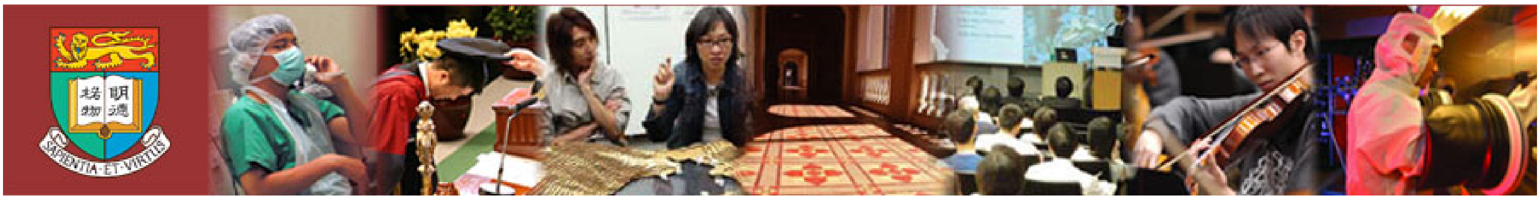

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Coverage of Renewable Powered Cellular Networks

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***Abstract*—Powering a radio access network using renewables such as wind and solar power promises dramatic reduction of the network operation cost and of the networks' carbon footprints. However, the spatial variation of the energy field can lead to fluctuation in power supplied to the network and thereby affects its coverage. To quantify the effect, the paper considers a cellular downlink network with hexagonal cells and powered by harvesting energy. The network coverage of mobiles is specified by an outage constraint. A novel model of the energy field is developed using stochastic geometry. In the model, fixed maximum energy intensity occurs at Poisson distributed locations, called *energy centers*; the intensities fall off from the centers following an exponential-decay function of squared distance; the energy intensity at an arbitrary location is given by the decayed intensity from the nearest energy center. First, consider single harvesters deployed on the same sites as base stations (BSs). The mobile outage probability is shown to decrease exponentially with the product of the energy-field parameters: the energy-center density and exponential rate of the energy-decay function. Next, consider distributed harvesters whose generated energy is aggregated and then re-distributed to BSs. As the number of harvesters per aggregator increases, the power supplied to each BS is shown to converge to a constant proportional to the number of harvesters per BS, which counteracts the randomness of the energy field.**

I. Introduction

The exponential growth of mobile data traffic causes the energy consumption of radio access networks such as cellular and WiFi networks to increase rapidly. A promising solution for the energy issues is to power the networks using alternative energy sources, which will be a feature of future networks [1]. However, the spatial randomness of renewable energy can severely degrade the performance of large-scale networks and thus is a fundamental issue to address in network design. Considering a cellular network with renewables powered BSs, the paper addresses the issue by proposing a novel model of the energy field and quantify the relation between its parameters and network coverage. Furthermore, the proposed technique of energy aggregation is shown to effectively counteract energy spatial randomness.

Researchers have investigated the effects of both the spatial and temporal randomness of renewables on the coverage of different wireless networks spread over the horizontal plane [2]–[5]. Poisson point processes (PPPs) are used to model transmitters of a mobile ad hoc network (MANET) in [2] and BSs of a heterogeneous cellular network [3]. Energy arrival processes at different transmitters are modeled as identically and independently distributed (i.i.d.) stochastic processes, reducing the effect of energy temporal randomness to independent on/off probabilities of transmitters. Thereby, the feasible conditions of network parameters, such as transmission power and node density of the MANET [2] and densities of different tiers of BSs [3], can be analyzed under an outage constraint and a given distribution of energy arrival processes. The assumption of spatially independent distributions of energy is reasonable for specific types of renewables that can power small devices such as kinetic energy and electromagnetic (EM) radiation but does not hold for primary sources, namely wind and solar power. To some extent, energy spatial correlation is accounted for in [4], [5] that focus on EM energy harvesting and are also model network nodes as PPPs. As proposed in [4], nodes in a cognitive-radio network opportunistically harvest energy from radiations from a primary network. The idea of deploying dedicated stations for supplying power wirelessly to energy harvesting mobiles in a cellular network is explored in [5]. In [4], [5], radiations by transmitters with access to the grid form an EM energy field and its spatial correlation is determined by the power-law propagation that does not apply to other types of renewables e.g., wind and solar power.

