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On Electromagnetic Radiation Control for Wireless Power Transfer in Adhoc Communication Networks: Key Issues and Challenges

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ABSTRACT In this paper, we provide a holistic overview of the aspect of electromagnetic radiation (EMR) and its efficient control in wireless communication networks. Especially, we focus on the emerging technology of wireless power transfer (WPT). Our global perspective is to suggest methods for the effective control of EMR while keeping at high levels the QoS experienced by users as well as the charging efficiency of WPT. First, we provide formal definitions of EMR in wireless communications and propose related performance metrics and EMR evaluations in wireless communication networks. Then, we focus on EMR control in efficient wireless power transfer, under different WPT models. For the well-known scalar model, we assume finite energy reserves and batteries, and introduce the low radiation efficient charging problem. For this problem, we identify its computational complexity and provide efficient algorithms and heuristics. A vectorial model of WPT is then employed, allowing a more precise management of radiation, via directly exploiting interesting super-additive and cancellative phenomena of received power; we provide algorithms which achieve satisfactory tradeoffs of charging efficiency and radiation. Then, we present a more futuristic model and the method of peer-to-peer wireless power transfer where no strong, central charger stations are used, thus keeping radiation at almost zero levels. Another method of controlling EMR in the case of mobile nodes is adapting the charger change in a dynamic, on-line way so as to avoid unnecessarily large fixed changing ranges. Finally, we discuss some future challenges and related research directions, toward efficiently combining high WPT provisioning and low EMR. Such directions include the effective management of mobility in the network, the use of diverse WPT signal phase-configuration as well as efficient chargers' scheduling strategies.

INDEX TERMS Energy management, wireless power transfer, radiation control, power management, vector model.

I. INTRODUCTION

Rapid advances in embedded systems and the wide use of portable devices in everyday life, have motivated significant, novel research in wireless distributed systems and ad hoc wireless communication networks. However, due to the inherent limitations and constraints of such devices (size, cost and form), the effective management of energy remains a fundamental challenge. Energy consumption in such systems has a significant effect on important operational aspects, such as the longevity of the network and its robustness, as well as the quality of service offered to users.

At the same time, recent technological developments in the topic of Wireless Power Transfer (WPT) create new potential for the effective and efficient energy management in modern, power-hungry wireless systems. Active research is already considering new, suitable network models abstracting these new technologies. In general, every WPT system includes two kinds of modules; the first, called wireless transmitter is

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equipped with a large pool of energy that can be transferred via rf signals and has the same functionality with a common charger. The second entity, called receiver (node or mote) is equipped with an antenna that enables the energy harvesting from rf signals produced by chargers. In particular, modern technology of very efficient WPT becomes available for energy harvesting over near and far field applications. Using strong coupled magnetic resonances, we can achieve a 40% efficiency in applications where 60 Watts can travel over a distance of more than 2 meters [1]. At the same time, commercial prototypes and products become available, improving the efficiency up to 75% for chargers that transmit with 60 Watts power while at the same time reach 1 meter distance [2]. Nowadays, plenty of products enabling WPT technology can be purchased from the market. Finally, the Wireless Power Consortium [3], mobilizing diverse partnerships including IC and smartphone manufacturers as well as telecom operators, are established towards WPT international standardization.

However, potentially problematic implications of WPT in modern wireless systems have not received yet the level of attention needed. WPT introduces new sources of electromagnetic radiation (EMR) on top of many other already existing wireless technologies that have been used extensively in everyday life such as Wi-Fi, Bluetooth, etc. Continious exposure to high electromagnetic radiation, has been proven that can cause irreparable problems to human health. Particularly for WPT, high radiation levels can be found due to the coexistence of many fields coming from different sources. So far, electromagnetic radiation is the one side of the wireless technologies coin. For us, it is more than essential to understand and control it in a way that the trade of with the wireless communication quality of service coin side can reach a balance. Our wish is to have adaptive systems with respect to radiation awareness and provide fundamental principles in both algorithmic and networking designs.

In this paper we aim for a global, systematic study of the topic of Electromagnetic Radiation (EMR) and how to efficiently control in modern wireless networks. We choose to particularly concentrate on the emerging technology of WPT, due to its potentially high impact to the cumulative EMR. Our aim is to propose methods for the effective control of EMR without affecting much the QoS enjoyed by system users as well as the efficiency of WPT charging.

To this end, abstract yet precise definitions of EMR in wireless networks and related performance metrics are proposed. Using these definitions and metrics we evaluate EMR in common wireless topologies.

As discussed, we choose to focus on EMR in efficient WPT systems. Different WPT models of diverse precision and applicability are provided. Typical scalar models (based on the well known Friis law) are not ignored; however we impose to them much more realistic assumptions, such as finite energy sources at the chargers and finite batteries at the receivers. Under these modeling assumptions, we introduce the Low Radiation Efficient Charging Problem, bringing together the aspects of efficient charging and EMR control. We study the computational complexity of this problem and provide efficient algorithms and heuristics.

Then we move to a vectorial modeling of WPT, allowing a very precise management of radiation, on the basis of interesting phenomena of EM waves interactions (super-additive and cancellative) on received power. Such accurate management of EMR offers us a good basis for effective trade-offs between charging efficiency and radiation. Subsequently, even more futuristic models are considered, assuming capabilities of peer to peer wireless energy charging in the lack of any powerful, central chargers; this facilitates keeping radiation at negligible levels.

We conclude by identifying selected emerging and future challenges and relevant major topics of new research. Such major topics include the impact and management of diverse mobility of network nodes, as well as the employment of phase-configuration in WPT waves and signals.

A main message this paper wishes to convey is the need for a diverse suite of abstract yet precise models, as well as the necessity of rigorous foundations and efficient algorithmic for the emerging WPT technology to achieve its full potential. Also, we wish to highlight the emerging need to seriously address potential implications of this fascinating technology in terms of the EMR it creates, via the proper management of charging efficiency and radiation control trade-offs, towards offering the users of modern wireless systems high quality yet safe services.

II. FORMAL DEFINITION OF RADIATION IN WSN

In what follows, we assume that we have a Wireless Communication Network $\mathcal{N}$ consisting of m wireless power devices or *wireless chargers* that operate within an area of interest $\mathcal{A}$ (typically inside $\mathbb{R}^2$). As a result, every point inside $\mathcal{A}$ is exposed to *Electromagnetic Radiation (EMR)*, which is loosely defined as the quantity of ''electromagnetic level'' it is exposed to. In this paper, we follow the usual assumption that the electromagnetic radiation is linearly related to the *power* at that point:

Definition 1 (Electromagnetic Radiation (EMR)): Let $\mathcal{N}$ be a Wireless Communication Network operating within an area $\mathcal{A}$ and let $\mathbf{x} \in \mathcal{A}$ be a point. If $P_{\mathcal{N},\mathbf{x}}(t)$ is the power caused by $\mathcal{N}$ to $\mathbf{x}$ at time t, then the Electromagnetic Radiation $\mathbf{x}$ is exposed to at t is given by

$$R_{\mathcal{N},\mathbf{x}}(t) = \gamma \cdot P_{\mathcal{N},\mathbf{x}}(t), \tag{1}$$

where γ is a constant that depends on the hardware of the wireless devices of $\mathcal{N}$ and the environment.

Notice that $R_{\mathcal{N},\mathbf{x}}(t)$ (and therefore also $P_{\mathcal{N},\mathbf{x}}(t)$) is a function of t, since wireless devices may become active or inactive during different time intervals. It is also evident from the above the definition that, $R_{\mathcal{N},\mathbf{x}}(t)$ refers to the radiation *rate* that point $\mathbf{x}$ is exposed to; to find the *total radiation a point is exposed to during a time interval* $[\tau_1, \tau_2]$, we simply write

$$R_{\mathcal{N},\mathbf{x}}([\tau_1, \tau_2]) \stackrel{def}{=} \int_{\tau_1}^{\tau_2} R_{\mathcal{N},\mathbf{x}}(t)dt = \int_{\tau_1}^{\tau_2} \gamma P_{\mathcal{N},\mathbf{x}}(t)dt \tag{2}$$

Path radiation. We extend the above definitions on trajectories within $\mathcal{A}$ as follows: $\mathcal{W}$ denotes a (finite, connected) route in $\mathcal{A}$. Assume that an individual moves on $\mathcal{W}$ with constant speed. Let $\mathcal{W}[\tau_1, \tau_2]$ be the part of $\mathcal{W}$ that the individual traverses between time τ_1 and τ_2. We also denote by $\mathcal{W}_t$ the individual's location at time t. The *path radiation that the individual walking on $\mathcal{W}$ is exposed to during* $[\tau_1, \tau_2]$ is

$$R_{\mathcal{N},\mathcal{W}}([\tau_1, \tau_2]) \stackrel{def}{=} \int_{\mathcal{W}[\tau_1,\tau_2]} R_{\mathcal{N},\mathcal{W}_t}(t)dt \tag{3}$$

Given a time duration τ, we also define the *maximum path radiation that an individual walking on $\mathcal{W}$ is exposed to during* $[\tau_1, \tau_2]$:

$$\max R_{\mathcal{N},\mathcal{W}}([\tau_1, \tau_2], \tau) \stackrel{def}{=} \max_{\tau_1 \le t \le \tau_1 - \tau} R_{\mathcal{N},\mathcal{W}}([\tau_1, \tau_2]). \tag{4}$$

Notice that $\max R_{\mathcal{N},\mathcal{W}}([\tau_1, \tau_2], \tau)$ is a function of τ (as well as $\mathcal{N}, \mathcal{W}$ and $[\tau_1, \tau_2]$) and it is *different* than the maximum radiation (rate) that the individual is exposed to during $[\tau_1, \tau_2]$, the latter being equal to $\max_{\tau_1 \le t \le \tau_2} R_{\mathcal{N},\mathcal{W}_t}(t)$.

Upon inspection of Definition 1, we point out that, to get a mathematical formula for $R_{\mathcal{N},\mathbf{x}}$, we first need to have a mathematical formula for the power $P_{\mathcal{N},\mathbf{x}}$. There are two prevalent approaches in the literature, which roughly correspond to *macroscopic* and *microscopic* study of electromagnetism.

A. SCALAR MODEL

The usual assumption here is that, the (absolute) power created by a wireless device $u \in \mathcal{N}$ at a point $\mathbf{x}$ of $\mathcal{A}$ at time t, given that *only* u operates in $\mathcal{N}$ is constant and equal to

$$P_{u,\mathbf{x}}(t) = \frac{a \cdot r_u^2}{(1 + \text{dist}(u, \mathbf{x}))^2}, \tag{5}$$

where r_u is a constant expressing the *operation level* of u, a is a parameter depending on the environmental settings and the hardware of u, and $\text{dist}(u, \mathbf{x})$ is the Euclidean distance among the location of u at time t and point $\mathbf{x}$. We note that, up to constant multipliers, equation (5) expresses Frii's formula for the received power by a single receiver under the constraint that there are no other receivers within a certain area. It is also worth mentioning that, there are cases in the literature, the exponent in the denominator is allowed to take values other than 2 so that the dependence on the distance is either emphasized or suppressed. Additionally, some authors use a cut-off bound D, meaning that the power created by u becomes equal to 0 for all points further than D from u.

The crucial assumption in the scalar model, which makes it more tractable than others, is that *power from different sources is additive*. In particular, for any subset $\mathcal{S} \subseteq \mathcal{N}$, the cumulative power created by $\mathcal{S}$ to $\mathbf{x}$ at time t is calculated by

$$P_{\mathcal{S},\mathbf{x}}(t) = \sum_{u \in \mathcal{S}} P_{u,\mathbf{x}}(t). \tag{6}$$

Therefore, by Definition 1, the cumulative electromagnetic radiation $\mathbf{x}$ is exposed to at time t because of $\mathcal{N}$ is

$$R_{\mathcal{N},\mathbf{x}}(t) = \sum_{u \in \mathcal{N}} R_{u,\mathbf{x}}(t). \tag{7}$$

We note that, even though the assumption that power from different sources is additive may seem naive at first, nevertheless it gives quite good approximations, especially when distances between wireless devices of the network and points of interest $\mathbf{x}$ are large compared to the inverse of the frequency of operation of the wireless devices, namely the wave length of the corresponding electromagnetic wave. This is the reason why this case corresponds to a kind of macroscopic study of radiation.

B. VECTOR MODEL

The vector model is a generalization of the Friis' formula which is a single-dimension abstraction and allows a more detailed study of the power created by wireless devices and thus also electromagnetic radiation, at the cost of increased analytical difficulty compared to the additive power model. Particularly, the *electric field* from a wireless source device u, working in maximum level of power, at some point $\mathbf{x}$ is a *2-dimesional vector* given by

$$\begin{aligned} \mathbf{E}_{u,\mathbf{x}} &\stackrel{def}{=} \beta \cdot \frac{1}{\text{dist}(u, \mathbf{x})} \cdot e^{-j\frac{2\pi}{\lambda}\text{dist}(u,\mathbf{x})} \\ &= \beta \cdot \frac{1}{d} \cdot \begin{bmatrix} \cos\left(\frac{2\pi}{\lambda}\text{dist}(u, \mathbf{x})\right) \\ -\sin\left(\frac{2\pi}{\lambda}\text{dist}(u, \mathbf{x})\right) \end{bmatrix}, \end{aligned} \tag{8}$$

where λ is the wavelength which depends on the transmitter's frequency band, and β is a configuration parameter that describes the transmitter's hardware and the environmental conditions.[1]

An important assumption in the vector approach, that distinguishes it from other more tractable but less realistic models in the wireless power transfer state of the art, is that the sum of the electric field created by a wireless network $\mathcal{N}$ at a point $\mathbf{x}$ is the *vector-sum* of the corresponding individual electric fields, which is

$$\mathbf{E}_{\mathcal{N},\mathbf{x}} \stackrel{def}{=} \sum_{\mathbf{u} \in \mathcal{N}} \mathbf{E}_{u,\mathbf{x}}. \tag{9}$$

Furthermore, the total available *power* at $\mathbf{x}$ is given by

$$P_{\mathcal{N},\mathbf{x}} = \delta \cdot \|\mathbf{E}_{\mathcal{N},\mathbf{x}}\|^2, \tag{10}$$

where $\|\cdot\|$ denotes the length (2-norm) of the vector. The constant δ depends on the hardware of the transmitter and the RF-to-DC conversion efficiency.

[1] Actually, the detailed formula in [4] for the electric field is $\mathbf{E}_{u,\mathbf{x}} \stackrel{def}{=} \sqrt{\frac{Z_0 G_u P_u}{4\pi \text{dist}(u,\mathbf{x})^2}} \cdot e^{-j\frac{2\pi}{\lambda}\text{dist}(u,\mathbf{x})}$, where Z_0 is a physical indicator for the wave-impendance of a plane wave in free space, G_u denotes gain and P_u is the the transmitter's output power. Therefore, the constant β actually depends on u. Nevertheless, when all wireless devices in $\mathcal{N}$ are identical, we can assume that β is a constant.

The above model has been proven to be able to describe with great precision phenomena that were not previously possible, and this by using physic's rules and more specifically superposition of electromagnetic field rules. In addition, besides intuition, we got a better understanding and we can study particular situations such as constructive (superadditive) and destructive (cancellation) cases [5]–[7].

