaluate the effect on network performance of key system parameters, such as IRS density, IRS reflecting element number, charging stage ratio, etc. Compared with the conventional RF-powered IoT network, IRS passive beamforming brings the same level of enhancement in both energy coverage and UL coverage, leading to the unchanged optimal charging stage ratio when maximizing spatial throughput.

Index Terms—Intelligent reflecting surface, Internet of Things, RF-powered IoT network, coverage probability, spatial throughput, power efficiency, stochastic geometry.

I. INTRODUCTION

WITh the booming Internet of Things (IoT), the number of IoT devices is expected to reach tens of billions. To meet the vision of sustainable development of the IoTs, an efficient utilization of energy has been served as the principal issue. Recent advances in wireless energy harvesting (EH) technology, particularly radio frequency (RF) EH [1], have broken new ground to support IoT devices to collect energy from natural energy sources or ambient RF sources. It gave birth to the wireless powered communication networks (WPCNs) [2] in which wireless nodes harvest energy from the base station (BS) RF signals and then transmit information by using the harvested energy. However, one of the major technical challenges in WPCN is the low efficiency of power transmission over long distances, resulting in the limited amount of energy harvested and poor network performance.

In recent years, the application of intelligent reflect surface (IRS) technology has attracted extensive attentions in wireless communications from both academia and industry. Served as a promising candidate technology for future wireless communications, IRS can smartly reconfigure the wireless channels by electronically configuring the absorption, reflection, refraction and phases via tuning the IRS reflecting elements or meta-atoms [3], [4]. Compared with the traditional active relaying or beamforming scheme, the passive reflection of IRSes consumes very limited energy by adopting the low-cost elements [5]. Moreover, by properly adjusting the phase-shifts of IRS reflecting elements, the coverage probability, network throughput and energy efficiency can be greatly improved.

Using IRSs to boost the availability of WPCNs, IRS-assisted WPCN can be served as a potential network paradigm for future wireless communications. Understanding the gain achieved by IRSs in RF-powered IoT network is of great significance to speed up the application of IRSs and also help in the ingenious design of IRS-assisted WPCNs. The application of IRSs in WPCNs has been discussed in the very recent works [6], [7], [8], [9], [10], [11], [12], [13]. The authors in [6], [7], [8] considered the IRS-assisted WPCN...
In such a network, the spatial randomness of node locations, the time-varying channel fading, and the resulted complicated signal and interference distributions (caused by the reflection of IRSs) made it extremely difficult to evaluate the gain achieved by IRSs. To address the aforementioned challenges, stochastic geometry has been explored over the past few years as a powerful tool in obtaining the average spatial throughput and the power efficiency, respectively. We then evaluate the influence of some key system parameters, such as BS density, IRS density and IRS reflecting element number on the derived performance metrics.

- With the Gamma approximation method, we first characterize the signal power distributions in both charging and UL stages, and the interference distribution in the UL stages, based on which we further derive the tractable expressions of the energy coverage probability in the charging stage, the UL coverage probability in the UL stage, the overall coverage probability, the spatial throughput and the power efficiency, respectively. We then evaluate the influence of some key system parameters, such as BS density, IRS density and IRS reflecting element number on the derived performance metrics.

- Compared with the conventional RF-powered IoT network, IRS passive beamforming significantly enhances the harvested signal power in the charging stage and the desired signal power in the UL stage, both of which are shown to scale with the number of IRS reflecting elements.
increasing the interference power. With the objective to maximize the network spatial throughput, the proposed framework allows to find the optimal charging stage ratio of the IRS-assisted RF-powered IoT network, which is shown to be the same as that without IRSs due to the same level of enhancement contributed by IRS passive beamforming on energy coverage and UL coverage.

II. SYSTEM MODEL

A. Network Model

In this paper, we consider an IRS-assisted cellular-based IoT network where the IoT devices are battery-less and solely powered by the ambient RF energy only from cellular transmissions [27], [28]. We focus on the UL transmission, where the energy required by an IoT device to transmit in a given time slot should be harvested in the same time slot. Specifically, all IoT devices are assumed to adopt the time-switching receiver architecture, with which an IoT device first harvests energy for a fraction of time and then transmits packets for the rest of time. As is shown in Fig. 1(a), each time slot is divided into the charging stage and UL stage with durations $T_{ch} = \tau T$ and $T_{tr} = (1 - \tau)T$, in which $T$ is the duration of each time slot, and $\tau$ is defined as the charging stage ratio. The antenna switching time between the two stages is neglected to facilitate the analysis. The IoT device is assumed to have a supercapacitor with large charging and discharging rates to store and use the harvested energy during the same time slot. The remaining energy by the end of the time slot is assumed to be unavailable for the future transmissions taking into account the large leakage current of the supercapacitor [28]. We assume that both BSs and IoT devices are equipped with the single antenna. The BSs are assumed to have the same height $H_B$ with horizontal locations following a 2-dimensional (2D) PPP $\Lambda_B$ of density $\lambda_B$. Distributed IRSs are deployed to assist in both EH and UL transmissions, which are of the same height $H_I$ with the horizontal locations being modeled by a 2D PPP $\Lambda_I$ of density $\lambda_I$. IoT devices are scattered according to a PPP $\Lambda_u$ of density $\lambda_u$. We adopt the orthogonal multiple access technology, such that only one IoT device within a cell can be active at any given time slot and sub-channel.

We assume open access and consider the nearest association policy, with which a given IoT device associates with the nearest BS, as well as the nearest IRS. According to Slivnyak’s theorem [29], it is sufficient to focus on a typical IoT device, referred to as UE 0 which is located at the origin and assumed to associate with BS 0 and IRS 0 (Fig. 1(b) and 1(c)). We define $x_m, d_j$ and $r_{m,j}$ as the 2D distance from the BS $m$ to UE 0, the 2D distance from the IRS $j$ to UE 0, and the 2D distance from the BS $m$ to IRS $j$, respectively. Considering the limited reflective capability of an IRS, we define a practical local region of radius $D$ with the typical UE 0 being the center, so that each IRS can only provide services for a limited number of UEs nearby. We denote IRSs within the local region by the set $j \triangleq \{j \in \Lambda_I | d_j \leq D\}$. Due to the densely deployed IRSs, we assume that there exists at least one IRS within set $j$, and ignore the case $j = \emptyset$. We consider the worst case where all IRSs are in working state no matter whether there are IoT devices to associate with, such that all IRSs can reflect the signal/interference from co-channel BSs to the typical UE 0. Considering the severe attenuation of wireless signals, the interference reflected by far away IRSs can be neglected. Thus, to simplify the analysis, we assume that only IRSs within set $j$ contribute interference to the typical UE 0.

B. IRS-Assisted EH and UL Transmission

As is shown in Fig. 1(b), in the charging stage, all the BSs are served as RF chargers to broadcast energy signals. In Fig. 1(c), during the UL stage, the IoT device with sufficient harvested energy transmits packets to its served BS. In both stages, all the IRSs within set $j$ provide signal enhancement via random scattering or passive beamforming. Specially, to assist the EH and UL transmissions of UE 0, dedicated passive
beamforming is adopted at its associated IRS 0, while other IRSs within $D$ only scatter the incident signal of BS 0.

To support the UL transmission, the energy collected in the charging stage should reach a certain energy threshold $E_{\text{min}}$, which is defined as the minimum energy required for the subsequent UL transmission. We adopt the fractional power control strategy for IoT devices where the transmit power of the typical IoT device is $\rho(x_0^2 + H_B^2)^{\alpha/2}$ with $x_0$ denoting the 2D distance between UE 0 and its serving BS, $\rho$ is the BS receiver sensitivity, and the symbol $\epsilon \in (0, 1]$ is defined as the power control parameter. According to the fractional power control strategy, $E_{\text{min}}$ is given by

$$E_{\text{min}} = (1 - \tau)T\rho(x_0^2 + H_B^2)^{\alpha/2}. \quad (1)$$

Define $E_h$ as the energy harvested by UE 0 during a charging stage, and UE 0 is allowed to transmit during the subsequent UL stage, as long as $E_h \geq E_{\text{min}}$ is satisfied.

C. Channel Model

For the sake of simplicity, we assume single antenna for both BSs and UEs, and define $N$ as the number of reflecting elements per IRS. We consider both the large-scale path loss and small-scale fading to characterize the channel model. For large-scale fading, the path loss exponent of BSs and IRSs is denoted by $\alpha$ with $\alpha > 2$. We consider Rayleigh fading with unit power for the small-scale fading, which leads to an exponential channel power gain. Define $\sigma^2$ as the additive white Gaussian noise (AWGN). In the following, we discuss the channel model in charging stage and UL stage, respectively.