For tractable analysis of network performance, a novel energy-field model is developed based on stochastic geometry and it has the following key features. The random locations of fixed maximum energy intensity, called *energy centers*, are distributed as a PPP with density λ_e. From an energy center, the energy intensity decays exponentially with the squared distance normalized by a constant, called the *shape parameter* and denoted as ν, which specifies the area of significant effect by the said center. It is worth mentioning that the decay function is popularly used as weigh factors for spatial interpolation of measured data for solar-field mapping [8]. The energy intensity at an arbitrary location is then given by the decayed intensity with respect to the nearest energy center.

In the paper, using the classic hexagonal-cell model of the cellular network, BSs are assumed to be deployed on a hexagonal lattice while mobiles are distributed as a PPP. The network is assumed to operate in the noise-limited regime where interference is suppressed using techniques such as orthogonal multiple access or multi-cell cooperation. The regime is the most interesting from the perspective of energy harvesting since network performance is sensitive to changes on transmission powers or equivalently harvested energy. A mobile is said to be under (network) coverage if an outage constraint is satisfied and the outage probability is the performance

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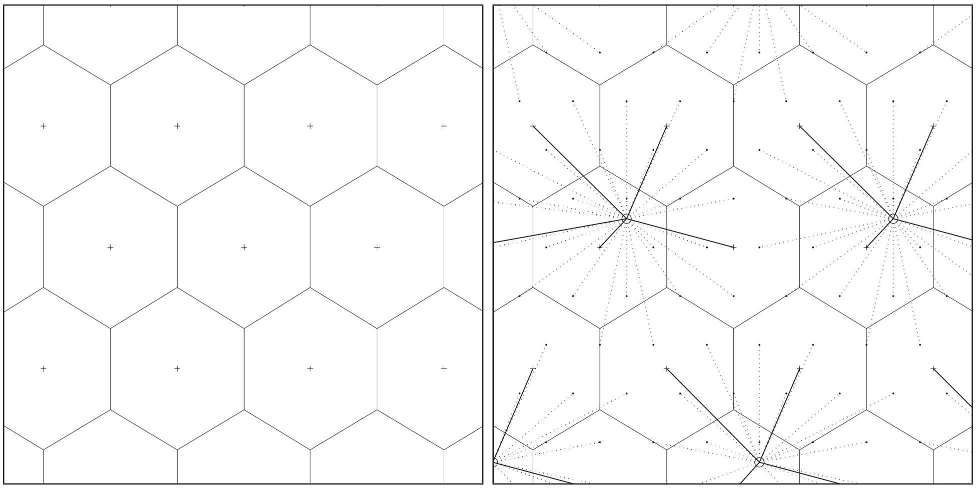


Fig. 1. Geometric patterns of hexagonal cells, BSs, harvesters and aggregators plotted/marked using solid lines, crosses, dots and circles, respectively. (Left) On-site harvesters overlapping with BSs. (Right) Distributed harvesters. Power-transmission lines from harvesters to aggregators and those from aggregators to BSs are plotted using dashed and solid lines, respectively.

metric. A BS allocates transmission power simultaneously to mobiles by equal division of available power. Each BS is powered by either an *on-site harvester* or a remote (energy) *aggregator* that collects energy generated by a set of nearby *distributed harvesters* over transmission lines. Aggregators and distributed harvesters are deployed on separate lattices with different densities.

