

SWIPT-based Real-Time Mobile Computing Systems: A Stochastic Geometry Perspective

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Abstract—In this paper, we propose the use of simultaneous wireless information and power transfer (SWIPT) to control distributed computation process while delivering power to perform the computation tasks requested. A real-time mobile computing (MC) system is considered, meaning that the trade-off between the information rate and the energy harvested must be carefully chosen to guarantee that the central processing unit (CPU) may perform tasks of given complexity before receiving a new control signal. In order to provide a system-level perspective on the performance of such a SWIPT-MC network, we make use of stochastic geometry to characterise the rate-energy trade-off of the system. The resulting achievable performance region is then put in relation with the CPU energy consumption to investigate the operating conditions of real-time computing systems.

Index Terms—Simultaneous wireless information and power transfer (SWIPT), RF energy harvesting, mobile computing (MC), trade-off, stochastic geometry, network analysis.

I. INTRODUCTION

In the recent years, the saturation of the smartphone market penetration fostered the development of new applications to connect human beings with smart objects. The collection of sensors, actuators, algorithms and connectivity enabling complex machine-to-machine and human-to-machine interactions is mostly referred to as *the internet of things* (IoT). With challenges about the possible limitations in energy storage and computing capacity for the *mobile low power devices* (LPDs), a technological breakthrough towards a new generation of LPDs with enhanced real-time processing capability that would support the IoT vision is required. In this sense, the appealing solutions proposed so far delineate a new framework for the design and the optimisation of wireless networks in which computation and traditional communication aspects are merged into a unified perspective [1].

Following this line of thought, it appears that the implementation of such mobile computing (MC) systems is confronted with the restrictions on the amount of energy available to perform sophisticated computation tasks, and the limited capacity of the radio links. A potential solution to overcome these obstacles consists in a joint exploitation of the communication and computation facilities to decompose demanding tasks and execute them across the whole network, [1]–[3]. Within this context, an enticing emerging research direction is the integration of wireless power transfer (WPT)

and MC. In WPT-MC systems, the computation power can be obtained through radio frequency energy harvesting (RFEH) to prolong the battery life of the LPDs [4]–[6]. For example, in [4], the authors analysed a multi-user wireless powered MC system with computation offloading capability and proposed a mode selection scheme to maximise the sum of the computation rates. Concurrently, the authors of [5] studied an optimal resource allocation scheme to minimise the total energy consumption under computation latency constraints. Lately, in [6], simultaneous wireless information and power transfer (SWIPT) was proposed to jointly provide power and information to LPDs in an MC system.

A crucial aspect to be considered in designing WPT systems is the attenuation of radio waves with distance, which is known as the path loss. Path loss is particularly detrimental for energy transfer and may even question its relevance! The only possible strategy to counteract path loss is to densely deploy wireless energy sources, thus enabling lower transmit power requirements and increased levels of the energy delivered to the LPDs.

Stochastic geometry (SG) has been introduced as a random and spatial model to analyse the performance of dense networks [7]. In SWIPT-MC systems, differently from the conventional communication systems, the spatial distribution of the network nodes would play a major role, not only on the performance of the communication links, but also in determining the computation capacity of the LPD nodes. This is mainly due to the fact that the complexity of the allowed computation tasks is limited by the amount of harvestable power. In particular, in SWIPT-MC systems, the ability of an LPD to perform given tasks is reflected on specific rate-energy trade-offs, i.e. more energy is furnished to the LPDs, more likely the multi-user interference will weaken the communication capacity, [8]. A mathematical framework for the SG analysis of an outdoor SWIPT network was originally proposed in [9]. This analysis was extended in [10] for multi-input multi-output (MIMO) SWIPT networks. More recently, in [8], the authors proposed an accurate SG framework for the analysis of the rate-energy trade-off in dense MIMO SWIPT indoor networks. However, for what concerns SWIPT-MC systems, a study that quantifies the impact of the computation requirements on the achievable trade-offs at a network level is still missing in the literature. The main objective of this paper is to close this gap.