1) Charging Stage: In the charging stage, it is necessary to measure how much energy has been collected at the typical IoT device which depends upon the channel power gain. The baseline equivalent channels between BS $m$ and IRS $j$, between IRS $j$ and UE 0, and between BS $m$ and UE 0 are represented by $a_{i,m}^{(j)} \triangleq \left[a_{i,m,1}, \ldots, a_{i,m,N}\right] \in \mathbb{C}^{N \times 1}$, $a_{i}^{(j)} \triangleq \left[a_{i,1}, \ldots, a_{i,N}\right] \in \mathbb{C}^{N \times 1}$, and $a_{d,m} \in \mathbb{C}$, respectively, where the symbols $[\cdot]^T$ and $\mathbb{C}$ denote the matrix transpose and the collection of complex numbers, respectively. 2. Define $\phi_{i}^{(j)} \triangleq \left[\phi_{i,1}^{(j)}, \ldots, \phi_{i,N}^{(j)}\right]$ and $\Phi(\cdot) \triangleq \text{diag}\left\{e^{j\phi_{1}^{(j)}}, \ldots, e^{j\phi_{N}^{(j)}}\right\}$ (i denotes the imaginary unit) as the phase-shift matrix of IRS $j$, where $\phi_{i}^{(j)} \in [0, 2\pi)$ is the phase-shift of the element $n$ of IRS $j$ on the incident signal. To achieve the maximal beamforming gain from IRS, we presume that the reflection coefficient of each reflecting element can achieve the unit amplitude [30]. Therefore, the cascaded BS-IRS-UE channel which is divided into BS-IRS transmission, IRS reflecting and IRS-UE transmission, is given by

$$a_{i,r,m}^{(j)} \triangleq \left[a_{i,m,1}^{(j)}, \ldots, a_{i,m,N}^{(j)}\right]^T \Phi(\cdot) \alpha_{i,r}^{(j)} = \sum_{n=1}^{N} a_{i,m,n}^{(j)} a_{r,n}^{(j)} e^{j\phi_{n}^{(j)}}, \quad m \in \Lambda_B. \quad (2)$$

The channel power gains between BS $m$-UE 0, between BS $m \in \Lambda_B$ and the element $n$ of IRS $j$, and between the element $n$ of IRS $j$ and UE 0 are, respectively, given by

$$|a_{d,m}|^2 = g_{d,m} \omega_{d,m}, \quad |a_{r,n}|^2 = g_{r,n} \omega_{r,n}, \quad |a_{i}|^2 = g_{i} \omega_{i,m,n}. \quad (3)$$

In (3), $g_{d,m} = \beta(x_0^2 + H_B^2)^{-\alpha/2}$, $g_{r,n} = \beta(r^2_m + (H_B - H_1)^2)^{-\alpha/2}$ and $g_{i} = \beta(d^2_f + H_1^2)^{-\alpha/2}$ denote the corresponding average channel power gains, $\omega_{d,m}$, $\omega_{r,n}$ and $\omega_{i,m,n}$ are the small scale fading, and $\beta = (4\pi f_c/c)^{-2}$ is the average channel power gain at a reference distance of 1 m with $f_c$ being the carrier frequency, and $c = 3.0 \times 10^8 \text{ (m/s)}$ denoting the light speed. To reveal the effectiveness of IRSs in assisting the performance of commercial 5G networks operating on sub-6 GHz, we consider $f_c = 2 \text{ GHz}$ as the carrier frequency.

2) UL Stage: For the UL stage, the baseband equivalent channels between UE $k$ and IRS $j$, between IRS $j$ and BS 0, and between UE $k$ and BS 0 are denoted by $b_{i,k}^{(j)} \triangleq \left[b_{i,k,1}^{(j)}, \ldots, b_{i,k,n}^{(j)}\right] \in \mathbb{C}^{N \times 1}$, $b_{i,k}^{(j)} \triangleq \left[b_{i,k,1}, \ldots, b_{i,k,N}\right]^T \in \mathbb{C}^{N \times 1}$ and $b_{d,k} \in \mathbb{C}$, respectively. Define $\varphi_{i}^{(j)} \triangleq \left[\varphi_{i,1}^{(j)}, \ldots, \varphi_{i,N}^{(j)}\right]$ and $\Psi(\cdot) \triangleq \text{diag}\left\{e^{j\varphi_{1}^{(j)}}, \ldots, e^{j\varphi_{N}^{(j)}}\right\}$ as the phase-shift matrix of IRS $j$, of which $\varphi_{i}^{(j)} \in [0, 2\pi]$ represents the phase-shift of reflecting element $n$ on the incoming signal. Therefore, the cascaded UE-IRS-BS channel can be decomposed into three components: UE-IRS transmission, IRS reflecting, and IRS-BS transmission, expressed as

$$b_{i,r,k}^{(j)} \triangleq \left[b_{i,k}^{(j)}\right]^T \Psi(\cdot) b_{i,k}^{(j)} = \sum_{n=1}^{N} b_{i,k,n} h_{r,n} e^{j\varphi_{n}^{(j)}}, \quad k \in \Lambda_u. \quad (4)$$

The channel power gains between UE $k$ and BS 0, between UE $k$ and the element $n$ of IRS $j$, and between the element $n$ of IRS $j$ and BS 0 are, respectively, given by

$$|b_{d,k}|^2 = \beta d_{k} \epsilon_{s,d,k}, \quad |b_{i,k,n}|^2 = f_{i,k} \epsilon_{s,i,k,n}^{(j)}, \quad |b_{r,n}|^2 = f_{r} \epsilon_{s,r,n}^{(j)} \epsilon_{s,r,n}^{(j)} \epsilon_{s,r,n}^{(j)}. \quad (5)$$

where $f_{d,k} = \beta(y_k^2 + H_B^2)^{-\alpha/2}$, $f_i = \beta d_{k,j}^2 + H_1^2)^{-\alpha/2}$ and $f_r = \beta(d_f^2 + H_1^2)^{-\alpha/2}$ denote the corresponding average channel power gains, $\epsilon_{s,d,k}$, $\epsilon_{s,i,k,n}^{(j)}$ and $\epsilon_{s,r,n}^{(j)}$ are the small scale fading. The symbol $y_k$ denotes the horizontal distance from UE $k$ to the tagged BS, and $D_k$ is the horizontal distance from the $k$-th device to its associated BS. According to the fractional power control strategy, the transmit power of UE $k$ is $\rho D_k^2 + H_B^2)^{\alpha/2}$. To determine the transmit power of UE $k$, $\rho$. To determine the transmit power of UE $k$, $\rho$.
we obtain the distribution of $D_k$ conditioned on $y_k$ [14], which is given by
\begin{equation}
f_{D_k}(r|y_k) = \frac{2\pi\lambda_0 r \exp(-\pi\lambda_0 r^2)}{1 - \exp(-\pi\lambda_0 y_k^2)}, \quad 0 \leq r \leq y_k.
\end{equation}

\section*{D. Channel Power Statistics}
To facilitate the performance analysis, we need to first derive the channel power statistics caused by the involvement of IRSs in charging stage and UL stage, respectively.

\textit{1) Charging Stage:} In the charging stage, IoT devices harvest energy from the RF signals of BSs with the help of IRSs. With regards to the link BS $m$-IRS $j$-UE 0 in (2), the reflected channel via element $n$ can be derived by
\begin{equation}
a_{ir,m,n}^{(j)} \triangleq a_{i,m,n}^{(j)} a_{r,n} e^{j\phi_n^{(j)}},
\end{equation}
where the channel amplitude $|a_{ir,m,n}^{(j)}| \triangleq |a_{i,m,n}^{(j)}| |a_{r,n}^{(j)}|$ and the cascade channel phase $\angle a_{ir,m,n}^{(j)} \triangleq \phi_n^{(j)} + \angle a_{i,m,n}^{(j)} + \angle a_{r,n}^{(j)}$.

What’s more, the amplitudes $|a_{i,m,n}^{(j)}|$ and $|a_{r,n}^{(j)}|$ follow the Rayleigh distribution with the scale parameters being $g_{r,m}^{(j)}$ and $g_{r,n}^{(j)}$, respectively. As a result, each channel amplitude $|a_{ir,m,n}^{(j)}|$ is a double-Rayleigh RV with independent $|a_{i,m,n}^{(j)}|$ and $|a_{r,n}^{(j)}|$. We can derive the expectation and variance of $|a_{ir,m,n}^{(j)}|$ as
\begin{align}
\mathbb{E} \left\{ |a_{ir,m,n}^{(j)}| \right\} & \triangleq \frac{\pi}{4} \sqrt{g_{r,m}^{(j)} g_{r,n}^{(j)}}, \\
\text{var} \left\{ |a_{ir,m,n}^{(j)}| \right\} & \triangleq \left( 1 - \frac{\pi^2}{16} \right) g_{r,m}^{(j)} g_{r,n}^{(j)}.
\end{align}

According to the central limit theorem (CLT), the summation of $N$ independent and identically distributed (i.i.d.) RVs $X_1, X_2, \ldots, X_N$, i.e., $Y = \sum_{n=1}^{N} X_n$, can be approximated as a Gaussian distribution when $N$ is sufficiently large.

With the IRS-customized channel estimation method [31], [32], we can obtain the reflection cascade channel phase of each element on IRS 0. To be specific, IRS 0 can reconfigure each reflecting element’s phase-shift by setting
\begin{equation}
\phi_n^{(0)} = -\angle (g_{i,0,n}^{(0)} g_{r,n}^{(0)}), \quad n = 1, \ldots, N,
\end{equation}
leading to the same phase of all $N$ reflected signals at UE 0, where $g_{i,0,n}^{(0)}$ and $g_{r,n}^{(0)}$ is defined as the average channel power gains between BS 0 and the element $n$ of IRS $0$ and between the element $n$ of IRS 0 and UE 0, respectively. As a result, the signal at the typical UE 0 is the sum of $N$ reflected signals. Thus, the BS 0-IRS 0-UE 0 channel can be derived by
\begin{equation}
|a_{ir,0}^{(0)}| = |a_{i,0}^{(0)}| |a_{r,0}^{(0)}| = \sum_{n=1}^{N} |a_{i,0,n}^{(0)}| |a_{r,n}^{(0)}|,
\end{equation}
which is the summation of $N$ i.i.d. double-Rayleigh RVs, the channel amplitude is approximated to follow the Gaussian distribution
\begin{equation}
|a_{ir,0}^{(0)}| \approx \mathcal{N} \left( N \frac{\pi}{4} \sqrt{g_{i,0}^{(0)} g_{r,0}^{(0)}}, N \left( 1 - \frac{\pi^2}{16} \right) g_{i,0}^{(0)} g_{r,0}^{(0)} \right).
\end{equation}

Therefore, the average signal power of the cascaded BS 0-IRS 0-UE 0 channel can be computed by the second moment of $|a_{ir,0}^{(0)}|$ which is obtained by
\begin{equation}
g_{ir,0}^{(0)} \triangleq \mathbb{E} \left\{ |a_{ir,0}^{(0)}|^2 \right\} = \left[ \frac{\pi^2}{16} N^2 + \left( 1 - \frac{\pi^2}{16} \right) N \right] g_{i,0}^{(0)} g_{r,0}^{(0)},
\end{equation}
where $G_{sc} = \left[ \frac{\pi^2}{16} N^2 + \left( 1 - \frac{\pi^2}{16} \right) N \right]$ denotes the beamforming coefficient of $g_{i,0}^{(0)} g_{r,0}^{(0)}$, growing with $N$ in the order of $O(N^2)$.