A Basic Assumption: Upon closer inspection of equation (8), we notice that, the length of the vector of the electromagnetic field becomes arbitrarily large when we consider points x very close to u. In the additive power case, this issue was fixed by adding 1 to the denominator, which is acceptable since (as mentioned before) this model gives a good approximation provided $\text{dist}(u, \mathbf{x})$ is large, and thus $1 + \text{dist}(u, \mathbf{x}) \sim \text{dist}(u, \mathbf{x})$. In fact, the two models are equivalent when $\mathcal{N}$ consists of a single wireless transmitter u and we consider points $\mathbf{x}$ far away from u.

The truth behind the limitation in equation (8) is that the equation only holds for points $\mathbf{x}$ for which $\text{dist}(u, \mathbf{x}) \geq \lambda$, and more complex laws apply otherwise. To avoid confusion and to avoid introducing models that are too complicated to analyse, we thus assume that the placement of wireless devices and points of interest satisfies the aforementioned inequality. Mind that, in the majority of the cases if not all of them, λ does not exceed some centimeters. Hence, those deployment restrictions will not be too restrictive for current wireless devices.

III. LOW RADIATION CHARGING IN WIRELESS NETWORKS

Low radiation charging results in a WSN under the scalar model are presented in this section. The overall setting is as follows: The network $\mathcal{N}$ consists of n rechargeable nodes $\mathcal{P} = \{v_1, v_2, ..., v_n\}$ and m wireless power chargers $\mathcal{M} = \{u_1, u_2, \ldots, u_m\}$ located in the $\mathcal{A} \subseteq \mathbb{R}^2$ plane. For both chargers and nodes we assume that their operational parameters and locations are defined at time 0 and this holds for the rest of the time.

$E_u^{(t)}$ is the *given amount of energy* that a transmitter u makes use to charge receivers inside a specific *radius* r_u. For every transmitter $u \in \mathcal{M}$ the radii r_u, is static in the meaning that it can be set at time 0 and hold this value from that time on. Moreover, by $C_v^{(t)}$ is denoted the *residual amount of energy* of a node $v \in \mathcal{P}$ at t time-slot (mind that the energy of node v is $C_v^{(0)}$ at time 0).

For the charging model, we employ the scalar model with cut-off r_u, but we also consider the energy availability of the charger and the capacity of the nodes. In particular, a receiver $v \in \mathcal{P}$ receives energy by a transmitter $u \in \mathcal{M}$ with *power* given by

$$P_{u,v}(t) = \begin{cases} \dfrac{\alpha r_u^2}{(1 + \text{dist}(v,u))^2}, \\ \quad \text{if } E_u^{(t)}, C_u^{(t)} > 0, \text{dist}(v,u) \leq r_u \\ 0, \quad \text{otherwise}, \end{cases} \tag{11}$$

where $\alpha > 0$ defines the environmental conditions and the hardware configuration of a transmitter and a receiver. Particularly, this equation measures the harvesting power of the receiver v from a transmitter u if the first is inside the radii of the latter. This holds by time that either u is out of energy or v cannot be further charged. Besides the dependencies regarding the topology of u and v, power $P_{v,u}(t)$ takes into account time t. Hence, for a receiver $v \in \mathcal{P}$ having less than r_u distance from a transmitter u, power equals to $\frac{\alpha r_u^2}{(\beta + \text{dist}(v,u))^2}$ between $[0, t^*_{u,v}]$ time slots and 0 otherwise. Equation (11) implies that at time slot $t^*_{u,v}$ where $P_{v,u}(t)$ equals to 0 means that either v is fully charged (that also depends on the number of transmitters which have v inside their radii) or u is out of energy. Îdherefore, $t^*_{u,v}$ value differs on the whole network, i.e. the initial energy storage capacity and topology of each receiver and the radii, initial energy pool and topology of the receivers. However, we can use the ideas presented in Section III-B by using a trivial modification of `ObjectiveValue` algorithm to find $t^*_{u,v}$ value. Thus, it looks like we cannot provide a "nice" closed formula for $t^*_{u,v}$.

Following the characteristics of the scalar model, we also assume that the nodes received energy is constructive. Hence, receiver v harvests a total amount of energy in a time slot $[0, T]$ is given by

$$H_v(T) = \sum_{u \in \mathcal{M}} \int_0^T P_{v,u}(t) dt. \tag{12}$$

By equations (11) and (12), we have that $\sum_{u \in \mathcal{M}} E_u^{(0)} \geq \sum_{v \in \mathcal{P}} H_v(T)$, for any $T > 0$, i.e, the nodes' total energy received is upper bounded by the sum of the transmitters' initial energy. Furthermore, the total energy that can be stored by all nodes is never less than the total harvested energy, i.e., $\sum_{v \in \mathcal{P}} C_v^{(0)} \geq \sum_{v \in \mathcal{P}} H_v(T)$, for any $T > 0$.

Related Work: Electromagnetic radiation concept has recently attract research community attention from many diverse research fields has been drawn by the impact of . Therefore, in Wireless Networks, radiation related problems have been studied by researchers. In [8], it is presented how we can keep low radiation levels for an agent moving around a wireless sensor network. Authors study and mathematically evaluate the above concept in both random typologies and other well known networks. An evaluation via simulations has also been conducted for the proposed online algorithms and the corresponding heuristics, achieving a near optimal solution given by an offline algorithm. Angelopoulos *et al.* [9] aim in maintaining low amounts of radiation created by different wireless transmissions while they offer efficient quality of service in wireless sensor networks regarding data propagation latency. Oblivious routing and greedy heuristics are presented with respect to radiation effects. Afterwards, they enhance their approaches by adopting temporal backoff schemes that make use of network's local knowledge and aim to distribute radiation under a spatio-temporal manner. In [10], it is presented a work that considers a problem of covering. More specifically, a group of facilities is located

inside a defined area, while they aim to minimize the number of stations in a way that there is no point in the region out of the radii of a station. At the same time the dangerous range of a station prevent building to be included. Those concepts are network's devices oriented regarding radiation, and do not address transmitters setups.

Recently lots of work has been conducted regarding Wireless Power Transfer combined with electromagnetic radiation awareness in networks configurations. Dai *et al.* [11] provide a scheduling strategy which guarantees that there is no location in the plane where electromagnetic radiation (EMR) level is higher than a given value, while stationary transmitters aim to maximize the energy fueled in the network. The authors provide a design that that follows multidimensional 0/1 knapsack problem and a Fermat-Weber problem. The method includes bounded EMR function approximation, reduction and constraint conversion, a tailored Fermat-Weber heuristic and area expansion and discretization. For evaluation purposes, the authors created a testbed which consist of eight transmitters. Dai *et al.* [12] again consider the scheduling of stationary transmitters, in order to increase as possible the charging utility of the transmitters, while keeping electromagnetic radiation distribution at any given point inside a specific area below a threshold value. In this instance of the problem transmitters are able to adjust their contribution and power. A new discretization technique is presented that aims to help re-formulating the problem and make it possible to be solved by a linear program. Further, the authors propose a distributed redundant constraint reduction schema to reduce the computational load of the problem by decreasing the number of restrictions. Even thought the subject of [12] is related to the work of this section, nevertheless our approach of the topic of efficient charging with respect to radiation is completely different. This results from the fact that we define a different power transmitting model, which considers both hardware constrains of the transmitters and receivers of the network. Those restrictions imply non-linearity for our case that did not show in [12] approach.

Contribution: Assuming the above scalar charging model (with cut-ff), in [13] we studied the *Low Radiation Efficient Charging Problem* (LREC), in which we aim to maximize the utility of energy harvested by the receivers from the transmitters (under threshold radiation value restriction). Fundamental properties of the problem have been presented while giving indications of its hardness in the idealized power transfer no lossy case. Nevertheless, our algorithmic solutions and model can be easily generalized to accommodate more realistic lossy scenarios.

We also presented a relaxation of LREC, namely the *Low Radiation Disjoint Charging Problem* (RLDC), which makes easier the function of finding the maximum electromagnetic radiation inside a field where transmitters and receivers are located. Although this seems a simpler version of our main problem, is shown to be NP-hard, by reduction from the Independent Set Problem in Disc Contact Graphs. Nevertheless, LRDC admits an integer program formulation, which we solve after a suitable linear relaxation and rounding and we use the solution as a lower bound for LREC.

Finally, we proposed a repetitive local improvement heuristic for LREC, which has been evaluated through extensive simulation process and runs in polynomial time. The advantage of the mechanism is that it decouples the computation of the maximum radiation from the computation of the objective function and also is independent from the exact formula used for the computation of the electromagnetic radiation in each point of the network, achieving good tradeoffs between radiation control and charging efficiency; it also exhibits good energy balance properties. We provide extensive simulation results supporting our claims and theoretical results.

A. PROBLEM STATEMENT AND FIRST RESULTS

Generally, we aim to maximize the transmitters' efficiency in a way that the radiation level is maintained inside an acceptable range. More specifically, we study the following computational problem which is called as Low Radiation Efficient Charging (LREC):

Definition 2 (Low Radiation Efficient Charging (LREC)): Assume we deploy inside $\mathcal{A}$ plane a family of rechargeable motes $\mathcal{P}$ and a family of transmitters $\mathcal{M}$. Assume also, that every mote $v \in \mathcal{P}$ has initial energy capacity $C_v^{(0)}$ and every transmitter $u \in \mathcal{M}$ initially has an energy pool $E_u^{(0)}$. Configure to every transmitter $u \in \mathcal{M}$ a radii r_u, so that the electromagnetic radiation in every location of $\mathcal{A}$ does not exceed ρ threshold while we maximize the cumulative usable energy of the network's motes.

Let $\mathbf{r} = (r_u : u \in \mathcal{M})$, $\mathbf{E}^{(0)} = (E_u^{(0)} : u \in \mathcal{M})$ and $\mathbf{C}^{(0)} = (C_v^{(0)} : v \in \mathcal{P})$. The *objective function* that we want to maximize in the LREC problem is:

$$f_{\text{LREC}}\left(\mathbf{r}, \mathbf{E}^{(0)}, \mathbf{C}^{(0)}\right) \stackrel{def}{=} \sum_{v \in \mathcal{P}} \left(\lim_{t \to \infty} C_v^{(t)}\right) = \sum_{u \in \mathcal{M}} \left(E_u^{(0)} - \lim_{t \to \infty} E_u^{(t)}\right). \tag{13}$$

The last equality holds cause we assume a non-lossy energy transfer setup from the transmitters to the motes (extension to lossy case can be easily done, but it is not considered in [13]). In fact, we only need to consider finite values for t, because the energy values $E_u^{(t)}$ will be unchanged after time $t^* \stackrel{def}{=} \max_{v \in \mathcal{P}, u \in \mathcal{M}} t^*_{u,v}$, where $t^*_{u,v}$ is the time at which either the energy of u is depleted or v is fully charged, and so $P_{v,u}(t)$ becomes 0. Therefore $f_{\text{LREC}}\left(\mathbf{r}, \mathbf{E}^{(0)}, \mathbf{C}^{(0)}\right) = \sum_{v \in \mathcal{P}} C_v^{(t)} = \sum_{u \in \mathcal{M}} \left(E_u^{(0)} - E_u^{(t)}\right)$, for any $t \geq t^*$. In fact, the following upper bound holds, which is independent of the initial radius choice for each charger:

Lemma 1: t^* can be at most

$$T^* = \frac{(1 + \max_{u \in \mathcal{M}, v \in \mathcal{P}} dist(v, u))^2}{\alpha(\min_{u \in \mathcal{M}, v \in \mathcal{P}} dist(v, u))^2} \max_{u \in \mathcal{M}, v \in \mathcal{P}} \{E_u^{(0)}, C_v^{(0)}\}.$$

As will be clear later, given $\mathbf{r}, \mathbf{E}^{(0)}$ and $\mathbf{C}^{(0)}$, the exact value of $f_{\text{LREC}}\left(\vec{r}, \vec{E}^{(0)}, \vec{C}^{(0)}\right)$ can be computed by using

Algorithm 1 `ObjectiveValue`

Input : Initial configuration $\Sigma^{(0)} = (\mathbf{r}, \mathbf{E}^{(0)}, \mathbf{C}^{(0)})$

Set $t = 0$

while $\left[\bigcup_{v\in\mathcal{P}} \left\{\left(C_v^{(t)} > 0\right) \; AND \; \left(\sum_{u\in\mathcal{M}_v^{(t)}} E_u^{(t)} > 0\right)\right\}\right]$ **do**

  Set $t_{\mathcal{M}} = \min_{u\in\mathcal{M}\setminus\mathcal{M}_{\emptyset}^{(t)}} \left\{t' : t' \sum_{v\in\mathcal{P}_u^{(t)}} P_{v,u}(t) = E_u^{(t)}\right\}$

  Set $t_{\mathcal{P}} = \min_{v\in\mathcal{M}\setminus\mathcal{P}_{\emptyset}^{(t)}} \left\{t' : t' \sum_{u\in\mathcal{M}_v^{(t)}} P_{v,u}(t) = C_v^{(t)}\right\}$

  Set $t_0 = \min\{t_{\mathcal{M}}, t_{\mathcal{P}}\}$

  For all $u \in \mathcal{M}\setminus\mathcal{M}_{\emptyset}^{(t)}$, set $E_u^{(t+t_0)} = E_u^{(t)} - t_0 \sum_{v\in\mathcal{P}_u^{(t)}} P_{v,u}(t)$

  For all $v \in \mathcal{P}\setminus\mathcal{P}_{\emptyset}^{(t)}$, set $C_v^{(t+t_0)} = C_v^{(t)} - t_0 \sum_{u\in\mathcal{M}_v^{(t)}} P_{v,u}(t)$

  Set $t = t + t_0$ and update $\mathcal{M}_{\emptyset}^{(t)}$ and $\mathcal{P}_{\emptyset}^{(t)}$

Output: $\sum_{u\in\mathcal{M}}(E_u^{(0)} - E_u^{(t)})$

Algorithm `ObjectiveValue` in Section III-B). However, the optimal choices for the radii of the chargers is not so easy to determine, as the following result highlights.