Consider on-site harvesters. The outage probability is shown to decrease *exponentially* with the product of the energy-field parameters $\nu\lambda_e$, where the base is proportional to the expected number of mobiles per cell and the inverse of the expected propagation distance. Next, consider distributed harvesters. With fixed harvester density and decreasing aggregator density, energy aggregation is shown to counteract the spatial randomness of the energy field and thereby stabilizes the power supply for BSs. Specifically, as aggregator density decreases, the power it distributes to each BS converges to a constant proportional to the number of harvesters per BS.

II. Network Models and Metrics

A. Energy-Harvester Model

Recall that two scenarios are considered for harvester deployment: on-site and distributed harvesters. As illustrated in Fig. 1, while the first scenario is straightforward, the other one is more complex and involves an aggregator network for energy aggregation and re-distribution to BSs. The aggregators and harvesters are assumed to be placed on two separate hexagonal lattices with densities λ_a and λ_h, respectively. Harvesters are connected by cables to the nearest aggregators to minimize power-transmission loss, called *aggregation loss*. Each aggregator supplies power to λ_b/λ_a BSs over cables, assuming λ_b/λ_a is an integer for simplicity. High-voltage is assumed for power distribution such that the power loss is negligible. Consequently, the specific graph of connections between aggregators and BSs has no effect on the analysis except for the number of BSs each aggregator supports. However, it is impractical to assume high-voltage transmission from harvesters and thus aggregation loss can be significant.

The energy field is represented by Ψ that is determined by the function $g(X)$ mapping a location X to energy intensity. The discussion of the geometric model of the energy-field is postponed to Section III while its relation with energy harvesting is described below. Let $g(X,t)$ represent the time-varying version of $g(X)$ with t denoting time. Harvesters are assumed to be homogeneous and time is partitioned into slots of unit duration. The amount of energy harvested at X in the n-th slot is $\eta g_n(X) = \eta \int_n^{n+1} g(X,t)dt$. The multiplier $\eta \in (0,1)$ combines factors such as the harvester physical configuration and conversion efficiency, referred to as the *harvester aperture* by analogy with an antenna aperture. Then the power generated by a harvester at X can be represented by the time sequence $\{g_n(X)\}$ and the discrete-time energy field by $\Phi_{h,n} = \{g_n(X) \mid X \in \Phi_h\}$ with $n = 1, 2, \cdots$, which is assumed to be ergodic. To simplify analysis, the energy harvested by harvesters within a particular slot is assumed to be *completely consumed* in the next slot by the cellular network. This avoids complicated issues such as the temporal evolution of stored energy and corresponding transmission-power control (see e.g., [9]) which are outside the scope of this paper. The assumption allows the analysis to focus on an arbitrary realization of the energy field represented by Ψ.

B. Cellular-Network Model

BSs are deployed on a hexagonal lattice with density λ_b, denoted as Φ_b, and consequently the plane is partitioned into hexagonal cells with areas of $1/\lambda_b$. Let B_0, P_0 and K_0 denote the typical BS, its transmission power and the number of simultaneous mobiles the BS serves, respectively. Circuit power of each BS is assumed to be negligible compared with P_0 and as a result P_0 is equal to the power supplied to the BS. Scheduled mobiles are assumed to be distributed as a PPP with density λ_u. Then K_0 is a Poisson random variable with mean λ_u/λ_b. A signal transmitted by a BS at X with power P is received at an mobile at Y with power given as $PH_{XY}|X-Y|^{-\alpha}$ where $\alpha > 2$ is the path-loss exponent and the random variable H_{XY}, called a channel coefficient, models fading or shadowing. The channel coefficients are assumed to be i.i.d. Assuming unit noise variance, the received power also gives the received SNR.