With regards to any other IRS $j \in j$ without providing beamforming for UE 0, it scatters the incident signal from BS $m$ randomly, leading to a uniformly random phase $\angle a_{i,m,n}^{(j)}$ based on $\angle a_{i,m,n}^{(j)}$ and $\angle a_{r,n}^{(j)}$. Therefore, for each reflecting element $N$, the cascaded channel $a_{ir,m,n}^{(j)}$ has zero mean and independent in-phase and quadrature-phase components each with variance $\frac{1}{2} a_{i,m,n}^{(j)} a_{r,n}^{(j)}$. According to the CLT, for a practically large $N$, we can approximate both the in-phase and quadrature-phase of $a_{ir,m,n}^{(j)} = \sum_{n=1}^{N} a_{i,m,n}^{(j)}$ by Gaussian distribution $\mathcal{N}(0, \frac{1}{2} a_{i,m,n}^{(j)} a_{r,n}^{(j)})$. As a result, we use the following CSGC distribution to approximate the BS $m$-IRS $j$-UE 0 channel, given by
\begin{equation}
a_{ir,m,n}^{(j)} \approx \mathcal{CN} \left( 0, N g_{i,m,n}^{(j)} g_{r,n}^{(j)} \right).
\end{equation}

Thus, the average channel power of BS $m$-IRS $j$-UE 0 link can be derived by
\begin{equation}
g_{ir,m,n}^{(j)} \triangleq \mathbb{E} \left\{ |a_{ir,m,n}^{(j)}|^2 \right\} = N g_{i,m}^{(j)} g_{r,n}^{(j)}.
\end{equation}

\textit{2) UL Stage:} In the UL stage, IoT devices that harvest sufficient energy transmit packets to their serving BSs with the help of IRSs. With regards to the tagged BS 0, considering the link UE $k$-IRS $j$-BS 0 in (4), the reflected channel via element $n$ can be derived by
\begin{equation}
b_{ir,k,n}^{(j,k)} \triangleq g_{i,k,n}^{(j,k)} e^{j\phi_n^{(j,k)}} = |b_{i,k,n}^{(j,k)}| e^{j\phi_n^{(j,k)}} |b_{r,n}^{(j,k)}| e^{j\phi_n^{(j,k)}},
\end{equation}
where the channel amplitude $|b_{ir,k,n}^{(j,k)}| \triangleq |b_{i,k,n}^{(j,k)}| |b_{r,n}^{(j,k)}|$ and the cascade channel phase $\angle b_{ir,k,n}^{(j,k)} \triangleq \phi_n^{(j,k)} + \angle b_{i,k,n}^{(j,k)} + \angle b_{r,n}^{(j,k)}$.

What’s more, the amplitudes $|b_{i,k,n}^{(j,k)}|$ and $|b_{r,n}^{(j,k)}|$ follow the Rayleigh distribution with the scale parameters being $f_{i,k}^{(j,k)}$ and $f_{r}^{(j,k)}$, respectively. Similarly, the amplitude of the UE 0-IRS 0-BS 0 channel is derived as
\begin{equation}
|b_{ir,0}^{(0)}| = |b_{i,0}^{(0)}| |b_{r,0}^{(0)}| = \sum_{n=1}^{N} |b_{i,0,n}^{(0)}| |b_{r,n}^{(0)}|,
\end{equation}
which for large $N$ is approximated as Gaussian distribution.
\begin{equation}
|b_{ir,0}^{(0)}| \approx \mathcal{CN} \left( N \frac{\pi}{4} \sqrt{f_{i,0}^{(0)} f_{r}^{(0)}}, N \left( 1 - \frac{\pi^2}{16} \right) f_{i,0}^{(0)} f_{r}^{(0)} \right).
\end{equation}

For a sufficiently large $N$, we can use the CSGC distribution to approximate the UE $k$-IRS $j$-BS 0 channel, which is obtained by
\begin{equation}
b_{ir,k,n}^{(j)} \approx \sum_{n=1}^{N} b_{i,k,n}^{(j)} \approx \mathcal{CN} \left( 0, N f_{i,k}^{(j)} f_{r}^{(j)} \right).
\end{equation}
Therefore, the UE 0-IRS 0-BS 0 and UE k-IRS j-BS 0 average channel power are, respectively, given by
\[
\begin{align*}
    f_{ir,0}^{(0)} & \triangleq \mathbb{E} \left[ |a_{ir,0}^{(0)}|^2 \right] = G_{sc} f_t^{(0)}, \\
    f_{ir,k}^{(j)} & \triangleq \mathbb{E} \left[ |a_{ir,k}^{(j)}|^2 \right] = N f_t^{(j)},
\end{align*}
\]
where \( G_{sc} \triangleq \left[ \pi^2 N^2 + (1 - \pi^2)N \right] \) denotes the beamforming coefficient of \( f_{t,0}^{(0)} \), growing with \( N \) in the order of \( O(N^2) \).

### E. Performance Metrics

In this subsection, we detail the performance metrics considered in this work. To be specific, we consider the following metrics: energy coverage probability in the charging stage, UL coverage probability during the UL stage, overall coverage probability, and network spatial throughput.

1) **Energy Coverage Probability:** Define \( P_t \) as the BS transmit power. Under the condition that UE 0 is associated with the nearest BS 0, the amount of energy harvested from BS 0 is composed of the following three parts: from the direct transmission of BS 0, from the reflected transmission through IRS 0 performing beamforming, and from the reflected transmission through other IRSs \( \in j \) performing random scattering. Specifically, the harvested signal power from BS 0 is obtained by
\[
S_{dr} \triangleq P_t \cdot |a_{d,0} + \sum_{j \in j} |a_{ir,0}^{(j)}|^2. \tag{21}
\]
Similarly, the amount of harvested signal power from BS \( m \in \Lambda_B \setminus \{0\} \) consists of the following two parts: from the direct transmission of BS \( m \), and from the reflected transmission through all IRSs \( \in j \) performing random scattering. To be specific, the harvested signal power from BS \( m \) can be derived as
\[
S_{id} \triangleq P_t \cdot \sum_{m \in \Lambda_B \setminus \{0\}} |a_{d,m} + \sum_{j \in j} |a_{ir,m}^{(j)}|^2. \tag{22}
\]
In summary, the overall amount of harvested energy at UE 0 is given by
\[
E_h = \tau T \eta (S_{dr} + S_{id}) \quad \text{Joules}, \tag{23}
\]
where \( \eta < 1 \) indicates the RF energy conversion efficiency. To simplify the analysis, we adopt the linear energy-harvesting model as in [7] and assume that the input power to the circuit of receiver belongs to the low power regime without saturation of EH. Note that our work can be extended to the non-linear EH models by considering the saturation regime. To show the effectiveness of EH, we define the energy coverage probability during the charging stage, which is given by
\[
P_{en} \triangleq \mathbb{E} \left[ \mathbb{I} \{ E_h \geq E_{\min} \} \right], \tag{24}
\]
where \( E_{\min} = (1 - \tau)T \rho (x_0^2 + H_0^2)^{\alpha/2} \) in (1) with \( \mathbb{I} (\cdot) \) being the indicator function.

2) **UL Coverage Probability:** According to the UL fractional power control strategy, the transmit power of UE 0 and UE \( k \in \Lambda_u \setminus \{0\} \) is, respectively, given by \( P_h = \rho (x_0^2 + H_0^2)^{\alpha/2} \) and \( P_k = \rho (x_k^2 + H_k^2)^{\alpha/2} \). The desired signal received at the tagged BS 0 is composed of direct signal from UE 0 and the reflected signal of UE 0 via all IRSs \( \in j \) (i.e., performing beamforming and random scattering). Therefore, we derive received signal power by
\[
S_{UL} \triangleq \rho (x_0^2 + H_0^2)^{\alpha/2} \cdot |b_{d,0} + \sum_{j \in j} b_{ir,0}^{(j)}|^2. \tag{25}
\]
After the charging stage, the active IoT devices that are harvesting sufficient energy and transmitting on the same time-frequency resource block with UE 0 can be approximated to follow a PPP \( \sim \Lambda_u \) of density \( \lambda_u = P_{en} \lambda_B \) with \( P_{en} = \mathbb{E} \left[ \mathbb{I} \{ E_h \geq E_{\min} \} \right] \) given by (24). Therefore, the overall interference received by BS 0 is given by
\[
I \triangleq \sum_{k \in \Lambda_u \setminus \{0\}} I_k = \sum_{k \in \Lambda_u \setminus \{0\}} \rho (D_k^2 + H_k^2)^{\alpha/2} |b_{d,k} + \sum_{j \in j} b_{ir,k}^{(j)}|^2. \tag{26}
\]
The received SINR at BS 0 is given by
\[
\gamma \triangleq \frac{S_{UL}}{I + \sigma^2} = \frac{\rho (x_0^2 + H_0^2)^{\alpha/2} \cdot |b_{d,0} + \sum_{j \in j} b_{ir,0}^{(j)}|^2}{\sum_{k \in \Lambda_u \setminus \{0\}} \rho (D_k^2 + H_k^2)^{\alpha/2} |b_{d,k} + \sum_{j \in j} b_{ir,k}^{(j)}|^2 + \sigma^2}. \tag{27}
\]
The UL coverage probability is actually a conditional coverage probability under the condition that the typical UE 0 has harvested sufficient energy by
\[
P_{ul} \triangleq \mathbb{P} \{ \gamma \geq \tau | E_h \geq E_{\min} \}, \tag{28}
\]
where \( \tau \) is the SINR threshold.