In this paper we develop a methodology to analyse an MC system in which SWIPT is used to simultaneously deliver

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power and control information to the LPDs. We assume that the MC system supports a given set of services and that each service is associated with a list of computation tasks to be performed by multiple LPDs in a distributed fashion. Each LPD embeds a software enabling the execution of the computation tasks associated with one or more services. Each transmitter is allocated to only one service during a single time slot and it transmits the control information to the LPDs associated with the same service. The control signal is used to select specific tasks out of the set associated with the LPD's service. Differently from other studies, we account for the complexity of the computation tasks as well as the rate at which those tasks are performed to map the rate-energy trade-off onto a value of achievable computation rate. Finally, it is worth remarking that we target a real-time MC system, meaning that the computation capability of the LPD must rely on the energy harvested during a single transmission slot. To achieve this, the computation tasks are modelled through the number of logical operations per bit that must be performed and the size of the local data to be processed.

A. Notations

$j = \sqrt{-1}$ denotes the imaginary unit. $\mathbb{1}\{\cdot\}$ is the indicator function. $\text{Im}\{\cdot\}$ denotes the imaginary part. $\Gamma(\cdot, \cdot)$ is the upper-incomplete Gamma function [11, Eq. 8.350.2]. ${}_pF_q(a_1, \dots, a_p; b_1, \dots, b_q; \cdot)$ is the generalized hypergeometric function [11, Eq. 9.14.1]. $\mathcal{H}(\cdot)$ denotes the Heaviside function and $\bar{\mathcal{H}}(\cdot) = 1 - \mathcal{H}(\cdot)$.

II. SYSTEM MODEL

In this section, we model a MIMO SWIPT-MC system operating in an indoor environment. The objective of the MC system is to provide a set of services $\mathcal{S}$, where the attributes of a generic service $s \in \mathcal{S}$ are a collection of computation tasks. Each computation task processes N bits representing contextual information (e.g. sensed data, information on the activity of a human user, mobility patterns) locally collected and stored at the LPD. The SWIPT waveform received is used to simultaneously decode the control signal that will select the computation tasks to be executed and extract the power needed to perform those tasks. According to this model, instead of considering the signal propagation as the sole restriction, we recognise that the SWIPT signals are sent with the purpose of enabling the execution of computation tasks. Hence, besides the signal propagation model, we also present a practicable model for the central processing unit (CPU) energy consumption at the LPD.

A. Network model

The network infrastructure is composed of a set of SWIPT transmitters, also referred to as power heads (PHs), randomly located over a finite region. We assume that the PHs have been deployed following a homogeneous Poisson Point Process (PPP) distribution, Ψ , with density λ_{PH} . At each time slot, a generic PH is associated with the service s with probability q_s . We denote with $\mathcal{P}_s$ the subset of PHs allocated to the service

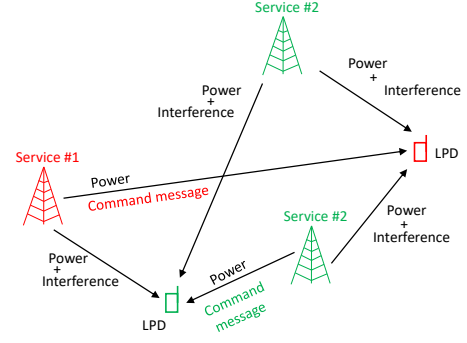


Fig. 1: SWIPT-MC system model

s . During an initial discovery phase, the LPDs broadcast a packet containing a message indicating their associated services. Then, each LPD establishes a communication link with the PH $p \in \mathcal{P}_s$ ensuring the minimum average signal attenuation. We also assume that all the PHs share the same radio resources, so that all the PHs but p are considered as interferers for the information transfer process. The set of interferers for the l th LPD is denoted by $\Psi^{(l)}$. An illustration of the SWIPT-MC system is provided in Fig. 1.

The PHs and LPDs are equipped with n_t transmit antennas and n_r receive antennas, respectively. Moreover, maximum ratio transmission (MRT) is utilised at the transmitter side while maximum ratio combining (MRC) is implemented at the receiver side. The LPDs embed a SWIPT receiver with a power splitting (PS) architecture to decode information and harvest energy simultaneously. The received signal is split into two streams of different power levels for decoding and harvesting using a PS ratio $0 \leq \rho \leq 1$.