Since the network is noise limited, the condition for reliable decoding at a mobile is specified by the outage constraint that the received SNR exceeds a given threshold θ except for small probability ϵ. The outage probability is the network-performance metric. Let R_0 and H_0 denote the propagation distance and channel coefficient of an arbitrary user in the typical cell, respectively. Then the outage probability, denoted as p_{out}, is written as

$$p_{\mathsf{out}} = \Pr\left(\frac{P_0 H_0 R_0^{-\alpha}}{K_0} < \theta\right). \tag{1}$$

III. Energy-Field Model

The energy field Ψ refers to the set of energy intensities at different locations in the horizontal plane. The PPP modeling the energy centers and the corresponding energy intensity are denoted as $\Phi \subset \mathbb{R}^2$ and γ, respectively. The energy-intensity function $g(X)$ is defined for a given location X as follows:

$$g(X) = \gamma \max_{Y \in \Phi_e} f(|X-Y|) \tag{2}$$

where the energy-decay function f is defined as $f(d) = e^{-d^2/\nu}$ with $d > 0$. The positive parameter ν controls the shape of f, thus called the *shape parameter*, and thereby determines the area of influence of an energy center. As observed from the plots in Fig. 2, increasing λ_e or decreasing ν introduces more "ripples" in the energy field; the field is almost flat for large parametric values e.g., $\lambda_e = 10$ and $\nu = 1$.

The distribution function of the energy intensity can be easily obtained by relating it to a Boolean model. To this end, define $r(x)$ as the distance from an energy center to a location with the decayed energy intensity x:

$$r(x) = f^{-1}(x/\gamma) = \sqrt{\nu \ln \gamma/x}. \tag{3}$$

Moreover, let $B(X, r)$ denote a disk centered at X and with a radius r. The region of the energy field where energy intensities exceed a threshold x corresponds to a Boolean model $\bigcup_{X\in\Phi_e} B(X, r(x))$. Then for given X and $x \in [0, \gamma]$, the distribution function of $g(X)$ can be written in terms of the model and obtained as

$$\begin{aligned}\Pr(g(X) \le x) &= \Pr\left(X \notin \bigcup\nolimits_{X\in\Phi_e} B(X, r(x))\right)\\ &= e^{-\pi\lambda_e r^2(x)} = (x/\gamma)^{\pi\nu\lambda_e}\end{aligned} \tag{4}$$

where the last equality is obtained by substituting (3). It is interesting to observe that the result as well as the outage probability derived subsequently depend on the product $\nu\lambda_e$ instead of individual parameters.

IV. Network Coverage: On-Site Harvesters

For ease of notation, the outage probability is decomposed as $p_{\mathsf{out}}^{\mathsf{id}} = p_a + p_b$ with p_a and p_b defined as

$$p_a = \Pr\left(K_0 H_0^{-1} R_0^{\alpha} > \frac{\eta\gamma}{\theta}\right), \tag{5}$$

$$p_b = \Pr\left(\frac{P_0 H_0 R_0^{-\alpha}}{K_0} < \theta, K_0 H_0^{-1} R_0^{\alpha} \le \frac{\eta\gamma}{\theta}\right). \tag{6}$$

Though it is difficult to derive the outage probability in closed form, a simple upper bound can be obtained. To this end, p_b can be bonded using Markov's inequality as

$$p_a \le \frac{\theta\lambda_u \mathsf{E}\left[H_0^{-1}\right]\mathsf{E}\left[R_0^{\alpha}\right]}{\eta\gamma\lambda_b}. \tag{7}$$

