On the Scalability of Energy in Wireless RF Powered Internet of Things

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***Abstract*— Wireless RF power transfer requires the deployment of multiple energy transmitters (ETs) to cover an entire area of interest. This letter aims at bounding the minimum cumulative power that ETs need to inject into the network, such that the recipient nodes harvest sufficient power to operate. The main findings are that, in the worst case, this scales as $O(s^{1-\alpha/2})$, where s and α are the number of ETs and the channel path loss. That is, the overall power decreases with the number of ETs. It is also shown that sophisticated design for power transmission can further improve the scalability by s^{-1}.**

***Index Terms*— Wireless power transmission, Internet of Things, scalability.**

I. Introduction

Wireless RF power transfer has transitioned from proof-of-concept deployments to commercial products over the recent years, indicating its feasibility in powering unattended Internet of Things (IoT). This approach consists of harvesting the RF radiation from controllable energy transmitters (ETs) to supply the power demands of the networked nodes [1].

The high path-loss of the RF signal in free-space constrains the range of the transmission of energy to relatively short distances (i.e., up to a few tens of meters) [2]. Hence, considerable efforts have been undertaken for extending the power transfer range to cover a larger area, within the limitations of the regulatory bodies (e.g., FCC), ET hardware costs, and the specific capabilities of the ETs [1]. One such viable direction involves using antenna arrays and directional antennas that allow harvesting energy from 60 μW of incident power, with the receiver placed a considerable distance away from the energy source (i.e., 4.1 km). However, this setup increases the dimensions of the antenna to a few tens of centimeters, since it requires a typical broadband UHF TV antenna [3]. MIMO-based approaches, on the other hand, permit on-demand energy beam-forming, thereby reducing the energy spread [4]. However, despite these methods, multiple ETs may be needed to cover the entire area of interest leading to concerns of scalability [1], [5].

This letter aims at answering a fundamental question: *In order to guarantee sufficient power at the deployed nodes, is it better to increase the number of ETs, to increase their transmitted power or to increase their system complexity?* For this, a scalability analysis of the cumulative power that ETs need to inject into the network to guarantee the sensor nodes operation is provided for three different multiple access methods for multi-ET transmissions, namely cellular-based planning, orthogonal multiple access methods and distributed beamforming. To analyze the former, a closed-form expression of the minimum cumulative injected power is derived. Then, this is numerically evaluated to analyze and compare the three proposed methods. The presented analysis is agnostic of any underlying physical layer capability.

The main findings of our work are that this power metric is bounded, in its worst case, by $O(s^{1-\alpha/2})$, where α refers to the propagation path-loss exponent. That is, the injected power is independent of the number of deployed ETs in free-space conditions, whereas it is decreasing in typical indoors propagation environments ($\alpha > 2$). By implementing optimal power transmission schemes, this bound scales up to approximately s times faster in ideal transmission channels, whereas this improvement becomes less noticeable at higher values of the path-loss exponent.

In summary, our work shows increasing the number of deployed ETs is scalable in terms of aggregated transmitted power and that the propagation channel conditions the way in which multiple ETs should coordinate to mitigate mutual signal overlapping and generate maximum constructive signal addition at the energy-receiving sensors. We show that for the correct operation of such networks it is necessary to research and develop sophisticated signal-overlapping-aware schemes for near-ideal channel conditions, and also demonstrate that simple approaches can provide similar performance when the channel degrades.

The rest of this letter is organized as follows. In Sec. II, we briefly overview the fundamentals of wireless RF power transfer. In Sec. III, an upper bound for the scalability of power is provided. Sec. IV discusses the impact of multiple access methods for wireless RF power transfer. Finally, in Sec. VI we conclude our work.

II. A Channel Model for Power Transfer

In this section we revise the fundamentals of wireless RF power transfer and the channel model considerations.

A. Point-to-Point Power Transfer

We consider the following path-loss model, which is described by the transmitted power, P_T, the path loss at 1 meter distance, L_0, the transmission distance, R and the path-loss exponent, α [6]. L_0 also accounts for additional multiplicative constants that play a role in the wireless medium and do not depend on the distance, such as the antenna gain or directivity. The power which is received at the antenna is

Manuscript received August 14, 2016; accepted September 5, 2016. Date of publication September 21, 2016; date of current version December 8, 2016. This work has been funded in part by the Spanish Ministry of Science and Innovation under grant DPI2013-47799-C2-2-R and the US National Science Foundation under grant CNS-1452628. The associate editor coordinating the review of this letter and approving it for publication was T. Han.

