# Energy-Optimal RAN Configurations for SWIPT IoT

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***Abstract*—Internet of Things (IoT) devices often have batteries of limited capacity, which are not easily replaced or recharged. This implies very short device lifetimes, and calls for a very careful device configuration to achieve the optimal trade-off between performance and power consumption. SWIPT (Simultaneous Wireless Information and Power Transfer) deals with this problem by harvesting energy at IoT devices from the received RF signals. Studying the efficiency of SWIPT in dealing with the energy and data transfer demands of IoT nodes leads to a number of open issues. In this paper, we devise an analytical model based on stochastic geometry for a SWIPT radio access network with a *dense* population of IoT users. With our model, it is possible to accurately study the impact of the system parameters on the key system performance indicators, while accounting in a realistic manner for device performance, and for the statistics of time scheduling at base stations. This allows us to understand (not without some surprise) what are the most effective strategies to minimize energy consumption in a SWIPT network, and what is their potential for energy savings.**

## I. Introduction

The Internet of Things (IoT) paradigm is playing an increasing role in determining the overall energy footprint of cellular radio access networks (RANs), while reshaping their design and operations. Indeed, IoT is predicted to bring the share of energy consumed by ICT to almost one fifth of the whole energy consumption by 2025 [1]. One of the key factors that may limit the diffusion and the potential of the IoT paradigm is the limited power available to a large fraction of IoT devices, many of which are battery operated, with no access to a stable power source. This poses stringent limits to the amount of sensing, computing and actuation they can perform, as well as to their availability, connectivity and operational lifetime. To overcome these limitations, several techniques for energy harvesting (EH) have been proposed in IoT systems. Among these, simultaneous wireless information and power transfer (SWIPT) [2] is of special interest, since it enables the delivery of power through the same cellular infrastructure used to deliver data, and thus in a potentially more cost effective manner than alternative approaches.

Several works recently focused on the performance analysis of SWIPT networks. A large share of them focus on modeling performance and optimizing operations, in terms of energy efficiency maximization, and on modeling the impact of the delivery of both connectivity and power on the overall network energy consumption. For example, [3] considers the characterization of the data rate vs. energy trade-off, while [4] considers the optimization of transmit power allocation to each user. [5] proposes a Markov Chain model to study a joint power and connectivity outage probability. However, these works mainly consider simple scenarios, composed of a base station (BS) (possibly a broadband unit with several remote radio heads) and a population of EH devices. [6] proposes an algorithm to minimize the total energy consumption of a set of BSs and a population of IoT devices, over sub-carrier and transmit power allocation. However, since the strategies proposed in those works focus on optimizing the operations of a network in a specific configuration, they do not give an idea of the average performance and of the overall potential for energy saving allowed by the approach. Thus, they leave open the more general issue of what are the most effective management strategies to achieve system-level energy proportionality in a SWIPT network, as a function of the main system parameters.

Another set of works perform a system-level analysis, modeling the average behavior of a SWIPT network, such as the data rate vs. energy tradeoff (e.g., see [7]–[9]). Surprisingly, all these results do not account for the effects of resource allocation and scheduling among users, such as the statistics of the sharing of BS time across all associated users. Thus, they do not enable an accurate and realistic characterization of the main performance trade-offs, and thus of the potential for QoS-aware energy-efficient operation of SWIPT networks.

In this paper we address these issues, and we propose an analytical framework based on stochastic geometry (SG) for system-level analysis and optimization of SWIPT cellular networks providing connectivity and power to a heterogeneous population of broadband users and IoT EH users. The use of SG allows focusing on the average behavior of the system over many realizations of the process of UE (user equipment) and BS spatial distributions, thus enabling the analysis of the potential for QoS-aware energy optimization of SWIPT-enabled networks. We formulate an energy minimization problem, which allows deriving the optimal network configuration, shedding light on the main performance trade-offs and on the impact of the main system parameters. More specifically, for a given user density, we propose an approach for deriving a configuration (in terms of density of active BSs, split ratio, and transmit power) which minimizes the mean total power consumption of the network, while achieving a target QoS level for both information transfer (in downlink and uplink) and wireless power delivery. We use the proposed framework to characterize some of the key performance and resource efficiency trade-offs of SWIPT networks. This allows us to observe some rather surprising effects, like, in some cases, a decrease of the optimal density of BSs required to serve an increasingly dense population of UEs, and the irrelevance of active BS charging for very dense UE populations.

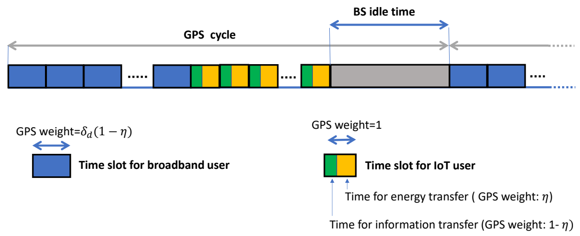


Fig. 1: Downlink time scheduling for a SWIPT BS, with GPS weights.

## II. System Model

We assume that BSs are distributed in space according to a homogeneous planar Poisson Point Process (PPP) with a density equal to $\lambda_b$ BSs per $km^2$. UEs are distributed in space according to a homogeneous PPP with an intensity equal to $\lambda_u$ UEs per $km^2$. UEs are either broadband (BB) terminals, or IoT (Internet of Things) devices. We assume the latter are a fraction $\gamma$ of the total number of UEs.