Define a random variable $\bar{R}_0$ as $\bar{R}_0 = \sqrt{\lambda_b} R_0$ that gives the propagation distance of a mobile uniformly distributed in a cell of unit area. Note that the boundary of a hexagon of unit area is bounded by a disk with an area of $\frac{2\pi}{3\sqrt{3}}$. Thus, $\bar{R}_0 \preceq D$ where D has the following distribution:

$$\Pr(D \le x) = \frac{3\sqrt{3}}{2}x^2, \qquad 0 \le x \le \sqrt{2/3\sqrt{3}} \tag{8}$$

and $\preceq$ represents the relation of stochastic dominance. Using this result and the definition of $\bar{R}_0$, it is obtained that $\mathsf{E}\left[R_0^{\alpha}\right] \le c_3/\lambda_b^{\frac{\alpha}{2}}$ where the constant $c_3 = \frac{2}{2+\alpha}\left(\frac{2}{3\sqrt{3}}\right)^{\frac{\alpha}{2}}$. Combining the inequality and (7) gives

$$p_a \le \frac{c_3\theta\lambda_u \mathsf{E}\left[H_0^{-1}\right]}{\eta\gamma\lambda_b^{1+\frac{\alpha}{2}}}. \tag{9}$$

Next, given $P_0 = \eta g(B_0)$, p_b is upper bounded using (1), (4) and the definition of $\bar{R}_0$ as

$$p_b \le \left(\frac{\theta}{\gamma\eta\lambda_b^{\frac{\alpha}{2}}}\right)^{\pi\psi} \mathsf{E}[K^{\pi\psi}]\mathsf{E}\left[H_0^{-\pi\psi}\right]\mathsf{E}\left[\bar{R}_0^{\alpha\pi\psi}\right]. \tag{10}$$

It follows from the inequality $\bar{R}_0 \preceq D$ and the distribution of D in (8) that

$$\mathsf{E}\left[\bar{R}_0^{\alpha\pi\psi}\right] \le \frac{2c_2^{\pi\psi}}{2+\alpha\pi\psi} \tag{11}$$

where $c_2 = \left(\frac{2}{3\sqrt{3}}\right)^{\frac{\alpha}{2}}$. By combining the inequality with (10),

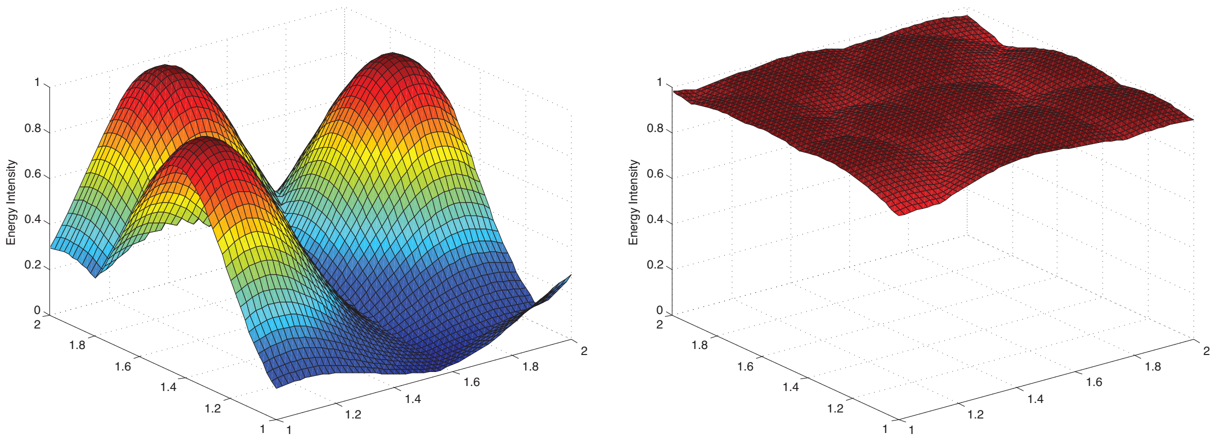
$$p_b \le \frac{2}{2+\alpha\pi\psi}\left(\frac{c_2\theta}{\gamma\eta\lambda_b^{\frac{\alpha}{2}}}\right)^{\pi\psi}\mathsf{E}[K_0^{\pi\psi}]\mathsf{E}\left[H_0^{-\pi\psi}\right]. \tag{12}$$