Since an indoor environment is considered, the signal propagation model is composed of distance dependent path loss, wall blockages and small scale fading. To model the wall blockages, we consider randomly distributed walls following a Manhattan Poisson Line Process (MPLP) distribution with frequency λ_W for both the x - and y - dimensions. The joint effect of path loss and wall blockages gives rise to the following propagation model [8]:

$$l_W(r) = \begin{cases} \frac{\kappa r^\beta}{K^W} & \text{if } r \geq \kappa^{-1/\beta} \\ 1 & \text{otherwise,} \end{cases} \quad (1)$$

where r is the distance between the PH and the LPD, β is the path-loss exponent, $K \in (0, 1]$ is the penetration loss and W is a random variable indicating the number of walls between a generic PH and the LDP. $\kappa = \left(\frac{4\pi}{v}\right)^2$ is the path loss constant, where $v = c_0/f_c$ is the transmission wavelength, f_c and c_0 being the carrier frequency in Hz and the speed of light in m/sec, respectively.

B. Computation Model

As mentioned above, the objective of our MC system is to provide a set of services $\mathcal{S}$. To achieve this, the generic PH $p \in \mathcal{P}_s$ transmits a command message with a fixed length of

M bits to trigger the execution of a specific task to process the data gathered locally. It is worth mentioning that in this study, we consider only the first phase of the system (downlink) and study the impact of the computation requirements on the achievable rate-energy trade-offs in the downlink. Second phase (uplink, i.e. sending the results of the processed data to the PHs) is left for future work. Each computation task is characterised by k logical operations per bit. The primary engine for local computation at the LPD is the CPU, where the energy consumption per logical operation depends on the CPU clock speed. Therefore, under the assumption of low CPU voltage, the energy consumed by the CPU to execute a task can be modelled as [12]

$$E_C = \sum_{i=1}^{kN} \xi f_i^2 \quad (2)$$

in which N is the number of bits encoding the contextual information, ξ is the effective capacitance coefficient and f_i denotes the CPU frequency (i.e. the clock speed) for each CPU cycle $i \in \{1, \dots, kN\}$.

III. RATE-ENERGY TRADE-OFF ANALYSIS

In order to analyse the performance of the SWIPT-MC network through the achievable trade-offs between the harvested power and the information rate, we consider a typical LPD, indexed by $l = 0$ and denoted with LPD_0 , that is located at the centre of a circular area with radius R_D . Typically, the PH experiencing the minimum signal attenuation is assumed to be the serving PH for the LPD_0 . However, assuming that the LPD_0 is only associated with a subset of services $\mathcal{S}_{LPD} \subseteq \mathcal{S}$, it may not be able to answer to the PH's request. In such a case, the PH will initiate a communication with another LPD, thus creating interference to the LPD_0 . It follows that the serving PH shall belong to the subset of PHs that were allocated to a service $s \in \mathcal{S}_{LPD}$. Therefore, we introduce the concept of hit probability, $q_{hit} = \sum_{s \in \mathcal{S}_{LPD}} q_s$, defined as the probability that a generic PH is allocated to one of the services implemented by the LPD_0 . The original PPP, Ψ , is then partitioned into two homogeneous PPPs: $\Psi_{q_{hit}}$ with density $q_{hit} \lambda_{PH}$ and $\Psi_{\bar{q}_{hit}}$ with density $\bar{q}_{hit} \lambda_{PH}$, where $\bar{q}_{hit} = 1 - q_{hit}$.

In order to analyse the attenuation due to the blockage objects, we follow the procedure originally proposed in [8], in which homogeneous PPPs are decomposed into the sum of inhomogeneous PPPs, each of which being associated with the probability of experiencing W blockage objects. Hence, we have

$$\Psi_{q_{hit}} = \sum_{W=0}^{W_{max}} \Psi_{W, q_{hit}} \quad (3)$$

and

$$\Psi_{\bar{q}_{hit}} = \sum_{W=0}^{W_{max}} \Psi_{W, \bar{q}_{hit}}. \quad (4)$$

The expressions of densities for $\Psi_{W, q_{hit}}$ and $\Psi_{W, \bar{q}_{hit}}$ can be obtained from [8, Eq.2] by substituting λ_{PH} with $q_{hit} \lambda_{PH}$ and

$\bar{q}_{hit} \lambda_{PH}$, respectively. Here W_{max} is the maximum number of obstacles that can be encountered in the region of interest.