Lemma 2: The function $f_{LREC}\left(\mathbf{r}, \mathbf{E}^{(0)}, \mathbf{C}^{(0)}\right)$ *is not necessarily increasing in* $\mathbf{r}$. *Furthermore, the optimal radius for a charger is not necessarily equal to the distance from some node.*

B. COMPUTING THE OBJECTIVE FUNCTION

Here, we present an algorithm which given the motes' energy capacities, transmitters' radius and the residual energy of the transmitters, computes the energy amount provided to the motes from the transmitters (which is our objective function). In particular, assume that each mote $v \in \mathcal{P}$ can store $C_v^{(t)}$ amount of energy and each transmitter $u \in \mathcal{M}$ has residual energy $E_u^{(t)}$ at a specific time t. The tuple $\Sigma^{(t)} = (\mathbf{r}, \mathbf{E}^{(t)}, \mathbf{C}^{(t)})$, where $\mathbf{r} = (r_u : u \in \mathcal{M})$, $\mathbf{E}^{(t)} = (E_u^{(t)} : u \in \mathcal{M})$ and $\mathbf{C}^{(t)} = (C_v^{(t)} : v \in \mathcal{P})$, is called the *configuration of the network at time* t. Let $\mathcal{M}_{\emptyset}^{(t)} \overset{def}{=} \{u \in \mathcal{M} : E_u^{(t)} = 0\}$ be the family of transmitters that ran out of energy by time t. Furthermore, let $\mathcal{P}_{\emptyset}^{(t)} \overset{def}{=} \{v \in \mathcal{P} : C_u^{(t)} = 0\}$ be the family of motes that are in full energy by time t. For every $v \in \mathcal{P}$ let $\mathcal{M}_v^{(t)} \overset{def}{=} \{u : v \in \mathcal{P}_u^{(t)}, E_u^{(t)} > 0\}$ be the family of transmitters that have v inside their radius and still have available energy at time t. For every $u \in \mathcal{M}$, let $\mathcal{P}_u^{(t)} \overset{def}{=} \{v : \text{dist}(v, u) \leq r_u, C_v^{(t)} > 0\}$ be the family of motes inside r_u radius from u that have not reach full capacity at time t.

The following algorithm aims to compute the objective function. We can figure out which is going to be the next transmitter or mote that will run out of energy or will reach its energy capacity respectively and when, given the system's configuration at time t. The algorithm continuous as long as there are motes that can still be charged, which happens either when all transmitters that can reach it still have energy (i.e. $\sum_{u\in\mathcal{M}_v^{(t)}} E_u^{(t)} \neq 0$) or they have not reached yet their capacity limit (i.e. $C_v^{(t)} \neq 0$).

Mind that, algorithm `ObjectiveValue`, in each loop sets to 0 the capacity or the energy level of at least one transmitter or mote. In fact, the result holds that bounds the number of while-iterations (and thus also the running time up to a multiplicative $\Theta(\max\{m, n\})$ factor):

Lemma 3: Algorithm `ObjectiveValue` *terminates in at most* $n + m$ *while-iterations.*

C. COMPUTING THE MAXIMUM RADIATION

One of the challenges that arises in the LREC problem under the scalar model with cut-off radius is the computation of the highest radiation value inside plane $\mathcal{A}$, as well as finding the point (or points) where this maximum is achieved. In particular, it seems that some kind of discretization of $\mathcal{A}$ is needed as it is not clear the location the highest radiation level is placed inside our plane. In fact, in the experimental evaluation conducted in [13], the following generic MCMC procedure was used: for sufficiently large $K \in \mathbb{N}^+$, choose randomly and uniformly K points from $\mathcal{A}$, compute radiation on each of these points and return the maximum value. This procedure is efficient, since the calculation of the EMR at any point takes $O(m)$ time, as it is a matter of the distance of this particular point from each of the m transmitters.

The drawback of the method mentioned above is that the approximation it achieves depends on the value of K (which equals to the discretization level) for computing the maximum radiation. Indeed, there could exist a better algorithm that considers also the spatial electromagnetic radiation distribution given by Definition 1 and equation (11). On the other hand, the latter is also one of the strengths of the overall approach; indeed, the iterative algorithm `IterativeLREC` which is presented in Section III-D is independent from a specific formula for the EMR, and this is legitimate in some cases (particularly for scientist's understanding of radiation, as is still at an early stage).

D. A LOCAL IMPROVEMENT HEURISTIC FOR LREC

In view of the above, we now have all the required tools for describing a heuristic to approximate by LREC the optimal solution, which was given in [13]. Therefore, notice that, for a transmitter $u \in \mathcal{M}$, we can approximately (the approximation factor depending on a parameter l) define the radii r_u of u in order to achieve the highest objective function value, given fixed radii for all other transmitters $\mathbf{r}_{-u} = (r_{u'} : u' \in \mathcal{M}\setminus u)$ as follows: Define $r_u^{\max}$ to be the largest distance of any point in $\mathcal{A}$ from u and let $l \in \mathbb{N}^+$ be a sufficiently large integer. For $i = 0, 1, \ldots, l$, set $r_u = \frac{i}{l} r_u^{\max}$ and compute the objective function value (using algorithm `ObjectiveValue`) as well as the maximum radiation (using the method described in Section III-C). We assign to u the radii that satisfies the radiation restrictions of LREC and performs the best objective function value. Given that the discretization of $\mathcal{A}$

Algorithm 2 `IterativeLREC`

Input : Charger and node locations

1 $counter = 1$
2 **repeat**
3 Select u.a.r. a charger $u \in \mathcal{M}$
4 Find (an approximation to) the optimal radius for u given that the radii of all other chargers are fixed
5 $counter = counter + 1$
6 **until** $counter = K'$

Output: $\vec{r} = (r_u : u \in \mathcal{M})$

used to compute the maximum radiation has K points in it, and using Lemma 3, we can see that running time of the above procedure to approximately determine the best radius for u is $O\left(l(n+m)\max\{n,m\} + mK\right)$. We mention here that the above procedure can be easily generalized to approximately compute optimal radii for any set of (a constant number) c chargers, in which case the running time becomes $O\left(l^c(n+m)\max\{n,m\} + mK\right)$. In fact, for $c = m$ we would have an exhaustive-search algorithm for LREC, but the running time would be exponential in m, making this solution impractical.

`IterativeLREC` follows the below main idea: in each loop, uniformly and randomly pick a transmitters u and configure (an approximation to) the optimal radii for u given that the radius of the rest of the transmitters are fixed. The algorithm breaks the loop when a predefined number of steps $K' \in \mathbb{N}^+$ has been reached. Therefore, the running time of `IterativeLREC` is $O\left(K'(l(n^2+m^2)+mK)\right)$.

E. A RELAXATION OF LREC

It appears that the main obstacles for finding an exact solution to LREC problem are the following: (a) Firstly, it is not obvious that there is a closed formula as a function of the radius and the locations of the transmitters for the maximum radiation inside the $\mathcal{A}$ plane. (b) Subsequently, following the suggestion of Lemma 2, there is no obvious potential function that can improve the objective function value by providing directions inside $\mathbb{R}^m$.

In view of the above difficulties, we apply the following relaxation to the LREC problem, which circumvents the problem of finding the maximum radiation caused by multiple sources:

Definition 3 (Low Radiation Disjoint Charging (LRDC)): Assume $\mathcal{P}$ is a family of receivers and $\mathcal{M}$ is a family of wireless transmitters which are located inside $\mathcal{A}$ interest area. Assume also that each receiving mote $v \in \mathcal{P}$ has $C_v^{(0)}$ initial energy capacity and every transmitter $u \in \mathcal{M}$ initially has $E_u^{(0)}$ available energy. Configure each transmitter's $u \in \mathcal{M}$ radii r_u, in order to maximize the total usable energy fueled to the network's receivers while the electromagnetic radiation in any point of $\mathcal{A}$ respects ρ threshold. We suppose that rf charging starts at time 0 and the model we follow is the scalar model with cut-offs r_u. Finally, we impose the restriction that no receiver should be charged by more than a single transmitter.

Note that LRDC is very similar to LREC, except for the last constraint. By using a reduction from the Independent Set in Disc Contact Graphs [14], we can prove the following (which is also a strong indication for the hardness of LREC):

Theorem 1: LRDC is NP-hard.

LRDC can be formulated as an integer program (called as `IP-LRDC`) as follows: Initially mind that, for every transmitter $u \in \mathcal{M}$, the distance of points/receivers in $\mathcal{P}$ from u configures a (complete) ordering σ_u in $\mathcal{P}$. Particularly, for a transmitter $u \in \mathcal{M}$ and for any two receivers $v, v' \in \mathcal{P}$, holds that $v \leq_{\sigma_u} v'$ if and only if $\text{dist}(v,u) \leq \text{dist}(v,u)$. For every transmitter u, we denote by $i_{\text{rad}}^{(u)}$ the receiver that has the bigger distance from u and can be charged by u while u respects the regulations of radiation limit which is than ρ value. In the same way, let $i_{\text{nrg}}^{(u)}$ be the furthest receiver from u with the difference that if u has radii at least $\text{dist}(i_{\text{nrg}}^{(u)}, u)$, then u's energy will run out. Assuming we break ties in σ arbitrarily, receivers $i_{\text{rad}}^{(u)}$ and $i_{\text{nrg}}^{(u)}$ are uniquely defined for any transmityter u. `IP-LRDC` is given below.

$$\max \sum_{u \in \mathcal{M}} \left(E_u^{(0)} x_{i_{\text{nrg}}^{(u)},u} + \sum_{v \leq_{\sigma_u} i_{\text{nrg}}^{(u)}} (x_{v,u} - x_{i_{\text{nrg}}^{(u)},u}) C_v^{(0)} \right)$$

$$\text{subject to: } \sum_{u \in \mathcal{M}} x_{v,u} \leq 1, \quad \forall v \in \mathcal{P} \tag{14}$$

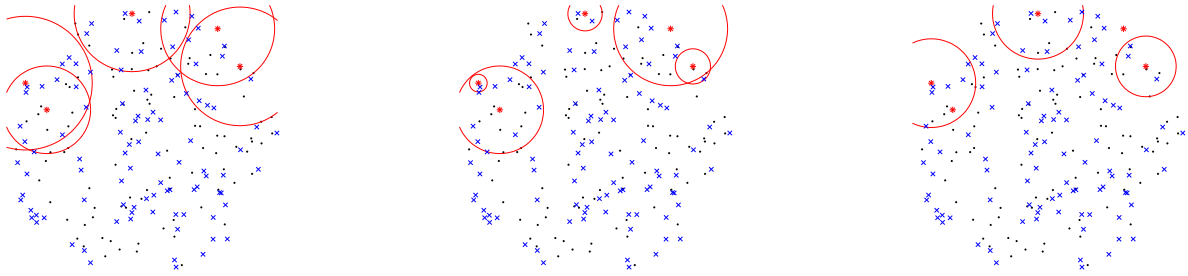
$$x_{v,u} - x_{v',u} \geq 0, \quad \forall v, v' \in \mathcal{P},\ \forall u \in \mathcal{M} : v \leq_{\sigma_u} v' \tag{15}$$

$$x_{v,u} = 0, \quad \forall v \in \mathcal{P},\ \forall u \in \mathcal{M} : v >_{\sigma_u} i_{\text{rad}}^{(u)} \text{ or } v >_{\sigma_u} i_{\text{nrg}}^{(u)} \tag{16}$$

$$x_{v,u} \in \{0,1\}, \quad \forall v \in \mathcal{P},\ \forall u \in \mathcal{M}. \tag{17}$$

In the above IP, the indicator variables $x_{v,u}$ are equal to 1 if and only if u is the (unique) transmitter that reaches v. Constraint (14) guarantees that exists at most one transmitter per receiver in a feasible assignment of LRDC. Furthermore, (15) guarantees that if a receiver v' can be reached by u, then u can also reach all receivers that are closer to it. Finally, (16) makes sure that the radiation regulations hold and have been taken into account and also suggests that there is no need for a transmitter to try to reach receivers further than $i_{\text{nrg}}^{(u)}$.

Concerning the the objective function of `IP-LRDC`, we note that, for any tyransmitter $u \in \mathcal{M}$, if $r_u \geq \text{dist}(i_{\text{nrg}}^{(u)}, u)$ (which implies $x_{i_{\text{nrg}}^{(u)},u} = 1$), the useful energy transferred from u to the nodes of the network will be exactly $E_u^{(0)}$. Indeed, $E_u^{(0)} x_{i_{\text{nrg}}^{(u)},u} + \sum_{v \leq_{\sigma_u} i_{\text{nrg}}^{(u)}} (x_{v,u} - x_{i_{\text{nrg}}^{(u)},u}) C_v^{(0)} = E_u^{(0)}$, when $x_{i_{\text{nrg}}^{(u)},u} = 1$, since, by constraint (15), we have that $x_{v,u} = x_{i_{\text{nrg}}^{(u)},u}$, for any $v \leq_{\sigma_u} i_{\text{nrg}}^{(u)}$. On the other hand, when $x_{i_{\text{nrg}}^{(u)},u} = 0$, charger u will not be able to transfer all of its energy, because the nodes it can reach cannot store it all. This is also captured by the objective function, since $E_u^{(0)} x_{i_{\text{nrg}}^{(u)},u} + \sum_{v \leq_{\sigma_u} i_{\text{nrg}}^{(u)}} (x_{v,u} - x_{i_{\text{nrg}}^{(u)},u}) C_v^{(0)} = \sum_{v \leq_{\sigma_u} i_{\text{nrg}}^{(u)}} x_{v,u} C_v^{(0)}$, when $x_{i_{\text{nrg}}^{(u)},u} = 0$, which is



(a) (b) (c)

FIGURE 1. Network snapshot using 5 chargers. **(a)** `ChargingOriented`. **(b)** `IterativeLREC`. **(c)** `IP-LRDC`.

equal to the total energy that the nodes reachable from u could harvest in total.

In the experimental evaluation, we find a solution LRDS by first solving a linear relaxation to `IP-LRDC` and then rounding the solution so that the constraints (14), (15) and (16) are satisfied. Clearly, the value that we compute this way is a lower bound to the optimal solution of the LREC problem. This bound is used to evaluate the performance of the iterative algorithm `IterativeLREC` (see Section III-D).

F. PERFORMANCE EVALUATION

In our simulations, we compared `IterativeLREC`, `IP-LRDC` (after the linear relaxation) and an additional transmitter configuration scheme in which each transmitter u sets its radii equal to $\text{dist}(u, i_{rad}^{(u)})$. This new configuration is referred to as `ChargingOriented` because it assigns the maximum radii to each transmitter, without individually violating the radiation threshold. In particular, `ChargingOriented` gives the best possible rate of transferring energy in the network and serves as an upper bound on the charging efficiency of the performance of `IterativeLREC`, but is expected to achieve a poor performance on keeping the radiation low, due to frequent, large overlaps. Our evaluation setup consist of a uniform network deployment with $|\mathcal{P}| = 100, |\mathcal{M}| = 5$ and $K = 100$, which is depicted in Fig. 1. We observe that the radius of the transmiters in the `ChargingOriented` case are larger than the other two cases. In the case of `IP-LRDC` the radiation constraints lead to a configuration where two transmitters are not operational. `IterativeLREC` provides a configuration in between the `ChargingOriented` and `IP-LRDC`, in which some overlaps of smaller size are present.

For the main simulation phase, we deployed uniformly at random $|\mathcal{P}| = 100$ identical network receivers, $|\mathcal{M}| = 10$ identical wireless transmitters and $K = 1000$ points of pointes of interest regarding radiation. The following parameters has been set to the following valuses $\alpha = 0, \beta = 1, \gamma = 0.1$ and $\rho = 0.2$ in order to get the best results regarding illustration. Additionally, the above experiment has been conducted 100 times to provide the corresponding statistical analysis that the reader expects. The findings presents a statistical smoothness (the median, lower and upper quartiles, outliers of the samples) as they demonstrate very high concentration around mean value. Our analysis is mainly focused on three basic metrics: charging utility, energy balance and radiation levels.

