Abstract—Extremely high reliability and energy efficiency are crucial in sixth generation (6G) mobile networks to accommodate the diverse range of end-user devices in the era of the Internet of Everything. The concept of simultaneous wireless information and power transfer (SWIPT) has been emerged as a promising solution to boost the reliability of wireless communication systems through prolonging the battery lifetime by harvesting energy from the received radio-frequency signals. In this paper, we propose a low complexity threshold-based pair switching (TbPS) technique for SWIPT in the context of large-scale cellular networks, where the multiple-antenna mobile users (MUs) employ maximum ratio combining technique and adopt the random waypoint model. Under the TbPS technique, a subset of MU's antennas is allocated for information decoding (ID), only when their post-combiner signal-to-interference ratio, exceeds a certain threshold, while the remaining antennas are allocated for energy harvesting (EH). Contrary to traditional approaches which assume the existence of either uncorrelated or fully correlated interference, our proposed technique takes into consideration the interference correlation between nearby antennas. In order to further alleviate the inter-cell interference and energy consumption, we propose a traffic load-based sleeping (TLbS) technique in the context of finite-area network deployments, where lightly-loaded cells switch into sleep mode. By leveraging tools from stochastic geometry, we derive analytical expressions for the ID, EH as well as joint ID and EH success probability of MUs based on the proposed techniques. Our results demonstrate the optimal parameters (i.e., antenna selection and traffic load threshold) of our proposed techniques, that maximize the joint ID and EH success probability. Finally, it is shown that, by properly selecting the threshold values, both the proposed TbPS scheme and TLbS mechanism outperform the conventional techniques in terms of the SWIPT capability of the MUs.

Index Terms—6G networks, SWIPT, stochastic geometry, random waypoint, wireless power transfer, mobility

I. INTRODUCTION

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unlimited and ubiquitous wireless connectivity [2]. Such point-of-view is adopted by the Internet of Everything (IoE) which promises wireless connectivity to a wide range of applications, ranging from small static sensors to autonomous devices. In the concept of IoE, these devices are typically battery-powered, requiring long-term operation and even no battery replacement. Although existing 5G networks are able to support basic IoT services, it is debatable whether they can deliver future massive advanced IoT applications. One of the major challenges lies in the sustainable energy supply for enormous network nodes. More specifically, since the majority of mobile devices participating in the IoE concept will be battery-operated, such as portable devices, sensors, etc., the lifetime of such devices poses a significant impact on the overall network performance. Hence, with 6G going towards denser networks deployments along with the diverse range of end-user devices (i.e., static and/or mobile), the sustainable energy supply is of paramount importance on the way to 6G success.

To prolong the lifetime of wireless sensor networks, the concept of energy harvesting (EH) is adopted. Specifically, EH wireless networks provide the ability to the devices to harvest energy from their nearby environment, where the harvested energy may provide the essential energy to the sensor nodes for long-lasting, or even permanent operation. In contrast to the harvested energy originated from solar, wind or other renewable energy sources, the EH from radio frequency (RF) sources are more sustainable since RF signals can be continuously acquired from the surrounding transmitters. Current advances in EH technology allow base stations (BSs) to realize simultaneous wireless information and power transfer (SWIPT), where both information and energy can be extracted from the same received RF signals [3]. Although information theoretical studies preferably assume that the receiver is capable of decoding information and extracting energy separately from the same RF signal, this method has been previously regarded as an infeasible approach due to practical limitations [4]. Fortunately, the concept of SWIPT becomes feasible by separating the received RF signal into two parts; one part is used for information transfer and another part is used for power transfer. The partitioning of the RF signal can be implemented in the time, the power or the space domain [3].

The SWIPT technology in the context of large-scale networks has been widely-investigated in the literature. The authors in [5] proposed a stochastic geometry-based framework for the analysis of SWIPT-enabled multiple-input multiple-
output (MIMO) systems, and the trade-off between the data rate and the harvested energy was illustrated. In [6], the authors investigated the simultaneously joint information decoding (ID) and EH performance under time switching and power splitting schemes, and the optimal partitioning parameters to achieve maximum joint ID and EH performance were demonstrated. In [7], the idea of SWIPT in intelligent reflecting surface (IRS)-assisted cellular networks was explored, highlighting that the IRSs can promote the compensation of high RF signal attenuation over long distance and hence create efficient energy harvesting/charging zones in their vicinity. Most of the above work focuses on SWIPT-enabled networks that are based on protocols with either power splitting or time switching schemes. Nevertheless, the strict synchronization constraint for the TS approach and the demand of the adequate power-splitting circuit for the power splitting approach, increase the complexity and cost of the required hardware [8]. Antenna switching (AS), on the other hand, is a promising low-complexity alternative approach in the 6G mobile networks, where massive multi-antenna IoT devices such as sensors will be deployed [9].

The enormous amount of wireless connections that will host 6G mobile networks, leads to an unprecedented increase of inter-cell interference, which compromises the ID performance of the end-users. For the SWIPT-enabled multi-antenna receivers, the interference observed across different antenna elements is spatially correlated [5] [10]. While it has been long recognized that the correlated fading reduces the performance gain of multi-antenna communication systems, the concept of interference correlation has been overlooked until recently. Such spatial correlation of interference power affects the diversity gain of the system, especially in high path loss environments [10]. In [11], the authors dealt with the interference correlation issues of the multiple-antenna users and characterized the performance of a maximum ratio combining (MRC) in the presence of spatially-correlated interference across antennas. In [12], the authors characterized the spatiotemporal interference correlation as well as the joint coverage probability at two spatial locations in a cellular network and showed that the interference correlation and the joint coverage probability decrease with the increase of the users’ speed.

Mobility of wireless nodes is another key issue that has a fundamental impact on the performance of 6G wireless networks [2], [9]. Since it is difficult to obtain actual movement patterns, a common approach is to use synthetic mobility models which resemble the behaviour of actual mobile devices. Over the past decade, several research efforts have been carried out on characterizing the performance of a variety of wireless networks under several standard mobility models [13]–[15]. Due to its generality and tractability, the most commonly used mobility model is the random waypoint (RWP) model [15]–[17]. A detailed analytical framework of the spatial node distribution generated by the RWP model was first investigated in the context of ad hoc networks in [15]. The authors in [16] investigated two key parameters in the mobile networks, namely, handover rate and sojourn time, based on the RWP model with infinite network area. Moreover, the RWP model was utilised to characterize the performance for an infinite drone cellular network in [17]. In the context of small cells, where the coverage area is finite due to the high path loss experienced by the RF signals [18], it has been noticed in [19], [20], that the spatial distribution of the nodes that move according to the RWP model is non-uniform. Nevertheless, the majority of existing analytical results assumes uniform/homogeneous spatial deployments. Therefore, an analytical framework is required, which takes into account the occurred non-uniform deployment of network nodes due to their mobility in finite areas. In [19], several geometries of finite network areas, e.g. circular, square, hexagon areas, were investigated based on the RWP model, while it has been proven that the employment of RWP-based mobility model results in the concentration of the nodes around the center of the area. Similarly, the authors in [20] demonstrated that in the finite area mobile networks, the mean interference at the center under the RWP model was much higher than the interference at the border of the network area.

To the best of our knowledge, the performance of SWIPT-enabled mobile users (MUs), that exhibit spatial interference correlation, in the context of 6G mobile networks, is overlooked from the literature. Hence, the aim of this work is to fill this gap by modelling and analyzing such networks and by providing new analytical results for the network performance in a stochastic geometry framework. Specifically, the main contributions of this paper are summarized as follows:

- We develop a mathematical framework based on stochastic geometry, which comprises the modelling of SWIPT-enabled MUs in the context of cellular networks. The developed framework takes into account the existence of spatially correlated interference between the users’ antenna elements, and the ability of users to move within the network area based on a RWP model. Moreover, the performance of the considered system is assessed under two different network topologies as shown in Fig. 1, i.e. large-scale and small-scale networks, which cover an infinite and a finite area, respectively.

- In the infinite area scenario, i.e. large-scale outdoor environment, a novel antenna pairs switching scheme is
proposed for cellular networks, aiming at facilitating the MUs’ allocation either for ID or for EH. In particular, based on the proposed scheme, the receiver antenna elements are divided into pairs, and a subset of antenna pairs is allocated for ID, only when their post-combiner signal-to-interference ratio (SIR) is beyond a certain threshold, while the remaining pairs are allocated for EH. In addition, the interference power within each pair of antenna elements are assumed to be fully-correlated and for the different pairs, interference observed are assumed to be independent.