3) **Overall Coverage Probability:** By definition, the overall coverage probability is defined as the joint probability of the aforementioned two events, which can be expressed by
\[
P_{cov} \triangleq \mathbb{E} \left[ \mathbb{I} \{ E_h \geq E_{\min} \} \mathbb{I} (\gamma \geq \tau) \right]. \tag{29}
\]
4) **Spatial Throughput:** Based on the overall coverage probability, the average spatial throughput can be obtained as
\[
\nu = \left(1 - \tau \right) \lambda_u \mathbb{E} \left[ \log (1 + \tau | E_h \geq E_{\min} \} \right] \times \mathbb{I} (\gamma \geq \tau) \}= \left(1 - \tau \right) \mathbb{E} [\log (1 + \gamma)] P_{cov}, \tag{30}
\]
where \( P_{en} \) and \( P_{cov} \) are given by (24) and (29), the expressions of which will be derived in the following section.

5) **Power Efficiency:** We consider the following two performance metrics to illustrate the power efficiency: energy harvesting efficiency (EHE) [33] in the charging stage and energy efficiency (EE) [34] in the UL stage, where the former is defined as the amount of power scavenged by all the IoT devices per unit power consumed by the BS, while the latter refers to the number of bits transmitted by an IoT device per Joule. The EHE can be expressed as
\[
E_{\text{HCE}} = \frac{\mathbb{E} [E_h] \lambda_u}{\tau T \lambda_B (P_{cb} + \frac{T}{\eta})}, \tag{31}
\]
where $\mathbb{E}\{E_k\}$ is the average amount of energy harvested by the typical UE 0 during the charging stage, $\eta_j \in (0, 1]$ represents the efficiency of the power amplifier efficiency of a BS, $P_{cb}$ and $P_l$ denote the static power and transmit power of a BS, respectively. The EE of the typical UE 0 can be expressed as

$$\mathcal{EE} = \frac{(1 - \tau)T \log (1 + \tau)P_{\text{cov}}}{\langle P_{il} + \frac{1}{T} \mathbb{E}\{P_l\} \rangle (1 - \tau)T},$$

where the numerator denotes the number of bits transmitted within the UL stage, and the denominator represents the average energy consumption of the typical UE 0 with $\mathbb{E}\{P_l\}$ being the transmit power, $\eta_j \in (0, 1]$, being the efficiency of the power amplifier efficiency of an IoT device, and $P_{\text{cov}}$ being the static power of typical UE 0, respectively.

### III. Performance Analysis

In this section, we first study the signal power distribution in both stages, and then characterize the interference distribution in the UL stage. The aforementioned performance metrics are finally obtained.

#### A. Signal Power Distribution

The signal power distribution is related not only to the charging stage, but also the UL stage. To be specific, in the charging stage, all BSs broadcast energy signals which are harvested by IoT devices. While in the UL stage, for BS 0, only that originated from UE 0 is the desired signal.

In the charging stage, the energy harvested from BSs is contributed from both the direct signal and the reflected signals via all IRSs within set $j$. In the following, we first derive the signal power distribution from BS 0 conditioned on $x_0$ and $d_0$. The overall conditional signal can be expressed as $a_{d_0} + \sum_{j \in \{j \neq 0\}} a_{d_0}^{(j)}$, the summation of a RV of Rayleigh distribution and $N$ RVs of Gaussian distribution. Because of the difficulty in deriving the exact signal power distribution from BS 0, we use the Gamma distribution [35] as an alternative. Specifically, we use Gamma distribution to approximate the distribution of $S_{dr}$, given by

$$S_{dr}|d_{0},x_{0} \approx \mathcal{G}[\kappa_{dr}, \theta_{dr}],$$

where $\kappa_{dr}$ and $\theta_{dr}$ represent the shape parameter and scale parameter, respectively. With the moment matching technique [36], we have

$$\kappa_{dr} = \frac{\mathbb{E}\{S_{dr}|d_{0},x_{0}\}^2}{\text{var}\{S_{dr}|d_{0},x_{0}\}}, \quad \theta_{dr} = \frac{\text{var}\{S_{dr}|d_{0},x_{0}\}}{\mathbb{E}\{S_{dr}|d_{0},x_{0}\}}.$$

To obtain $\kappa_{dr}$ and $\theta_{dr}$, we derive the first and second moments of $S_{dr}$ conditioned on $d_{0}$ and $x_{0}$.

$$\mathbb{E}\{S_{dr}\}|d_{0},x_{0} \approx P_l \cdot (\mathbb{E}\{a_{1}^2\}|d_{0},x_{0}) + \mathbb{E}\{a_{2}^2\}|d_{0},x_{0}),$$

$$\mathbb{E}\{S_{dr}^2\}|d_{0},x_{0} = P_l \cdot (\mathbb{E}\{a_{1}^4\}|d_{0},x_{0}) + \mathbb{E}\{a_{2}^4\}|d_{0},x_{0}) + 4 \mathbb{E}\{a_{1}^2\}|d_{0},x_{0} \mathbb{E}\{a_{2}^2\}|d_{0},x_{0}).$$

The first two moments of $S_{dr}|d_{0},x_{0}$ can be derived by the first two moments of $a_{1}, a_{2}, |a_{1}|^2$ and $|a_{2}|^2$. With the similar method proposed in Appendix B of [19] and the approximation of $r_{0,j} \approx x_{0j}$, $g_{0}^{(j)} \approx g_{d_0}$ for $j \in j$, the first two moments of $a_{1}, a_{2}, |a_{1}|^2$ and $|a_{2}|^2$ can be derived by

$$\mathbb{E}\{a_{1}\}|d_{0},x_{0} = 0, \quad \mathbb{E}\{a_{2}\}|d_{0},x_{0} = 0,$$

$$\mathbb{E}\{|a_{1}|^2\}|d_{0},x_{0} = 0, \quad \mathbb{E}\{|a_{2}|^2\}|d_{0},x_{0} = 0,$$

$$\mathbb{E}\{|a_{1}|^4\}|d_{0},x_{0} \approx g_{d_0}(1 + G_{sc}g_{0}^{(0)} + N \frac{\pi}{4} \sqrt{\pi g_{0}^{(0)}}),$$

$$\mathbb{E}\{|a_{2}|^4\}|d_{0},x_{0} \approx 2\left(\frac{\pi^3 N^3}{64} + \frac{3\pi N^2(1 - \frac{\pi^2}{16})}{4}\left[g_{0}^{(0)}\right]^2\right) + \frac{\pi^4 N^4}{256} + \frac{3N^2(1 - \frac{\pi^2}{16})^2}{8}\left[g_{0}^{(0)}\right]^2,$$

$$\mathbb{E}\{|a_{2}|^4\}|d_{0},x_{0} \approx N g_{d_0} E_{S_{1}}(d_0),$$

$$\mathbb{E}\{|a_{2}|^4\}|d_{0},x_{0} \approx 2N^2 g_{d_0}^2 E_{S_{2}}(d_0),$$

where $g_{d_0}$ and $g_{0}^{(0)}$ denote the average channel power gain of the BS 0-UE 0 and IRS 0-UE 0 link, i.e.,

$$g_{d_0} \triangleq \beta \left(\frac{\alpha_0^2 + H_0^2}{2}\right)^{-\frac{\beta}{2}}, \quad g_{0}^{(0)} \triangleq \beta \left(d_0^2 + H_0^2\right)^{-\frac{\beta}{2}},$$

and $E_{S_{1}}$ denotes the expectation of $\sum_{j \in \{j \neq 0\}} g_{r_{0,j}}$ which is given by

$$E_{S_{1}}(d_0) = \frac{2\pi \lambda_1 \beta}{\alpha - 2} \left[(d_0^2 + H_0^2)^{-\frac{\beta}{2}} - (D^2 + H_0^2)^{-\frac{\beta}{2}}\right],$$

and

$$E_{S_{2}}(d_0) = \frac{\pi \lambda_1 \beta^2}{\alpha - 1} \left[(d_0^2 + H_0^2)^{-\alpha} - (D^2 + H_0^2)^{-\alpha}\right].$$

Therefore, we can derive the first and second moments of $S_{dr}$ conditioned on $d_{0}$ and $x_{0}$. The variance is derived by $\text{var}\{S_{dr}\}|d_{0},x_{0} \triangleq E\{S_{dr}^2\}|d_{0},x_{0} - (E\{S_{dr}\}|d_{0},x_{0})^2$. By substituting the above expressions into (34), we derive the shape parameter $\kappa_{dr}$ and $\theta_{dr}$, respectively.