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Digital Object Identifier 10.1109/LCOMM.2016.2612189

given by:

$$P_H = P_T L_0 R^{-\alpha}. \tag{1}$$

As a general case, α is generally comprised between 2 (free space) and 6 within urban areas (both outdoors and indoors) [7].

B. Multiple Power Transfers

When multiple ETs are required to cover a large networking area, the wirelessly propagated RF waves may constructively or destructively combine. We find that the received power at the harvesting antenna, when it harvests from a number s of ETs is given by [8]:

$$P_R = \sum_{i=1}^{s} P_{Hi} + \sum_{\substack{i,l=1\\ i\neq l}}^{s} \rho_{il}\sqrt{P_{Hi}P_{Hl}} \tag{2}$$

where P_{Hi} refers to the received power from the i-th ET and ρ_{il} stands for the correlation between the i and l transmissions, in case of random signals, or orthogonality factor in case of deterministic signals. This value is bound in such that $-1 \leq \rho_{il} \leq 1$.

In order to exemplify this factor, let us consider two deterministic RF sine waves that arrive at a receiver node with same power $P = P_1 = P_2$, frequencies f_1 and f_2 and phases ϕ_1 and ϕ_2. If $f_1 \neq f_2$, we have that $\rho = 0$, then the received power equals $2P$. If $f_1 = f_2$ and $\phi_1 = \phi_2$, the RF waves constructively combine and the received power equals $4P$. Finally, if $f_1 = f_2$ and $\phi_1 = \phi_2 + \pi$, the RF waves destructively combine and the received power is zero.

III. Multiple Access for Multi-ET Transmissions

In this section, we revise the design space in multiple access for multi-ET transmissions. Multiple access methods to handle signal overlapping in wireless RF power transfer can be classified as follows:

A. Cellular-Based planning

Each ET has an associated region in the space, where this is in charge of transferring the energy. To avoid neighboring signal overlapping, each ET has an associated transmission slot (either in frequency or in time). After a certain distance, cells could re-use slots [9]. The received power from a given node is simplified to:

$$P_R = P_{H\max}, \tag{3}$$

where $P_{H\max}$ refers to the most energetic reception from the set of ETs. Given that ETs do not cooperate to maximize the power transfer, this approach stands as the worst case.

B. Orthogonal Methods

Classical orthogonal approaches appear as a second approach to mitigate the signal destruction due to signal overlapping. In this group, simple schemes such as FDMA, TDMA or advanced modulations, such as CDMA, FHMA or OFDMA can be implemented at the ETs [10]. This approach aims at vanishing the correlation factors between RF waves ($\rho_{il} = 0\ \forall i,l$) hence, reducing the received power equation to:

$$P_R = \sum_{i=1}^{s} P_{Hi}. \tag{4}$$

These methods have been employed to implement off-the-shelf ETs and potentially offer better performance than Cellular-based planning.

C. Distributed Beam-Forming Methods

This last approach aims at leveraging the constructive combination of RF waves, hence optimizing parameters, such as the transmission phase at each ET to either maximize the received power at all locations or to guarantee a minimum delivered power. In this direction, energy-on-demand (EoD) MAC protocols have been proposed to maximize the constructive combination of RF waves [11]. Recent works in massive MIMO for energy transmission has shown that ETs can constructively combine at all sensor node locations if each ET has at least k separated antennas, being k the number of users or deployed nodes in the network [8]. Due to the large number of required antennas per ET and the excessive node to ET channel state information (CSI) communication feedback, this approach may render unpractical. Accordingly, it sets the best-case performance in wireless RF power transmission.

Analytically, this approach aims at providing the best correlation factors, hence being upper bound (i.e., $\rho_{il} = 1$) by:

$$P_R = \sum_{i=1}^{s} P_{Hi} + \sum_{\substack{i,l=1\\ i\neq l}}^{s} \sqrt{P_{Hi}P_{Hl}} \tag{5}$$

As reported in [12], the received power considering this approach shows a gain of s, with s being the number of considered ETs, compared to orthogonal methods.

IV. A Theoretical Bound for Cellular Planning

In this section, we bound the minimum cumulative injected power per unit area as a function of the number of ETs in a cellular-based planning set-up. In this context, nodes are able to harvest power only from their nearest ET and disregard the received power from any other ET.