Given the partition of the original PPP into elementary elements, the average propagation loss experienced by the serving PH can be expressed as

$$L^{(0)} = \min_W \left\{ \min_{n \in \Psi_{W, q_{hit}}} \{l_W(r^{(n)})\} \right\} \quad (5)$$

where $r^{(n)}$ denotes the distance from a generic PH to the LPD_0 .

The rate-energy trade-offs are analysed through the joint complementary cumulative distribution function (J-CCDF) of the achievable information rate, R , and the average harvested power, Q :

$$F_c(R^*, Q^*) = \Pr\{R \geq R^*, Q \geq Q^*\} \quad (6)$$

where $R^* \geq 0$ and $Q^* \geq 0$ represent the minimum required information rate and harvested power, respectively. Assuming that the transmission bandwidth is equal to B and that each PH transmits with average power P , we have

$$R = B \log_2 \left(1 + \frac{P g^{(0)} / L^{(0)}}{P \mathcal{I}_{MU} + \sigma_n^2 + \sigma_c^2 / (1 - \rho)} \right), \quad (7)$$

$$Q = \rho \zeta P \left(\frac{g^{(0)}}{L^{(0)}} + \mathcal{I}_{MU} \right)$$

where ρ is the power splitting ratio, ζ is the efficiency of the RFEH, σ_n^2 denotes the variance of the thermal noise and σ_c^2 indicates the variance of the noise due to the RF-to-DC conversion of the received signal. The random variable $g^{(0)}$ characterises the power gain of the link between the serving PH and the LPD_0 , including MRT and MRC, and its probability density function (PDF) is given in [13]. Moreover, $\mathcal{I}_{MU}$ denotes the multi-user interference and can be expressed as

$$\mathcal{I}_{MU} = \sum_{W=0}^{W_{max}} \left(\sum_{n \in \Psi_{W, q_{hit}}^{(\setminus 0)}} \frac{h^{(n)}}{l_W(r^{(n)})} \mathbb{1} \{l_W(r^{(n)}) > L^{(0)}\} + \sum_{n \in \Psi_{W, \bar{q}_{hit}}} \frac{h^{(n)}}{l_W(r^{(n)})} \right) \quad (8)$$

where $h^{(n)}$ represents the gain of the n th interfering link that is assumed to be an exponentially distributed random variable with unit variance. We can notice that $\mathcal{I}_{MU}$ is composed of two parts. The first one represents the interference produced by all the PHs belonging to $\Psi_{W, q_{hit}}^{(\setminus 0)}$, while the second one refers to the interference generated by the PH belonging to $\Psi_{W, \bar{q}_{hit}}$.

Following the same approach as in [8], we can find all the statistical characterizations of $L^{(0)}$, $\mathcal{I}_{MU}$ and $g^{(0)}$. Eventually, the J-CCDF $F_c(R^*, Q^*)$ is obtained through the expression, [10],

$$F_c(R^*, Q^*) = \mathcal{K}_{m,n} \sum_{s=1}^m \sum_{t=n-m}^{(n+m-2s)s} a_{s,t} \left(J_{s,t}^{(1)} - J_{s,t}^{(2)} \right) \quad (9)$$

$$J_{s,t}^{(1)} = \int_1^\infty \int_0^\infty \frac{1}{\pi\omega} \text{Im} \left\{ \exp \left(-j\omega \frac{q_*}{P} \right) \left(s - \frac{j\omega}{y} \right)^{-(1+t)} \Gamma \left(1+t, \frac{\mathcal{T}_*}{P} (sy - j\omega) \right) \prod_{W=0}^{W_{max}} \Phi_W(\omega; y) \right\} \\ \times \left(\sum_{W=0}^{W_{max}} \hat{\Lambda}_{W,q_{hit}}([0, \alpha]) \exp \left\{ - \sum_{W=0}^{W_{max}} \Lambda_{W,q_{hit}}([0, \alpha]) \right\} \right) d\omega dy, \quad (10)$$