Based on (35), (39), (41) and (42), the conditional mean signal power is the product of $g_{d_0}$ and $\kappa_{dr}(d_0) \triangleq 1 + G_{sc}g_{0}^{(0)} + N \frac{\pi}{4} \sqrt{\pi g_{0}^{(0)} + NE_{S_{1}}(d_0)}$ which depends on the locations of BS 0 and IRS 0. The dominant term in $\kappa_{dr}(d_0)$ is $G_{sc}g_{0}^{(0)}$ which scales in $O(N^2)$ or $O(d_0^{-\frac{\beta}{2}})$ when $d_0$ is sufficiently small. For the large $d_0$, the IRS power gain is given by $G_{sc}g_{0}^{(0)} \leq 1$ and hence $\kappa_{dr}(d_0) \approx 1$. It reveals that when UE 0 is closer to IRS 0, IRS 0 provides more power gain.
Then we derive the harvested signal power originated from all BSs \( m \in \Lambda_B \setminus \{0\} \) and reflected by IRSs \( j \in J \), which is given by
\[
S_{id} \triangleq \sum_{m \in \Lambda_B \setminus \{0\}} S_{id}^{(m)} = P_t \left[ \sum_{m \in \Lambda_B \setminus \{0\}} g_{d,m} \right] + N \sum_{j \in J} \left( g_{j,m} + \sum_{m \in \Lambda_B \setminus \{0\}} g_{j,m} \right).
\] (47)

We consider the following approximation \( g_{j,m} \approx g_{d,m} \) for \( j \in J \), and thus, we have \( S_{id}^{(m)} \approx v_S g_{d,m} \) and hence
\[
S_{id} \approx P_t v_S \sum_{m \in \Lambda_B \setminus \{0\}} g_{d,m},
\] (48)
where \( v_S = 1 + N \sum_{j \in J} g_{j,m} \) represents the relative power gain of reflecting or scattering paths originated from IRSs in \( j \) over the direct path.

To characterize the distribution of the signal power \( S_{id} \) originated directly from other BSs and reflected via all IRSs, we first derive the Laplace transform \( \mathcal{L}_{S_{id} | d_0, x_0}(s) \) in Lemma 1, in which the instantaneous signal power \( S_{id} \) can be approximated by
\[
S_{id} \approx P_t v_S \sum_{m \in \Lambda_B \setminus \{0\}} g_{d,m} \omega_m.
\] (49)

According to (49), conditioned on \( x_0 \), \( \mathbb{E}\{S_{id}\} \) is given by
\[
\mathbb{E}\{S_{id}\} | x_0 \approx P_t v_S \sum_{m \in \Lambda_B \setminus \{0\}} g_{d,m} \omega_m | x_0 = \left( P_t(1 + N E_{S1}(0)) \omega_m \right) \int_{x_0}^{\infty} g_d(x) x dx
\]
\[
= \frac{2 \pi \beta \lambda_B (1 + N E_{S1}(0)) P_t \left( \frac{\alpha - 2}{\omega_m \lambda_B} \right) x_0^2 + H_B^2}{\left( \alpha - 2 \right) (x_0^2 + H_B^2)^{\alpha - 2}}.
\] (50)

Note that \( a \) is due to the PPP-distributed BS locations and \( \mathbb{E}\{v_S\} = N E_{S1}(0) \) based on (44).

**Lemma 1:** Conditioned on \( d_0 \) and \( x_0 \), the Laplace transform of \( S_{id} \) is given by
\[
\mathcal{L}_{S_{id} | d_0, x_0}(s) \triangleq \mathbb{E}\{e^{-s S_{id}} | d_0, x_0 \} \approx \exp \left( -2 \pi \lambda_B U_s \right),
\] (51)

where the function \( U \) is defined as
\[
U(x) \triangleq \frac{\pi}{\alpha \sin \left( \frac{\pi}{\alpha} \right)} \left( \beta x \right)^{\frac{\alpha}{2}} - \frac{x^2 + H_B^2}{2} x^2 
\times F_1 \left( 1, \frac{\alpha}{2}, \frac{\alpha}{2} - 1, \frac{1}{g_{d,0}}, x \right).
\] (52)

with \( g_{d,0} \equiv g_d(x) \big|_{x=x_0} \) and \( 2 F_1 \) being the Gauss hypergeometric function [37].

**Proof:** The results can be proved by a minor modification of Proposition 4 in [19]. We omit the full proof due to the space limitation. \( \square \)

Thus, the cumulative distribution function (CDF) of \( S_{id} | d_0, x_0 \) can be derived via the inverse Laplace transform of (51), i.e.,
\[
F_{S_{id} | d_0, x_0}(x) = \mathcal{L}^{-1} \left[ \frac{1}{s} \mathcal{L}_{S_{id} | d_0, x_0}(s) \right](x),
\] (53)
which can be computed directly in standard computing software, such as Wolfram Mathematica.

We then study the UL signal power distribution in the UL stage. Similar to the charging stage, we still use Gamma distribution to approximate the conditional distribution \( S_{UL} \) which is given by
\[
S_{UL} | d_0, x_0 \approx \Gamma[k_{UL}, \theta_{UL}].
\] (54)

With the moment matching technique [36], we have
\[
k_{UL} \triangleq \frac{\mathbb{E}\{S_{UL}\} | d_0, x_0)^2}{\mathbb{E}\{S_{UL}\} | d_0, x_0}, \quad \theta_{UL} \triangleq \frac{\mathbb{E}\{S_{UL}\} | d_0, x_0}{\mathbb{E}\{S_{UL}\} | d_0, x_0}.
\] (55)

To obtain \( k_{UL} \) and \( \theta_{UL} \), we derive the first and second moments of \( S_{UL} \) conditioned on \( d_0 \) and \( x_0 \),
\[
\mathbb{E}\{S_{UL}\} | d_0, x_0 \approx P_0 \cdot (\mathbb{E}\{|b_1|^2\} | d_0, x_0 + \mathbb{E}\{|b_2|^2\} | d_0, x_0),
\] (56)
\[
\mathbb{E}\{S_{UL}^2\} | d_0, x_0 \approx P_0 \cdot (\mathbb{E}\{|b_1|^2\} | d_0, x_0 + \mathbb{E}\{|b_2|^2\} | d_0, x_0 + 4 \mathbb{E}\{|b_1|^2\} | d_0, x_0 \mathbb{E}\{|b_2|^2\} | d_0, x_0).
\] (57)

The first two moments of \( S_{UL} | d_0, x_0 \) are determined by the first two moments of \( b_1, b_2, |b_1|^2 \) and \( |b_2|^2 \). Following the similar approach to derive the first and second moment of \( S_{dr} | d_0, x_0 \) and the approximation of \( r_{0,j} \approx x_0 \), \( j_{f,0} \approx f_{0,d} \) for \( j \in J \), we can obtain the first two moments of \( b_1, b_2, |b_1|^2 \) and \( |b_2|^2 \) by replacing \( a_1, a_2, g_{d,0} \) and \( g_{0,0} \) in (37)–(42) with \( b_1, b_2, f_{0,d} \) and \( f_{0,0} \).

Finally, by integrating \( \mathbb{E}\{S_{UL}\} | d_0, x_0 \) over \( d_0 \) and \( x_0 \), we obtain \( \mathbb{E}\{S_{UL}\} \) by
\[
\mathbb{E}\{S_{UL}\} = \int_0^b \int_0^D \mathbb{E}\{S_{UL}\} | d_0, x_0 f_{d_0}(d_0) f_{x_0}(x_0) dd_0 dx_0,
\] (58)
where \( f_{d_0}(d_0) \) and \( f_{x_0}(x_0) \), denote the probability density functions (PDFs) of \( d_0 \) and \( x_0 \) given by,
\[
f_{d_0}(d_0) \triangleq 2 \pi \lambda_B d_0 e^{-\lambda_B d_0^2},
\] (59)
\[
f_{x_0}(x_0) \triangleq 2 \pi \lambda_B x_0 e^{-\lambda_B x_0^2}.
\] (60)

**B. Interference Power Distribution**

We derive the interference power distribution in the UL stage in this subsection. Specifically, the interference is from active users transmitting information in the same time-frequency resource block.

Referring to (18), the UE \( k \)-IRS \( j \)-BS 0 channel has been approximated by the CSCG distribution \( \mathcal{CN} \left( 0, N F_{f,k} f_{r,j} \right) \).