We consider the case in which IoT devices harvest the needed energy, while BB users don't. To this end, each IoT device is equipped with two separate receivers, one for information and another for energy, and it is capable of exploiting downlink signals for decoding its intended information, as well as downlink and uplink signals from both BSs and UEs for charging its battery. The receiver operating mode is *time splitting* [10], by which a fraction $\eta$ (the *time split ratio*, with $0 \leq \eta \leq 1$) of the time dedicated by a BS to serve an associated IoT device in downlink is devoted to active power transfer, i.e., it is used by the UE for harvesting energy from the signal received from the BS. The rest of that time is used for receiving information[1]. We assume $\eta$ is the same for all devices. Thus, IoT devices harvest energy not only from their serving BS (*active charging*), but also from the signal received from all of the other BSs, as well as from uplink transmissions from both IoT and BB UEs (*passive charging*).

We assume that BSs use a generalized processor sharing (GPS) mechanism to divide BS time among all the connected UEs. In downlink, the GPS weights are 1 for IoT UEs, and $\delta_d(1-\eta)$ for BB UEs. $\delta_d$ is thus the ratio between the BS time dedicated to information transfer to a BB UE, and to an IoT UE. The time spent by the BS without transmitting is modeled as a user with a GPS weight $\beta_d$. As for uplink, the GPS weights are 1 for IoT UEs, $\delta_u$ for BB UEs, and $\beta_u$ for the uplink BS time not assigned to any UE.

We assume IoT UEs to periodically cycle between two operational states. During the *active state*, they send and receive data, plus possibly they perform some other task, such as sensing, while harvesting energy from active and passive sources. In the *low power* state, IoT devices only harvest energy. We assume that each IoT device is disconnected from the power grid, and it possesses an ideal battery (i.e., with efficiency equal to one) with enough capacity to compensate for the fluctuations in the energy consumed and harvested. With $\phi$ we denote the fraction of time spent by an IoT device in the active state. BB users are instead assumed to always be in the active state.

We assume the system is in saturation, i.e., BSs have always data to send to users, and users in the active state have always data to transmit. Moreover, we adopt a linear EH model, by which the ratio between the harvested power and the received power $\xi$ is constant, though our approach extends easily to other EH models, as well as to consider non-ideal batteries and finite battery capacity.

[1]Note however that our approach easily extends to other receiver architectures, such as power splitting mode [10].

Given that the cellular RAN delivers two classes of services to two different types of UE, the performance metrics are defined as follows:

- **Information transfer**: For all UEs, the end-user performance metric is the *per-bit delay* $\tau$ of data transfers, defined as the inverse of the short-term user throughput, i.e., the actual rate at which the user is served.
- **Power transfer**: The performance parameter is the amount of power harvested by an IoT device, denoted with $h$.

As a result of the scheduling strategy (both in downlink and uplink), the amount of harvested energy may vary substantially across the various devices. These metrics must be considered relatively to the corresponding application demands. As an example, the energy harvested by each device during a complete on-off cycle (and therefore the value of the parameter $h$) must be sufficient to compensate for the energy consumed during the cycle by such tasks as sensing, processing, storing and distributing data, while accounting for battery efficiency and for fluctuations in consumption patterns due to changes in the operational state of IoT devices. Accordingly, the target performance for information transfer are related to application specific requirements.

### A. Channel and Service Model

Our channel model does not consider the effect of fading and shadowing, and only takes into account distance-dependent path loss. We assume that *random frequency reuse* is in place, with reuse factor $k$. That is, every BS is assigned one out of $k$ frequency bands with equal probability.

We assume that UEs are associated with the BS with the largest SINR at the user location. We consider urban scenarios, where the high capacity demand justifies the use of strategies for energy efficient network planning and management, and where the assumption of high attenuation (with exponent $\alpha \geq 3$) typically holds. In these settings, as no fading is considered and all BSs use the same transmit power, assuming that users associate to the closest BS is a reasonable approximation [11]. We assume BS antennas use beamforming, and we denote with $G$ the beamforming gain and with $L$ the side lobes attenuation. Denote by $S(x)$ the location of the BS that is closest to a UE located at $x$. We denote the capacity to a user located at a distance $r$ from the BS by $C(r, P, G, I)$ bit/s per Hertz, where $P$ is the BS transmit power, and $I$ the total received interfering power. We model $C(r, P, G, I)$ using Shannon's capacity law:

$$C(r, P, G, I) = (B/k) \log_2 \left(1 + \frac{PGr^{-\alpha}}{N_0 + I}\right) \quad (1)$$

where $\alpha$ is the attenuation factor, $N_0$ the power spectral density of the additive white Gaussian noise, and $k$ the reuse factor.

### B. Base Station and UE Energy Consumption Model

The power consumed by a BS depends on a number of factors, which vary according to the BS type (e.g. macro, micro, femto) and the implementation technology (e.g. standalone vs cloud-RAN), among others. In what follows, we refer to the following BS energy model, proposed in [12], [13]:

$$q_1 + U_d[q_2 + q_3(P - P_{min})] \quad (2)$$

where $U_d$ is the downlink BS utilization and $P$ is its transmit power, which we assume varies within the interval $[P_{min}, P_{max}]$. The component $q_1$ models the total power consumed when the BS is idle, which does not depend on load or transmit power. In what follows we assume that, when transmitting, a BS is using the whole bandwidth at its disposal. $q_2U_d$ models that fraction of consumed power which depends on utilization, but not on transmit power (such as part of baseband and RF processing).The third component models the fraction of consumed power due to the power amplifier which depends, at the same time, on the transmit power $P$ and on the amount of active resources at the BS.