1) CHARGING EFFICIENCY

The objective values achieved were 80.91 by the `ChargingOriented`, 67.86 by the `IterativeLREC` and 49.18 by the `IP-LRDC`. As expected, the `ChargingOriented` method is the most efficient and fast regarding charging, while at the same time high levels of radiation are created. As we observe in Fig. 2a, it distributed the energy in the network in a very short time. The efficiency of `ChargingOriented` both in terms of objective value and in terms of time is explained by the frequent charger radii overlaps that are created during the configuration of the chargers (e.g., Fig. 1). `IP-LRDC` achieves the lowest efficiency of all due to the small charging radii and consequently small network coverage by the chargers. Our heuristic `IterativeLREC` achieves high enough efficiency w.r.t. the radiation constraints. It's performance lies between the performance of `ChargingOriented` and `IP-LRDC`, both in terms of objective value and in terms of time.

2) MAXIMUM RADIATION

Mind that this factor is critical concerning the safety awareness per transmitting method. Dangerous radiation exposure, created in network force us to have second thought on methods application in real life. this case is verified with `ChargingOriented`, which despite its high efficiency in charging, it exhibits elevated levels of radiation (Fig. 2b). On the other hand, `IterativeLREC` performs quite well, since it respects the radiation threshold while fuels the network with sufficient amoun of energy.

3) ENERGY BALANCE

Even though the proposed algorithmic solutions were not designed having energy balance in mind, nevertheless, this metric is crucial for the lifetime of Wireless Distributed Systems, since early disconnections are avoided and nodes tend to save energy and keep the network functional for as long as

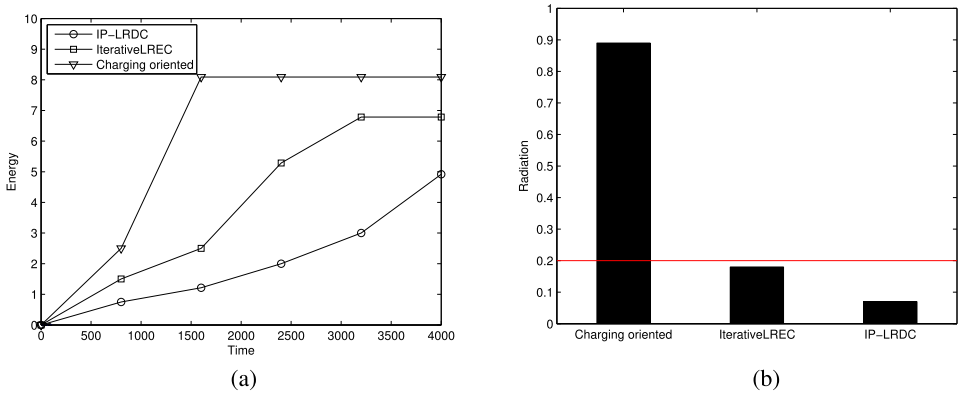


FIGURE 2. Efficiency and radiation. (a) Charging efficiency over time. (b) Maximum radiation.

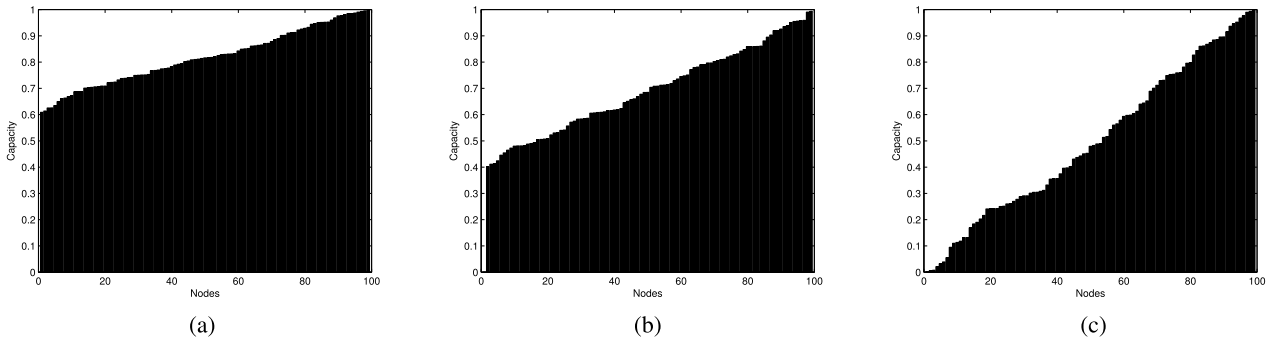


FIGURE 3. Energy balance. (a) `ChargingOriented`. (b) `IterativeLREC`. (c) `IP-LRDC`.

possible. This is why we chose to measure the performance of the three algorithms with respect to this metric. Fig. 3 gives a graphical representation of the energy provided in the network throughout the experiment. By sorting nodes by their final energy level, we can see that `IterativeLREC` achieves efficient energy balance that approximates the performance of the powerful `ChargingOriented`.

IV. EFFICIENT ALGORITHMS FOR POWER MAXIMIZATION IN THE VECTOR MODEL

In this section, our intention is to stand out from the majority of the state of the art works and present a special model and the corresponding algorithmic approach for two optimization problems concerning energy management in WPT networks.

In particular, Katsidimas *et al.* [15] use a model that naturally derives from the basic properties of the superposition of electromagnetic waves which can capture constructive and destructive effects. With respect to this model, they study two problems of particular interest for the maintenance of the wireless power transmitters efficiency, so as to maximize the overall power in the system, which can be solved in polynomial time. A distributed solution running in pseudo-polynomial time is presented, and also provide theoretical performance guarantees. Last but not least, three new heuristics have been designed and evaluated for the second problem.

Related Work: Several research has been done on a number of problems concerning the field of wireless charge. The overwhelming majority, if not all, are studying such problems based on the scalar model. For example, Zhang *et al.* [16] aim in maximizing charging quality in a two dimensional field, in the meaning that given a number of predefined candidate locations for placing transmitters, provide as an outcome the power allocation and the location of each transmitter with respect to an initial power budget. In Addition, [7] provides experiments to evaluate the charging rate, the packet loss rate increased by interference effects, and efficient ranges for power and data transfer of the transmitters. There is an analysis that on how the charging process is affected by placement and relative distances of many chargers. Similarly to us, they study additive and cancellation energy aggregation at the nodes, but also the merit of having different channels for charging and data propagation in different frequencies.

Tong *et al.* [17] search for the wireless charging technology impact on both routing management and sensor network topology. They provide a formalization for the deployment and routing problem and achieve to prove that is a NP-complete problem. Finally, they design and evaluate through extensive simulations efficient heuristics, for the corresponding problem. Reference [18] presents the first distributed MAC protocol for wireless power receivers/sensors, and through an extensive evaluation that both includes experimental and simulation results, they present a significant network

throughput improvement that reaches 112% in average over the modified unslotted CSMA MAC protocol. In particular, the experimental test-bed showed how the topology of the transmitters, the frequency that they use and their number can improve or not the receivers charging time. An extension of the same research team is presented in [19], where the authors study the setup of directional wireless power transmitters and the network's data communication cost. This particular concept requires sharing channel techniques in the medium access control layer while particular handling also needs the trade-off between wireless power transfer and data transmitting functions. An experimental evaluation presents here as well that the transmitters deployment, the transmitting frequency and the number of the chargers affects the charging quality of the sensors.

Recently, radiation complementary problem has attracted more researchers to work on it as wireless power transfer must be aware of such regulations concerning human health. In specific, Dai *et al.* [12], Li *et al.* [20] aim to optimize the utility of the receivers by configuring the transmitting power of the charging device with respect that we do not meet high radiation concentration in a particular filed of action. Similarly, Leeuwen *et al.* [21] aim to maximize the receiving power by remote devices that are located in a long distance while the radiation maintains in low levels near the transmitters position. A centralized algorithm is provided to address the problem above that both has a good approximation to the optimal and satisfies the EMR threshold. Some of the health risks and the safety constrains that should be followed can be found in [22], where a scientific analysis is provided to present the importance of radiation awareness in modern energy devices. Concerning wireless communication and more specific in networks that consist of medical devices, a review is presented in [23], where issues of electromagnetic interference for medical equipment are addressed.

Finally, in [24] a more dynamic setup is presented as the problem defines to configure both the orientation of a number of directional antennas that the transmitters are equipped with and the deployment location. The target is to maximize the total charging efficiency with respect to some connectivity restrictions. Algorithms and evaluation are both provided to verify the performance of their solution. In most of the sensor networks that combine WPT technology we come up with problems like: the sensor's energy is not enough, a high latency packet delivery, sensor's limited storage capacity etc. All the above cause a low duty cycle sensor operation. Gao *et al.* [25] provide an algorithm that finds the optimal sleeping scheme for a node by increasing the number of power transmitters. Wireless Power transfer has been also been adopted in UAV applications where systems that enable wireless power transfer to those systems, recharge not only sensors but also other electronics. Prototypes for both the uav and the transmitters installation are presented in [26]. On the contrary, [27] presents a study that proves how the data link procedure of a uav suffers from the electromagnetic radiation that co-exist in the same area. Both analysis and experiments showed that communication efficiency is quite sensitive in such applications.

Contribution: In view of the above vector charging model, this study is the first to our knowledge that algorithmically study a more precise model, that can describe super-additive and cancellation effects which rise from the superposition of the electromagnetic fields. Thus, two new problems are introduced for the efficient utilization of the emitted power by the chargers. Particularly, we first consider to find the operation level of each transmitter to optimize the cumulative power received by the receivers set, while in the second one, we aim to configure the operation levels of the chargers that maximize the total power of all k sets of receivers with the minimum power sum.

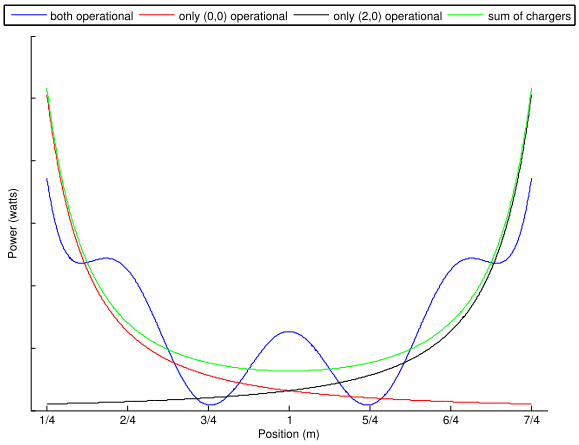
The first problem, named as `MAX-POWER` is presented in a quadratic form and prove that we can get an optimal solution in pseudo-polynomial time. Thus, a family of distributed algorithms are presented depending on the system's knowledge levels, which in practice are quite fast as we figure out from the simulations. Last but not least, an extensive simulation procedure can be found for the three heuristics designed to address the second one called as `MAX-`k`MIN-GUARANTEE`.

To get a clearer and intuitive picture of the above definitions regarding *vector model*, we give the following indicative example: Consider that our system consist of two chargers, C_1 and C_2 which are located at $(0, 0)$ and $(2, 0)$ locations, inside our area of interest. Furthermore, assume a receiver R is located at $(1, 0)$. Note that, for clarity reasons, the following constants are set to 1, $\lambda = \beta = \delta = 1$. For the first case, in which a single charger is working in full capacity, the power that R receives is $P(C_1, R) = P(C_2, R) = \|\mathbf{E}(C_1, R)\|^2 = \|\mathbf{E}(C_2, R)\|^2 = \left(\frac{1}{\text{dist}(C_1,R)}\right)^2 = 1$. For the second case that both chargers work in full capacity, the receiving power by R is provided by (9), that is

$$P(\{C_1, C_2\}, R) = \|\mathbf{E}(C_1, R) + \mathbf{E}(C_2, R)\|^2.$$

Mind that, since R is equidistant from both transmitters C_1 and C_2, the vectors $\mathbf{E}(C_1, R)$ and $\mathbf{E}(C_2, R)$ share the same direction. Thus, $P(\{C_1, C_2\}, R) = 4\,P(C_1, R) = 2(P(C_1, R) + P(C_2, R)) = 4$. It is worth to mention that the total receiving power by R when both transmitters are operational with respect to vector model is 4 times more than the corresponding sum of powers in which we just sum the powers' amplitudes for the two chargers as Friis model suggests; this phenomenon can be characterized as superadditive and is visible in the blue curve at location (1,0) in Figure 4a.

Still in the same instance but in a different case, consider a receiver R' located at $\left(\frac{5}{4}, 0\right)$. Then by equation (8), $\mathbf{E}(C_1, R') = \frac{4}{5} \cdot \begin{bmatrix} 0 \\ 1 \end{bmatrix}$, and also $\mathbf{E}(C_2, R') = \frac{4}{3} \cdot \begin{bmatrix} 0 \\ -1 \end{bmatrix}$. By equation (9), the total receiving power by R' when both transmitters work in full capacity is $P(\{C_1, C_2\}, R') = \left(\frac{8}{15}\right)^2 \approx 0.28$. Here, we have to highlight what we call destructive or cancellation case and visible in local minima



(a) The power distribution between the two chargers. Different curves represent different operation levels of the chargers.

FIGURE 4. Example showing the superadditive and cancelation effects. (a) The power distribution between the two chargers. Different curves represent different operation levels of the chargers.

in the curve shown in Figure 4a. More specifically, the total receiving power by R' when the two chargers work in full capacity is less than the individual power that is offered per charger which is $\min\{P(C_1, R'), P(C_2, R')\} = \left(\frac{4}{5}\right)^2 \approx 0.64$.

A. PROBLEM DEFINITION

Assuming we have a topology that both includes a set $\mathcal{R}$ of rf receivers and a set $\mathcal{C}$ of rf power transmitters. For every transmitter $C \in \mathcal{C}$, let $\mathbf{x}_C \in [0, 1]$ (called the configuration of a charger) be a variable that servers to quantify the transmitting power of C in the meaning that if x equals to 1 then C works in 100% of its capacity, while if x equals to zero then C is off. Thus, in the general case where we also introduce the configuration of the charger, equation (8), turns to have the following form $\mathbf{x}_C \cdot \mathbf{E}(C, R) = \mathbf{x}_C \cdot \beta \cdot \frac{1}{\text{dist}(C,R)} \cdot e^{-j\frac{2\pi}{\lambda}\text{dist}(C,R)}$. Also let $\mathcal{C}(\mathbf{x})$ be the configuration setup for a set of transmitters in a system.

We initially consider the following problem:

*Definition 4 (*MAX−POWER*): For a set of receivers $\mathcal{R}$ and a set of transmitters $\mathcal{C}$, come up with the transmitters' configuration that optimizes the receiving power to $\mathcal{R}$. That is, find $\mathbf{x}^*$ such that*

$$\mathbf{x}^* \in \arg \max_{\mathbf{x}\in[0,1]^{\mathcal{C}}} P(\mathcal{C}(\mathbf{x}), \mathcal{R}), \tag{18}$$

where $P(\mathcal{C}(\mathbf{x}), \mathcal{R}) = \sum_{R\in\mathcal{R}} P(\mathcal{C}(\mathbf{x}), R)$.