$$J_{s,t}^{(2)} = \int_1^\infty \int_0^\infty \frac{1}{\pi\omega} \text{Im} \left\{ \exp \left(j\omega \frac{\sigma_*^2}{P} \right) \left(s + \frac{j\omega\gamma}{y} \right)^{-(1+t)} \Gamma \left(1+t, \frac{\mathcal{T}_*}{P} (sy + j\omega\gamma) \right) \prod_{W=0}^{W_{max}} \Phi_W(\omega; y) \right\} \\ \times \left(\sum_{W=0}^{W_{max}} \hat{\Lambda}_{W,q_{hit}}([0, \alpha]) \exp \left\{ - \sum_{W=0}^{W_{max}} \Lambda_{W,q_{hit}}([0, \alpha]) \right\} \right) d\omega dy, \quad (11)$$

$$\Lambda_{W,q_{hit}}([0, \alpha]) = \frac{4 q_{hit} \lambda_{PH}}{W!} \sum_{i=0}^\infty \frac{(-1)^i}{i!(i+W+2)} \lambda_w^{i+W} \left[\frac{2^{\frac{i+W}{2}} \sqrt{\pi} \Gamma(\frac{i+W+1}{2})}{\Gamma(\frac{i+W+2}{2})} - \frac{\sqrt{2} {}_2F_1\left(\frac{1}{2}, \frac{i+W+1}{2}, \frac{i+W+3}{2}, \frac{1}{2}\right)}{i+W+1} \right] \\ \times \left[R_D^{W+2+i} \mathcal{H} \left(\alpha - \frac{R_D^\beta \kappa}{K^W} \right) + \left(\frac{\alpha K^W}{\kappa} \right)^{\frac{W+i+2}{\beta}} \tilde{\mathcal{H}} \left(\alpha - \frac{R_D^\beta \kappa}{K^W} \right) \right] \quad (12)$$

where $\mathcal{K}_{m,n} = \prod_{i=1}^m ((m-i)!(n-i)!)^{-1}$ with $m = \min(n_t, n_r)$ and $n = \max(n_t, n_r)$, and the coefficients $a_{s,t}$ can be computed using [13, Algorithm 1]. The functions $J_{s,t}^{(1)}$ and $J_{s,t}^{(2)}$ are defined as in (10) and (11), respectively where $\sigma_*^2 = \sigma_n^2 + \frac{\sigma_c^2}{1-\rho}$, $q_* = \frac{Q_*}{\rho\zeta}$, $\mathcal{T}_* = \frac{q_* + \sigma_*^2}{\gamma+1}$ and $\gamma = 1/(2^{R^*/B_c} - 1)$. Here $\Lambda_{W,q_{hit}}([0, \alpha])$, whose expression is given in (12), is the intensity of the process $L_{W,q_{hit}}^{(\setminus 0)} = \left\{ l_W(r^{(n)}), n \in \Psi_{W,q_{hit}}^{(\setminus 0)} \right\}$ and $\hat{\Lambda}_{W,q_{hit}}([0, \alpha])$ denotes the first derivative of $\Lambda_{W,q_{hit}}([0, \alpha])$ with respect to α . Moreover, $\Phi_W(\omega; L^{(0)})$ is the characteristic function of the interference generated from the PHs associated with $\Psi_W = \Psi_{W,q_{hit}} + \Psi_{W,\bar{q}_{hit}}$ and can be expressed as

$$\Phi_W(\omega; L^{(0)}) = \Phi_{W,q_{hit}}(\omega; L^{(0)}) \Phi_{W,\bar{q}_{hit}}(\omega). \quad (13)$$

Here $\Phi_{W,q_{hit}}(\omega; L^{(0)})$ and $\Phi_{W,\bar{q}_{hit}}(\omega)$ are the characteristic functions of the interference generated from the PHs associated with $\Psi_{W,q_{hit}}^{(\setminus 0)}$ and $\Psi_{W,\bar{q}_{hit}}$, respectively. Since all the signals associated with $\Psi_{W,\bar{q}_{hit}}$ are interfering signals for LPD_0 and the propagation loss is lower bounded by 1 (see (1)), we can obtain the characteristic function of the second term of $\mathcal{I}_{MU}$ (see (8)), $\Phi_{W,\bar{q}_{hit}}(\omega)$, by replacing $q_{hit}\lambda_{PH}$ with $\bar{q}_{hit}\lambda_{PH}$ and substituting $L^{(0)} = 1$ in the closed expression of $\Phi_{W,q_{hit}}(\omega; L^{(0)})$ which is given in (14) and (15) at the top of the next page.