- In the finite area scenario, i.e. the indoor environment or small cells, we evaluate the performance of SWIPT-enabled MUs, in the context of a novel sleeping mechanism. Specifically, our proposed approach switches off cells in a probabilistic way based on their traffic load, which is non-uniform spatially distributed due to the MUs’ mobility, aiming the joint optimization of users’ throughput and EH performance. To guarantee the quality-of-service (QoS), the users of sleeping BSs are offloaded to active neighbouring BSs.

Analytical expressions for the success probability of ID and EH, as well as for the joint success probability, i.e. ID and EH, are derived for the considered network deployments. Moreover, under specific practical assumptions, closed-form expressions for the Laplace transform of the received interference are derived. These closed-form expressions provide a quick and convenient methodology of evaluating the system’s performance and obtaining insights into how key parameters affect the performance. Moreover, the optimal design parameters related to our proposed two techniques are illustrated that maximise the joint ID and EH ability of MUs.

- Finally, our numerical and simulated results show that, by properly selecting the parameters, i.e. SIR and traffic load thresholds based on the network deployment, the proposed two techniques outperform the conventional techniques, e.g. traditional antenna switching and non-sleeping schemes, in the context of ID and EH success probabilities of SWIPT-enabled MUs.

The rest of the paper is organised as follows: Section II introduces the network model together with channel, mobility model and SWIPT-enables networks. Section III presents our proposed SWIPT-based antenna pair switching scheme and the associated analytical framework. Section IV describes the cell sleeping mechanism as well as investigates the MUs’ ability of ID and EH, by using a similar mathematical framework with Section III. Finally, analytical and simulation results are presented in Section V, followed by our conclusions in Section VI.

Notation: \( \mathbb{R}^d \) denotes the d dimensional Euclidean space; \( ||x|| \) denotes the Euclidean norm of \( x \in \mathbb{R}^d \); \( \mathbb{P}[X] \) denotes the probability of the event \( X \) and \( \mathbb{E}[X] \) represents the expected value of \( X \); \( \Gamma(\cdot), \Gamma^*(\cdot, \cdot) \) and \( \gamma(\cdot, \cdot) \) denote the complete, the upper incomplete and the lower incomplete Gamma functions, respectively; \( _2F_1(\cdot, \cdot; \cdot; \cdot) \) is the Gauss hypergeometric function; \( \mathcal{H}(\cdot) \) is the Heaviside function and \( \bar{\mathcal{H}}(x) = 1 - \mathcal{H}(x) \).

II. System Model

In this section, we provide details for the considered system model. The network is studied from a large-scale point-of-view by leveraging tools from stochastic geometry. The main mathematical notations related to the system model are summarized in Table I.

A. Network Model

We consider the downlink of a single-tier bi-dimensional wireless cellular network, where all network’s nodes are confined on a circular region \( \mathcal{A} \) with radius \( R \in (0, \infty) \). The locations of the BSs are modelled as a homogeneous Poisson point process (PPP), \( \Phi_B = \{x_i \in \mathcal{A} \} \) with spatial density \( \lambda_b \) and unit transmit power, where \( x_i \) denotes the spatial coordinates of the \( i \)-th node. In addition, the locations of the MUs follow an arbitrary independent point process \( \Phi_u \) with spatial density \( \lambda_u \). We consider the case where all BSs are equipped with a single transmit antenna [10]. Regarding the adopted association scheme, we assume that each MU communicates with its closest BS at \( x_o \).

B. Channel Model

All wireless signals are assumed to experience both large-scale path loss effects and small-scale fading [10]. Regarding the small-scale fading, since channels between MUs and BSs are more probably to be in non-line-of-sight (NLoS) state due to the MUs’ mobility, we adopt the well-known Rayleigh fading model, where different links are assumed to be independent and identically distributed [21]. Hence, the channel power gain follows an exponential distribution with unit mean, i.e. \( h \sim \exp(1) \). For the large-scale path loss between a receiver at \( X \) and a transmitter at \( Y \), we assume an unbounded singular path loss model, where the path loss only depends on the spatial distance between \( X \) and \( Y \), and is given by \( L(X, Y) = ||X - Y||^{\alpha} \), where \( \alpha > 2 \) is the path loss exponent [10]. Throughout this paper, we will denote by \( r_i \) the distance between the considered MU and the \( i \)-th BS.

C. User Mobility Model

The process representing the RWP-based movement of a MU within an area \( \mathcal{A} \in \mathbb{R}^2 \) can be described as follows. Initially, each MU is placed at the point \( P_1 \) chosen from the uniform distribution \( \Phi_u \in \mathcal{A} \). Then, each MU uniformly chooses a destination (also called waypoint) \( P_2 \) in the region \( \mathcal{A} \) and moves towards it with randomly selected speed i.e., \( v \in [v_{\min}, v_{\max}] \), which remains constant during that movement. A new direction and speed are chosen only after the MU reaches the destination. For a long running time of the movement process, a stationary distribution, also known as steady-state distribution, is achieved [15]. It is important to mention here that, the uniform movement of MUs within an infinite-area network deployment leads to a uniform MUs’ steady-state distribution, and hence, the performance of infinite-area networks deployments does not affected by the users’ mobility process. Contrary, in the finite-area network deployments, the MUs bounce back when they reach the boundary, aiming the
number of MUs in $\mathcal{A}$ to remain constant, i.e. $|\mathcal{A}_u \mathcal{A}|$ [15]. Hence, a MU starting near the boundaries of the network area clearly finds more destination waypoints in directions toward the center of the area than toward the border. As time passes and the MUs perform a number of movement periods, the spatial distribution of the MUs becomes more and more non-uniform.

D. SWIPT-Enabled Cellular Networks

We assume that all BSs have a continuous power supply, while all MUs are battery-operated. Specifically, we assume that each MU has SWIPT capabilities and thus it can decode the information and also harvest energy from the received signal simultaneously. We consider that the EH process is accomplished by using either our proposed threshold-based pair switching (TbPS) technique (see Section III-A) or the conventional power splitting receiver architecture. A TbPS-based receiver allocates a subset of antennas for ID, only when its post-combiner signal-to-interference (SIR), exceeds a certain threshold, while the remaining antennas are allocated for EH. In a power splitting-based single-antenna receiver, the received power is divided into two parts with power splitting factor $\rho \in [0,1]$, where a fraction $(1-\rho)$ of the received power is used for decoding while the remaining power is inputted to the EH circuit [3], [22].

III. SWIPT WITH THRESHOLD-BASED PAIR SWITCHING TECHNIQUE

In this section, we propose a TbPS technique in the context of infinite-area cellular networks, where the multi-antenna MUs employ a MRC technique in the presence of spatial interference correlation. In particular, we evaluate the ability of a MU to successfully decode the received signal and harvest sufficient energy. Based on the proposed low-complexity TbPS technique, analytical expressions for the ID, EH, and joint ID and EH success probability are derived by using tools from stochastic geometry. Without loss of generality, based on the Slivnyak’s theorem, we perform our analysis for the typical MU, which is located at the origin [23], but the results hold for all users of the network.

Fig. 2. An $N$-antenna TbPS receiver with $\eta$ pair of antennas, where $\nu$ pairs of antennas are connected to decoding circuit and $(\eta - \nu)$ pairs of antennas to harvesting circuit.

A. Threshold-based Pair Switching Scheme

Even though the channels between the BSs and each antenna element of a MU are assumed to be independent with each other, the received interference across different antenna elements is neither independent nor identical [5], [10]. More precisely, the interference terms observed at the different antennas are partially correlated random variables due to the common locations of the interfering BSs [10]. Therefore, as shown in Fig. 2, motivated by the extremely narrow spacing between adjacent antenna elements of a MU, we divide the set of antenna elements into $\eta$ pairs of two adjacent antenna elements, i.e. $\eta = N/2$, where $N$ is the number of antennas of a MU. Such approach could capture the interference correlation between adjacent antenna elements and keep the tractability for the analytical framework. In particular, we assume that the observed interference between each antenna element of a pair is fully-correlated, while the intended received signal and interference between pairs are regarded uncorrelated. Then, based on the AS protocol [3], our proposed scheme allocates a subset of paired antenna elements, i.e. $\nu$ pairs, for ID purpose and the remaining $(\eta-\nu)$ pairs, for EH. Let $S_k$ and $I_k$ denote the power of the intended signal and observed interference at the $k$-th antenna element of a MU, respectively, where $k = \{1, \cdots , N\}$. Due to the full-correlation of the interference within each antenna pair, the interference