We will denote by $\binom{\mathcal{R}}{k}$ the set of all subsets of $\mathcal{R}$ containing k nodes. Subsequently, we define and study the following generalization of MAX−POWER, which finds a configuration that aims to optimize the k-sets nodes with small receiving power levels:

*Definition 5 (*MAX−kMIN−GUARANTEE*): In a system that consist of a set of nodes $\mathcal{R}$ and a set of transmitters $\mathcal{C}$, come up with the transmitters' configuration that optimize the minimum total receiving power for all possible subsets of k size that can be made from $\mathcal{R}$. Hence, configure $\mathbf{x}^*$ in a way that*

$$\mathbf{x}^* \in \arg \max_{\mathbf{x}\in[0,1]^{\mathcal{C}}} \min_{A\in\binom{\mathcal{R}}{k}} P(\mathcal{C}(\mathbf{x}), A), \tag{19}$$

where $P(\mathcal{C}(\mathbf{x}), A) = \sum_{R\in A} P(\mathcal{C}(\mathbf{x}), R)$.

B. MAXIMUM TOTAL POWER

The subsection describes an algorithm for MAX−POWER. Consider a set of nodes $\mathcal{R} = \{R_1, \ldots, R_n\}$, where $n = |\mathcal{R}|$ and a set of wireless transmitters $\mathcal{C} = \{C_1, \ldots, C_m\}$, where $m = |\mathcal{C}|$, . Assume that $\mathbf{x} \in [0, 1]^m$ is the transmitters' configuration and $\mathbf{x}_j$ is the capacity level of charger $C_j, j \in [m]$.

Initially, we write MAX−POWER problem as a quadratic program. Hence, for each $R \in \mathcal{R}$, define $\mathbf{Q}^{(R)}$ be a $2 \times m$ matrix whose j-th column is the two dimension vector of the electric field created from C_j at R, i.e. $\mathbf{Q}^{(R)}_{:,j} = \sqrt{\gamma} \cdot \mathbf{E}(C_j, R)$, for each $j \in [m]$. Hence, the harvesting power by the node R can be written as:

$$\begin{aligned} P(\mathcal{C}(\mathbf{x}), R) &= \gamma \|\mathbf{E}(\mathcal{C}(\mathbf{x}), R)\|^2 \\ &= \gamma \left\| \sum_{C\in\mathcal{C}} \mathbf{x}_C \mathbf{E}(C, R) \right\|^2 \\ &= \left(\sum_{C\in\mathcal{C}} \mathbf{x}_C \sqrt{\gamma} \mathbf{E}(C, R) \right)^T \left(\sum_{C\in\mathcal{C}} \mathbf{x}_C \sqrt{\gamma} \mathbf{E}(C, R) \right) \\ &= (\mathbf{Q}^{(R)}\mathbf{x})^T \mathbf{Q}^{(R)}\mathbf{x}, \end{aligned}$$

where $(\cdot)^T$ denotes the transpose of a matrix or vector. Therefore, setting $\mathbf{H} \stackrel{def}{=} \sum_{R\in\mathcal{R}} \left(\mathbf{Q}^{(R)}\right)^T \mathbf{Q}^{(R)}$, the solution to MAX−POWER is given by

$$\mathbf{x}^* \in \arg \max_{\mathbf{x}\in[0,1]^m} \mathbf{x}^T \mathbf{H}\mathbf{x}. \tag{20}$$

In general, the maximization of a quadratic form is a non-convex quadratic program (even when $\mathbf{H}$ is positive semi-definite, which is the case here), hence cannot be solved in polynomial time. Nevertheless, by taking into account several properties and the special form of our problem, we are able to provide an efficient algorithm for MAX−POWER.

We first need the following elementary lemma that considerably reduces the size of the search space.

Lemma 4: If $\mathbf{x}^*$ is an optimal solution to MAX−POWER*, then $\mathbf{x}^* \in \{0, 1\}^m$. In particular, there exists an optimal solution to* MAX−POWER *in which each charger either operates at full capacity or not at all.*

The proof uses some positive semi-definite (PSD) matrices properties. Mind that, Lemma 4 and Theorem 2 below imply that any local maxima of the objective function $P(\mathcal{C}(\mathbf{x}), R) = (\mathbf{Q}\mathbf{x})^T \mathbf{Q}\mathbf{x}$ are also global maxima that belong to $\{0, 1\}^m$. This means, that the gradient descent method can be used to find a global maximum (i.e. an optimal solution to MAX−POWER). In the experimental evaluation, we used a pseudopolynomial

Algorithm 3 `IterativeMaxPower`

Input : $dist, \mathcal{R}, \mathcal{C}, communication\_range$
Output: $\mathbf{x}$

begin
  $\mathbf{x} \in \{0,1\}^m$ is a random initial charger configuration;
  while $\exists C_j \in \mathcal{C} : P(\mathcal{C}(\mathbf{x}), \mathcal{R}) < P(\mathcal{C}(\mathbf{x}^{(j,a)}), \mathcal{R}),\ a \in \{0,1\}$ **do**
    choose randomly a charger $C_j \in \mathcal{C}$;
    $\mathcal{R}_{C_j} = 0$;
    foreach $R \in \mathcal{R}$ **do**
      if $dist(C_j, R) \leq communication\_range$ **then**
        $\mathcal{R}_{C_j} = \mathcal{R}_{C_j} \cup R$
        //at this point C_j communicates with R and receives $\mathbf{E}(\mathcal{C}(\mathbf{x}), R)$;
    $\mathbf{x}_{C_j} = \arg\max_{a\in\{0,1\}} P(\mathcal{C}(\mathbf{x}^{(j,a)}), \mathcal{R}_{C_j})$;
  return $\mathbf{x}$;

distributed algorithm for computing the *exact* optimum configuration for `MAX-POWER`, which is quite fast in practice. We present this algorithm later in this section.

Theorem 2: A configuration $\mathbf{x}^* \in \{0,1\}^m$ *is an optimal solution to* `MAX-POWER` *if and only if* $P(\mathcal{C}(\mathbf{x}^*), \mathcal{R}) \geq P(\mathcal{C}(\mathbf{y}), \mathcal{R})$*, for each* $\mathbf{y}$ *that comes from* $\mathbf{x}$ *by setting exactly one of its coordinates to either 0 or 1.*

Lemma 4 and Theorem 2 suggest that the following distributed algorithm (called `IterativeMaxPower`) can be used to find an *exact* optimum configuration for `MAX-POWER`: At first, we begin from an arbitrary configuration in $\{0,1\}^m$. In each subsequent step, we scan the set of chargers to find a charger $C \in \mathcal{C}$ such that the total power received by R can be increased by flipping the operation level of C (e.g. if C operates at full capacity, it checks whether the received power is increased if it is not operational and vise versa). The algorithm terminates if there is no such charger C.

For a given topology of a set $\mathcal{C}$ of chargers and a set $\mathcal{R}$ of receivers, define $\delta(\mathcal{C}, \mathcal{R}) \stackrel{def}{=} \min\{|P(\mathcal{C}(\mathbf{x}), \mathcal{R}) - P(\mathcal{C}(\mathbf{x}^{j,a}), \mathcal{R})| : \mathbf{x} \in \{0,1\}^m, a \in \{0,1\}, j \in [m]\}$. In particular, $\delta(\mathcal{C}, \mathcal{R})$ is the minimal increment in the total received power that can be incurred by a single iteration of `IterativeMaxPower`. In addition, notice that every such iteration takes $O(m^3)$ time. Finally, given that the chargers and receivers satisfy the placement constraints of Subsection *Vector model*, a crude upper bound for the maximum total power is $nm^2\gamma\beta^2\frac{4\pi^2}{\lambda^2} = O(nm^2)$. Therefore, we have the following:

Theorem 3: In a system that consist of a set $\mathcal{R}$ *of* n *nodes that comply with the deployment restrictions of Vector model Subsection and a transmitters' set* $\mathcal{C}$ *of size* m*, Algorithm* `IterativeMaxPower` *aims to provide an optimal solution of* `MAX-POWER` *in* $O\left(\frac{1}{\delta(\mathcal{C},\mathcal{R})} nm^5\right)$.

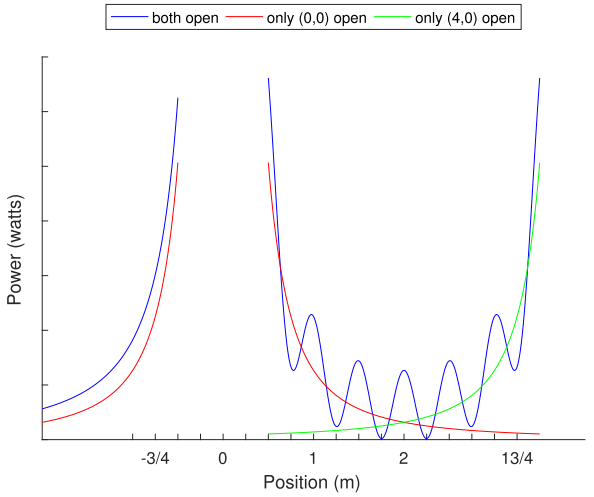
Note: Different levels of knowledge of the wireless system have been considered in the implementation of `IterativeMaxPower`. Hence, we define the *communication radii* of a transmitter as the area where it can communicate by *messages* from nodes. To this end, the transmitters ignore any information coming from nodes outside from the communication radii that each one covers. For the case that a transmitter C_j exchange messages with a receiver R, the node propagates to C_j the electric field vector $\mathbf{E}(\mathcal{C}(\mathbf{x}), R)$, where $\mathbf{x}$ is the configuration at the time when the communication took place. This information suffice for the transmitter to find $P(\mathcal{C}(\mathbf{x}^{(j,a)}), R)$, for each $a \in \{0,1\}$, since $P(\mathcal{C}(\mathbf{x}^{(j,a)}), R) = \gamma\|\mathbf{E}(\mathcal{C}(\mathbf{x}), R) + (a - \mathbf{x}_j)\mathbf{E}(C_j, R)\|^2$. By using the above it is easy to compute $P(\mathcal{C}(\mathbf{x}^{(j,a)}), \mathcal{R}_{C_j})$ for each $a \in \{0,1\}$, where $\mathcal{R}_{C_j} \subseteq \mathcal{R}$ is the receivers subset that can communicate with C_j. Algorithm 3 implements `IterativeMaxPower` in a distributed manner. For example, the transmitters check for their configuration every a predefined period of time, but for the above algorithm we only check those that can positively contribute to the total power of the system by changing their state.

C. MAXIMUM k-MINIMUM GUARANTEE

The current section, presents the general version of `MAX-POWER`, which we previously defined as `MAX-`k`MIN-GUARANTEE` and the corresponding algorithms that attempt to solve it. Although, we have the feeling that the problem tends to be computational hard, we could not provide a formal proof.

Algorithms that exhaustively search every possible solution is not our case for this kind of problem. Still we provide the simulation of such approach for performance comparison purposes. Different to Lemma 4 we show in the following example that different to $x \in \{0,1\}^m$ capacity transmitting levels of the chargers succeed in resulting better performance. Once again there are two nodes R_1 and R_2 which are located at $(-\frac{3}{4}, 0)$ and at $(\frac{13}{4}, 0)$ respectively and two transmitters C_1 at $(0,0)$ and C_2 at $(4,0)$. Also, let $\lambda = \beta = \gamma = 1$. Figure 5a depicts the case in which a fractional power capacity of C_1 achieves to result a better $\min\{P(\{C_1, C_2\}, \{R_1\}), P(\{C_1, C_2\}, \{R_2\})\}$ value. So, $x \in \{0,1\}^2$ offers us 4 configuration cases. We just analyze the 3 out of 4 as the one which suggests both transmitters to be off does not provide any interest. Thus, for the first case where just C_1 works, we result $P(C_1, R_1) = (\frac{4}{3})^2 = 1.77$ and $P(C_1, R_2) = (\frac{4}{13})^2 = 0.094$. The second case suggests that C_2 is the only one to work. For this configuration we resulted $\min\{P(C_2, R_1), P(C_2, R_2)\} = (\frac{1}{4})^2 = 0.0625$. In the final case, where $x_{C_1} = x_{C_2} = 1$, the power at the points is $P(\{C_1, C_2\}, R_1) = (\frac{4}{3} + \frac{4}{19})^2 = 2.38$ and $P(\{C_1, C_2\}, R_2) = (\frac{4}{3} - \frac{4}{13})^2 = 1.025$. Clearly if the power from R_1 is less by e, then $P(\{C_1, C_2\}, R_2)$ succeeds to have an increase minimum while the $P(\{C_1, C_2\}, R_1)$ remains high.

With respect to the above hardness indications, we are forced to apply a relaxation to `MAX-`k`MIN-GUARANTEE` where we aim to find the optimal configurations among $\{0,1\}^m$, i.e. the possible configuration options are 2, either



(a) The power distribution in the straight line from the two chargers. Different curves represent different operation levels of the chargers.

FIGURE 5. Counter-example for fractional operation level of the chargers in MAX-*k*MIN-GUARANTEE problem. (a) The power distribution in the straight line from the two chargers. Different curves represent different operation levels of the chargers.

the transmitter works in full power or it is off. Bellow you can find the 4 approaches solving the relaxed version of the problem, including an optimal algorithm and three heuristics.

1) OPTIMAL CONFIGURATION

We present this approach in order to provide a performance indicator for the three heuristics bellow. Indeed, *Optimal Algorithm (OPT)* cannot be practically used as both the search area and execution time are prohibitive. Nevertheless, OPT checks every possible configuration of the transmitters and finally choose the one (among 2^m) that better serves our case.

2) GREEDY ALGORITHM (GRE)

GRE, as its name implies it follows a greedy strategy to find the transmitters' configurations. In each round, a transmitter is selected uniformly at random and checks which of the two possible configurations achieve the best result at the current stage. The sequence that the transmitters are chosen does not affect the outcome neither the initial random configuration of the transmitters at the beggining as we are going to show in the evaluation subsection.

3) SAMPLING ALGORITHM (SAM)

In an effort to avoid solving the problem for such a large instance, we designed an algorithm that relies on the well-known strategy of sampling. So instead of finding the best configuration for every possible $k-set$ in the network, we are trying to find a solution that best serves a smaller subset (σ $k-$sets) with the prospect of giving us a reliable solution.

In specific, SAM runs in two stages. Initially it creates the σ $k-$sets uniformly at random and matches the optimal transmitters' configuration that came up from 3 per each k-set. Having the optimal configurations per $k-set$ an iterative process begins in which we check the contribution of a charger chosen randomly when works in full capacity and when it is off for every $k-set$. The operation stage that has the bigger contribution is chosen as the charger's operational status. Step by step and by following the above process, after m loops the σ $k-sets$ will share the same transmitters' configuration. In this approach we can skip the possibility for our algorithm to get trapped in a local optima. To this end it's obvious the trade-off we have to pay in performance due to sampling technique.

4) FUSION ALGORITHM (FUS)

FUS algorithm meets the benefits of the previous two approaches. Similar to SAM, FUS begins by matching to each receiver the transmitters' group configuration that maximizes its received power quantity. It is obvious that in this step we have n different configurations (one per receiver). Afterwards, the algorithm tries to change the different configurations which in the last step we get a single one, with respect to the following conditions: pick the charger's configuration that in the current step provide the larger sum of the k nodes with the less power. Mind that FUS initiates from the best individual setup and ends up with all receivers sharing a common chargers' configuaration.