### C. Base station service model

We define the utilization $U(S(x))$ of the BS serving a UE at location $x$ as the average fraction of time in which the BS is busy transmitting (in downlink) or receiving (in uplink), respectively. Thus, its expression is given by the fraction of BS time dedicated to all active users:

$$U_d(S(x)) = \frac{N_{iot}(S(x)) + \delta_d(1-\eta)N_{bb}(S(x))}{N_{iot}(S(x)) + \delta_d(1-\eta)N_{bb}(S(x)) + \beta_d}$$

$$U_u(S(x)) = \frac{\phi N_{iot}(S(x)) + \delta_u N_{bb}(S(x))}{\phi N_{iot}(S(x)) + \delta_u N_{bb}(S(x)) + \beta_u} \quad (3)$$

Given $\eta$, by tuning $\beta_j$ it is possible to vary the mean amount of service received by UEs for both communication and energy transfer, and the overall BS utilization.

**Definition II.1.** The ideal per-bit delay perceived by a UE is the one if the associated BS had utilization equal to 1.

Note that the above definition does not assume that *all* of the BSs have utilization equal to one, but only the BS serving the considered UE.

From expressions 3 and from the above definition, we have that for a UE at $x$, the relationship between the ideal per bit delay $\tau_j^{id}$, $j \in d, u$ and the actual per bit delay, both in uplink and in downlink, is given by

$$U_j(S(x))\tau_j(S(x)) = \tau_j^{id}(S(x)), \quad j \in d, u$$

Indeed, from the expression of the utilization, the ratio between the ideal an the actual per bit delay is equal to the fraction of time the BS is active.

For each UE type, and for both uplink and downlink, a notion of target minimum quality of service (QoS) is defined. Namely, UEs are said to perceive satisfactory performance if the average per-bit delay experienced by a *typical* BB user (resp. IoT device)[2] are less than their respective predefined target values. In what follows, for a given $\eta$, we assume each BS adopts the values of $\beta_j$, $j \in d, u$ (and thus of utilization in downlink and uplink) which achieve the target QoS for communications. This makes the average of the actual per bit delays (over all the users associated to that BS) coincide with the target values.

## III. Modeling User Perceived Performance

In this section, we characterize the main performance parameters, e.g. the per-bit and per-joule delays perceived by a typical user who is just beginning service, as well as the mean harvested power, as a function of the main system parameters. The expression of the power harvested by a user at $x$ is given by the following result.

**Lemma 1.** The power harvested by a user at $x$ is

$$h(x) = \xi \Bigg\{ Pr(x)^{-\alpha} \left[ GK(x) + LU_d(S(x)) - \frac{LK(x)}{\eta} \right] + + \left( 1 - K(x)\frac{(1-\eta)}{\eta} \right) (I(r(x),k) + O(x)) \Bigg\} \quad (4)$$

with $K(x) = \frac{\eta}{N_{iot}(S(x)) + \delta_d(1-\eta)N_{bb}(S(x))} U_d(S(x))$.

$r(x)$ is the distance of the user at $x$ from its serving BS, and $I(r(x),k)$ is the total power harvested by the user at $x$ from BSs other than the one with which it is associated. $O(x)$ is the power harvested from UE transmissions, averaged over time, and $U_d(S(x))$ the downlink utilization of the BS with which the user in $x$ is associated.

For a proof, please refer to Appendix C. $\xi$ is a factor which accounts for several technological factors affecting the efficiency of the energy harvesting process, ranging from receiver antenna gain, to exposure of the specific IoT device, among others.

From its definition, and from the service model description, it derives that in downlink the ideal per-bit delay perceived by a BB UE at $x$ is given by

$$\tau_d^{id}(x) = \frac{N_{iot}(S(x)) + \delta_d(1-\eta)N_{bb}(S(x))}{\delta_d(1-\eta)C(r(x), P, G, I)} \quad (5)$$

where $N_{bb}(S(x))$ ($N_{iot}(S(x))$) are the number of broadband (resp. IoT) users associated with the BS serving the UE at $x$. For the uplink instead we have

$$\tau_u^{id}(x) = \frac{\phi N_{iot}(S(x)) + \delta_u N_{bb}(S(x))}{\delta_u C(r(x), P_I, 1, 0)} \quad (6)$$

For IoT users, the ideal per-bit delay perceived is $\tau_{j,I}^{id}(x) = \delta_j \tau_j^{id}(x)$, $j = d, u$. With $\bar{\tau}_j$ ($\bar{\tau}_{j,I}$) we denote the average per-bit delay perceived in downlink (resp. in uplink) by broadband and IoT users, respectively. The following result derives an expression for the average per-bit delay perceived by the typical user (BB or IoT) which is just beginning service.

**Theorem 1.** The mean ideal per-bit delays in downlink and uplink, and the mean ideal per-Joule delay perceived by a typical best-effort user joining the system are given by:

$$\bar{\tau}_d = H(\delta_d, \eta, C(r, P, G, \bar{I})) \quad (7)$$

$$\bar{\tau}_u = H\left(\frac{\delta_u}{\phi}, 0, C(r, P_I, 1, 0)\right) \quad (8)$$

$$\bar{\tau}_{j,I} = \delta_j \bar{\tau}_j, j \in \{d, u\} \quad (9)$$

Where:

$$H(\delta_j, \eta, g(r)) = \int_0^\infty f(r, \eta, \delta_j) \frac{e^{-\lambda_b \pi r^2} \lambda_b 2\pi r}{\delta_j(1-\eta)g(r)} \, \mathrm{d}r. \quad (10)$$

with

$$f(r, \eta, \delta_j) = \lambda_u \int_0^\infty \int_0^{2\pi} e^{-\lambda_b A(r,x,\theta)} x d\theta dx \cdot \cdot [1 - \gamma(1 - \delta_j(1-\eta))]$$

$A(r, x, \theta)$ is the area of the circle centered at $(x, \theta)$ with radius $x$ that is not overlapped by the circle centered at $(0, -r)$ with

[2]The definition of the typical user in the system is provided by classical Palm theory [14].

radius $r$. $C(r, P, G, \bar{I})$ is given by (1), with the interference term $\bar{I}$ given by

$$\bar{I}(r,k) = \frac{PL\lambda_b 2\pi r^{2-\alpha}}{k(\alpha-2)} \frac{\bar{\tau}_d}{\tau_d^0}$$

For the proof, please refer to appendix A.