IV. SWIPT BASED REAL TIME COMPUTATION

In this work, we aim at analysing a real-time SWIPT-MC system whose objective is to harvest enough energy to support the CPU chore in processing the N bits of local data at a given rate. As already stated in the system model, the

LPDs' activities are remotely controlled by the PHs through control messages which determine the tasks to be executed. Upon decoding the M bits of the command message, the LPD exploits the harvested energy to perform the computation tasks requested and the triggered tasks must be executed prior to the reception of the next message. In other words, the information rate of the wireless link determines the maximum time that can be devoted to the computation (i.e. $\sum_{i=1}^{kN} \frac{1}{f_i} \leq \frac{M}{R}$). At the same time, larger values of rate correspond to smaller values of energy harvested. From (2), this amounts to saying that the CPU must perform less cycles or reduce its clock speed. Clearly, this causes a conflict between communication and computation performance. The following describes a procedure to determine the best compromise between communication and computation for a given J-CCDF.

The computation capacity can be determined by optimising the clock frequencies to minimise the CPU energy consumption. Minimizing the energy consumption, considering the fact that execution of the triggered task must be finished before next command message arrives, will result in equal frequencies of $f_i = \frac{kNR}{M}, \forall i$ as shown in [5]. By substituting f_i into (2) the minimum power needed to support real-time operations is obtained as

$$Q = \frac{E_c R}{M} = \xi \frac{(kNR)^3}{M^3}. \quad (16)$$

Finally, we can define the outage probability of the real-time SWIPT-MC system as a function of the targeted information rate as

$$P_{out} = 1 - F_c \left(R, \xi \frac{(kNR)^3}{M^3} \right). \quad (17)$$

Interestingly, the information rate can also be interpreted as the

$$\Phi_{W,q_{hit}}(\omega; L^{(0)}) = \exp \left\{ \frac{4 q_{hit} \lambda_{PH}}{W!} \sum_{i=0}^{\infty} \frac{(-1)^i}{(i!)(i+W+2)} \lambda_w^{i+W} \left[\frac{2^{\frac{i+W}{2}} \sqrt{\pi} \Gamma(\frac{i+W+1}{2})}{\Gamma(\frac{i+W+2}{2})} - \frac{\sqrt{2} {}_2F_1(\frac{1}{2}, \frac{i+W+1}{2}, \frac{i+W+3}{2}, \frac{1}{2})}{i+W+1} \right] \right. \\ \left. \times \Delta_{W,q_{hit}}(\omega; L^{(0)}) \bar{\mathcal{H}} \left(L^{(0)} - \frac{R_D^\beta \kappa}{K^W} \right) \right\} \quad (14)$$

$$\Delta_{W,q_{hit}}(\omega; L^{(0)}) = \left(\frac{L^{(0)} K^W}{\kappa} \right)^{\frac{(i+W+2)}{\beta}} \left(1 - {}_2F_1 \left(1, -\frac{(i+W+2)}{\beta}, 1 - \frac{(i+W+2)}{\beta}, \frac{j\omega}{L^{(0)}} \right) \right) \\ - R_D^{(i+W+2)} \left(1 - {}_2F_1 \left(1, -\frac{(i+W+2)}{\beta}, 1 - \frac{(i+W+2)}{\beta}, \frac{j\omega K^W}{R_D^\beta \kappa} \right) \right) \quad (15)$$

rate at which the local data must be updated before initiating a new computation. Hence, (17) provides also insights into the maximum task complexity given the refresh rate of the data gathered at the LPD.