### Table I

| Symbol | Description |
|--------|-------------|
| $\alpha$ | Path loss exponent |
| $d$ | The distance from a MU to the centre of the small-scale networks |
| $\gamma_{th}$ | The selection threshold for TbPS scheme |
| $h_i$ | The channel power gain of the link between MU and the $i$-th BS |
| $I_k$ | The interference power observed at the $k$-th antenna of multi-antenna MUs |
| $\lambda_u$ and $\lambda_b$ | Density of the MUs and the BSs, respectively |
| $N$ | The number of antenna elements of multi-antenna MUs |
| $\rho$ | Power splitting factor |
| $r_o$ | The distance between a MU and its serving BS |
| $r_i$ | The distance between a MU and the $i$-th interfering BS |
| $R$ | The radius of considered network area |
| $S_k$ | The intended signal power received at the $k$-th antenna of multi-antenna MUs |
| $\chi$ and $Q$ | The threshold of ID and EH, respectively |
| $\zeta$ | Energy conversion efficiency |
across antennas in each pair is identical, i.e., $I_k = I_{k+1} = I_n$ where $k = 2n - 1$ and $n = \{1, \ldots, \eta\}$. Thus, based on the MRC technique, the SIR of the $n$-th antenna pair of the typical MU, is given by

$$\Xi_n = \frac{S_{2n-1} + S_{2n}}{I_n} = \frac{(h_{2n-1,O} + h_{2n,O}) L^{-1}(x_o)}{\sum_{x_i \in \Phi^O} h_{n,i} L^{-1}(x_i)}.$$  \hspace{1cm} (1)$$

Regarding the selection of the number of antenna pairs, $\nu$, we develop a threshold-based approach based on the MRC [24]. Let $\Gamma_\nu$ denote the post-combiner SIR for the MRC at the receiver when $\nu$ pairs of antenna elements are selected, which is equal to $\Gamma_\nu = \sum_{n=1}^\nu \Xi_n$, where $\Xi_n$ is given by the expression (1). Based on the TbPS scheme, the number of antenna pairs, $\nu$, is selected so that the post-combiner SIR at the receiver exceeds a certain predefined threshold $\Gamma_{th}$ (dB). Starting from the single-pair case, the TbPS scheme gradually raises the number of selected pairs aiming to satisfy the aforementioned condition. The previous actions are repeated until $\Gamma_\nu$ is greater than the threshold $\Gamma_{th}$. It should be noted that, in order to maintain the minimum harvested energy power, at least one pair is allocated for EH, i.e., for the case $\Gamma_{\eta-1} \leq \Gamma_{th}$, $\eta-1$ pairs are allocated for ID and the remaining one pair is allocated for EH. It is worth mentioning that, the proposed TbPS is a low-complexity antenna selection scheme, since the channel state information (CSI) is only required to be estimated at a fraction of the antenna elements. More specifically, once the post-combiner SIR reaches the threshold $\Gamma_{th}$, then no more CSI is needed for the remaining antenna elements, where the number of antennas that require CSI, i.e., $c$, is bounded within the interval $2 \leq c \leq N - 4$.

### B. Information Decoding Success Probability of MUs with TbPS Scheme

Initially, we assess the conditional cumulative distribution function (cdf) of $\Xi_n$, i.e., $\mathbb{P}[\Xi_n < Y|x_o]$, where $Y$ is the decoding threshold, which is useful for evaluating the ID, EH, and the joint ID and EH success probability. The following lemma evaluates the conditional cdf of the SIR at the $n$-th antenna pair of the typical MU.

**Lemma 1.** The conditional cdf for the SIR of the $n$-th antenna pair of the typical MU, i.e., $\Xi_n$, is given by

$$\Xi(Y|x_o) = 1 - L_{I_n}(s) + s \frac{\partial L_{I_n}(s)}{\partial s},$$

where $s = \mathbb{Y}L(x_o)$, $L_{I_n}(s)$ and $\partial L_{I_n}(s)/\partial s$ are the Laplace transform and the derivative of the Laplace transform of the interference observed at the $n$-th antenna pair, which are given in (2) and (3), respectively, and $r_o$ is the distance from the typical MU to its serving BS, i.e. $r_o = ||x_o||$.

**Proof.** See Appendix A. \hfill $\Box$

The following Remark investigates a special case of Lemma 1, where $\alpha = 4$, which is a common practical value for path-loss exponent in outdoor urban environments, where the closed-form expressions of the Laplace transform and the derivative of the Laplace transform of the interference are obtained.

**Remark 1.** For the special case $\alpha = 4$, the Laplace transform and the derivative of the Laplace transform of the interference observed at the $n$-th antenna pair can be simplified as

$$L_{I_n}(s) = \exp \left(-\pi \sqrt{5} s \tan^{-1} \left(r_o^{-2} \sqrt{5}\right)\right),$$

and

$$\frac{\partial L_{I_n}(s)}{\partial s} = - \frac{L_{I_n}(s) \pi s b}{2} \left(\frac{r_o^2}{r_o^2 + s} + \frac{\tan^{-1} \left(r_o^{-2} \sqrt{5}\right)}{\sqrt{5}}\right),$$

where $\tan^{-1}(\cdot)$ is the inverse of the tangent function.

Based on the adopted association scheme, i.e., each MU communicates with its closest BS at $x_o$, the complementary cumulative distribution function of the distance $r_o$ between a MU and its serving BS, is given by $\mathbb{P}[r_o > r] = \exp(-\pi s b r^2)$, and the probability density function (pdf) of the distance $r_o$, i.e., $f_r(r) = \frac{d}{dr} \left(1 - \mathbb{P}[r_o > r]\right)$, is given by [10]

$$f_r(r) = 2 \pi s b r \exp(-\pi s b r^2).$$  \hspace{1cm} (4)$$

Then, we focus on the evaluation of the ID success probability in the context of our proposed TbPS scheme, which can be formulated as

$$F_{ID}(\chi, \Gamma_{th}) = \mathbb{P} \left[ \Gamma_1 \geq \chi \ & \Gamma_1 \geq \Gamma_{th} \right] + \sum_{\nu=2}^{\eta-2} \mathbb{P} \left[ \Gamma_{\nu} \geq \chi \ & \Gamma_{\nu-1} < \Gamma_{th} < \Gamma_{\nu} \right] + \mathbb{P} \left[ \Gamma_{\eta-1} \geq \chi \ & \Gamma_{\eta-2} < \Gamma_{th} \right],$$

where $\chi$ (dB) is the decoding threshold.

It should be noted that, the proposed TbPS scheme is applicable for any MUs, of which the number of antenna elements is not less than four, i.e., at least one antenna pair is allocated for ID and one pair for EH. In addition, in order to achieve the adaptive and dynamic allocation of antenna pairs based on the instantaneous signal quality, i.e. SIR, the minimum number of antenna elements required at MUs is six.
Hence, in this work we consider the scenario where \( N = 6 \), for the sake of simplicity. The aforementioned scenario holds for practical wireless devices that are typically equipped with a small number of antenna elements, due to space limitations and complexity constrains, e.g., smartphones, WiFi routers [11], [25]. For this special case, the following proposition characterizes the resulting performance in terms of ID success probability.

**Proposition 1.** For the special case where MUs are equipped with six antenna elements, i.e., \( N = 6 \), the ID success probability, \( \mathcal{F}_{\text{ID}}(\chi, \gamma_{th}) \), is given by

\[
\mathcal{F}_{\text{ID}}(\chi, \gamma_{th}) = \int_0^\infty \mathcal{J}_{\text{ID}}(\chi, \gamma_{th}, r) f_r(r) \, dr,
\]

where

\[
\mathcal{J}_{\text{ID}}(\chi, \gamma_{th}, r) = 1 - H(\chi - \gamma_{th}) \mathcal{F}(\chi - \gamma_{th}) f(r) \, dy - \mathcal{F}(\chi - \gamma_{th}) \mathcal{F}(\gamma_{th}) f(r) \, dy + \mathcal{F}(\chi - \gamma_{th}) \mathcal{F}(\gamma_{th}) \mathcal{F}(\gamma_{th}) f(r) \, dy + \int_{\chi - \gamma_{th}}^\chi \mathcal{F}(\chi - \gamma_{th}) f(r) \, dr.
\]

Then, based on the number of selected pairs, \( \nu \), the EH success probability achieved by the TbPS scheme, can be formulated as

\[
\mathcal{F}_{\text{EH}}(Q, \gamma_{th}) = \mathbb{P}[\Gamma_1 \geq \gamma_{th}] \mathbb{P} \left[ \left( \sum_{j=1}^\eta S_{2j-1} + S_{2j} + 2 \tilde{I} \right) \geq Q \right] + \sum_{\nu=2}^{\eta-\nu} \mathbb{P} \left[ \Gamma_{\nu-\nu} < \gamma_{th} < \Gamma_{\nu} \right] \mathbb{P} \left[ \left( \sum_{j=1}^\eta S_{2j-1} + S_{2j} + 2 \tilde{I} \right) \geq Q \right] + \mathbb{P} \left[ \Gamma_{\eta-2} \leq \gamma_{th} \leq \Gamma_1 \right] \mathbb{P} \left[ \left( \sum_{j=1}^\eta S_{2j-1} + S_{2j} + 2 \tilde{I} \right) \geq Q \right],
\]

where \( Q \) is the reliability threshold. For the special case where \( N = 6 \), the following proposition characterizes the resulting performance in terms of EH success probability.