We say that the considered system is in the *dense IoT regime* when the density of IoT users is such that the probability of having a cell without IoT users is negligible.

**Theorem 2.** In the dense IoT regime, the cumulative distribution function $CDF_h$ of the power harvested by an IoT user who is just beginning service is

$$CDF_h(h_0) = CDF_r(g^{-1}(h_0))$$

for all $h_0 \geq 0$, where $CDF_r$ is the cumulative distribution function of the distance of the user to its serving BS:

$$CDF_r(r) = \int_0^r e^{-\lambda_b \pi y^2} \lambda_b 2\pi y dy$$

where

$$g(r) = \xi \left[ Pr^{-\alpha} L \frac{\bar{\tau}_d}{\tau_d^0} + k\bar{I}(r,k) + \bar{O} \right] + \frac{X(r)}{f(r,\eta,\delta_d)}$$

$$X(r) = \xi \frac{\bar{\tau}_d}{\tau_d^0} \left[ Pr^{-\alpha}(G\eta - L) - (1-\eta)(k\bar{I}(r,k) + \bar{O}) \right]$$

$$\bar{O} = \frac{(1-\gamma)\delta_u P_{bb} + \phi\gamma P_I}{(1-\gamma)\delta_u + \phi\gamma} \frac{\lambda_b \pi \alpha}{\alpha - 2} \frac{\bar{\tau}_u}{\tau_u^0} \tag{11}$$

For the proof, please refer to Appendix B. $P_{bb}$ and $P_I$ denote the transmit power of BB and IoT UEs, respectively.

## IV. Energy-Optimal Network Configuration

One of the main open issues in SWIPT networks is to determine, as a function of the main system parameters as well as of the energy and traffic demands, how the main network parameters should be tuned in order to optimize the energy consumed by the system. To this end, we present below the formulation of the optimization problem which provides, for a given BS energy model, as well as for a given user mean density, the energy optimal BS transmit power, the optimal density of active BSs, as well as the optimal amount of BS time dedicated to power transfer, which satisfy the performance constraints.

**Problem 1.**

$$min_{P,\lambda_b,\eta} \;\; \lambda_b \left[ q_1 + \frac{\bar{\tau}_d(\eta, P, \lambda_b)}{\tau_d^0} (q_2 + q_3(P - P_{min})) \right]$$

Subject to:

$$\frac{\bar{\tau}_d(\eta, P, \lambda_b)}{\tau_d^0} \leq 1, \quad \frac{\bar{\tau}_u(\eta, P, \lambda_b)}{\tau_u^0} \leq 1 \tag{12}$$

$$P_{min} \leq P \leq P_{max} \tag{13}$$

$$0 \leq \eta \leq 1 \tag{14}$$

$$CDF_h(h_0, \eta, P) \leq \mu \tag{15}$$

$$0 \leq \lambda_b \leq \lambda_{b,max} \tag{16}$$

where $h_0$ in constraint (15) is the minimum harvested power required by each IoT device to operate, computed based on the amount of energy required by the device during a whole on-off cycle. $\mu$ is the maximum acceptable ratio of IoT users which harvest less than $h_0$ Joules per second. $\bar{\tau}_d$, $\bar{\tau}_u$ are given by Theorem 1. $\lambda_{b,max}$ derives from practical constraints to BS deployments in urban settings.

Problem 1 is non-convex and nonlinear. However, being a function of three variables defined over finite intervals, it can be solved efficiently by exhaustive search.

## V. Numerical Results

### A. Setup

Base stations work at a frequency of 1 GHz, and use a bandwidth of 50 MHz. Unless otherwise indicated, we assume a percentage of IoT devices equal to 20% of the total number of UEs, a transmit power equal to 0.1 W for both IoT and BB UEs, a frequency reuse factor of 3, a beamforming gain equal to 5, that is assumed constant over the whole main lobe aperture of 45 degrees, and a path loss exponent $\alpha = 3$, typical of urban areas. We assume a linear EH model, with a conversion efficiency of 0.9 and no lower/upper threshold. We assume the BS transmit power to vary between 1 and 11 W, and we set a target mean per-bit delay in downlink for BB (resp. IoT) UEs equal to $10^{-5}$ s (resp. $10^{-3}$ s), and in uplink equal to $10^{-4}$ s for all UEs, (e.g. typical of IoT systems for environmental monitoring [6]). We consider the user density to vary from $10^{-4}$ users per m$^2$ (typical of settings with a high share of BB users, at night) to $10^{-1}$ users per m$^2$ (modeling scenarios with crowds of BB UEs and with high density of IoT deployments). We assume IoT UEs to be active for 2% of the time, and to require a minimum harvested power of 100 mW. We set to 5% the maximum acceptable share of IoT users which are not able to harvest the target minimum energy.