Since both the direct interference channel and the cascaded UE \( m \)-IRS \( j \)-BS 0 channel follow the CSCG distribution, the composite interference channel \( b_{d,k} + \sum_{j \in J} b_{r,k} \) from UE \( k \in \Lambda_k \setminus \{0\} \) is the summation of independent CSCG RVs, which follows the CSCG distribution with zero mean.
and covariance $\mathbb{E}\{ |b_{d,k}|^2 \} + \sum_{j \in \mathcal{J}} \mathbb{E}\{ |b_{d,k}^{(j)}|^2 \}$. Therefore, the composite interference power $I_k = |b_{d,k}|^2 + \sum_{j \in \mathcal{J}} |b_{d,k}^{(j)}|^2$ follows an exponential distribution with the expression given by

$$I_k \triangleq T_k \xi_k = P_k \left( f_{d,k} + N \sum_{j \in \mathcal{J}} f_{i,k}^{(j)} \right) \xi_k, \quad (61)$$

where $T_k$ is the average interference power and $\xi_k \overset{\text{dist}}{=} \xi \sim \text{exp}(1)$. Therefore, given the locations of IoT devices and IRSs, the aggregated interference power from all the active UEs is given by

$$\sum_{k \in \Lambda_u \setminus \{0\}} \mathbb{E}\{ |b_{d,k}|^2 \} + \sum_{j \in \mathcal{J}} \mathbb{E}\{ |b_{d,k}^{(j)}|^2 \}.$$

To derive the spatial throughput later, we first obtain the interference power distribution conditioned on $d_0$ and $x_0$, which can be represented by the Laplace transform of the aggregated interference in Lemma 2. The aggregated interference can be expressed as

$$I \overset{\text{def}}{=} \sum_{k \in \Lambda_u \setminus \{0\}} P_k f_{d,k} \xi_k.$$

By using the approximation $r_{k,j} \approx y_k, f_{r}^{(j)} \approx f_{d,k}$ for $j \in \mathcal{J}$, we have $T_k \approx v_1 f_{d,k}$ and

$$\mathbb{E}\{ I \} \approx v_1 \sum_{k \in \Lambda_u \setminus \{0\}} P_k f_{d,k}, \quad (64)$$

**Lemma 2:** The Laplace transform of interference power conditioned on $d_0$ and $x_0$ is given by

$$\mathcal{L}_I|_{d_0,x_0}(s) = \exp\left\{ -2\pi \lambda^2 \left( s v_1 + \rho \right) \right\},$$

where the function $U_1(\cdot)$ is defined as

$$U_1(x) \triangleq \int_0^\infty \int_0^y 1 \frac{2 \pi \lambda \Lambda D_k e^{-\lambda_\alpha \pi D_k^2}}{1 + x(y^2 + H_B^2)^{-\alpha/2}(D_k^2 + H_B^2)^{-\alpha/2}} \delta D_k y \delta y.$$

**Proof:** See Appendix A. \qed

Based on (64) and $\xi_k \overset{\text{dist}}{=} \xi \sim \text{exp}(1)$, the mean interference power is given by

$$\mathbb{E}\{ I \} \approx v_1 \mathbb{E}\{ \xi \} \mathbb{E}\{ v_1 \} \mathbb{E}\{ \sum_{k \in \Lambda_u \setminus \{0\}} f_{d,k} \} = v_1 E_1, \quad (67)$$

where $E_1$ denotes the expectation of the summation of direct channel power from interfering UEs $k \in \Lambda_u \setminus \{0\}$ conditioned on $x_0$, which is given by

$$E_1 \overset{(a)}{=} 2\pi \lambda^2 \int_0^\infty \int_0^y 2\pi \lambda e^{-\lambda_\alpha \pi D_k^2} \left( D_k^2 + H_B^2 \right)^{-\alpha/2} \cdot \left( y^2 + H_B^2 \right)^{-\alpha/2} \delta D_k \delta y, \quad (68)$$

Note that (a) is due to the PPP-distributed UEs locations, which helps calculate the aggregated interference over the 2D plane.

**C. Coverage Probability and Spatial Throughput**

In this section, we derive the energy coverage probability and UL coverage probability. In separate stages based on the derived signal power distribution and interference power distribution, which leads to the overall coverage probability and spatial throughput eventually.

1) Energy Coverage Probability: Based on the derived channel power gain distribution in (33), we derive the energy coverage probability in Theorem 1.

**Theorem 1:** The probability that the energy harvested in the charging stage is higher than $E_{\text{min}}$ is given by

$$\mathbb{P}_{\text{en}} = \int_{x_0=0}^\infty \int_{d_0=0}^D \mathbb{P}_{\text{en}|_{d_0,x_0}}(f_{d_0}(d_0) f_{x_0}(x_0) d_0 dx_0) \delta d_0 dx_0, \quad (69)$$

where $\mathbb{P}_{\text{en}|_{d_0,x_0}}$ is the conditional energy coverage probability given by

$$\mathbb{P}_{\text{en}|_{d_0,x_0}} \approx \mathbb{P}\{ S_{\text{dr}} > C(\tau) \} |_{d_0,x_0} + \mathbb{P}\{ S_{\text{id}} > C(\tau) \} |_{d_0,x_0}
+ \mathbb{P}\{ S_{\text{dr}} + S_{\text{id}} > C(\tau) \} |_{d_0,x_0}
\cdot \mathbb{P}\{ S_{\text{dr}} < C(\tau) \} |_{d_0,x_0}
- \mathbb{P}\{ S_{\text{dr}} > C(\tau) \} |_{d_0,x_0} \cdot \mathbb{P}\{ S_{\text{id}} < C(\tau) \} |_{d_0,x_0}, \quad (70)$$

while for $k_{\text{dr}}$ is less than the given threshold $\bar{k}_{\text{dr}}$, the conditional probabilities of $\{ S_{\text{dr}} > C(\tau) \}, \{ S_{\text{id}} > C(\tau) \}$ and $\{ S_{\text{dr}} + S_{\text{id}} > C(\tau) \} |_{d_0,x_0}$ are, respectively, given by

$$\mathbb{P}\{ S_{\text{dr}} > C(\tau) \} |_{d_0,x_0}
\approx \sum_{i=0}^{k_{\text{dr}}-1} \left( -1 \right)^i \frac{\partial^i}{\partial s^i} \left[ \mathcal{L}_{S_{\text{id}}}|_{d_0,x_0}(s) \right]_{s=1}, \quad (71)$$

$$\mathbb{P}\{ S_{\text{id}} > C(\tau) \} |_{d_0,x_0}
\approx 1 - \mathcal{L}^{-1} \left[ \frac{1}{8} \mathcal{L}_{S_{\text{id}}}|_{d_0,x_0}(s) \right](z), \quad (72)$$

$$\mathbb{P}\{ S_{\text{dr}} + S_{\text{id}} > C(\tau) \} |_{d_0,x_0}
\approx \sum_{i=0}^{k_{\text{dr}}-1} \left( -1 \right)^i \frac{\partial^i}{\partial s^i} \left[ \exp \left\{ \frac{-s C(\tau)}{\theta_{\text{dr}}} + 2\pi \lambda_B U \left( s v_1 + \rho \right) \right\} \right]_{s=1}. \quad (73)$$

**Proof:** See Appendix B. \qed

**Remark 1:** It is worth noting that there exists correlation between the two events $\{ S_{\text{dr}} > C(\tau) \}$ and $\{ S_{\text{id}} > C(\tau) \}$, which is extremely hard to derive. Thus, to simplify the analysis, we ignore the correlation and assume that the two
events are independent. We will show that the approximation is acceptable in Fig. 2 in the numerical results part.

2) UL Coverage Probability: Due to the correlation between the locations of BSs and scheduled IoT devices, it’s challenging to derive the exact UL analysis [14]. The authors in [14] proposed an approximation method by assuming that the locations of devices follow a PPP and handling the dependence between the locations of BSs and scheduled IoT devices, it's challenging to derive the exact UL analysis [14]. The authors in [14] proposed an approximation method by assuming that the locations of devices follow a PPP and handling the dependence between the locations of BSs and scheduled IoT devices, it's challenging to derive the exact UL analysis [14].

Theorem 2: The probability that the received SINR of the typical UE 0 is greater than a given threshold $\gamma$ is given by

$$P_{UL} = \int_{x_0=0}^{\infty} \int_{d_0=0}^{D} P_{UL\mid d_0,x_0} f_{d_0}(d_0) f_{x_0}(x_0) dd_0 dx_0,$$  \hspace{1cm} (74)

where $P_{UL\mid d_0,x_0}$ is the conditional coverage probability given by

$$P_{UL\mid d_0,x_0} \approx \sum_{i=0}^{k_{UL} - 1} \frac{(-1)^i}{i!} \frac{\partial^i}{\partial \tau^i} \left[ - \frac{s\sigma W}{\theta_{UL}} - 2\pi\lambda_{UL} U_{I} \left( \frac{s\sigma U_{I}}{\theta_{UL}} \right) \right]_{s=1}.$$  \hspace{1cm} (75)

Proof: See Appendix C.  \hspace{1cm} □

Remark 2: The results derived in (74) degenerates into the traditional regularly powered IRS-assisted UL transmission case without EH, by setting $P_{en} = 1$ and $\lambda_0 = \lambda_{B}$.

In both Theorem 1 and Theorem 2, we need to discuss the scale parameters $k_{dr}$ and $k_{UL}$ of Gamma distribution. For non-integer $k_{dr}$ ($k_{UL}$), its upper and lower bounds are utilized to approximate the conditional energy (UL) coverage probability. Take Theorem 1 as an example, we approximate $P_{en\mid d_0,x_0}$ by the following linear combination [19].

$$P_{en\mid d_0,x_0} = \Omega P_{en\mid d_0,x_0,\lfloor k \rfloor} + (1 - \Omega) P_{en\mid d_0, x_0,\lfloor k \rfloor},$$  \hspace{1cm} (76)

where $\lfloor \cdot \rfloor$ and $\lceil \cdot \rceil$ are the ceiling and floor functions, and $\Omega$ is the weight between the ceiling and is the weight functions given by

$$\Omega \triangleq \frac{\zeta (\lceil k \rceil - k)}{\zeta (\lfloor k \rfloor - k) + (k - \lfloor k \rfloor)},$$  \hspace{1cm} (77)

where $\zeta > 0$ is a parameter to illustrate the relationship between $P_{en\mid d_0,x_0}$ and $k$. The weights $\Omega$ and $(1 - \Omega)$ are set as $\Omega = M_{\lceil k \rceil} - M_{\lfloor k \rfloor}$. 