**Proposition 2.** For the special case where MUs are equipped with six antenna elements, i.e., \( N = 6 \), the EH success probability, \( \mathcal{F}_{\text{EH}}(Q, \gamma_{th}) \), is given by

\[
\mathcal{F}_{\text{EH}}(Q, \gamma_{th}) = \int_0^\infty \mathcal{J}_{\text{EH}}(Q, \gamma_{th}, r) f_r(r) \, dr,
\]

where

\[
\mathcal{J}_{\text{EH}}(Q, \gamma_{th}, r, \nu) = \mathcal{F}(\gamma_{th}(r), \nu) \mathcal{F}(\gamma_{th}(r), \nu) \mathcal{F}(\gamma_{th}(r), \nu) + \sum_{\nu=2}^{\eta-\nu} \mathcal{F}(\gamma_{th}(r), \nu) \mathcal{F}(\gamma_{th}(r), \nu) \mathcal{F}(\gamma_{th}(r), \nu) + \mathcal{F}(\gamma_{th}(r), \nu) \mathcal{F}(\gamma_{th}(r), \nu) \mathcal{F}(\gamma_{th}(r), \nu).
\]

**Proof.** See Appendix B. \( \square \)

**D. Joint Information Decoding and Energy Harvesting Success Probability of MUs with TbPS Scheme**

In this section, we address the trade-off between the ID and the EH in the context of the TbPS scheme, by evaluating the joint ID and EH success probability [6]. In particular, the joint ID and EH success probability, \( \mathcal{F}_{\text{ID&EH}}(\chi, Q, \gamma_{th}) \), refers to the capability of a MU to achieve both the ID and EH threshold simultaneously. Hence, \( \mathcal{F}_{\text{ID&EH}}(\chi, Q, \gamma_{th}) \) can be evaluated as

\[
\mathcal{F}_{\text{ID&EH}}(\chi, Q, \gamma_{th}) = \mathbb{P}[\chi & \geq \chi \& \Gamma_1 \geq \gamma_{th}] \mathbb{P} \left[ \left( \sum_{j=1}^\eta S_{2j-1} + S_{2j} + 2 \tilde{I} \right) \geq Q \right] + \sum_{\nu=2}^{\eta-\nu} \mathbb{P} \left[ \chi \& \Gamma_{\nu-\nu} < \gamma_{th} < \Gamma_{\nu} \right] \mathbb{P} \left[ \left( \sum_{j=1}^\eta S_{2j-1} + S_{2j} + 2 \tilde{I} \right) \geq Q \right] \times \mathbb{P} \left[ \left( \sum_{j=1}^\eta S_{2j-1} + S_{2j} + 2 \tilde{I} \right) \geq Q \right] + \mathbb{P} \left[ \chi \& \Gamma_{\eta-2} \leq \gamma_{th} \leq \Gamma_1 \right] \mathbb{P} \left[ \left( \sum_{j=1}^\eta S_{2j-1} + S_{2j} + 2 \tilde{I} \right) \geq Q \right].
\]

In the following proposition, we evaluate the joint ID and EH success probability for the special case with \( N = 6 \) antennas.

**Proposition 3.** For the special case where MUs are equipped with six antenna elements, i.e., \( N = 6 \), the joint ID and EH...
success probability is given by

$$ P_{\text{ID\&EH}}(\chi, Q, \gamma_{\text{th}}) = \int_0^\infty P_{\text{ID\&EH}}(\chi, Q, \gamma_{\text{th}}, r) f_r(r) dr, $$

where

$$ P_{\text{ID\&EH}}(\chi, Q, \gamma_{\text{th}}, r) = \mathcal{H}(\chi - \gamma_{\text{th}}) \left( S_2(Q|r) \tilde{F}(\chi|r) + S_1(Q|r) \tilde{F}(\gamma_{\text{th}}|r) \right) $$

$$ \times \int_0^y \tilde{F}(\chi - y|r) f(y|r) dy, $$

and

$$ + \mathcal{H}(\chi - \gamma_{\text{th}}) \left( S_2(Q|r) \tilde{F}(\gamma_{\text{th}}|r) + S_1(Q|r) \tilde{F}(\gamma_{\text{th}}|r) \right) $$

$$ \times (1 - S_1(Q|r)) \int_x^\infty \tilde{F}(\chi - y|r) f(y|r) dy, $$

where $\tilde{F}(\cdot) = 1 - F(\cdot), S_1(\cdot)$ and $S_2(\cdot)$ are derived in Proposition 2.

Proof. The proof follows the similar methodology with the Proposition 1 and Proposition 2, and hence is omitted. □

IV. CELL SLEEPING MECHANISM IN SWIPT-ENABLED MOBILE NETWORKS

In order to provide a general and universal insight on the SWIPT-enabled mobile networks, we now focus our attention on another type of the wireless network, i.e. the finite-area network deployment, such as small cells and indoor environment. In such scenario, the mobility of MUs based on RWP model results in a non-uniform distribution of MUs, which subsequently leads to the significantly different network performance compared to the large-scale infinite area networks [20]. Therefore, we now investigate the additional achieved gains on the network performance, by exploiting the ability of BSs to perform an interference resource management approach, namely sleeping technique, based on its traffic load. More specifically, the main idea of the traffic load-based sleeping (TLbS) mechanism is to switch off idle or lightly-loaded BSs in order to reduce the aggregate interference and power consumption, triggering a non-trivial trade-off between ID and EH success probability. On the one hand, the observed interference is characterized as the main degradation factor in conventional networks, while on the other hand, it can be viewed as a useful aggregate energy signal that could be exploited for the harvesting purposes of IoE devices. Hence, by exploiting our proposed technique, the overall balance of the counter-posed effects introduced by the aggregate interference on finite-area cellular networks can be addressed.

A. Traffic Load-based Cell Sleeping Mechanism

The steady-state distribution of the MUs’ locations within a finite-area network, i.e. $|\mathcal{A}| < \infty$, is a non-uniform distribution. Specifically, the intensity function of the steady-state distribution, is given by [15], [20]

$$ \lambda_u(r) = \lambda_u^w(r) = 2\lambda_u \left( 1 - \frac{r^2}{R^2} \right), $$

where $r$ represents the distance from a MU to the center of the considered region $\mathcal{A}$ and $\lambda_u$ is the initial density of MUs.

Since the steady-state distribution of the MUs’ locations is no longer uniform on the considered circular disk area, i.e. MUs are more likely to be present around the centre; in the meantime, the density of the MUs near the border areas has dropped significantly. The TLbS mechanism dynamically determines the state of the BSs, i.e. either active or in sleeping mode, based on traffic load-based policy. Specifically, we consider a BS as active, if and only if, the number of MUs $n$ in its coverage region is larger than $N$; otherwise, we consider that this particular BS is switched into the sleeping mode. In order to guarantee the QoS, the users of sleeping BSs are offload to active neighbouring BSs. It should be noted that, the TLbS mechanism is also of low-complexity for the MUs devices; more specifically, the switching between active and sleeping modes is operated by the BSs, based on the number of MUs located within the coverage area of each BS. In the modern wireless networks, the BSs can obtain the MUs’ location information through positioning reference signals [28]. Then, based on the proposed TLbS mechanism, the distribution of the active BSs is characterized in the following lemma.

Lemma 2. Based on the proposed TLbS mechanism, the location of the active BSs follows a non-homogeneous PPP $\Phi_b$ with intensity function $\lambda_b(r)$, which is given by

$$ \lambda_b(r) = \lambda_b(\delta(r)), $$

where $\delta(r)$ represents the active probability of a BS at distance $r$ and is given by

$$ \delta(r) = 1 - \sum_{k=0}^{N-1} \frac{\lambda_b(r)^k \Omega^K \gamma [K + k, \pi R^2 \lambda_u(r) + \Omega]}{\beta(r)^k k! \gamma [K, \Omega] (R^2 \beta(r))^K}, $$

where $r$ is the distance from a network node to the center of the considered region $\mathcal{A}, \Omega = K R^2 \lambda_u; \beta(r) = \lambda_u(r) + K \lambda_b, \lambda_u(r)$ is the intensity function of the MUs given in (6), and $K = 3.575$ [29].