The parameters of the BS energy model are chosen to fit two different types of BSs. A first type (labelled LLP – low load proportionality) reflects the behavior of the majority of current stand-alone BSs, and it is characterized by a 27% load proportionality (with $q_1 = 1100$, $q_2 = 100$, and $q_3 = 30$). Conversely, the high load proportionality (HLP) BS type (with $q_1 = 482.3$, $q_2 = 48.23$, and $q_3 = 144.69$) corresponds to a 75% load proportionality, achievable, e.g., through time-domain duty-cycling at the sub-system level, i.e., through micro-sleep techniques involving modules of the BS or of the BBU in cloud-RAN designs. For the sake of comparison, these parameters were chosen to fit a per-BS maximum consumed power of 1500 W, typical of stand-alone BSs.

### B. Model validation

In order to assess the accuracy of our results, we simulated the system for several values of user and BS densities. For every configuration, the simulated scenario was set to include a number of BSs $\geq$ 1000, and an amount of users $\geq$ 10000. In these settings, we compared the measured per-bit delay, as well as the CDF of harvested energy, with the values predicted by our analysis. Simulation results have confidence intervals at 95% confidence of width at most equal to 5% of the mean.

As Fig. 2 and Fig. 3 show, our modeling approach is extremely accurate across very diverse system configurations. In particular, a very good accuracy is achieved even for low values of user density, for which the dense IoT assumption of Theorem 2 does not hold. As can be seen in Fig. 2, the distribution of harvested power exhibits a fat tail for the largest values, with a non-negligible probability of achieving values of harvested power up to two orders of magnitude larger than the mean. This implies not only that the system cannot be dimensioned based on the average harvested power, but also that the standard deviation of

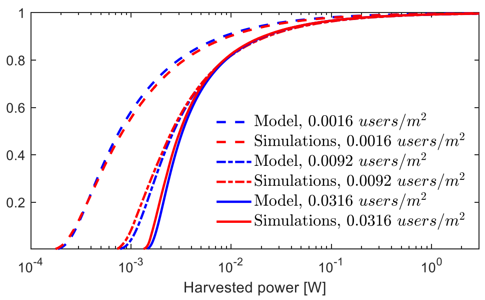


Fig. 2: CDF of harvested power from our model, and empirical CDF of harvested power from simulations.

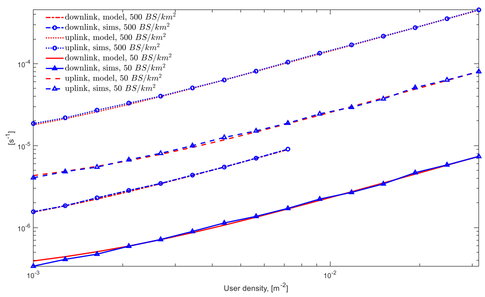


Fig. 3: Mean ideal per-bit delay over user density.

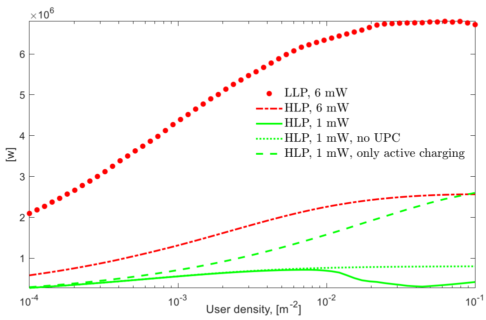


Fig. 4: Power per $km^2$ consumed at the optimum vs user density, for different target minimum harvested power and IoT UE receiver configurations.

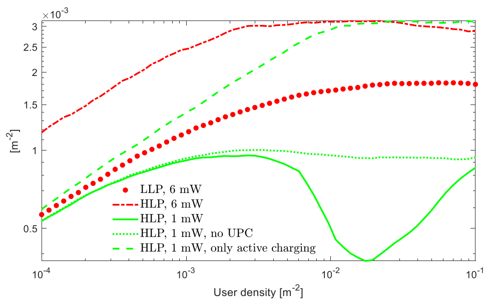


Fig. 5: Optimal BS density vs user density, for different target minimum harvested power and IoT UE receiver configurations.

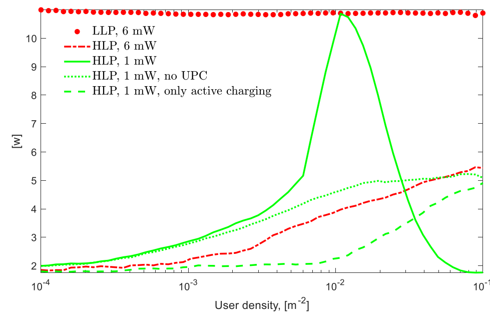


Fig. 6: Optimal BS transmit power vs user density, for different target minimum harvested power and IoT UE receiver configurations.

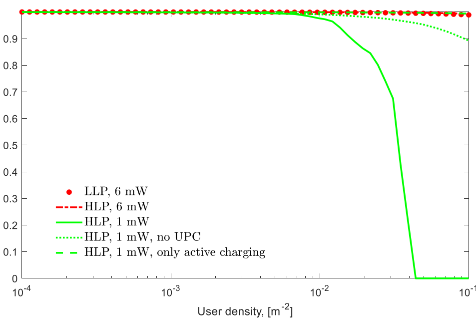


Fig. 7: Optimal time split ratio vs user density, for different target minimum harvested power and IoT UE receiver configurations.

the harvested power, being substantially larger than the mean, is not informative of the lower tail of the distribution.