V. NUMERICAL RESULTS

A. Setup

The parameters are set as follows unless otherwise specified. A circular area with radius of $R_D = 60\text{m}$ is considered. The PHs are randomly distributed using a PPP with a density of $\lambda_{PH} = 1/(\pi d_{PH}^2)$, where $d_{PH} = 3\text{m}$ is half of the average minimum distance between PHs. The average transmit power is set to 1W , i.e. $P = 30\text{dBm}$. The signal bandwidth is assumed to be $B = 200\text{kHz}$ centred around a frequency of $f_c = 2.1\text{GHz}$. The frequency of the walls is also fixed to $\lambda_w = 0.03$. At the LPDs, the variance of the noise due to the RF to DC conversion is set to $\sigma_c^2 = -70\text{dBm}$ and the thermal noise variance is given by $\sigma_n^2 = -174 + 10 \log_{10}(B) + \mathcal{F}_n$, where $\mathcal{F}_n = 10\text{dB}$ is the noise figure. The effective capacitance coefficient is set to $\xi = 10^{-28}$, the energy harvesting efficiency is assumed to be $\zeta = 0.8$. Here it is worth to mention that in [8], the authors have obtained the same values of maximum achievable information rate for all values of power splitting ratio ρ due to the fact that, with the level of densification required to receive a total power belonging to the microwatt region, the system is essentially interference limited and the SINR does not depend on realistic levels of noise. By concluding that the power splitting ratio must be as large as possible it is set to $\rho = 0.99$. The number of antennas at the LPD is $n_r = 2$ and the number of transmit antennas is set to $n_t = 4$. The length of the control messages is fixed to $M = 32\text{bits}$ and the number of bits at the LPD is assumed to be $N = 0.6\text{kb}$. Moreover, the path loss exponent is assumed to be $\beta = 2.5$ and the penetration loss K is -10dB per crossed wall according to [14, Table 3].

B. Results

1) *Validation of the analytical findings:* Fig.2 shows the trade-off between the information rate and the harvested power

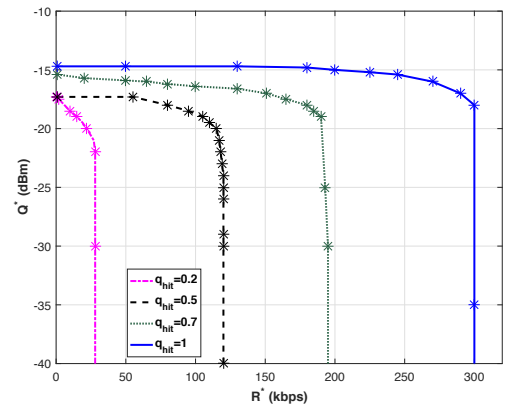


Fig. 2: Rate-energy trade-off: theoretical results and Monte Carlo simulations for different values of q_{hit} .

for several values of q_{hit} when $F_c(R^*, Q^*) = 0.75$. In order to validate our analysis, both theoretical results (lines) and Monte Carlo simulations (markers) are reported. An almost perfect match between the Monte Carlo simulations and the analytical curves is observed. Besides, it can be observed how the hit probability impacts the rate-energy trade-off. In fact, when the hit probability increases, more PHs will be allocated to one of the services implemented by the LPD₀. As a result, the probability of experiencing a relatively moderate signal attenuation between the PH and the LPD₀ will be larger, which, in turns will give rise to higher values of signal to interference plus noise ratio (SINR) at the SWIPT receiver. For instance, by increasing q_{hit} from 0.2 to 1, the information data rate increases from 28Kbps to 300Kbps for -25dBm of harvested power. From Fig.2 we can also observe that the maximum harvested power increases when q_{hit} increases. This is mainly due to the fact that serving PH which takes the advantage of MRT process has a greater probability of being closer to the LPD₀. For example at 22kbps of information rate, with $q_{hit} = 1$, the power harvested is 5.3dB greater than the one relevant to $q_{hit} = 0.2$.

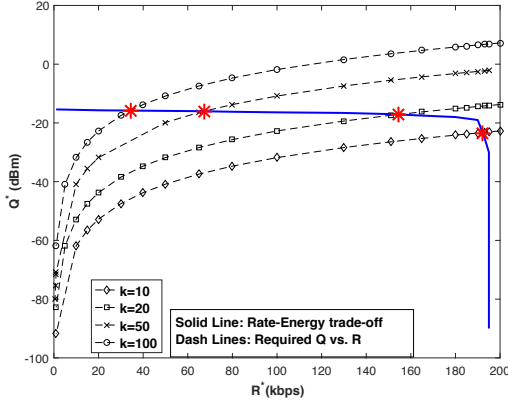


Fig. 3: Operating points on the rate-energy trade-off for different values of k .