Proof. See Appendix D. □

B. Information Decoding Success Probability of MUs with TLbS Mechanism

In this section, we investigate the ability of a MU to successfully decode the received signal power, i.e. the ID success probability. In order to maintain the complexity at a lower level, we assume that all MUs are equipped with single antenna element and perform ID and EH based on a power splitting approach [3]. As previously mentioned, the MUs’ movement and the TLbS technique, causing the existence of non-uniform spatial distribution of the MU and the active BS, respectively. Without loss of generality, we focus our analysis on a general MU with distance $d$ from the origin, where $0 \leq d \leq R$. The scenarios where $d = 0$ and $d = R$ refer to the case where MUs are located at the center and the edge of the network area $\mathcal{A}$, respectively. Then, based on the power
\[
\psi(t, r_o) = \exp \left( -2 \int_0^A d\cos(\theta) + \sqrt{R^2 - \xi^2 \sin^2(\theta)} \left( 1 - \frac{1}{1 - j\xi t - \alpha} \right) \frac{\lambda_b(z)}{z} dz d\theta \right) \quad (11)
\]

splitting approach, the ID success probability of a general MU with distance \(d\) to the origin, is defined as [6]
\[
\mathcal{G}_{\text{ID}}(I, d) \doteq \mathbb{P} \left[ \frac{S}{I + \sigma_N^2 + \sigma_C^2} \geq \chi \right], \quad (9)
\]
where \(\sigma_N^2\) is the thermal noise power, \(\sigma_C^2\) accounts for the noise introduced during the conversion from radio frequency to baseband. Since, power splitting approach is considered, \(\sigma_C^2 = \sigma_{\text{cov}}^2/(1 - \rho)\), \(\rho\) is the power splitting parameter; \(S\) is the intended received signal power from the serving BS, \(I\) is the aggregate interference observed at the MU, and \(\chi\) (dB) is the ID threshold.

We first assess the conditional cdf of the aggregate interference observed at a general MU, i.e. \(\mathbb{P}[I \leq X|r_o]\), which is useful for evaluating the considered performance metrics. The following lemma characterizes the conditional cdf of the aggregate interference.

**Lemma 3.** The conditional cdf of the aggregate interference observed at a MU is given by [21]
\[
F_I(X, r_o) = \frac{1}{\pi} - \frac{1}{\pi} \int_0^\infty \frac{1 - \exp(-jtx)}{t} \psi(t, r_o) dt, \quad (10)
\]
where \(j = \sqrt{-1}\), \(\text{Im}\{\cdot\}\) is imaginary operator and \(\psi(t, r_o)\) is the characteristic function of interference \(I\), which is given by (11) and
\[
A = \begin{cases} 
\pi, & r_o \leq R - d, \\
\arccos \left( \frac{d^2 + r_o^2 - R^2}{2dr_o} \right), & r_o \geq R - d.
\end{cases} \quad (12)
\]

**Proof.** See Appendix E. \(\square\)

Therefore, based on the proposed TLbS mechanism, the ID ability of a MU is characterized by the following theorem in terms of ID success probability.

**Theorem 1.** Based on the proposed TLbS mechanism, the ID success probability of a general MU, i.e. \(\mathcal{G}_{\text{ID}}(\chi, d)\) is given by
\[
\mathcal{G}_{\text{ID}}(\chi, d) \doteq \frac{1}{\pi} - \int_0^{R+d} \int_0^\infty \frac{1 - \exp(-jtx)}{\pi t} f_r(r_o, d) dt dr_o, \quad (13)
\]
where \(\chi\) and \(\psi(\cdot)\) is the characteristic function of interference \(I\) and \(f_r(r_o, d)\) is the pdf of the distance \(r_o\) from a MU to its serving BS, which is given by
\[
f_r(r_o, d) = \begin{cases} 
- \frac{d}{dr_o} \exp(-\Lambda_1(r_o, d)), & r_o \leq R - d \\
- \frac{d}{dr_o} \exp(-\Lambda_2(r_o, d)), & R - d < r_o \leq R + d,
\end{cases}
\]

where \(\Lambda_1(\cdot)\) is the intensity function of the active BSs, which is given in Lemma 2, \(\Lambda_1(\cdot)\) and \(\Lambda_2(\cdot)\) are given by (14) and (15), respectively; \(\theta_1 = \arccos \left( \frac{d^2 + r_o^2 - R^2}{2dr_o} \right), \theta_2 = \arccos \left( \frac{R^2 + d^2 - r_o^2}{2dr_o} \right)\), and
\[
\gamma = \frac{\sqrt{(d + r_o + R)(d - r_o + R)(d + r_o - R)(r_o + R - d)}}{2d}.
\]

**Proof.** See Appendix F. \(\square\)

Moreover, the ID success probability of the MUs located at the center of the considered finite region \(A\) can be further simplified due to the symmetrical properties of \(\lambda_b(\cdot)\), which is given in the following corollary.

**Corollary 1.** Based on the proposed TLbS mechanism, the ID success probability of the MUs located at the origin, i.e. \(\mathcal{G}_{\text{ID}}(\chi, 0)\) is given by
\[
\mathcal{G}_{\text{ID}}(\chi, 0) = \int_0^R f_r(r_o, 0) \exp \left( - \int_{r_o}^R \frac{2\pi v \lambda_b(v)}{1 + \chi^{-1}(v/r_o)^\alpha} dv \right) 
\times \exp \left( - \chi r_o^\alpha (\sigma_N^2 + \sigma_C^2) \right) dr_o,
\]
where \(f_r(\cdot)\) is the pdf of the distance from the MU located at the origin to its serving BS, which can be simplified as
\[
f_r(r_o, 0) = 2\pi \lambda_b(r_o) r_o \exp \left( -2\pi \int_{r_o}^R \lambda_b(v) v dv \right).
\]

### C. Energy Harvesting Success Probability of MUs with TLbS Mechanism

In this section, we evaluate the ability of a general MU to harvest sufficient energy, i.e. the EH success probability, which is defined as
\[
\mathcal{G}_{\text{EH}}(Q, d) = \mathbb{P}[\zeta \lambda_b(S + 1) \geq Q], \quad (16)
\]
where \(\zeta\) accounts for conversion efficiency of the energy harvester and \(\rho\) is the power splitting factor. Therefore, by using the tools from stochastic geometry, the expression for the EH success probability of a MU is derived in the following theorem.

**Theorem 2.** Based on the proposed TLbS mechanism, the EH success probability of a general MU, i.e. \(\mathcal{G}_{\text{EH}}(Q, d)\) is given by
\[
\mathcal{G}_{\text{EH}}(Q, d) = \int_0^{R+d} f_r(r_o, d) \left[ 1 - \exp(-\hat{Q} r_o^\alpha) + \frac{1}{2} \int_0^\infty \frac{1 - \exp(-j\xi t - \alpha)}{\pi t} dt dr_o, \quad (13)
\]
where \(\hat{Q} = Q/\zeta\), \(\psi(\cdot)\) is the characteristic function given by (11) and \(f_r(\cdot)\) is the pdf of the distance from a MU to its serving BS given by (13).
\begin{align}
\Lambda_1(r_o, d) &= \int_0^{r_o} \int_0^{2\pi} \lambda_a \left( \sqrt{\rho^2 + d^2 - 2\rho d \cos(\theta)} \right) \rho d\rho d\theta \\
\Lambda_2(r_o, d) &= 2 \int_0^{r_o} \int_0^{\theta_1} \lambda_b \left( \sqrt{\rho^2 + d^2 - 2\rho d \cos(\theta)} \right) \rho d\rho d\theta + 2 \int_0^{r_o} \lambda_b (\rho) \rho d\rho d\theta \\
&- 2 \int \int \left( \frac{\lambda_b}{\pi \sigma_N^2} \right) \lambda_b(\sqrt{x^2 + y^2}) \ dx \ dy
\end{align}

\begin{equation}
X(t, r_o) = \frac{\exp(-\bar{Q}r_o^\alpha) - \exp \left( \frac{-r_o^\alpha (\mathcal{Q} + \sigma_N^2 + \sigma_C^2) + j t (\mathcal{Q} - \sigma_N^2 - \sigma_C^2)}{\chi + \zeta} \right)}{j t r_o^{-\alpha} - 1} - \frac{\exp \left( \frac{-r_o^\alpha (\mathcal{Q} + \sigma_N^2 + \sigma_C^2) + j t (\mathcal{Q} - \sigma_N^2 - \sigma_C^2)}{\chi + \zeta} \right)}{j t r_o^{-\alpha} + 1}
\end{equation}

**Proof.** See Appendix G.

Since the harvested energy of a MU is mainly associated to its serving BS, especially for the case with a large number of traffic load threshold \( N \), the interference power could be ignored for the simplification purpose. Hence, the EH success probability is approximated in the following corollary.