### C. Energy optimal configuration

To investigate the properties of the solutions of Problem 1, in Fig. 4 we plot the power per km$^2$ consumed by the network at the optimum, as a function of user density, while in Fig. 5 to 7 we plot the corresponding optimal values of base station density, of transmit power, and of time split ratio. The red curves refer to a target minimum harvested power of 6 mW, while the green curve refers to the case of 1 mW. As expected, for a same target QoS, at any user density, high levels of load proportionality enable a substantial decrease in the power consumed, thanks to the tuning of the three main system parameters mentioned above (note the difference between the two red curves). At low user densities, an energy-optimal tuning of the system brings to an almost linear proportionality between user density and consumed power. However, in sharp contrast to RANs delivering only connectivity, at high user densities the service capacity of a SWIPT network is complemented by the signals transmitted by users, which thus contribute to the delivery of power to IoT users. As a result, in the two red configurations, the optimal consumed power grows more slowly with user density, and it decreases in the green configuration. Moreover, this brings to a consumed power per user which, at the optimum, keeps on decreasing steadily with increasing user density in all configurations. This is true even for networks of highly load proportional BSs, and shows that optimal (and possibly dynamic) configuration tuning holds the potential to play a key role in minimizing the energy footprint of a SWIPT network, by making it more and more energy efficient when the demand (of both energy and communication) it must satisfy grows.

In particular, at high user densities, the optimal network configuration and the resulting consumed power are the result of the interplay between the detrimental effect of interference on communications (which decreases the efficiency with which network resources are used), and the beneficial effect of many user transmissions on the amount of power harvested by IoT users. Indeed, from Fig. 4, in low-power IoT scenarios (solid green curve), when increasing user density, these two contrasting effects bring the power consumed to actually decrease with respect to that consumed at low user densities, before increasing again due to the effects of high levels of interference levels on user-perceived QoS for data.

As Fig. 5 shows, in 6 mW IoT scenarios, at high user densities the optimal BS density does not vary significantly when increasing service demand, thanks to a corresponding increase in user-supplied service capacity. In low-power (1 mW) IoT scenarios, for some values of user density this effect brings to optimal BS densities which are even lower than those for low user densities, thus suggesting (quite surprisingly) patterns of BS sleep modes which, in contrast to those for non-SWIPT RANs, turn off BSs when demand increases.

Fig. 6 and 7 offer some key insight on how tuning transmit power and power split ratio contributes to achieving energy optimal operation of a SWIPT network. For low load proportional BSs, the optimal strategies consist in keeping transmit power and power split ratio at its maximum value. In high load proportional BS settings, such as C-RANs, the optimal strategy consists in adapting transmit power to user density. In the low power IoT case, for low user densities this brings to increasing BS transmit power when demand grows. However, when the user supplied service capacity is sufficiently high, the optimal BS transmit power and power split ratio actually decrease with growing user density, and beyond a given user density ($4.5 \cdot 10^{-2}$ m$^{-2}$ in the considered setting) the SWIPT network effectively stops to actively deliver power to IoT users (the solid green curve goes to zero), as passive power supply from ambient sources is sufficient to achieve the target QoS for energy harvesting.

Finally, we have analyzed the impact of receiver architecture on the energy optimal configurations of a SWIPT network, by considering the case in which users cannot harvest power from other users' transmissions (the "no UPC" case green curve) and the case in which only active power delivery is possible (the "only active charging" case green curve). Indeed, the larger the spectrum of frequencies over which an IoT device is assumed to harvest power, the more complex the receiver architecture, and the overall cost of the IoT device itself. As the figures show, with only active charging the optimal strategies in the low power IoT scenarios are very similar to the ones with more power hungry IoT devices. Indeed, in the latter case passive charging plays a secondary role in achieving the target QoS for power supply with respect to active power delivery. These curves also show the crucial role of eventually harvesting energy from other users, which, at high densities, offers the potential to achieve substantial savings both in the amount of power required to operate the network, and in the density of BSs required to serve users at the optimum.

## VI. Conclusions

In this paper we proposed an analytical framework for the characterization of the performance of a SWIPT network serving a combination of broadband users and EH IoT devices, and for the identification of energy-optimal network configurations satisfying constraints on user perceived QoS. Numerical results suggest that substantial energy savings are possible by schemes that adapt the main network parameters to fluctuations in user density. We also showed that such schemes remain essential even in more energy proportional cloud-RAN settings. The most interesting insight provided by our results concerns the interplay between energy harvesting and interference in cases of extreme densities of IoT devices. In such cases we observed that very high device densities facilitate energy harvesting before interference becomes a problem. As a result, the optimal base station density can be very low even when the network load is high. This implies that base station sleep modes in SWIPT networks should follow different dynamics with respect to networks that do not provide energy harvesting to IoT devices.

In Section IV, we have introduced the problem of optimizing the energy consumed by the system. We have approached this non-convex and nonlinear problem by assuming that the objective function variability is limited and using an heuristics where the solution space has been densely sampled within a grid and then a search for an optimal solution is done. As a future work, we intent to strengthen our work by exploiting a proper resolution approach to face the potentially many local minima, saddle points and widely varying curvature characterizing this class of optimization problems. In addition, there are various parameters that may potentially influence the energy harvesting process and its efficiency, but the impact of their variations on the overall process has not been wholly investigated. As a future work, we also intent to perform a sensitivity analysis when these parameters varies, such as changing the variance of the fading and shadowing processes, so as to have a glimpse of their effect on the CDF of the power harvested by an IoT user.