If $\pi\psi \le 1$, the upper bound on the outage probability can be reduced using Jensen's inequality as

$$p_b \le \frac{2}{1+\alpha\pi\psi}\left(\frac{c_2\theta\mathsf{E}[K_0]\mathsf{E}\left[H_0^{-1}\right]}{\gamma\eta\lambda_b^{\frac{\alpha}{2}}}\right)^{\pi\psi}. \tag{13}$$

If $\pi\psi > 1$, since larger ψ leads to more harvested energy and thus smaller outage probability, the inequality in (12) holds by setting $\pi\psi = 1$:

$$p_b \le \frac{2c_2\theta\mathsf{E}\left[H_0^{-1}\right]\lambda_u}{(2+\alpha\pi\psi)\gamma\eta\lambda_b^{1+\frac{\alpha}{2}}}. \tag{14}$$



(a) $\lambda_e = 1, \nu = 0.1$ (b) $\lambda_e = 10, \nu = 1$

Fig. 2. Energy field for different combinations of the energy-center density λ_e and shape parameter ν.

Combining (9), (13) and (14) gives the main result of this section as shown in the following proposition.

Proposition 1. For on-site harvesters, the outage probability can be bounded as follows:

$$p_{\text{out}}^{\text{id}} \le \frac{2}{2+\alpha\pi\psi}\left(\frac{c_2\theta\,\mathsf{E}\left[H_0^{-1}\right]\lambda_u}{\gamma\eta\lambda_b^{1+\frac{\alpha}{2}}}\right)^{\min(\pi\psi,1)} + \frac{c_3\theta\lambda_u\,\mathsf{E}\left[H_0^{-1}\right]}{\eta\gamma\lambda_b^{1+\frac{\alpha}{2}}}.$$

Consider the scenario where the product $\gamma\eta$ is large, corresponding to large peak energy density (e.g., direct sunshine at noon) or the deployment of harvesters with large apertures or both. As a result, the base in the exponential function in the inequality above is close to zero. Then the upper bound on the outage probability decreases exponentially with increasing ψ which is confirmed by simulation in the sequel.

The last term in the upper bound is independent with ψ or equivalently the spatial variation of the energy field. This term corresponds to the probability of the events of large propagation loss for a typical mobile or a large number of mobiles sharing the same BS such that even the maximum power generated by a harvester is insufficient for ensuring reliable received signal at the typical mobile.

V. Network Coverage: Distributed Harvesters

In this section, it is shown that aggregating energy harvested by many distributed harvesters stabilizes power supplied to BS's by the law of large numbers. It is assumed that the energy-aggregation loss is regulated such that the scaling factor of BS transmission powers due to such loss is smaller than a constant $\tau \in (0, 1)$. The harvester lattice partitions the plane into small hexagonal regions with area of $1/\lambda_h$. Whether each region contains an energy center can be indicated by a set of independent Bernoulli random variables $\{Q_n\}$ with probabilities $e^{-\lambda_e/\lambda_h}$ and $(1-e^{-\lambda_e/\lambda_h})$ for the values of 0 and 1, respectively. The energy intensity at each harvester is at least $\exp\left(-\frac{2}{3\sqrt{3}\nu\lambda_h}\right)$ if the corresponding small region contains an energy center or otherwise takes on some positive value. Based on the discussion, the transmission power of the typical BS is lower bounded as:

$$P_0 \ge \frac{\tau\gamma\eta\lambda_h}{\lambda_b} \times \frac{\lambda_a M_0}{\lambda_h} \times \frac{1}{M_0}\sum_{n=1}^{M_0} Q_n e^{-\frac{2}{3\sqrt{3}\nu\lambda_h}} \tag{15}$$

where M_0 represents the number of harvesters connected to the typical aggregator. Consider the scenario of sparse aggregators with each connected to many harvesters, corresponding to $\lambda_a \to 0$. As a result, $M_0 \to \infty$ and $\lambda_a M_0/\lambda_h \to 1$. Then it follows from (15) that

$$\lim_{\lambda_a \to 0} P_0(\lambda_a) \ge \frac{\tau\gamma\eta\lambda_h}{\lambda_b} \times \lim_{M_0\to\infty} \frac{1}{M_0}\sum_{n=1}^{M_0} Q_n e^{\left(-\frac{2}{3\sqrt{3}\nu\lambda_h}\right)}.$$

Invoking the law of large numbers gives the following lemma.