**Corollary 2.** The EH success probability of a general MU derived in Theorem 2 can be approximated by ignoring the received interference power, and thus is given by

\[ G_{\text{EH}}(Q, d) \approx \int_0^{R+d} \exp(-\bar{Q}r_o^\alpha) f_r(r_o, d) \ dr_o \]  

**D. Joint Information Decoding and Energy Harvesting Success Probability of MUs with TLbS Mechanism**

In this section, we focus on the joint ID and EH performance of a MU in the context of the joint ID and EH success probability, i.e. \( G_{\text{ID\&EH}}(\chi, Q, d) \), which refers to the ability of a MU to accomplish both ID and EH constraints simultaneously. Hence, similar as before, the joint probability of the ID and EH is defined as

\[ G_{\text{ID\&EH}}(\chi, Q, d) \triangleq P \left[ \frac{S}{I + \sigma_N^2 + \sigma_C^2} \geq \chi \ \& \ \zeta \rho (S + I) \geq Q \right], \]

where \( \chi \) and \( Q \) represent the ID and EH thresholds, respectively.

Therefore, by following the similar approaches used before, the analytical expression of the joint ID and EH success probability is derived in the following theorem.

**Theorem 3.** Based on the TLbS mechanism, the joint ID and EH success probability of a MU, i.e. \( G_{\text{ID\&EH}}(\chi, Q, d) \) is given by

\[ G_{\text{ID\&EH}}(\chi, Q, d) = \int_0^{R+d} \left( \frac{1}{2} \exp(-\bar{Q}r_o^\alpha) \right) f_r(r_o, d) \ dr_o, \]

where \( X(t, r_o) \) is given in (19).

**Proof.** See Appendix H.
at different antenna elements is independent with each other (denoted as "No correlation"). We can easily observe that the performance achieved by using the adopted assumptions provides a tight upper bound for the exact performance, with lower computational complexity. On the other hand, by ignoring the existence of spatial correlation between interference, it leads to a large deviation from the exact performance, especially, for higher path loss exponents. This was expected since, in dense urban areas, i.e. high path loss exponents, the aggregate interference is mainly composed by the interference caused by the closest interfering BS. Hence, if an antenna fails to decode the received signal, then the rest antennas will fail to decode the received signal with high probability, due to the existence of interference correlation.

Fig. 4 illustrates the effect of the threshold $\gamma_{th}$ on the ability of a MU to successfully decode the received signal power. In particular, Fig. 4 plots the ID success probability with respect to the threshold $\gamma_{th}$ for different decoding thresholds $\chi \in \{0, 5, 10\}$ dB. Both simulation and analytical results are presented in Fig. 4, denoted as "TbPS simulation" and "TbPS analysis", respectively. In addition, the scenario, where the interference power observed within each antenna pair is correlated but not equal, denoted as "Exact performance", is also presented here to validate the accuracy of the adopted assumption. It can be observed that there exists minimum gap between our analytical results and the exact performance. Moreover, we can easily observe that the ability of a MU to successfully decode the received signal power increases with the increase of the predefined threshold $\gamma_{th}$. This was expected since, the increase of $\gamma_{th}$ results in an increased number of antenna elements that perform ID, and consequently, the ability to successfully decode the received signal power is enhanced. However, beyond a critical value of $\gamma_{th}$, which is equal to $\gamma_{th} = \chi$, the ID success probability remains constant. This can be explained by the fact that, for large values of $\gamma_{th}$, a MU is unable to assign an additional pair of antennas for the ID due to the constrain of the existence of at least one pair of antennas for EH, i.e. the performance could be further boosted for the receiver with more pairs of antenna elements. Moreover, by increasing the decoding threshold $\chi$, the ID performance drops, which is from fact that greater decoding threshold requires higher post-combiner SIR to achieve the same success probability.

Similarly, Fig. 5 illustrates the effect of $\gamma_{th}$ on the EH success probability for different EH reliability thresholds $Q \in \{-15, -10, -5\}$ dBm and different density of BSs $\lambda_b \in \{1600 \text{BS/} \pi, 3200 \text{BS/} \pi\}$. Firstly it can be observed that denser BS deployments can boost the EH success probability based on the proposed TbPS technique. This is based on the fact that the increasing number of active BSs in the network results in a higher aggregated received signal power at the MUs, which can be harvested. Moreover, as expected, the harvested energy of MUs decreases as the predefined threshold $\gamma_{th}$ increases, since the number of antenna elements allocated for energy harvesting reduces, and hence the EH success probability drops. Moreover, Fig. 5 also demonstrates the impact of the considered approximation regarding the observed interference on the EH success probability. The small deviation from the simulation results shows that the overall network interference can be effectively approximated by the mean interference power, without being significantly deficient in accuracy. Moreover, we can conclude from Fig. 5 that, by changing network parameter (i.e.,density of BSs), a shifted EH performance is observed, while the curves’ shape maintains constant. These observation holds for all figures presented in our results.

Fig. 6 shows the impact of the threshold $\gamma_{th}$ on the ability of a MU to simultaneously satisfy the requirements for both ID and EH procedures. It is worth noting that, by increasing the threshold $\gamma_{th}$, the ability of a user to simultaneously satisfy the ID and EH constrains increases. This is because, as the value of the threshold $\gamma_{th}$ increases, the proposed TbPS scheme allocates a higher number of antenna elements for the ID part. Hence, the ability of a MU to successfully decode the received signal is significantly improved, while its ability to harvest energy is slightly reduced. However, beyond the critical point
\( \gamma_{th} = \chi \), the ability of a user to simultaneously satisfy the ID and EH constrains decreases. As indicated in Fig. 4 and Fig. 5, the ability of a user to successfully decode the received signal beyond a threshold equal to \( \chi \), remains constant, while the ability to harvest energy is reducing, and hence the joint ID and EH success probability is decreasing. Finally, we numerically evaluate the conventional AS scheme, where half number of antennas are used for ID and half for EH [3]. It can be observed that, the performance achieved with our proposed technique outperforms that of the conventional scheme in terms of the optimal joint ID and EH success probability, where a maximum 5% gain over the conventional AS scheme can be achieved based on the considered network parameters. Moreover, the proposed TbPS scheme is able to satisfy various ID and EH requirements of practical applications, by adjusting the predefined threshold.

**B. SWIPT performance of the TLbS mechanism in small-scale networks**

Fig. 7 shows the impact of our proposed TLbS mechanism on the ID performance of the MUs at different locations, i.e. \( d = \{0, 70, 100\} \) m. We can firstly observe that, for low values of traffic load threshold, \( N \), the ID success probability increases with the increase of the traffic load threshold. This was expected since, by increasing the value of \( N \), more and more BSs are switched to sleeping mode, the inter-cell interference is reduced, and therefore, the ability of MUs to successfully decode the received signal is enhanced. However, beyond a critical value of \( N \), the ID success probability decreases. This was expected since, by further increasing the traffic load threshold, the number of BSs that are in sleeping mode increases, resulting in the distances between the MU and its closest active BS to be greater, compromising the ability of a MU to successfully decode the received signal power. Moreover, we can observe that the ID success probability of the MUs located between the center and edge regions, i.e. \( d = 70 \) m, overcomes the performance achieved by the MUs that are located at the center and edge regions. This can be explained by the fact that, the MUs which are located at the center experience severe inter-cell interference, while the MUs at the edge receive a weak signal power from their serving BSs due to the non-uniform distribution of BSs imposed by the proposed TLbS technique. Finally, Fig. 7 also plots the achieved performance without sleeping mechanism (dash lines) [30], i.e. all BSs are active. It can be observed that, by appropriately selecting the values of \( N \), our proposed TLbS mechanism enables a higher ID success probability of MUs at different locations. This was expected since that, the inter-cell interference power is significantly reduced with TLbS mechanism, resulting in a higher SINR at MUs.

Fig. 8 demonstrates the impact of the traffic load threshold \( N \) on the EH success probability of the MUs at different locations, i.e. \( d = \{0, 70, 100\} \) m. We can easily observe that, the EH success probability of the MUs, regardless of the location, decreases with the increase of the traffic load threshold. We can easily observe, that the EH success probability of the...
BSs are active (dash lines) [30], i.e. the traffic load threshold
Moreover, Fig. 9 also plots the conventional schemes where all
away from the center of the network area, i.e.
the joint ID and EH probability attains its optimal value. The
optimal value of $N$, exists, where the joint ID and EH probability attains its optimal value. The optimal value of $N$, in particular, decreases as the MU moves away from the center of the network area, i.e. $d$ increases. Moreover, Fig. 9 also plots the conventional schemes where all BSs are active (dash lines) [30], i.e. the traffic load threshold $N=0$, for the comparison purpose. It can be observed that the TlbS mechanism enables a higher joint ID and EH success probability of MUs at different locations, with appropriate values of traffic load threshold $N$, where a maximum 20\% gain over the conventional scheme can be achieved by the TlbS mechanism. In addition, the TlbS mechanism enables the highest performance improvement for the MUs at the center, compared with the case where all BSs are active. It can be explained by the fact that, by properly selecting the traffic load threshold value $N$, the inter-cell interference power is reduced due to the de-activation of interfering BSs, while the MUs at center are still able to communicate with nearby serving BSs to maintain the acceptable signal strength.