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## APPENDIX

### A. Proof of Theorem 1

We consider the user at zero, but we drop this indication in what follows for ease of notation (i.e. $S(0)$ becomes $S$, and $r(0)$ becomes $D$). We start by computing the Palm expectation of the expression in (5):
$\bar{\tau}_d = E^0[\frac{N_{iot}(S)+\delta_d(1-\eta)N_{bb}(S)}{C(D,I)}]$
$= \int_0^\infty E^0[\frac{N_{iot}(S)+\delta_d(1-\eta)N_{bb}(S)}{C(D,I)}|r \le D \le r+dr]P(r \le D \le r+dr)$
$\approx \int_0^\infty \frac{E^0[N_{bb}(S)+\delta_d(1-\eta)N_{iot}(S)|r\le D\le r+dr]}{C(r,\bar{I}(r,k))}P(B(0,r)=\phi)\lambda_b 2\pi r dr$
where $\bar{I}(r,k)$ is the average interfering power for the typical user at $r$, given by $\bar{I}(r,k) = \frac{PL\lambda_b 2\pi r^{2-\alpha}}{k(\alpha-2)}\frac{\bar{\tau}_d}{\tau_d^0}$ ([15]). Thus
$\bar{\tau}_d \approx \int_0^\infty \frac{E^0[N_{bb}(S)+\delta_d(1-\eta)N_{iot}(S)|r\le D\le r+dr]}{C(r,\bar{I}(r,k))}e^{-\lambda_b \pi r^2}\lambda_b 2\pi r dr$
where $P(B(0,r) = \phi)$ is the probability that a ball of radius $r$ centered at the origin is empty. Let $N_{tot}(S) = N_{bb}(S) + N_{iot}(S)$. The palm expectation at the numerator becomes $[1-\gamma(1-\delta_d(1-\eta))]E^0[N_{tot}(D)|r \le D \le r+dr]$. The random variable $N_{tot}(D)$ is the total number of users present in the same cell as the user at the origin, when his distance from its serving base station is $D$. As users are distributed according to a PPP with intensity $\lambda_u$, $N_{tot}(D)$ is Poisson, with an intensity given by the conditional Palm expectation inside the integral. Using Campbell's formula [14], this expectation becomes
$E^0[\int_0^\infty \int_0^{2\pi} \mathbf{1}_{(S(x,\theta)=S|r\le D\le r+dr)}\lambda_u d\theta x dx[1-\gamma(1-\delta_d(1-\eta))]$
$= \int_0^\infty \int_0^{2\pi} \lambda_u P(S(x,\theta) = S|r \le D \le r+dr)d\theta x dx[1-\gamma(1-\delta_d(1-\eta))]$
The conditional probability within the integral is given by $\int_0^\infty \int_0^{2\pi} \lambda_u e^{-\lambda_b A(r,x,\theta)}d\theta x dx$, where $A(r,x,\theta)$ is ([16]):
$A(r,x,\theta) = \pi x^2 - [r^2 \arccos\left(\frac{r+x\sin(\theta)}{d(r,x,\theta)}\right) + x^2 \arccos\left(\frac{x+r\sin(\theta)}{d(r,x,\theta)}\right) +$
$-\frac{1}{2}(-(d(r,x,\theta)-x)^2+r^2)^{\frac{1}{2}}((d(r,x,\theta)+x)^2-r^2)^{\frac{1}{2}}]$.
By substituting, we get the expression for $\bar{\tau}_d$. The derivation of $\bar{\tau}_u$ follows along the same lines.The expressions of $\bar{\tau}_d$ and $\bar{\tau}_u$ obtained are implicit (i.e. they are a function of these same parameters). Thus they constitute a fixed point problem. It is easy to see however that the mapping operator associated to this fixed point is contractive, and thus that the problem admits a unique solution.

### B. Proof of Theorem 2

**Lemma 2.** The average power received from users for the typical user arriving in the system at a distance $r$ from the serving BS is approximated by

$$\bar{O} = \frac{(1-\gamma)\delta_u P_{bb} + \phi\gamma P_I}{(1-\gamma)\delta_u + \phi\gamma}\frac{\lambda_b \pi\alpha}{\alpha-2}\frac{\bar{\tau}_u}{\tau_u^0} \quad (17)$$

*Proof.* The mean transmit power from a user is $\frac{(1-\gamma)\delta_u P_{bb}+\gamma P_I}{(1-\gamma)\delta_u+\gamma}$. Let $x'_i(t), i \in \chi(j)$ be the position of the $i$-th user served by BS $j$ at time t, $d(x,x'_i(t))$ denote the distance between the two users considered, and $u(x'_i(t))$ the probability that the given user is transmitting at time $t$. Then we can write the expression of $O(x,t)$ as follows:

$$\sum_j \sum_{i\in\chi(j)} \frac{(1-\gamma)\delta_u P_{bb} + \gamma P_I}{(1-\gamma)\delta_u + \gamma} d(x,x'_i(t))^{-\alpha}u(x'_i(t)) \quad (18)$$

where $\chi(j)$ is the set of users served by BS j. As we assume the base station has utilization $\frac{\bar{\tau}_u}{\tau_u^0}$ in the uplink,

$$u(x'_i(t)) = \frac{1}{\lambda_u A_j}\frac{\bar{\tau}_u}{\tau_u^0}$$

where $A_j$ is the area of the Voronoi cell of BS j. Given that users are uniformly distributed in the plane, the palm expectation of (18) is well approximated by

$$\frac{(1-\gamma)\delta_u P_{bb} + \gamma P_I}{(1-\gamma)\delta_u + \gamma} E\left[\sum_j \frac{\int_{x'\in A_j} d(x,x')^{-\alpha}dx'}{\lambda_u A_j}\right]\frac{\bar{\tau}_u}{\tau_u^0} =$$