2) *Operating point vs task complexity*: Fig.3 indicates the operating points associated with different computation loads (expressed in number of logical operations per bit processed). The number of logical operations per bit is set to $k = 10, 20, 50, 100$, $F_c(R, Q) = 0.75$ and $q_{hit} = 0.7$. Required powers (dash lines) are obtained with the help of (16). Not surprisingly, for fixed information rates, more harvested power is required for performing more complex tasks. It can be observed that if $k = 10$ operations per bit are required we need $Q^* = -23.5\text{dBm}$ of power to perform $R^*/M = 192/32 = 6$ kilotasks/second. However, if $k = 100$, we can only execute 1 kilotasks/second by using $Q^* = -15.8\text{dBm}$ of harvested power.

3) *Outage probability*: In this subsection, we analyse the outage probability of the SWIPT-MC system. Fig. 4 illustrates the outage probability against the number of tasks per second, $\frac{R}{M}$, to be executed for $k = 10, 20, 50$. It is apparent that, for the same outage probability, the number of tasks per second decreases when the number of operations per bit increases. As an example, with a fixed outage probability of $P_{out} = 0.4$, we can perform 9 kilotasks/second with $k = 10$ operations per bit, while for $k = 20$ and $k = 50$ only 5 and 2 kilotasks/second can be executed, respectively. However, as shown in Fig.5, executing more tasks per second does not necessarily mean that we better utilise the CPU. In fact, from Fig. 5 we observe that for a fixed number of CPU cycles per second, $\frac{kNR}{M}$, the outage probability decreases when k increases. This is mainly due to the fact that the data rate is interference limited, so it is not always possible to perform low complexity tasks at a very high rate. Therefore, it can be more efficient to perform more complex tasks at low rate to optimise the CPU usage. Stated otherwise, it would be more efficient to trigger a large number of tasks with the same command message rather than sending command messages at a very high rate to select only a small number of tasks.

An improvement on this model would be an extension to a Mobile Edge Computing (MEC) system where both local computing and offloading are considered. Such a setup will

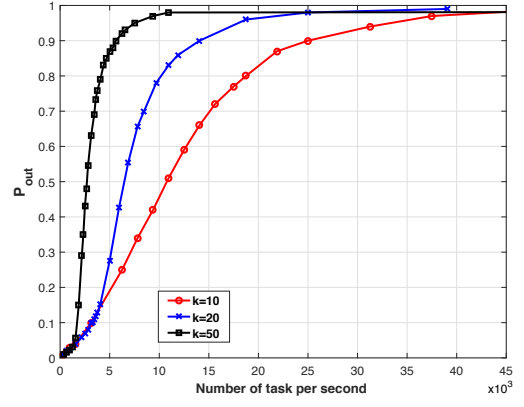


Fig. 4: Outage probability versus the number of tasks per second for different values of k .

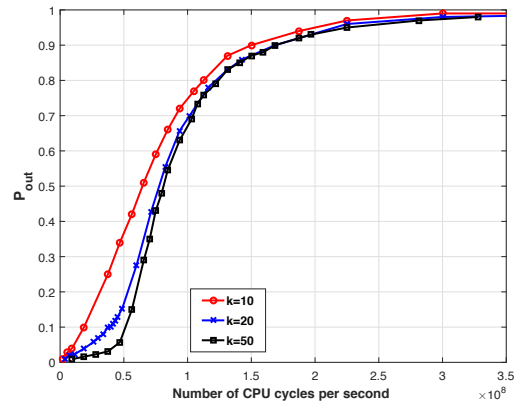


Fig. 5: Outage probability versus the number of CPU cycles per second for different values of k .

be investigated in our future work.

VI. CONCLUSION

In this paper, we proposed a model for real-time MIMO SWIPT-MC systems operating in an indoor environment. We analysed the considered system by making use of an SG framework, providing a comprehensive understanding of the rate-energy trade-off on a service basis. We then investigated the connection between the rate-energy trade-off and the computation capacity of the LPDs. In addition, we provided the optimal operating points guaranteeing real-time processing of the locally generated data for given task complexities. Finally, the outage probability of the SWIPT-MC system was studied for different network setups. The numerical results show that the best CPU utilisation is obtained when more complex tasks are performed at a lower rate instead of executing less complex tasks at a higher rate.

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