D. EVALUATION

In this subsection we present the corresponding performance simulations of the above mechanism. The tool used for the benchmarking is Matlab 2016a and the considered system consist of 15 chargers and 100 receiver points randomly distributed in a rectangular $10m^2$ area. The following parameters need to be clarified for your better understanding considering the antenna and transmitting technology. To this end, each charger is equipped with an omni directional, isotropic antenna of 2W power, with a 29cm wavelength and 2dbi gain, while the receivers' antenna is 1dbi.

The simulation results study the following performance metrics: primarily, the cumulative power fueled into the system and then some supplementary information on the messages exchanged and the communication overhead.

As cumulative power we define the sum of the power that each of the receivers harvest. As the chargers' communication radii gets larger, 3 succeeds in performing very good results regarding optimal solution. Fig 6 depicts the cumulative received power by the nodes over 4 different communication ranges of the transmitters for 90 rounds time period.

One of the most important observations is that the cumulative power with the global knowledge (open) never decreases over time like the others do. In different cases, where a limited communication radii is applied, we resulted that there are steps that the total received power decreases due to local knowledge ability of a transmitter. Since chargers see only receivers inside their neighbourhood, it is very likely to provide a configuration in favour of this particular subset that is not aligned with the total set of receivers.

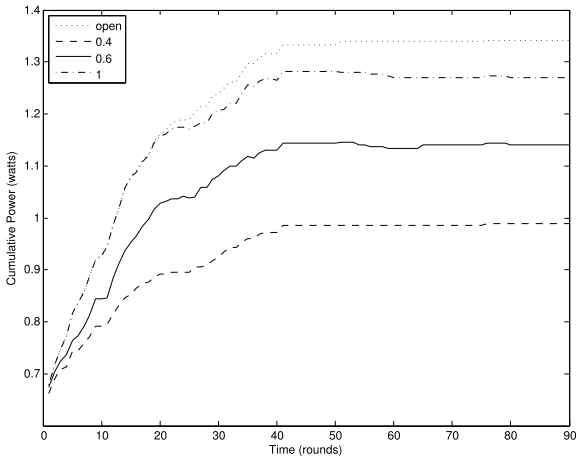


FIGURE 6. Cumulative power over time for different knowledge levels of `IterativeMaxPower`.

Another observation, is that in early steps it is possible to result with a better total power from limited communication radii rather than open. This happens cause the algorithm follows a greedy approach which in combination with a decision based on network's local knowledge can perform temporarily a better power value. Still in the end, the global network's knowledge will perform better.

We also observe that when the communication range is 1m we achieve a near optimal solution. This is because of the received power of the nodes far from the charger, which is reduced due to distance and they don't have added value to the cumulative received power.

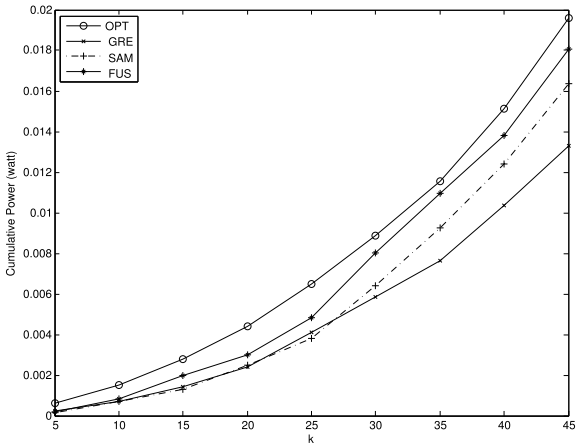


FIGURE 7. Algorithms' Cumulative power (of $k-$set with minimum power) for different values of k.

Regarding `MAX-`k`MIN-GUARANTEE` Fig 7 presents the performance of our heuristic over different size of k. What we observe in this evaluation process is two things. The first indicated that GRE has similar performance to SAM for $k < 27$. Indeed, this is due to the sampling procedure and especially when the sample is small. For the complementary case where $k > 27$ we result a significant improvement. As it was expected FUS heuristic is the one that approximates more efficiently the exhaustive OPT algorithm.

Fig 8a depicts the network's message overhead over different communications ranges that vary from 0.3 to 1.5. Those messages have been exchanged during running time while the transmitters try to configure their operational status via the distributed algorithm. What the reader can easily distinguish is that the communication radii grows together the number of messages exchanged within the network. At the same time, there is evidence that a trade-off exists between the amount of information exchanged and the effect of the resulting power. Finally it is noted that from the point of $1m - 1.2m$ communication range and after, the contribution of the exchanged messages becomes smaller.

V. PEER TO PEER WPT

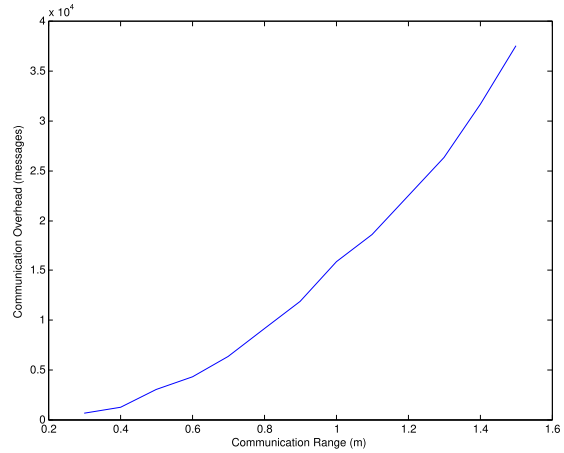
Peer to peer wireless power transfer is a new, futuristic method that achieves to almost nullify the emitted EMR due to wireless power transfer. This is due to the fact that this method does not require any strong network entity (i.e. chargers) to carry all the available energy and transfer it to the nodes of the network but lets the nodes to charge each other when they interact. The exact amount of energy depends on their needs and on other design aspects of the network.

In this section we will present some protocols for distributed networks which consist of computationally weak devices that form specific network structures and try to converge to some energy distributions, designed for the corresponding structure. More specifically, we will present protocols that construct the star network structure where one of the agents should be the central one and each other agents should be a peripheral. Also, the connections should be established only between the central agent and each peripheral agent.

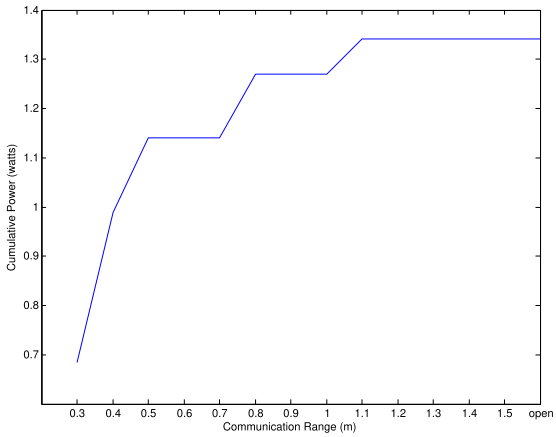
A. RELATED WORK

Wireless Power Transfer has been extensively studied in the context of (mobile) ad hoc networks. In most of these studies, powerful chargers are used with the sole purpose of replenishing the energy of the network nodes. However, there are some works in the literature that investigate WPT from a different viewpoint like [28] that evaluate WPT in the context of electromagnetic radiation (EMR) safety. They design protocols for the placement and configuration of chargers in static networks in order to guarantee EMR safety at any point of the network area. In the same context, the authors in [29] attempt to study (for the first time in the state-of-the-art) *path radiation* problem created by distinct electromagnetic sources with respect to vector model. In the light of the above, they design and evaluate both an algorithm and a heuristic that achieve different trade-offs between radiation and trajectory length of a moving agent.

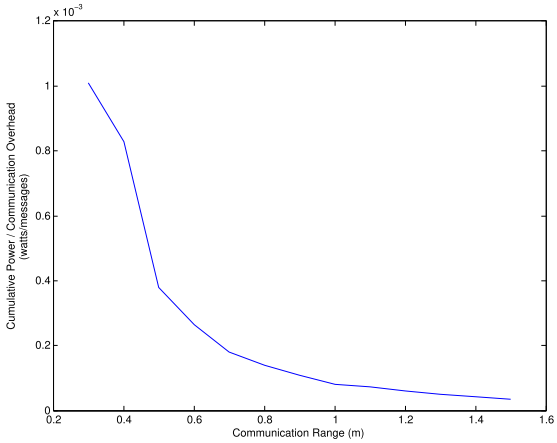
Madhja *et al.* [30] assume a network that consists of multiple mobile chargers with limited energy and static sensor nodes. The authors design efficient traversal and coordination strategies to extend the network lifetime of static sensor networks. In contrast, Angelopoulos *et al.* [31] investigate



(a)



(b)



(c)

FIGURE 8. Impact of communication range on different metrics. (a) Communication overhead over different communication ranges. (b) Cumulative power over different communication ranges at the 90*th* round of Algorithm 3. (c) Ratio of cumulative power to communication overhead over different communication ranges.

mobile ad hoc networks and a single mobile charger with infinite energy that traverses the network in order to recharge the agents as required.

Dhungana *et al.* [32] investigate the advantages of peer-to-peer energy exchange between mobile devices. They consider mobile devices can be charged either by using a charging cable or in a peer-to-peer manner based on their interactions with other devices and their goal is to minimize the amount of times a device will need to be charged through a charging cable. Reference [33] study the potential of crowdcharging. More specifically, authors investigate its feasibility and the challenges (software and hardware) that emerge for its use. Moreover, they develop an application which constructs a social network for the users, which manages the entire process of power sharing between the corresponding mobile devices.

Another interesting study in the literature [34] investigates the peer-to-peer energy transfer with tree network formation and appropriate desired energy distributions.

B. THE MODEL

The network consist of m mobile agents denoted as $\mathcal{M} = \{u_1, u_2, \ldots, u_m\}$ which are equipped with the appropriate wireless power transceivers in order to be able to perform energy exchanges. We assume the the agents are computationally very weak devices and their memory is very small. This limitation enforces us to use a very small amount of possible states which are used by the agents to self-operate and construct the network structure, following the rules of an interaction protocol.

Each agents u, at any time $t \geq 0$, has a configuration denoted as $C_u(t) \stackrel{def}{=} (E_u(t), q_u(t), R_u(t))$ where $E_u(t)$ is the energy level, $q_u(t)$ is the state from a predetermined set $\mathcal{Q}$ and $R_u(t)$ is the memory of agent u at time t. Also, we define a connection state $q_{\{u,v\}}(t)$ that describes the relationship between the agents u and v at time t. In our model, each pair of agents can be either connected or not and thus, this connection state can take values in {0, 1}.

All agents in the network run the same interaction protocol $\mathcal{P}$ when they interact. The interaction takes place between two agents when they come close to each other. The interaction protocol describes how the agents should update their configuration state, i.e.what is the new energy level, their new state and the values of the variables on their local memory.

It is important to note that at each time t, only the configuration of the two agents u and v that interact are updated. Also, only the connection state between this specific pair of agents that interact ($q_{\{u,v\}}(t)$) may change. Every other configuration and connection state between any pair of agents (even if u or v are involved) do not change.

Another critical issue that has been taken into consideration in this model is the *energy loss* of each wireless energy transfer. This energy loss factor β indicates the amount of energy that is not received by the receiver, although it is sent by the transmitter and it depends on environmental conditions and the material with which the agents are equipped with in order to be able to transfer energy wirelessly.

To further enhance our model and make it even more realistic, we consider a scenario, where energy loss factor β can be different at each interaction and it is *not known* by the agents. More specifically, in the experimental evaluation of our proposed algorithms we assumed that loss factor β is an independent random variable which follows the Normal Distribution $N(0.2, 0.05)$.

C. PROBLEM DEFINITION AND METRICS

Our problem, *Energy Aware Network Formation*, is to both construct specific network structure and to achieve a targeted energy distribution for the network agents. In order to evaluate our solutions, we designed two metrics, the *structural distance* and the *energy distance*.

A formal definition of our problem is the following. Assume two graphs G_1 and G_2 on the same set of vertices n. We denote by $H(G_1, G_2)$ the hamming distance between those graphs i.e. $H(G_1, G_2) \stackrel{def}{=} \sum_e |I_e(G_1) - I_e(G_2)|$, where $I_e(G_1)$ and $I_e(G_2)$) are the indicator variables for the existence of edge e in the corresponding graphs and the summation takes into account all possible edges of the graphs, i.e. $\binom{m}{2}$.

The *structural distance* of the state of the network at time t, denoted as $G(t)$ from the target graph $\mathbb{G}$ is defined as follows:

$$\delta_t^s(\mathbb{G}, G(t)) \stackrel{def}{=} \min_{G \sim G(t)} H(\mathbb{G}, G), \tag{21}$$

where the minimum is taken over all graphs G that are isomorphic to $G(t)$.

The definition of the *energy distance* metric is based on the well-known *Total Variation Distance* in stochastic processes and probability theory [35], [36]. Formally, let us denote by $\mathbb{E}$ the target energy distribution for the set of agents $\mathcal{M}$, by $\mathcal{E}_u(t) = \frac{E_u(t)}{\sum_u E_u}$ the relative energy level of agent $u \in \mathcal{M}$, by $\mathcal{E}(t)$ the relative energy distribution at time t and by S_m the permutations of m.

The energy distance of the energy distribution of the network at time t to the targeted energy distribution is defined as following:

$$\delta_t^e(\mathbb{E}, \mathcal{E}(t)) \stackrel{def}{=} \min_{\sigma \in S_m} \frac{1}{2} \sum_{i=1}^{m} |\mathbb{E}_i - \mathcal{E}_{\sigma(u_i)}(t)|, \tag{22}$$

where the minimum value is taken among all possible permutations of agents.

The problem that we study in this section is to design protocols that aim to nullify the structural distance (i.e. construct the targeted graph), minimize as much as possible the energy distance (i.e. the energy distribution should be very close to the targeted one) and also minimize the total energy loss in order to prolong the network lifetime. Formally, the problem is the following:

Definition 6 (Energy Aware Network Formation Problem): Consider a network that consists of a set of mobile agents $\mathcal{M}$. We denote by $\mathbb{G}$ the target graph on $\mathcal{M}$, by $\mathbb{E}$ the target energy distribution. and by $\epsilon, \theta > 0$ small constants. At each time t, a probabilistic scheduler selects two agents to interact according to an interaction protocol. The problem is to find an interaction protocol that at a time $t \geq 0$ achieves (i) $\delta_t^s(\mathbb{G}, G(t)) = 0$, (ii) $\delta_t^e(\mathbb{E}, \mathcal{E}(t)) \leq \epsilon$ and (iii) $E_{loss} = \sum_u E_u(0) - \sum_u E_u(t) \leq \theta$.

In this section we focus on star networks structures, i.e. the target graph is a star graph where only one node on the graph (called central) has edges to all other nodes and there is no any edge between any other pair of nodes. Since our network consists of m agents, the total number of edges in the target graph are $m - 1$ which equals to the degree of the central agent.

This network structure, by design, necessitates the central node to receive all network flow. The most critical consequence of this is that the central node consumes its energy in a much higher rate compared to the other nodes.