Consider, first, a set of s ETs, which are located over an area $\mathcal{A}$ with allocated power P_T. We define the minimum cumulative power density $\mathcal{P}$, defined as the sum of the transmitted power of every ET deployed in the networking area, such that it guarantees that the received power at each possible node location is above a minimum threshold. This is given by:

$$\mathcal{P} = \frac{\sum_i^s P_{Ti}}{\mathcal{A}} \tag{6}$$

where P_{Ti} refers to the allocated power at the i-th ET. In other words, it refers to the total power per unit area which is transmitted by the ETs to guarantee the power requirements at the sensor node locations. In this sense, requiring a single ET transmitting 4 W of power or four ETs transmitting 1 W of power each to cover a 10x10 m area, yield to the

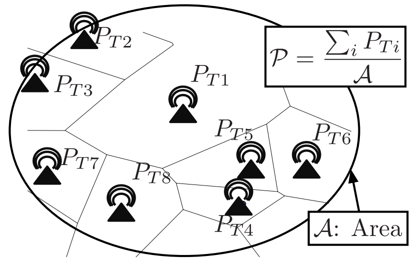

Fig. 1. Voronoi tesselation generated by the energy transmitters and graphical definition of the cumulative injected power density.

same minimum cumulative power density of 0.04 Wm^{-2}. A graphical description of this metric is shown in Fig. 1.

By considering a cellular-based planning, the allocated transmitted power at each ET needs to guarantee that possible nodes located at the furthest distance are still harvesting sufficient power. For this, let us define a Voronoi Tessellation, where the set of s ETs spatially distributed, following a Poisson Point Process along the area $\mathcal{A}$, are used as center of each cell. Then, we find that a given node k located at an arbitrary location harvests power from the i-th ET if the node is contained in the cell V_i, whereas possible nodes located at the vertices of the cells represent the furthest distances. To exemplify this, we show in Fig. 1 an example of an ET deployment and their associated cells, based on closer distance.

We then set the transmitted power at each ET to be such that the node located at the furthest distance within a cell is able to receive the minimum required power P_0 set by the IoT communication layer. By combining (1) and (6), we have that the minimum cumulative power density can be calculated as:

$$\mathcal{P} = \frac{\sum_{i=1}^{s} P_0 L_0^{-1} d_{max,i}^{\alpha}}{\mathcal{A}} \tag{7}$$

where P_0 refers to the requirements of power at the node location, L_0 stands for the path loss at the distance of 1 m, $d_{max,i}$ stands for the distance between the i-th ET and the furthest node located within its Voronoi cell V_i and α stands for the path-loss exponent.

Then, we bound $d_{max,i}$. This distance is bound by one of the vertices of the Voronoi cell, which, in turn, for arbitrarily large number of ES, s, and any integer $j > 0$, we can bound it by defining a disk of diameter R_j [13], which is given by:

$$R_j = 4 \cdot 3^{-1/4} \sqrt{\frac{j}{s-1}} \tag{8}$$

with probability $\geq 1 - 6e^{1-j}$. In other words, the maximum possible distance between the ET i and the furthest node associated to its cel,l V_i, is bounded by:

$$d_{max,i} < \frac{R_j}{2} < c_1 s^{-1/2} \tag{9}$$

with probability tending to one when $s \to \infty$, being c_1 a multiplicative term which does not have dependence on s.

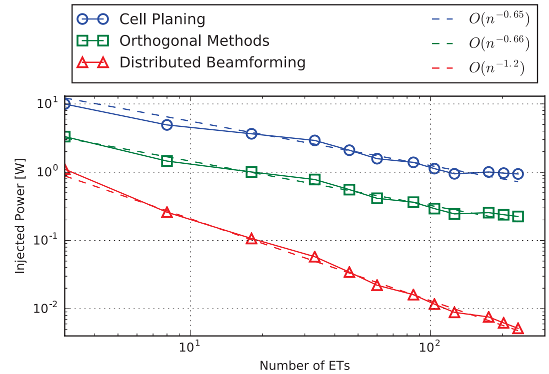

Fig. 2. Minimum cumulative power injected by the ETs to guarantee sufficient harvested power at any location, considering a regular hexagon deployment grid.

By combining (7) and (9), we find that the minimum cumulative power density is bounded by:

$$\mathcal{P} < \sum_{i \in \mathcal{S}} P_0 L_0 (c_1 s^{-1/2})^{\alpha} < c_2 s^{1-\alpha/2}, \tag{10}$$

which is a function of the number of ETs. Finally, we can say that the minimum cumulative power density is upper bounded by:

$$O\left(s^{1-\alpha/2}\right). \tag{11}$$

V. Numerical Results

We numerically evaluate the scalability of the three considered approaches. For this, we assume the ideal operation of the multiple access methods. We calculate the required power that it needs to be allocated at each ET, such that a sensor node placed at any point in the networking area can harvest a minimum power of $P_0 = 10\ \mu$W. The minimum cumulative power is then calculated by summing the allocated power at every ET. The network is placed over a 20×20 m^2 squared area. The deployed ETs are deployed over the networking area following regular hexagons and random positioning topologies.