As $A_j$ is statistically independent on $d(x,x')$, the approximated formula becomes

$$= \frac{(1-\gamma)\delta_u P_{bb} + \gamma P_I}{(1-\gamma)\delta_u + \gamma}\frac{\int_0^{+\infty} \lambda_u min(1,s^{-\alpha})2\pi s ds}{\lambda_u \bar{A}}\frac{\bar{\tau}_u}{\tau_u^0}$$

where $\bar{A}$ is the mean area of a Voronoi cell for a BS density of $\lambda_b$, which is equal to $\lambda_b^{-1}$. Assuming $\alpha > 2$, we get

$$= \frac{(1-\gamma)\delta_u P_{bb} + \gamma P_I}{(1-\gamma)\delta_u + \gamma}\frac{\lambda_b\pi\alpha}{\alpha-2}\frac{\bar{\tau}_u}{\tau_u^0}$$

□

*Proof.* (Theorem 2) Let $h(x) = F(x) + X(x)$, with:

$$F(x) = \xi\{P_{BS}r(x)^{-\alpha}LU_d(x) + (kI(r(x),k) + O(x))\}$$

$X(x) = \xi K(x)\left\{P_{BS}r(x)^{-\alpha}(G - \frac{L}{\eta}) - \frac{1-\eta}{\eta}(kI(r(x),k) + O(x))\right\}$
$= \xi K(x)Z(x)$.

Let's set $E^0[F(D)|r \le D \le r+dr] = F(r)$, and
$E^0[X(D)|r \le D \le r+dr] = \xi E^0[K(D)|r \le D \le r+dr]Z(r)$
$= \xi E^0\left[\frac{U_d(D)\eta}{1-\gamma(1-\delta_d(1-\eta))]N_{tot}(D)}|r \le D \le r+dr\right]Z(r)$
where $U_d(D)$ is the downlink utilization of the base station to which the user at the origin is associated.
$\approx \xi Z(r)\frac{\bar{\tau}_d}{\tau_0[1-\gamma(1-\delta_d(1-\eta))]}\eta E^0\left[\frac{1}{N_{tot}(D)}|r \le D \le r+dr\right]$.

For Jensen's inequality,
$E^0\left[\frac{1}{N_{tot}(D)}|r \le D \le r+dr\right] \le \frac{1}{E^0[N_{tot}(D)|r\le D\le r+dr]}$.
For a given cell, $N_{tot}(D)$ is Poisson distributed. Thus the ratio of the standard deviation of over the mean of this variable decreases with increasing user density. Therefore in the dense IoT regime, such an inequality is tight. The denominator is then computed as a function of $r$ as in the proof of Theorem 1. □

### C. Proof of Lemma 1

Let us consider that BS utilization is equal to 1. The power of the signal received by the user at $x$ by the base station, with the goal of getting charged wirelessly, is $P_{BS}r(x)^{-\alpha}$. $N_{iot}(S(x)) + \delta_d(1-\eta)N_{bb}(S(x))$ is the sum of the GPS weights of all users served by the base station serving the user at $x$. $\eta$ is the product of the GPS weight of the IOT user by the factor $\eta$, which denotes that fraction of BS time dedicated to the IoT user which is devoted to *active* power transfer (to distinguish it from *passive* power transfer, i.e. from power harvested by ambient radiation).

$$K(x) = \frac{\eta}{N_{iot}(S(x)) + \delta_d(1-\eta)N_{bb}(S(x))}$$

is *the fraction of total base station time dedicated to actively charging the user at* $x$, when downlink BS utilization is 1. In the more general case in which base station utilization is $U_d(S(x)) \leq 1$, the expression for $K(x)$ is

$$K(x) = \frac{\eta}{N_{iot}(S(x)) + \delta_d(1-\eta)N_{bb}(S(x))} U_d(S(x))$$

The amount of energy received by the user at $x$ during such time, and due to active charging, is therefore $\xi P_{BS} r(x)^{-\alpha} G K(x)$. $\frac{K(x)(1-\eta)}{\eta}$ is the fraction of total base station time dedicated to transmitting information to the IoT user at $x$, and it accounts for downlink base station utilization. Thus, $\left(1 - \frac{K(x)(1-\eta)}{\eta}\right)$ is the fraction of time during which the user at $x$ can harvest energy, because it is not receiving information. The fraction of time during which the BS to which the user at $x$ is associated is active and *not* serving it is $U_d(S(x))\left(1 - \frac{K(x)}{U_d(S(x))\eta}\right)$. The sources of energy from which IoT users can charge *passively* are: 1) the serving BS, due to downlink transmission to other users belonging to the same cell; 2) other base stations; 3) users in uplink, from all cells. The amount of power received due to (1) is thus obtained by the product of the power received by $x$ when its BS is serving other users, $P_{BS} r(x)^{-\alpha} L$, multiplied by the fraction of time during which the BS is active *and* serving other users:

$$\xi P_{BS} r(x)^{-\alpha} L U_d(S(x)) \left(1 - \frac{K(x)}{U_d(S(x))\eta}\right)$$

The contribution (2) is given by $\xi I(r(x), k)$ multiplied by $\left(1 - \frac{K(x)(1-\eta)}{\eta}\right)$, i.e. by the fraction of base station time dedicated to other than transmitting information to the user at $x$. Note that $I(r(x), k)$ account also for the downlink utilization of the interfering base stations. As for the contribution (3), we denote it with $\xi O(x) \left(1 - \frac{K(x)(1-\eta)}{\eta}\right)$.