Based on this observation, we define a targeted energy distribution where the targeted energy level of each agent is proportional to the degree of the agents in the graph. More specifically, at any time t, the targeted energy level for the central agent is $\frac{E_{total}(t)}{2}$ while for every peripheral agent is $\frac{E_{total}(t)}{2(m-1)}$.

D. THE PROTOCOLS

To study the *energy aware network formation* problem from different perspectives, we designed four protocols. All protocols construct star networks and try to converge to the targeted energy distribution. The main difference between the protocols is on the amount of registers and states that are available to agents (i.e. the size of their memory). The higher the size of memory the more sophisticated protocols are. As a consequence, the rules for the configuration of each agent when it interact, are different. Additionally, the amount of energy that is exchanged between the pair of agents that interact at each time is different.

Since the targeted graph structure is a star, the possible states of the agents are either central (c) or peripheral (p). Initially, the state of all agents is c and there is not any connection between them. As the protocols run and the agents interact, they change their states, add or remove the connections between them, exchange energies etc. However, for our more sophisticated protocols, we additionally introduce d halted states denoted as $h_i,\ i \in \{1, \ldots, d\}$ that are not actual network states but are useful to improve the agents decisions regarding the energy transmissions. Note that in protocols that use these halted states, the agents will eventually end up in peripheral state. In general, the set of all possible states is $\mathcal{Q} = \{c, p, h_1, \ldots, h_d\}$.

The time horizon T is discrete and at each time t only a pair of agents that is selected by the probabilistic scheduler interacts according to the protocol.

1) FULL TRANSFER PROTOCOL

This protocol requires the smallest amount of memory and serves as a lower bound of the performance of the rest, more powerful protocols.

The set of possible states is $\mathcal{Q} = \{c, p\}$ and all agents store in their memory the energy threshold E_{min}, which is the amount of energy they keep for their own operation.

The interaction rules depend on the current states of the agents that interact. The main cases are the following.

- (c, c) *Both agents are centrals:* One of them is *randomly* chosen to become peripheral and transfer all its energy to the central (except a small amount E_{min}). Also, a connection is established between them.
- (p, p) *Both agents are peripherals:* If a connection exists between them, it is removed.
- (c, p) *One agent is peripheral and the other one is central:* If there is no connection between them, it is established.

Note that all agents start as centrals and each time two central nodes interact, one of them becomes peripheral. Once an agent becomes peripheral, it does not change its state in the future. however, it may change its connection state to other agents in order to be connected to the final central agents and to not have any connection with any other agents that became peripheral. This guarantees that at the end, only one agent will remain in central state. The rules that contain at least one peripheral agent are used for correcting the communication states between the agents such that, at the end, all (and only these) connections between the peripherals and the central agent will exist (such that the constructed graph will be a star).

Regarding the energy transfer, the agents transfer almost all of their energy (except the threshold value that they keep for their own operations) when they change their state (from central to peripheral). So, any peripheral agents does not store any excess amount of energy to transfer and thus, there is no any further energy exchange between a pair of nodes that at least one of them is already peripheral. The pseudo-code of this protocols is presented in Protocol 4.

Protocol 4 Full Transfer P_{FT}

Input : Agents u, u' with energy levels $\varepsilon_u, \varepsilon_{u'}$ and states $q_u, q_{u'}$

if $q_u == c$ *AND* $q_{u'} == c$ **then**
  $agent = randomly\_select\_agent(u, u')$;
  if $agent == u$ **then**
    $q_{u'} = p$;
    $q_{\{u,u'\}} = 1$;
    $\varepsilon_{sent} = \varepsilon_{u'} - E_{min}$;
    $\varepsilon_u = \varepsilon_u + \varepsilon_{sent} * (1 - \beta)$;
    $\varepsilon_{u'} = \varepsilon_{u'} - \varepsilon_{sent}$;
  else
    $q_u = p$;
    $q_{\{u,u'\}} = 1$;
    $\varepsilon_{sent} = \varepsilon_u - E_{min}$;
    $\varepsilon_{u'} = \varepsilon_{u'} + \varepsilon_{sent} * (1 - \beta)$;
    $\varepsilon_u = \varepsilon_u - \varepsilon_{sent}$;
else if $q_u == p$ *AND* $q_{u'} == p$ **then**
  if $q_{\{u,u'\}} == 1$ **then**
    $q_{\{u,u'\}} = 0$;
else
  if $q_{\{u,u'\}} == 0$ **then**
    $q_{\{u,u'\}} = 1$;

2) HALF TRANSFER PROTOCOL

This protocol assumes that the agents can store in their memory their own initial energy levels. Note that although this assumption is weak (since they use local information only) it results in better performance compared to Full Transfer Protocol. Also, note that it does not require any additional memory space since it can be stored instead of E_{min} value used in Full Transfer protocol.

Similarly to Full Transfer protocol, the set of possible states of each agent is $\mathcal{Q} = \{c, p\}$ and the three main interaction cases are the following.

- (c, c) *Both agents are centrals:* The agent with *highest energy* will remain central, and the other will become peripheral. The peripheral, will *keep half of its initial energy* and transmit the rest to the central agent. Also, a connection is established between them.
- (p, p) *Both agents are peripherals:* If a connection exists between them, it is removed.
- (c, p) *One agent is peripheral and the other one is central:* If there is no connection between them, it is established.

An observation is that the cases where a peripheral nodes interact with either another peripheral or a central agent are exactly the same as in Full Transfer protocol where only the connection states are fixed in order to construct the star structure.

However, the interaction between two central agents is very different compared to Full Transfer protocol. The difference is both on the update rule for their states and on the energy exchange rule. More specifically, the decision of which of them will remain in central state is not random but is based on which of them has the higher energy. Also, the amount of energy that is transferred is different. In Half Transfer protocol, the agents keep half of their initial energy and transfer the rest. This energy exchange rule is very natural in order to achieve the targeted energy distribution where the central agent should store the half of the total energy of the network. Protocol 5 describes the pseudo-code of Half Transfer protocol.

3) DEGREE AWARE PROTOCOL

This protocol aims to reveal the size of the network (i.e. the number of the agents) and use this information in order to make the energy exchanges and update the states of the agents appropriately.

More specifically, the algorithm that is used by the agents to estimate the network size is the following. Every central agent stores as estimation, its degree. Similarly to the previous protocols, initially all agents are centrals and there is no any connection between them. Thus, the initial estimation of each agent is 0. Each non-central agents stores as

Protocol 5 Half Transfer P_{HT}

Input : Agents u, u' with energy levels $\varepsilon_u, \varepsilon_{u'}$, initial energies $\varepsilon_u^{initial}, \varepsilon_{u'}^{initial}$ and states $q_u, q_{u'}$

if $q_u == c$ *AND* $q_{u'} == c$ **then**
  $agent = NULL$;
  if $\varepsilon_u == \varepsilon_{u'}$ **then**
    $agent = randomly\_select\_agent(u, u')$;
  if $\varepsilon_u > \varepsilon_{u'}$ *OR* $agent == u$ **then**
    $q_{u'} = p$;
    $q_{\{u,u'\}} = 1$;
    $\varepsilon_{sent} = (\varepsilon_{u'} - \varepsilon_{u'}^{initial}/2)$;
    $\varepsilon_u = \varepsilon_u + \varepsilon_{sent} * (1 - \beta)$;
    $\varepsilon_{u'} = \varepsilon_{u'} - \varepsilon_{sent}$;
  else
    $q_u = p$;
    $q_{\{u,u'\}} = 1$;
    $\varepsilon_{sent} = (\varepsilon_u - \varepsilon_u^{initial}/2)$;
    $\varepsilon_{u'} = \varepsilon_{u'} + \varepsilon_{sent} * (1 - \beta)$;
    $\varepsilon_u = \varepsilon_u - \varepsilon_{sent}$;
else if $q_u == p$ *AND* $q_{u'} == p$ **then**
  if $q_{\{u,u'\}} == 1$ **then**
    $q_{\{u,u'\}} = 0$;
else
  if $q_{\{u,u'\}} == 0$ **then**
    $q_{\{u,u'\}} = 1$;

estimation, the highest value of an agent it has interacted with in the past, since at each interaction, the agents exchange the highest estimation (between them). These exchanges of he stored estimations of the maximum number of agents are used in order to propagate to the whole network the maximum value which eventually will be stable to the size of the network decreased by 1, since the maximum value will be the degree of the central agent, i.e. it will not include itself.

This protocol requires higher memory since the set of states for each agent is higher. More specifically, the set of possible states is $\mathcal{Q} = \{c, p, h_1, \ldots, h_d\}$ which includes d additional states, the halted ones. Every agent (except the final central one) will pass through all halted states before they become peripherals. These states are used in order to improve the estimation of the agents and postpone the energy exchanges in order to reduce energy loss due to insufficient energy transfers to agents that will not end up to be the central agent of the final star structure and to reduce the energy distance.

The update of the halted state of an agent (from h_i to h_{i+1}) is performed each time it interacts with a central agent that has higher estimation on the network size. The energy transfer is performed only by peripheral agents and if the agent it interacts with has higher estimation.

Another important property of this protocol is the energy exchange rule that is designed. More specifically, an energy exchange takes place when both following conditions are satisfied. The first one refers to the state of the agents that interact where one of them should be central and the other one should be either peripheral or in h_d state. The second condition is that the central node has higher estimation than the other node, i.e. its degree is higher that the stored estimation of the other node. If both conditions hold then the nodes exchange energy based on the following rule.

If the energy of an agent times the higher estimation of the network size between the pair of agents that interact is larger than the energy level of the other agent, it will transfer to it $(1/k) \times (E_u \times E_v)/(E_u + E_v)$ energy. Note that there is a parameter, denoted as k which is used in order to reduce the non-useful energy exchanged between the agents and thus reduce the energy loss, when the estimation is not equal to the actual network size.

Regarding the new halted states, and agent changes its central state to h_1 if it interact with another agent with higher estimation on the network size. The change of any halted state h_i to the next one h_{i+1} is applied when the halted agents interacts with a central agent that has higher estimation of the network size.

Due to the higher amount of possible states, the interaction rules are also higher. However, we grouped them and the main cases are the following.

- (c, c) *Both agents are centrals:* The agent with the lowest estimation becomes h_1. A connection is established between them and thus the estimation of the central agent is increased by one and this value is stored to the halted agent as well.
- $(\overline{c}, \overline{c})$ *None of the agents is central (i.e. are either halted or peripherals):* Agents exchange the maximum estimation and remove their connection, if it exists.
- (c, p) *One agent is peripheral and the other one is central:* If central agent has lower estimation, it becomes h_1 and stores as estimation, the estimation of the peripheral agent. Otherwise, agents check if they have a connection between them. If not, they establish a connection, increase the estimation of the central by 1 and store this value in peripheral agent as well. Also, in the case where the agents remain to their states, they apply the energy exchange rule described above.
- (c, h_i) *One agent is central and the other one is halted:* If the central agent has lower estimation, it changes its state to h_1. Otherwise, the level of the halted agent is important. If it is not in the last halted state (h_d) then it simply changes its state to the next halted state h_{i+1} and updates its estimation. However, if the agent is in h_d, then it becomes peripheral. Additionally, if the agents are not already connected they establish a new connection, increase the estimation of the central agent by one and store this value to the peripheral node as well. Also, the energy exchange rule is applied between the peripheral agent and the central one as described above.

A detailed pseudo-code for Degree Aware is presented in Protocol 6.

Protocol 6 Degree Aware P_{DA}

Input : Agents u, u' with energy levels $\varepsilon_u, \varepsilon_{u'}$ and states $q_u, q_{u'}$

$r_u = number\_of\_neighbors(u)$;
$r_{u'} = number\_of\_neighbors(u')$;
$x = max\{r_u, r_{u'}\}$;
if $q_u == c$ *AND* $q_{u'} == c$ **then**
  $agent = NULL$;
  if $r_u == r_{u'}$ **then**
    $agent = randomly\_select\_agent(u, u')$;
  if $r_u > r_{u'}$ *OR* $agent == u$ **then**
    $q_{u'} = h_1$;
    $r_u = r_{u'} = x + 1$;
    $q_{\{u,u'\}} = 1$;
  else
    $q_u = h_1$;
    $r_u = r_{u'} = x + 1$;
    $q_{\{u,u'\}} = 1$;
else if $q_u, q_{u'} \in \{p, h_1, \ldots, h_d\}$ **then**
  $q_{\{u,u'\}} = 0$;
  $r_u = r_{u'} = x$;
else if $q_u == c$ *AND* $q_{u'} \in \{p, h_1, \ldots, h_d\}$ **then**
  if $r_u \geq r_{u'}$ **then**
    if $q_{u'} \geq h_d$ *OR* $q_{u'} == p$ **then**
      $q_{u'} = p$;
      if $q_{\{u,u'\}} == 0$ **then**
        $q_{\{u,u'\}} = 1$;
        $r_u = r_u + 1$;
      $\varepsilon_{sent} = \frac{1}{k} * \frac{\varepsilon_u}{\varepsilon_u + \varepsilon_{u'}} * \varepsilon_{u'}$;
      if $\varepsilon_u < \varepsilon_{u'} * r_u$ **then**
        $\varepsilon_u = \varepsilon_u + \varepsilon_{sent} * (1 - \beta)$;
        $\varepsilon_{u'} = \varepsilon_{u'} - \varepsilon_{sent}$;
      else if $\varepsilon_u > \varepsilon_{u'} * r_u$ **then**
        $\varepsilon_{u'} = \varepsilon_{u'} + \varepsilon_{sent} * (1 - \beta)$;
        $\varepsilon_u = \varepsilon_u - \varepsilon_{sent}$;
      end if
    else
      $q_{u'} = h_{i+1}$;
    $r_{u'} = r_u$;
  else
    $q_u = h_1$;
    $r_u = r_{u'}$;
else if $q_u \in \{p, h_1, \ldots, h_d\}$ *AND* $q_{u'} == c$ **then**
  Similarly with the case above by symmetry.
end if

4) FULLY ADAPTIVE PROTOCOL

This protocol is the most powerful one compared to the other three protocols described above. Specifically, it is an enhancement of the Degree Aware protocol where additionally to the estimation of the network size, agents store the energy level of the last central agent they interacted with. Note that this energy level refers to the energy that the central node had at the time they interacted and does not indicate its current energy level (since the agent has to interact again with it in order to be able to be informed about this). Let us denote by e_u^c this energy level stored at agent u. Also let us denote as r_u the estimation of agent u regarding the network size.

The protocol is quite similar to the Degree Aware protocol. The difference is on the energy exchange rule. More specifically, in this protocol, agents can estimate their targeted energy levels and thus make the energy exchanges appropriately. This enables for the first time, two peripheral agents to exchange energy if one of them has higher amount of energy of the targeted one while the other agent has lower energy from the targeted energy level.

Specifically the energy exchange cases are the following:

Case I: (c, p) or (c, h_d): *Agent u is in state c and agent v is in state p or* h_d. In this case, the amount of energy that is exchanged between the two agents is

$$e_{sent} = \frac{1}{k} \frac{|E_u(r_u - 1) - E_v|}{r_u + 1}$$

Case II: (p, p): *Both agents u and v are peripherals.* As described above, the agents, before exchanging energy, should estimate their targeted energy level which equals to $e_u^p = e_u^c/(max(r_u, r_v) - 1)$ and $e_v^p = e_v^c/(max(r_u, r_v) - 1)$. After estimating the targeted energies, agents calculate if they can exchange energy. This decision is positive only if the agents' current energy levels are in the opposite site of each targeted energy level. More specifically, agents exchange energy if and only if $E_u > e_u^p$ & $E_v < e_u^p$ & $E_u > e_v^p$ & $E_v < e_v^p$.