Finally, Fig. 10 shows the impact of the power splitting factor on the SWIPT capabilities of the MUs located at the different locations. In particular, Fig. 10 plots the joint ID and EH success probabilities versus the power splitting factor, for $d \in \{0,70,100\}$ m . We can easily observe that, there exists an optimum power splitting factor for all MUs, which achieves the maximum joint ID and EH success probability. This was expected since, a trade-off exists between the ID and the EH performance of the MUs. Hence, for attaining the maximum performance for both MUs’ abilities, a careful selection of the power splitting factor has to be performed. Moreover, it is shown that, the MUs located at the center of the network area (i.e., $d = 0$ m) achieve the best SWIPT performance, while the edge MUs (i.e., $d = 100$ m) have the worst performance. This is expected since, based on the TlbS mechanism, the mobility of the MUs leads to a less number of active BSs around the network’s edge area, and hence, the received RF signal power is much less at the edge region compared to that at the center region of the network. Finally, we can easily observe that, the power splitting factor can be adjusted based on the practical scenarios, to satisfy the various requirements of the information decoding and energy harvesting applications.

VI. CONCLUSIONS

In this paper, we investigated the SWIPT-enabled 6G mobile networks, where users’ mobility is modelled based on RWP model. According to the areas of the considered networks, i.e. finite or infinite regions, we investigated the MUs’ ability of ID and EH with two proposed novel techniques, i.e. TbPS scheme and TlbS mechanism. In particular, TbPS scheme was proposed to enhance the ID and EH performance for the SWIPT-enabled multi-antenna MUs in the infinite area networks, where the existence of interference correlation between nearby antennas was considered. Moreover, TlbS mechanism was proposed to dynamically determine the state of the BSs, i.e. either active or in sleeping mode, based on the traffic load, aiming the joint optimization of users’ throughput and EH performance. By using the tools from stochastic geometry, the analytical expressions of ID, EH as well as joint ID and EH success probability were derived for MUs, based on TbPS or TlbS techniques. Finally, the optimal design parameters (i.e. antenna selection and traffic load threshold) of our proposed schemes were demonstrated, which could achieve the maximum joint ID and EH performance of MUs.
Appendix A

Proof of Lemma 1

Based on the expression (1), the conditional cdf of $S_{n}$, can be expressed as

$$\mathbb{F}(Y_i|x_o) = \mathbb{P}[\Xi_n \leq Y_i|x_o]$$

$$= \mathbb{P}[h_{2n-1,o} + h_{2n,o} \leq L(x_o)\mathcal{I}_n Y_i]$$

$$= \mathbb{E}[\gamma(2,sx_n)]$$

(20)

where $s = yL(x_o)$, and (20) follows from the fact that the sum of two exponential random variables follows the Gamma distribution [11]. Then, based on the moment generating function and $\gamma(x,y) = \Gamma(x) - (x-1)!e^{-y} \sum_{k=0}^{\infty} \frac{y^k}{k!}$, the final expression can be derived, where

$$L_{I_n}(s) = \mathbb{E}\left[\exp\left(-\sum_{i \in \Phi^n_I} \frac{h_{n,i} s}{L(x_i)}\right)\right]$$

$$= \exp\left(2\pi \lambda b \int_{r_0}^{\infty} (\phi(x,s) - 1) \, dx\right)$$

(21)

where (21) is obtained from the Probability Generating Function (PGFL) of PPPs [23] and $\phi(x,s)$ is

$$\phi(x,s) = \mathbb{E}_b \left[\exp\left(-\frac{h_{n,i} s}{L(x)}\right)\right] = \frac{1}{1 + sL^{-1}(x)}.$$ 

Therefore, by evaluating the integral and derivative, the expressions in Lemma 1 can be derived.

Appendix B

Proof of Proposition 1

For the special case where $N = 6$, the ID success probability can be formulated as

$$\mathcal{F}_{ID}(\chi, \gamma_{th}) = 1 - \mathbb{P}[\Xi_1 < \chi, \Xi_1 \geq \gamma_{th}]$$

$$- \mathbb{P}[\Xi_1 + \Xi_2 < \chi, \Xi_1 \geq \gamma_{th}].$$

For the scenario where $\gamma_{th} < \chi$, the above expression can be re-written as

$$\mathcal{F}_{ID}(\chi, \gamma_{th}) = 1 - \mathbb{P}[\gamma_{th} \leq \Xi_1 < \chi]$$

$$- \mathbb{P}[\Xi_1 < \chi - \Xi_2 | \chi - \Xi_2 \leq \gamma_{th}]$$

$$- \mathbb{P}[\Xi_1 < \gamma_{th} | \gamma_{th} \leq \chi - \Xi_2],$$

while for $\gamma_{th} \geq \chi$, is given by

$$\mathcal{F}_{ID}(\chi, \gamma_{th}) = 1 - \mathbb{P}[\Xi_1 < \chi - \Xi_2 \& \Xi_1 \leq \gamma_{th}]$$

$$= 1 - \mathbb{P}[\Xi_1 < \chi - \Xi_2].$$

Then, by using the cdf of $\Xi_n$, which is derived in Lemma 1, the final expression for $\mathcal{F}_{ID}(\chi, \gamma_{th})$ can be derived.

Appendix C

Proof of Proposition 2

For the considered scenario, i.e. $N = 6$, the TbPS mechanism either assigns a single or two pairs of antenna elements for energy harvesting, based on the number of antenna elements that is selected for the ID part of the system. For the case where the TbPS scheme assigns two antenna pairs for ID, i.e. $\nu = 2$, then a single pair is allocated for EH. In this case, the EH success probability can be calculated as

$$\mathcal{S}_1(Q|x_o) = \mathbb{P}[S_k + S_{k+1} + 2 \tilde{I} \geq \bar{Q}|x_o],$$

where $\bar{Q} = \bar{Q}/\xi$. Similar with the proof of Lemma 1, for the case where $\tilde{I} < \bar{Q}/2$, we have the condition that $\|x_o\| \geq \left(4\pi \lambda_b (\alpha - 2)^{-1}/\bar{Q}\right)^{1/(\alpha - 2)}$ and hence,

$$\mathcal{S}_1(Q|x_o) = \mathbb{P}[S_k + S_{k+1} \geq \bar{Q} - 2\tilde{I}|x_o]$$

$$= \mathbb{P}[\tilde{I} \leq \bar{Q} - 2\tilde{I}],$$

(22)

where (22) is from the same methodology of (a) in Lemma 1. Furthermore, for the case, where $2\tilde{I} \bar{Q}$, we have $\|x_o\| \leq \left(4\pi \lambda_b (\alpha - 2)^{-1}/\bar{Q}\right)^{1/(\alpha - 2)}$ and $\mathcal{S}_1(Q|x_o) = 1$. Hence, the final expression of $\mathcal{S}_1(Q|x_o)$ is derived. For the case where two pairs of antenna elements are used for EH, the EH success probability can be calculated as

$$\mathcal{S}_2(Q|x_o) = \mathbb{P}[\sum_{j=0}^{3} S_{k+j} \geq 2\tilde{I} Q|x_o].$$

The proof of $\mathcal{S}_2(Q|x_o)$ follows similar methodology, and hence it is omitted due to space limitations. Finally, by multiplying the probability of $\nu$ and following the similar methodology used in proof of Proposition 1, the Proposition 2 is proven.

Appendix D

Proof of Lemma 2

Based on the proposed TLbS mechanism, the active probability $\delta(r)$ of a BS, of which coverage area is $C$, is the probability that there are at least $N$ MUs within its coverage region, which can be formulated as

$$\delta(r) = \mathbb{P}\{n \geq N\}$$

$$= 1 -\mathbb{P}\{n = 0\} - \mathbb{P}\{n = 1\} - \cdots - \mathbb{P}\{n = N - 1\}$$

$$= \mathbb{P}\left[\sum_{k=0}^{N-1} \frac{(\lambda_u(r)C)^k}{k!} \exp(-\lambda_u(r)C)\right]$$

$$= \mathbb{E}_C \left[\sum_{k=0}^{N-1} \frac{(\lambda_u(r)C)^k}{k!} \exp(-\lambda_u(r)C)\right],$$

where (a) is from the probability mass function of Poisson distribution, and $C$ is a random variable representing the coverage area of a Voronoi cell supported by the considered BS at distance $r$ and its pdf is given by [29]

$$f_C(x) = \lambda_b^K \frac{K^K}{\Gamma(K) - \Gamma(K, Kx)} \lambda_b^{-1} \exp(-Kx).$$

Hence, the expression for $\delta(r)$ can be obtained by solving the following integral,

$$\delta(r) = \int_0^{\pi R^2} f_C(x) \left(1 - \sum_{k=0}^{N-1} \frac{(\lambda_u(r)C)^k}{k!} \exp(-\lambda_u(r)C)\right) \, dx.$$ 

Therefore, the resulting intensity function $\lambda_b(r)$ in Lemma 2 is derived.