For the large value of $k$, we approximate the Gamma distribution to the normal distribution with $\mu \triangleq \mathbb{E}\{ S \}_{d_0,x_0}$ as the mean value, and $\sqrt{\text{var} \{ S \}}_{d_0,x_0}$ as the standard deviation. Since the former is much larger than the latter, $S$ can be approximated by $\mu$.

According to Theorem 1 and Theorem 2, we derive the overall coverage probability in the next subsection.

3) Overall Coverage Probability and Spatial Throughput: With the derived energy coverage probability and UL coverage probability, we obtain the overall coverage probability in this subsection.

Corollary 1: The overall coverage probability $P_{cov}$ of the typical UE 0 is

$$P_{cov} = P_{en} \times P_{UL},$$  \hspace{1cm} (78)

where $P_{en}$ and $P_{UL}$ are given by (69) and (74), respectively.

Proof: By definition, the overall coverage probability can be derived by multiplying the energy coverage probability by the UL coverage probability.  \hspace{1cm} □

Remark 3: Note that the proposed analytical framework can be used to characterize the regularly powered IRS-assisted UL IoT network performance by specializing some system parameters. To be specific, the parameters that lead to the result $P_{en} \rightarrow 1$, for instance, a large BS density $\lambda_{UL}$, a large number of reflecting elements $N$, or a sufficiently large $\tau$ result in the regularly powered IRS-assisted UL IoT network. In this case, the coverage probability is equivalent to $P_{UL}$ in (74) by setting $\lambda_0 = \lambda_{B}$.

By definition, the spatial throughput $\nu$ in (30) can be derived by substituting $P_{en}$ and $P_{cov}$ in (69) and (78), respectively. The complete expression of spatial throughput is omitted to keep concise.

4) Power Efficiency: The EHE in charging stage and EE in UL stage can be calculated by substituting the expressions of $\{ E_{dr} \}$ and $\{ P_0 \}$ into (31) and (32), which are given by

$$\mathbb{E}\{ E_{dr} \} = \tau T_\eta \times \int_0^{\infty} \int_0^D \left( \mathbb{E}\{ S_{dr} \}_{d_0,x_0} + \mathbb{E}\{ S_{id} \}_{x_0} \right) f_{d_0}(d_0) f_{x_0}(x_0) dd_0 dx_0,$$  \hspace{1cm} (79)

$$\mathbb{E}\{ P_0 \} \sim \int_0^{\infty} \rho(x_0^2 + H_B^2\frac{c_0}{2} f_{x_0}(x_0) dx_0,$$  \hspace{1cm} (80)

where $f_{x_0}(x_0)$, $f_{d_0}(d_0)$, $\mathbb{E}\{ S_{dr} \}_{d_0,x_0}$ and $\mathbb{E}\{ S_{id} \}_{x_0}$ are given by (59), (60), (35) and (50), respectively.

Remark 4: The following technical challenges should be addressed when modifying the proposed analytical framework to adapt to the multiple-antenna BS case. Firstly, both active beamforming precoder/receiver at BSs and passive beamforming design of IRSs should be considered, and jointly optimized to maximize the network performance in charging stage and UL stage. Secondly, the signal power distributions in both charging stage and UL stage, and the interference distribution in UL stage are dependent on the joint beamformer design, which is unknown for the multiple-antenna BS case in the large-scale network scenario.
IV. NUMERICAL RESULTS

In this section, the analytical (Ana.) framework is verified via extensive simulations (Sim.) by evaluating the network performance in terms of energy coverage probability, UL coverage probability, overall coverage probability, network spatial throughput and power efficiency, respectively. To show the superiority of IRSs in enhancing the coverage probability, we choose the traditional RF-powered IoT network considered in [28] as a benchmark. Compared to the IRS-assisted RF-powered IoT network, the only difference is that there are no IRSs existing in the traditional RF-powered IoT network, denoted by “W/o IRS” in the simulations. Unless otherwise specified, we use the default values of the system parameters given in (69) in Theorem 4. The mean signal power $P_s = 46$ dBm [39], [40], $N = 1000$, $f_c = 2$ GHz, $\sigma^2 = -147$ dBm, $D = 25$ m, $\rho = -78.5$ dBm, $\eta = 0.5$, $\epsilon = 0.8$, $T = 0.01$ s, $\tau = 0.5$, $P_{th} = 2.5$ W, $P_{en} = 20$ mW [34] and $\eta_b = 0.2$ [33].

A. Energy Coverage Probability

In this subsection, we characterize the impact of IRSs in the charging stage by setting $\zeta = 0.5$ in (77). Fig. 2 depicts the energy coverage probability $P_{en}$ given in (69) in Theorem 4 along with the probabilities of events $\{S_{ul} > C(\gamma)\}$, $\{S_{ul} > C(\tau)\}$, and $\{S_{ul} + S_{id} > C(\gamma)\} \cap \{S_{dr} < C(\tau)\}$, respectively. We observe a very perfect match between the theoretical analysis and the simulation results except for $P_{en}$. The reason for this is that we ignore the correlation between the events $\{S_{ul} > C(\gamma)\}$ and $\{S_{ul} > C(\tau)\}$ to simplify the analysis, and the independent approximation leads to an acceptable gap. In Fig. 2, we observe that $P_{en}$ increases with the time slot ratio $\tau$. This is intuitive since a larger $\tau$ provides more opportunities for an IoT device to harvest energy, leading to a higher $P_{en}$.

In Fig. 3, we quantify the gains achieved by IRS beamforming in the charging stage by varying the IRS reflecting element number $N$. We observe that increasing BS density $\lambda_0$ or IRS reflecting element number $N$ leads to a higher $P_{en}$. This can be explained by the fact that a denser BS deployment or a larger IRS enhances the harvested RF power. Compared to the conventional network scenario without IRS deployment, IRS-assisted EH scheme with passive beamforming results in a more than 30% enhancement in $P_{en}$ for $N = 4000$ with BS density $\lambda_0 = 10^{-3}$ m$^{-2}$. Moreover, when $\lambda_0$ achieves $\lambda_0^*$, i.e., $\lambda_0^* = 5 \times 10^{-3}$ m$^{-2}$ for the given system parameters, the energy coverage condition $\{E_h \geq E_{min}\}$ satisfies with an extremely high probability, resulting in $P_{en} \rightarrow 1$.

B. UL Coverage Probability

In this subsection, we focus on the performance analysis of the UL transmission mode by setting $\zeta = 1$ in (77). In Fig. 4, the UL coverage probability is evaluated by varying SINR threshold $\tau$ and IRS reflecting element number $N$, with the conventional UL coverage probability without IRSs being given as a benchmark. We observe that $P_{UL}$ reduces with the increasing SINR threshold $\tau$, and grows with the element number $N$. This is because the passive beamforming gain provided by IRSs increases with $N$ in the order of $O(N^2)$ which enlarges the UL received signal power and hence the UL coverage probability. Compared to the benchmark, the coverage enhancement achieved by IRS passive beamforming can be as large as 0.65 with $N = 4000$ for $\gamma = 0$ dB.

In Fig. 5, we evaluate the UL coverage probability $P_{UL}$ as a function of IRS density $\lambda_1$ and IRS reflecting element number $N$. From Fig. 5, we find that $P_{UL}$ grows with the increasing $\lambda_1$ and $N$. This can be explained by the fact that $\lambda_1$ is large enough to achieve a full energy coverage, i.e., $P_{en} = 1$, and passive beamforming gain provided by IRS dominates the growing interference contributed by IRS random scattering, resulting in a higher $P_{UL}$.

C. Overall Coverage Probability and Network Spatial Throughput

In this subsection, we focus on the overall coverage probability and network spatial throughput. In Fig. 7, we set
BS density $\lambda_B = 5 \times 10^{-3}$ m$^{-2}$ and evaluate $P_{\text{en}}$, $P_{\text{UL}}$ and $P_{\text{cov}}$ with and without IRSs as a function of charging stage ratio $\tau$. To show the availability of the proposed IRS-assisted RF EH scheme, we plot the coverage probability with regularly powered IoT devices as the benchmark. In this case, all IoT devices are full of energy which is equivalent to $P_{\text{en}} = 1$. We observe that when $\tau$ reaches a certain value, $P_{\text{en}}$ approaches 1 and hence, $P_{\text{UL}}$ approaches $P_{\text{cov}}$. This is because although a growing $\tau$ enlarges the density of interferer which declines $P_{\text{UL}}$, the improvement in $P_{\text{en}}$ dominates the reduction in $P_{\text{UL}}$, leading to the growth in $P_{\text{cov}}$. By comparing with the traditional network without IRS deployment, we observe the significant superiority of IRS passive beamforming in both $P_{\text{en}}$ and $P_{\text{UL}}$. By comparing with the regularly powered benchmark, we observe that when $\tau$ reaches a certain value, i.e., $\tau = 0.4$ for the IRS case, the RF powered IoT network achieves nearly the same overall coverage probability as that of the regularly powered IoT network. What’s more, even for the regularly powered IoT network, IRSs passive beamforming brings huge enhancement in coverage, more than 0.3 with the given parameters. The comprehensiveness of the proposed analytical framework lies in that it degenerates into the IRS-assisted regularly-power IoT network when $P_{\text{en}} = 1$ is satisfied.

Fig. 8 depicts the overall coverage probability $P_{\text{cov}}$ by varying charging stage ratio $\tau$ for different power control factors $\epsilon$. We observe that a larger $\epsilon$ results in a lower $P_{\text{cov}}$. Note that $E_{\text{min}} = (1 - \tau)T\rho(\gamma_0^2 + H_0^2)^{\epsilon/2}$, a larger $\epsilon$ leads to an increasing $E_{\text{min}}$, which results in the decline of $P_{\text{en}}$, leading to a lower $P_{\text{cov}}$.