We first show in Fig. 2 the minimum cumulative injected power as a function of the number of deployed ETs. This numerical evaluation considers the office environment channel model provided in [7], which provides an $\alpha = 3.3$. In the figure, we compare the different multiple access methods. In addition, we also show the scalability trend that each curve offers. As it is observed, cellular planning offers the worst performance, requiring larger amounts of injected power. Nonetheless, we observe that it scales as predicted. Orthogonal methods, show very similar scalability as cellular planning, whereas offering an approximately three-fold performance improvement. Finally, we find that distributed beam-forming offers a substantial improvement, in terms of injected power and its scalability. Particularly, this scales as $O(s^{-1.2})$, instead of the theoretical $O(s^{-0.65})$.

Then, we show in Fig. 3 the design space for multiple access methods for Multi-ETs. In the figure we show the *scalability exponent* as a function of the path-loss exponent. The scalabilty exponent refers to the obtained exponent of s in

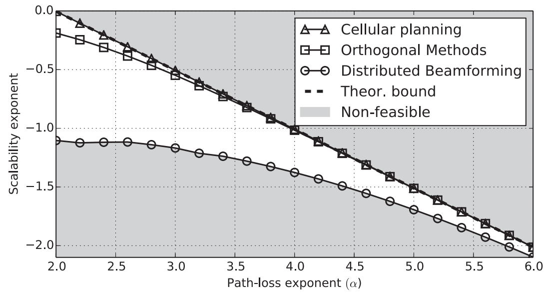

Fig. 3. Design space of multiple access methods for Multi-ETs in terms of the scalability of the minimum cumulative injected power as a function of the path-loss exponent.

the scalabiltiy trend (i.e., $1 - \alpha/2$ for cellular planning). The chosen topology has not evidenced any difference in terms of scalability. We first see that the numerically evaluated cellular planning matches the theoretical bound derived in the previous section. Then, we find that both orthogonal methods and distributed beam-forming approach the derived theoretical bound as the path loss increases. Finally, we find that distributed beam-forming achieves the best performance, as predicted in Sec. III.

VI. Discussion

In this section, we assess the question asked in Sec. I: *In order to guarantee sufficient power at the deployed nodes, is it better to increase the number of ETs, to increase their transmitted power or to increase their system complexity?* To provide an answer, we consider the following two use-cases:

The case $\alpha = 2$ refers to free-space propagation. In this scenario, the injected power scales as $O(1)$ in cellular-based planning. That is, the injected power is independent of the number of deployed ETs. As such, there is no preference between increasing the allocated power or increasing the number of deployed ETs, without taking into account practical constraints in the maximum power per ET. In these conditions, implementing sophisticated signal-overlapping-aware schemes extends this bound to $O(s^{-1.1})$, which responds to the theoretical s gain of distributed beam-forming over orthogonal methods predicted in [12].

The cases where $\alpha > 2$ generally apply to indoors and/or urban environments. In such cases, larger densities of ETs reduce the cumulative injected power. That is, larger path-losses constrain the power transfer to very few meters distance from the ETs, and this power very rapidly decays with the distance. For a fixed deployment, increasing the number of ETs reduces the transmitted power. It is noteworthy that as α increases, the large dispersion of the medium causes that the transmitted RF waves do not propagate over long distances and cannot combine among them. Hence, the derived bound for distributed beamforming approaches the theoretical bound.

The provided use-cases provide strong design guidelines in the deployment of ETs. It is first shown that large deployments of low-power ETs help reducing the overall transmitted power. Then, it is shown that the path-loss exponent conditions the multiple access for multi-ET design. Table I summarizes the achievable scalability of the minimum cumulative injected power and the recommended design guidelines, depending on the type of considered channel.

TABLE I
Summary of the Results and Proposed Recommendation

Channel	Scalability	Recommendation
Free-space	$O(s^{-1.1})$	Multiple ETs, sophisticated methods
Indoors	$O(s^{1-\alpha/2})$	Multiple ETs, simple cellular approach

VII. Conclusions

In this letter, the bounds for the cumulative power that energy transmitters (ETs) need to inject to supply a wireless RF powered Internet of Things have been addressed. These bounds compare the performance of different multiple access methods for multi-ET transmission, and define the design space for ET deployment. It has been shown that the required injected power decreases with the number of deployed ETs, hence motivating the deployment of a supporting network of ETs. Near-ideal channel conditions can leverage sophisticated schemes to further reduce the required injected power, whereas dispersive channels points to the design of simpler approaches.

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