Appendix E

Proof of Lemma 3

Based on the Gil-Pelaez inversion theorem, the conditional cdf of interference $I$ in (10) can be derived from its charac-
teristic function [6]. The calculation of characteristic function is just following the definition, i.e.
\[
\psi(t,r_0) = \mathbb{E}\left[\exp\left(jt\sum_{i\in\mathbb{N}}h_ir_i^{-\alpha}\right)\right]
\]
\[
\overset{(a)}{=} \exp\left(-2\int_0^{\pi} \int_0^{Z} \left(1 - \frac{1}{1+jtz^{-\alpha}}\right)\lambda_b(z)dzd\theta\right),
\]
where \(Z = d\cos(\theta) + \sqrt{R^2 - d^2\sin(\theta)^2}\), and \((a)\) is from the Probability Generate Function (PGFL) of PPPs [23]. In addition, the upper limits of the integral in (23), i.e. \(A\) can be evaluated by considering two cases as shown in Fig. 11. For the case that \(r_0 \leq R - d\), where the dash circle is inside the network area, the range of \(\theta\) is from \(-\pi\) to \(\pi\), and thus \(A = \pi\); while for the case that \(r_0 > R - d\), \(\theta \in [\theta_1, \theta_2]\), where \(\theta_2\) can be derived based on Cosine rule, and \(A = \arccos\left(\frac{d^2 + r_0^2 - R^2}{2dr_0}\right)\).

**APPENDIX F**
**PROOF OF THEOREM 1**

The proof is basically based on the distribution of interference, i.e. the ID success probability of a general MU defined in (9) can be rewritten as
\[
\mathcal{G}_{\text{ID}}(\chi,d) = \mathbb{E}_h \left[ I \leq \frac{h_0r_0^{-\alpha} - \sigma_N^2 - \sigma_C^2}{\chi} \right] = \mathbb{E}_h \left[ F_I \left( \frac{h_0r_0^{-\alpha} - \sigma_N^2 - \sigma_C^2}{\chi} \right) \right],
\]
where \(F_I(\cdot)\) is the conditional cdf of aggregate interference, derived in Lemma 3. Then substitute the expression of \(F_I(\cdot)\) and evaluate the expectation over the channel power gain \(h_0\), i.e.
\[
\mathcal{G}_{\text{ID}}(\chi,d) = \mathbb{E}_h \left[ \frac{1}{2} - \int_0^{\infty} \text{Im}\left\{ \int_0^{\infty} \exp\left(-jt\frac{h_0r_0^{-\alpha} - \sigma_N^2 - \sigma_C^2}{\chi^2}\right)e^{-h}dh\right\} \right].
\]
Finally, by calculating the above integral as well as evaluating the expected value over distance \(r_0\), the final expression in Theorem 1 is derived, where the pdf of \(r_0\) can be derived by calculating the derivative of its cdf, i.e.
\[
F_r(r_0) = 1 - \mathbb{P}[r \geq r_0] = 1 - \exp(-\Lambda(d,r_0)),
\]
where \(\Lambda(r_0,d)\) represents the intensity measure function. As shown in Fig. 11, \(\Lambda(r_0,d)\) can be calculated based on the two cases, i.e. the serving BS is close or far away from MUs. For both two cases, \(\Lambda(r_0,d)\) is derived by integrating \(\lambda_b(\cdot)\) over the intersection area of two circles using non-uniform measure. The angles \(\theta_1\) and \(\theta_2\) are used as integral limits in the calculation, which can be derived based on Cosine rule.

**APPENDIX G**
**PROOF OF THEOREM 2**

The proof of the EH success probability is also based on the distribution of the interference \(I\). More specifically, the EH success probability can be rewritten as
\[
\mathcal{G}_{\text{EH}}(Q,d) = \mathbb{P}[S \geq \tilde{Q}] + \mathbb{P}[I \geq \tilde{Q} - S | S \leq \tilde{Q}]
\]
\[
= \mathbb{P}[S \geq \tilde{Q}] + \mathbb{P} \left( I \geq \tilde{Q} - S | S \leq \tilde{Q} \right)
\]
\[
= \mathbb{P}[S \geq \tilde{Q}] + \mathbb{P}[S \geq \tilde{Q}],
\]
where \(\tilde{Q} = Q/(\rho \zeta)\) and \(\mathbb{F}_I(\cdot) = 1 - \mathbb{F}_I(\cdot)\). Therefore, we have,
\[
\mathcal{G}_{\text{EH}}(Q,d) = \mathbb{E}_{r_0} \left[ \exp(-\tilde{Q}_r^{-\alpha}) + \int_0^{\tilde{Q}_r^{-\alpha}} \mathbb{F}_I(\tilde{Q} - hr_0^{-\alpha}) \exp(-h)dh \right]
\]
\[
= \mathbb{E}_{r_0} \left[ 1 + \exp(-\tilde{Q}_r^{-\alpha}) \right]
\]
\[
+ \int_0^{\infty} \text{Im}\left\{ \int_0^{\tilde{Q}_r^{-\alpha}} \exp(-jt(\tilde{Q} - hr_0^{-\alpha})) \exp(-h)dh \phi(t,r_0) \right\} \frac{dt}{\pi t},
\]
where the integral over \(h\) can be computed in closed-form with the aid of the following notable results [21]:
\[
\int_0^{\infty} \text{exp}\left(-jt(A-B\xi)\right)\text{exp}(-\xi)\text{d}\xi = \text{exp}(-Ajt) - \text{exp}(Bjtx - Ajt - x)\overline{1 - Bjt}.
\]
Finally, by evaluating the expectation over \(r_0\), the final expression in Theorem 2 is derived.

**APPENDIX H**
**PROOF OF THEOREM 3**

The proof follows the similar method in [6]. First, we rewrite the joint ID and EH success probability defined in (18) as
\[
\mathcal{G}_{\text{ID\&EH}}(\chi, Q, d)
\]
\[
= \mathbb{P}\left[ \max\{0, Q/(\zeta \rho) - S\} \leq I \leq S/|\chi - \sigma_N^2 - \sigma_C^2| \right]
\]
\[
\overset{(a)}{=} \mathbb{P}\left[ \max\{0, Q - h_0r_0^{-\alpha}\} \leq I \leq h_0r_0^{-\alpha}/|\chi - \sigma_N^2 - \sigma_C^2| \right],
\]
where \(\tilde{Q} = Q/(\zeta \rho)\), and \((a)\) holds by introducing the inequality \(h_0r_0^{-\alpha} \geq \chi/(1 + \chi)(\tilde{Q} + \sigma_N^2 + \sigma_C^2)\). Hence, \(\mathcal{G}_{\text{ID\&EH}}(\chi, Q, d)\) can be evaluated by utilising the distribution of interference \(I\), and then by calculating the expected value over other random variables, i.e. \(h_0\) and \(r_0\), final expression can be derived. More
specifically,
\[
\mathcal{G}(\chi, Q, d) = \mathbb{E}[F_I\left(\frac{hr_r^\alpha}{\chi} - \sigma_N^2 - \sigma_C^2\right) - F_I(\max\{0, \hat{Q} - hr_r^\alpha\})] \\
= \mathbb{E}\left[\int_{\mathcal{A}(r_o)} F_I\left(\frac{hr_r^\alpha}{\chi} - \sigma_N^2 - \sigma_C^2\right) - F_I(\hat{Q} - hr_r^\alpha) e^{-b} dh + \int_{\mathcal{B}(r_o)} \left(F_I\left(\frac{hr_r^\alpha}{\chi} - \sigma_N^2 - \sigma_C^2\right) - F_I(0)\right) e^{-b} dh\right],
\]
where \(\mathcal{A}(r_o) = \frac{hr_r^\alpha}{\chi} (\hat{Q} + \sigma_N^2 + \sigma_C^2)\) is obtained from the inequality \(\hat{Q} - hr_r^\alpha \leq \frac{hr_r^\alpha}{\chi - \sigma_N^2 - \sigma_C^2}\), and \(\mathcal{B}(r_o) = \hat{Q} r_r^\alpha\) is from \(\hat{Q} - hr_r^\alpha \geq 0\).

Finally, by following the similar methodology in the Proof of Theorem 2, i.e. substitute the expression of \(F_I(\cdot)\) and evaluate the above integrals, the final expression of joint ID and EH success probability is derived.

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