Lemma 1. With the harvester density λ_h fixed, as the aggregator density $\lambda_a \to 0$, the transmission power for the typical BS converges as

$$\lim_{\lambda_a\to 0} P_0(\lambda_a) \ge \frac{\tau\gamma\eta\lambda_h}{\lambda_b}\left(1 - e^{-\frac{\lambda_e}{\lambda_h}}\right)e^{-\frac{2}{3\sqrt{3}\nu\lambda_h}}, \qquad \text{a.s.}$$

In other words, P_0 is lower bounded by a constant and thus its randomness due to energy spatial variation diminishes. If the energy centers are dense ($\lambda_e \gg \lambda_h$) and the shape parameter ν is large ($\nu\lambda_h \gg 1$), the transmission power approaches its upper bound $\gamma\eta\lambda_h/\lambda_b$.

The power stabilization by the spatial averaging of the energy field removes one random variable from the outage-probability. Using Lemma 1 and applying Markov's inequality, the outage probability in (1) for small aggregator density can be bounded as

$$\lim_{\lambda_a\to 0} p_{\text{out}}(\lambda_a) \le \frac{\theta\lambda_b\mathsf{E}[H^{-1}]\mathsf{E}[K]\mathsf{E}[R^{\alpha}]}{\tau\gamma\eta\lambda_h\left(1-e^{-\frac{\lambda_e}{\lambda_h}}\right)e^{-\frac{2}{3\sqrt{3}\nu\lambda_h}}}. \tag{16}$$

Substituting $\mathsf{E}[K] = \lambda_u/\lambda_b$ and the expression for $\mathsf{E}[R^{\alpha}]$ yields the first result in Proposition 2 as given below.

Proposition 2. With the harvester density λ_h fixed, as the aggregator density $\lambda_a \to 0$, the outage probabilities can be

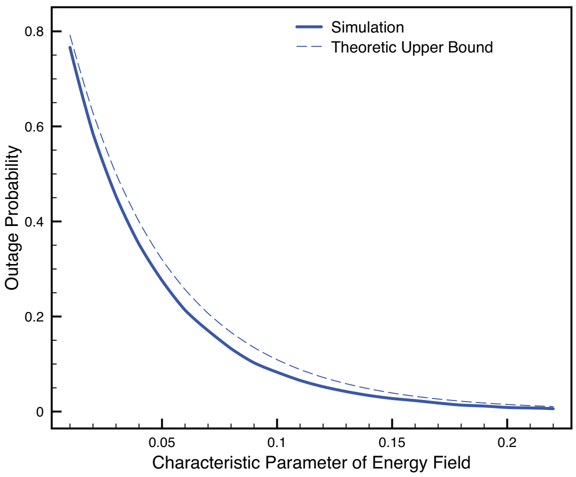


Fig. 3. Outage probability versus the characteristic parameter of the energy-field for the scenario of on-site harvesters.