In Fig. 9, we evaluate the average spatial throughput $\nu$ as a function of charging stage ratio $\tau$ and power control factor $\epsilon$. We observe that there exists an optimal $\tau$ to maximize the average spatial throughput $\nu$. A larger $\epsilon$ requires a higher proportion $\tau$ to achieve the largest spatial throughput.
D. Power Efficiency

The average spatial throughput is related to the product of $(1 - \tau)$, $P_{en}$ and $P_{cov}$. In addition, a tradeoff exists between $\tau$ and $P_{en}$. When $\epsilon = 0.6$, $E_{min}$ is easy to satisfy, and the spatial throughput is dominated by $\tau P_{cov}$. On the other hand, as $\epsilon$ further enlarges, $E_{min}$ grows exponentially and the spatial throughput is limited by $P_{en}$. In this case, a larger $\tau$ is required to achieve a higher spatial throughput. As $P_{en}$ grows to a certain value, $\tau$ dominates the spatial throughput, resulting in the decline of spatial throughput. Compared to the case without IRSs, we observe that deploying IRSs can greatly enhance the achievable network spatial throughput, while does not change the trend of $\nu$ as a function of the charging stage ratio $\tau$, and hence the the optimal $\tau$ that maximizes $\nu$. This is because with IRS passive beamforming, both the harvested signal power in the charging stage and the desired signal power in the UL stage are shown to scale with $N$ in the same order of $O(N^2)$, while only slightly increases the interference power, leading to the same level of enhancements in $P_{en}$ and $P_{UL}$.

D. Power Efficiency

In Fig. 10, we evaluate EHE as a function of IRS density $\lambda_1$ for different IRS reflecting elements number $N$. We observe that the EHE increases with both $\lambda_1$ and $N$. However, since the average distance between an IoT device and its associated BS is as large as 15.8 m, the EHE is small due to the large path loss. Compared to the traditional RF-powered network without IRSs, the higher EHE achieved by the IRS-assisted RF-powered network is credited to the passive beamforming gain.

In Fig. 11, we evaluate EE as a function of charging stage ratio $\tau$ for different power control factors $\epsilon$. We observe that as $\tau$ increases, the EE first increases and then converges to a constant value. A smaller $\epsilon$ results in a higher EE. Due to the power control strategy, the power consumption of an IoT device is mainly dependent on the static power $P_{cu}$, and thus, the tendency of EE is dominated by the overall coverage probability $P_{cov}$. The variation of EE with $\tau$ can be explained by the tendency of $P_{cov}$ with $\tau$, as discussed in Fig. 7. What’s more, referring to Fig. 8, a smaller $\epsilon$ leads to a higher $P_{cov}$, and thus a larger EE. The comparison with the traditional RF-powered network without IRSs shows the effectiveness of IRS beamforming in information transfer.

V. Conclusion

In this work, we evaluated the effect of IRS passive beamforming gain on an IRS-assisted RF-powered IoT network. We adopted the time-switch architecture in which each time slot was partitioned into the charging stage and UL stage, where IRS beamforming was adopted in both EH and UL packet transmission. With the Gamma approximation method, we first characterized the signal power distribution in both charging stage and UL stage, and the interference power distribution in the UL stage. Then, we derived the analytical expressions of energy coverage probability, UL coverage probability, overall coverage probability network spatial throughput and power efficiency. By comparing with the conventional RF-powered IoT network without IRSs, we quantified the gain achieved by IRSs in both EH and information transfer. We also optimized the time slot ratio to maximize the network spatial throughput. There are several interesting concrete future directions to extend this work. One possible direction is to consider the multiple-antenna BS network scenario with the joint optimization of active/passive beamformer design being the focus. Another possible direction is to consider the application of IRSs-assisted RF-powered IoT networks to the mmWave or sub-THz frequency band.

APPENDIX A

Conditioned on $d_0$ and $x_0$, the Laplace transform of the interference power from other BSs as

$$L_{I|d_0,x_0}(s) \triangleq \mathbb{E} \left\{ e^{-sI} \right\} |_{d_0,x_0}$$

$$\approx \mathbb{E} \left\{ e^{-s\left(\sum_{k \in \Lambda_1^c \setminus \{0\}} v_k P_k f,\xi_k\right)} \right\} |_{d_0,x_0}$$

$\mathbb{E}_{\Lambda_1^c} \left\{ \prod_{k \in \Lambda_1^c \setminus \{0\}} \mathbb{E}_\xi \left\{ \exp \left\{ -sv_{\xi_k} P_k f,\xi_k\right\} \right\} \right\} |_{d_0,x_0}^{(a)}$

$$\approx \exp \left\{ -2\pi \lambda_0 \int_0^\infty \left( 1 - e^{-\pi \lambda_0 y^2} \right) \times \left[ 1 - \mathbb{E}_{\xi,D_k} \left\{ -sv_{\xi_k} \left( y^2 + H_0^2 \right)^{-\alpha_B} \left( D_k^2 + H_0^2 \right)^{\frac{\alpha_B}{2}} \right\} \right] \right\} |_{d_0,x_0}^{(b)} x d y$$
where (a) is due to the i.i.d. channel power gain $\xi_k \sim \text{dist}(1, \forall k)$ and independent $\Lambda_n$, (b) follows from the PGFL of PPP in which the positions of interferers are modeled by a non-homogeneous PPP $\Lambda_n$ of density $\lambda(y) = \lambda_n(1 - \exp(-\pi \lambda_n y^2))$ which is a function of distance relative to the tagged BS, (c) follows from $E_X \{e^{-x}\} \triangleq \frac{1}{s+iT}$ for $\xi \sim \exp(1)$, and $U_I(\cdot)$ is given by

$$U_I(x) \triangleq \int_0^\infty \int_0^1 \frac{2\pi \lambda_k D_k e^{-\lambda_k \pi DS}}{1 + x(y^2 + H_B^2)^{-\alpha/2}} dD_k dy.$$  

(82)

**APPENDIX B**

Conditioned on $d_0$ and $x_0$, according to the definition of $P_{en}$ in (24), we have

$$P_{en|d_0,x_0} \triangleq P\{\tau T (S_{dr} + S_{id}) > E_{min}\} \mid d_0, x_0$$

$$= P\{S_{dr} + S_{id} > C(\tau)\} \mid d_0, x_0,$$  \hspace{1cm} (83)

where $C(\tau) \triangleq (1-\tau)\exp(-\tau)$ is a function of $\tau$.

Since either $S_{dr}$ or $S_{id}$ could be greater than $C(\tau)$, we need to consider the following three cases: $\{S_{dr} > C(\tau)\}$, $\{S_{id} > C(\tau)\}$ and $\{S_{dr} + S_{id} > C(\tau)\}$. It is worth noting that there exists correlation between the events $\{S_{dr} > C(\tau)\}$ and $\{S_{id} > C(\tau)\}$. To simplify the analysis and maintain the tractability, we neglect the correlation and assume that the two events are independent. According to the total probability formula, the conditional energy coverage can be converted to the following form

$$P\{S_{dr} + S_{id} > C(\tau)\} \mid d_0, x_0$$

$$\approx P\{S_{dr} > C(\tau)\} \mid d_0, x_0 + P\{S_{id} > C(\tau)\} \mid d_0, x_0$$

$$+ P\{S_{dr} + S_{id} > C(\tau)\} \mid d_0, x_0 \cdot P\{S_{dr} < C(\tau)\} \mid d_0, x_0$$

$$\times P\{S_{dr} < C(\tau)\} \mid d_0, x_0 \cdot P\{S_{id} < C(\tau)\} \mid d_0, x_0$$

$$- P\{S_{dr} > C(\tau)\} \mid d_0, x_0 \cdot P\{S_{id} > C(\tau)\} \mid d_0, x_0.$$  \hspace{1cm} (84)

We then need to derive the probabilities of the aforementioned three events. Specifically, we have approximated the distribution of $S_{dr|d_0,x_0}$ by the Gamma distribution $\Gamma [k_{dr}, \theta_{dr}]$ in (33). According to Appendix D of [19], for integer $k_{dr}$, the probability of $S_{dr} > C(\tau)$ conditioned on $x_0$ and $d_0$ is given by

$$P\{S_{dr} > C(\tau)\} \mid d_0, x_0$$

$$\approx \frac{\Gamma (k_{dr}, \frac{C(\tau)}{\theta_{dr}})}{\Gamma (k_{dr})} \mid d_0, x_0$$

$$= \sum_{i=0}^{k_{dr}-1} \frac{(-1)^i}{i!} \frac{\partial^i}{\partial s^i} L_{Y_{|d_0,x_0}}(s) \bigg|_{s=1},$$  \hspace{1cm} (85)
\[ \Gamma (\cdot, \cdot) \] denotes the upper incomplete Gamma function, and \( Y_t \sim \mathcal{N}(W, \theta) \). Based on (81) in Appendix A, the Laplace transform of \( Y_t \) conditioned on \( d_0 \) and \( x_0 \) is given by

\[
\mathcal{L}_{Y_t | d_0, x_0} (s) = \mathbb{E} \left[ e^{-sY_t} \right] |_{d_0, x_0} = \exp \left( -\frac{s \gamma W}{\theta_U} \right) \mathcal{L}_{I | d_0, x_0} \left( \frac{s \gamma}{\theta_U} \right)
\]

(92)

where \( V (s) = -\frac{s \gamma W}{\theta_U} - 2\pi \lambda' x_U I \).

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