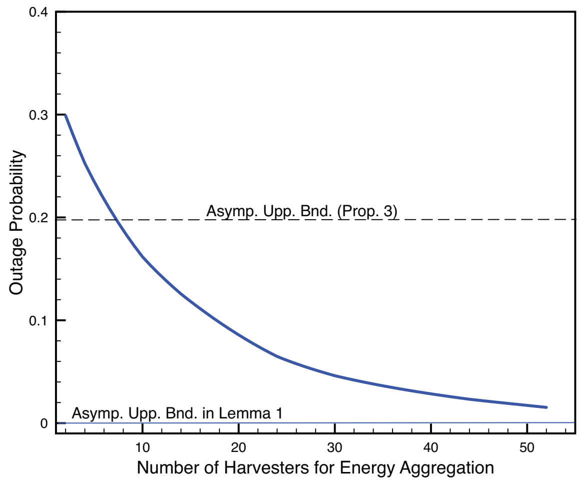


Fig. 4. Outage probability versus the number of harvesters for energy aggregation for distributed harvesters.

bounded as follows:

$$\lim_{\lambda_a \to 0} p_{\mathsf{out}} \leq \frac{c_3 \theta \mathsf{E}\left[H^{-1}\right] \lambda_u}{\tau \gamma \eta \lambda_b^{\frac{\alpha}{2}} \lambda_h \left(1 - e^{-\frac{\lambda_e}{\lambda_h}}\right) e^{-\frac{2}{3\sqrt{3}\nu \lambda_h}}}.$$

The results in Proposition 2 suggest that

$$\lim_{\lambda_a \to 0} p_{\mathsf{out}}(\lambda_a) \propto \frac{1}{\gamma\eta} \times \frac{1}{\lambda_h/\lambda_b} \times \frac{\lambda_u}{\lambda_b} \times \lambda_b^{-\frac{\alpha}{2}}$$

where the factors represent in order the inverses of the maximum power generated by a single harvester, the number of harvesters per BS, the expected number of active mobiles per cell, and the expected propagation loss.

It is worth mentioning that the transmission loss τ due to power aggregation increases as $\lambda_a \to 0$ unless harvester voltages scale up accordingly. The required scaling law is analyzed in the full paper due to the space limit.

VI. Simulation Results

The BS and mobile densities are $\lambda_b = 0.78$ /km^2 and $\lambda_m = 7.8$ /km^2, respectively. For propagation, the reference path loss is 70 dB measured at a distance of 100 m, $\alpha = 4$, and the noise power is -90 dBm. The product, $\gamma\eta$, gives the maximum power a harvester can generate, which is fixed as $\gamma\eta = 1$ kW for an on-site harvester and 10 W for a distributed one. For distributed harvesters, the harvester density is 15.6 /km^2. The SNR threshold θ is 8. The fading coefficients are i.i.d. and distributed as $\max(|\mathcal{CN}(1,1)|^2, 0.1)$ where the truncation at 0.1 accounts for the avoidance of deep fading by scheduling.

Consider on-site harvesters. The curves of outage probability versus the characteristic parameter ψ are plotted in Fig. 3. The upper bound on the outage probabilities as given in Propositions 1 is also shown. The outage probabilities are observed to decay exponentially with increasing ψ as predicted by analysis. As the product $\gamma\eta$ is large, significant power can be harvested even at locations far from energy centers. This is the reason that the outage probability is close to zero even for a small characteristic parameter (e.g., 0.2).

Next, consider distributed harvesters where the characteristic parameter is fixed as 0.05. In Fig. 4, the outage probability is plotted against the number of harvesters connected to a single aggregator for energy aggregation (that is approximately equal to λ_h/λ_a). For comparison, the figure also shows the asymptotic upper bound on outage probability as given in Proposition 2 as well as that generated by simulation and replacing transmission power with the asymptotic lower bound in Lemma 1. Aggregation loss is omitted assuming sufficiently high transmission voltage. It is observed that energy aggregation dramatically reduces outage probabilities, indicating energy randomness as the main reason for outage events. Most of the aggregation gain can be achieved with less than 50 harvesters per aggregator. For a large number of harvesters, the limits of outage probability depend little on the randomness of the energy-field and is mostly contributed by channel fading. Last, the asymptotic upper bound from Proposition 2 is observed to be loose due to the use of Markov's inequality but the bound based on Lemma 1 is tight.

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