If all above mentioned conditions hold then the agent with the highest amount of energy transfers the following amount of energy:

$$e_{sent} = \frac{1}{k} \frac{|E_v - E_u|}{2}$$

A detailed description of Fully Adaptive is presented in Protocol 7.

E. EVALUATION

In this subsection the performance evaluation of the populations protocols will be described. The simulation has been conducted in Matlab R2016a and the simulation setup is the following. The number of agents varies, from 20 to 100 and the total available energy of the network is $3000 \cdot [20 : 20 : 100]$ for 20, 40, 60, 80 and 100 agents respectively. Initially, agents start with different energy supplies for abstracting the diversity on a real-life network. Also, as described above, each energy exchange induces an energy loss β which is different at any time t and follows the Normal Distribution, $\beta \sim N(0.2, 0.05)$. Each simulation is conducted 100 times and the average values are presented.

Protocol 7 Fully Adaptive P_{FA}

Input : Agents u, u' with energy levels $\varepsilon_u, \varepsilon_{u'}$ and states $q_u, q_{u'}$

$r_u = number\_of\_neighbors(u)$;
$r_{u'} = number\_of\_neighbors(u')$;
$x = max\{r_u, r_{u'}\}$;
if $q_u == c$ *AND* $q_{u'} == c$ **then**
  $agent = NULL$;
  if $r_u == r_{u'}$ **then**
    $agent = randomly\_select\_agent(u, u')$;
  if $r_u > r_{u'}$ *OR* $agent == u$ **then**
    $q_{u'} = h_1$; $r_u = r_{u'} = x + 1$; $q_{\{u,u'\}} = 1$; $e^c_u = \varepsilon_u$;
  else
    $q_u = h_1$; $r_u = r_{u'} = x + 1$; $q_{\{u,u'\}} = 1$; $e^c_u = \varepsilon_{u'}$;
else if $q_u == p$ *AND* $q_{u'} == p$ **then**
  $q_{\{u,u'\}} = 0$; $r_u = r_{u'} = x$;
  $e^u_p = e^c_u / r_u$; $e^{u'}_p = e^c_u / r_{u'}$;
  $\varepsilon_{sent} = \frac{1}{k} * |\frac{\varepsilon_u - \varepsilon_{u'}}{2}|$;
  if $\varepsilon_u > e^u_p$ *AND* $\varepsilon_{u'} < e^u_p$ **then**
    if $\varepsilon_u > e^{u'}_p$ *AND* $\varepsilon_{u'} < e^{u'}_p$ **then**
      $\varepsilon_{u'} = \varepsilon_{u'} + \varepsilon_{sent} * (1 - \beta)$; $\varepsilon_u = \varepsilon_u - \varepsilon_{sent}$;
  else if $\varepsilon_{u'} > e^u_p$ *AND* $\varepsilon_u < e^u_p$ **then**
    if $\varepsilon_{u'} > e^{u'}_p$ *AND* $\varepsilon_u < e^{u'}_p$ **then**
      $\varepsilon_u = \varepsilon_u + \varepsilon_{sent} * (1 - \beta)$; $\varepsilon_{u'} = \varepsilon_{u'} - \varepsilon_{sent}$;
  end if
else if $q_{u/u'} \in \{p, h_1, \ldots, h_d\}$ *AND* $q_{u'/u} \in \{h_1, \ldots, h_d\}$ **then**
  $q_{\{u,u'\}} = 0$; $r_u = r_{u'} = x$;
else if $q_u == c$ *AND* $q_{u'} \in \{p, h_1, \ldots, h_d\}$ **then**
  if $r_u \geq r_{u'}$ **then**
    if $q_{u'} \geq h_d$ *OR* $q_{u'} == p$ **then**
      $q_{u'} = p$; $e^c_{u'} = \varepsilon_u$;
      if $q_{\{u,u'\}} == 0$ **then**
        $q_{\{u,u'\}} = 1$; $r_u = r_u + 1$;
      $e^c_{u'} = \varepsilon_u$; $\varepsilon_{sent} = \frac{1}{k} * |\frac{\varepsilon_{u'} * r_u - \varepsilon_u}{r_u + 1}|$;
      if $\varepsilon_{sent} < 0$ **then**
        $\varepsilon_{u'} = \varepsilon_{u'} + \varepsilon_{sent} * (1 - \beta)$;
        $\varepsilon_u = \varepsilon_u - \varepsilon_{sent}$;
      else if $\varepsilon_{sent} > 0$ **then**
        $\varepsilon_u = \varepsilon_u + \varepsilon_{sent} * (1 - \beta)$;
        $\varepsilon_{u'} = \varepsilon_{u'} - \varepsilon_{sent}$;
      end if
    else
      $q_{u'} = h_{i+1}$;
    $r_{u'} = r_u$;
  else
    $q_u = h_1$; $r_u = r_{u'}$;
else if $q_u \in \{p, h_1, \ldots, h_d\}$ *AND* $q_{u'} == c$ **then**
  Similarly with the above case by symmetry.
end if

The metrics that are used to evaluate the protocols are the structural distance, the energy distance, the energy loss and the convergence speed (i.e. the number of interactions that are required in order to achieve the desired energy distance).

1) FINE TUNING OF PARAMETERS d AND k

In order to evaluate the performance of the new protocols, it is required to select the best values for the parameters d and k that are used by the Degree Aware protocol and the Fully Adaptive protocol. To select this best values, various metrics and various network sizes are applied. More specifically the various network sizes are 20, 40, 60, 80 and 100 agents and both the energy loss and the energy distance are used as metrics.

In order to select one single best value for each parameter (for each protocol) the following new metric was designed.

$$w = t_i \cdot E_{loss}(t_i) \cdot \delta^e_{t_i}(\mathbb{E}, \mathcal{E}(t_i)) \tag{23}$$

where $E_{loss}(t_i)$ is the energy loss of each protocol at time t_i, $\delta^e_{t_i}(\mathbb{E}, \mathcal{E}(t_i))$ is the energy distance of each protocol at time t_i and t_i is the time that the protocol that has the worst performance, achieves its best energy distance.

The best values for the parameters d and k are the one that achieve the minimum value of w.

Best value of parameter d. The values $d = [1, 7]$ have been investigated while the value of parameter k has been set to 1. The best value for both Degree Aware and Fully Adaptive protocol is 1 which means that *only one halted state is required*.

Best value of parameter k. The values $k = [1, 8]$ have been investigated while the value of parameter d has been set to 1. The best value for the Degree Aware protocol is 7 while the best value for the Fully Adaptive protocol is 1.

In the following sections we present the performance of the four protocols described in the previous sections, after the fine tunning of the various parameters. Although we conducted simulations with different network sizes, i.e., with 20, 60, 80 and 100 agents respectively, we observed that each protocol has similar performance for each network size. Thus we will present the results for a network with 100 agents.

2) PROTOCOLS' PERFORMANCE ON TIME TO CONVERGE

In this section we compare the protocols performance on the two basic metrics that are designed specifically for this problem and described in the corresponding subsection above. More specifically we evaluate the protocols' performance on number of interactions they need to build a global star network structure, as well as to achieve a low energy distance.

a: STRUCTURAL DISTANCE

As shown in Fig. 9a, at the early rounds, the Full Transfer and the Half transfer protocols have an increase on their structural distances. This is natural since, in these protocols, the agents do not have any network knowledge and thus the naive rule of establishing connection between every central

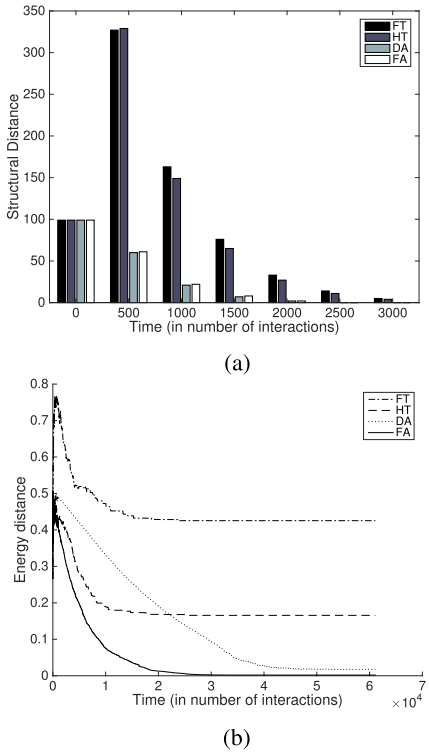


FIGURE 9. Speed comparison of the different protocols. (a) Structural Distance vs. interactions. (b) Energy distance vs. interactions.

and peripheral agent induces a lot of erroneous connections. However, as the time progresses and the central nodes become peripherals, when they re-interact, these erroneous connections are removed, resulting on a reduce on the structural distance and thus successfully formatting a star structure.

On the other hand, the Degree Aware protocol and the Fully Adaptive protocol that use one halted state achieve a quicker converge to the correct star structure since they do not create connections every time. More specifically, they create a connection if they interact for the second time and the central one is still in central state. Note that there are a lot of other interaction in between the two times that a specific pair of agent interacts again. So, in the meantime, each of the agent may have interacted with other agents and change its state. Thus, if the central agent has become a halted or peripheral until it re-interacts with this agent, they will never create a connection between them. So, a lot of unnecessary connections are avoided in the first place. Note that this is achieved by using just one halted state which reveals the power of two choices [37].

b: ENERGY DISTANCE

The protocols performance on the energy distance metric is shown in Fig. 9b. The energy distance metric refers to the number of interactions required in order to achieve a relatively low energy distance. As we can observe by the figure, the Full Adaptive protocol has the best performance since it achieves the lowest energy distance the entire time and also converges to an almost zero energy distance very soon. Although, the Degree Aware protocol eventually achieves its targeted energy distribution as well, it requires much more time.

On the contrary, the Full Transfer and Half Transfer protocols do not achieve the targeted energy distribution and their energy distance remains very high. However, they converge to their final energy distribution in a very small number of interactions.

3) PROTOCOLS' OVERALL PERFORMANCE

In this section we will present the performance of the designed interaction protocols on the energy loss that is induced to achieve the targeted energy distribution and the distance between the achieved energy distribution to the desired targeted one.

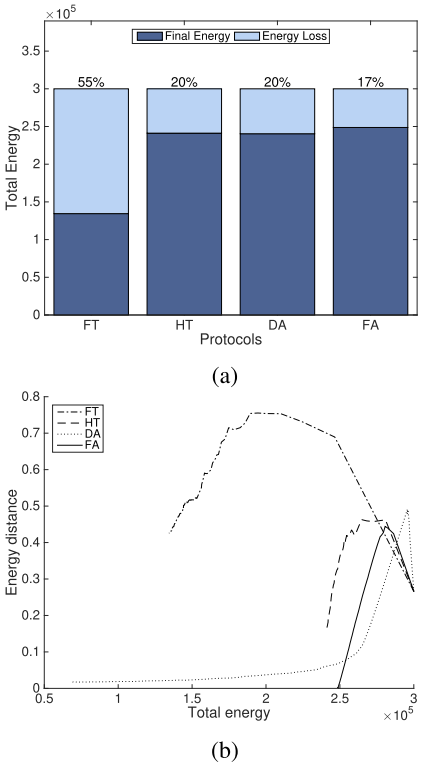


FIGURE 10. Energy comparison of the different protocols. (a) Energy loss to total energy. (b) Energy distance to total energy.

In Fig. 10a the total amount of energy that is lost is shown. All protocols started with the same initial energy but, the different rules the apply (due to different assumed power) results to different energy exchanges. The energy exchange rules differ not only on the cases they are applied but also on the amount of energy that is transmitted each time. As show in the figure, the Fully Adaptive protocol has the lowest energy loss. This is natural since this is the most powerful protocol and its energy exchange rules are very sophisticated. The Degree Aware protocol, although it converges very close to its targeted energy distribution, the energy distance is not zero. Thus, for fair comparison of the protocols, we depict

the energy loss when it achieves a very small energy distance equal to 0.05. The Half Transfer protocol, although its more naive compared to the previous ones, it achieves the same energy loss with the Degree Aware protocol. On the contrary, the Full Transfer protocol has the highest energy loss, as expected due to its extremely low power and its randomness.

Fig. 10b depicts the energy distance to total energy. During the early rounds, the Degree Aware protocol outperforms the Fully Adaptive one which makes sense since the value of parameter k is set to 7 which means that it transfer very small portion of energy when the estimation of the network size is still far from the actual value. As the time progresses the Fully Adaptive protocol achieves the best performance of all protocols. The Degree Aware protocol although it almost converges to the targeted energy distribution it spends all the available energy in the network. Half Transfer protocol although it reduces its energy distance, it wastes more energy. Finally, the Full Transfer protocol achieves the worst performance between all protocols.

VI. ADAPTIVE CHARGING RANGE ALGORITHMS

A new challenging research direction that aims to reduce the emitted EMR while maintaining a high QoS is to design protocols that select a different charging range at any time (in an online manner), according to the network requirements. A very interesting case is in mobile ad hoc networks, where the mobile devices (called agents) move around the network (randomly) and the static charger should manage its finite energy by selecting the appropriate charging range every time. The decision of the range selection is primarily based on the energy characteristics of the agents that travel across its range at the specific time, and on the specific goal it aims to achieve, i.e. to prolong the network lifetime. However, the general principle is to keep it as low as possible such that to store energy for future (and prolong the network lifetime) and reduce the emitted radiation while in parallel, the network is operational with a high QoS.

In the sections below, we will describe the underlying model, the optimizations problems and three adaptive heuristic algorithms which differ on the available network knowledge they have. Finally, we will present simulation results to show their performance on various metrics.

A. RELATED WORK

Mobile ad hoc networks have been extensively studied in the literature under different perspectives. Angelopoulos *et al.* [38] studied mobile ad hoc networks that consist of multiple static chargers. They designed and experimentally evaluated two algorithms that find which of the chargers should be active at each round, in order to maximize charging efficiency and achieve energy balance, respectively. In [31] authors also investigated mobile ad hoc networks. However, in their model, there exists a single mobile charger that has infinite energy and traverses the network in order to recharge the agents. They designed optimal traversal strategies for the mobile charger in order to prolong the network lifetime.

He *et al.* [5] investigated the energy provisioning problem, i.e. to minimize the number of chargers. Also, they computed where they should be located in the network area, so that all agents are always active (i.e., they have or get enough energy to complete their tasks). Dai *et al.* [39] showed that the agent's continuous operation cannot be guaranteed due to their velocity and battery capacity constraints. Moreover, authors introduced the Quality of Energy Provisioning (QoEP) metric to characterize the expected time that the agent is actually active.

Dai *et al.* [40] studied the safe charging problem with the goal of maximizing the charging utility, while ensuring that there is no point in the network area with electromagnetic radiation (EMR) that exceeds a threshold value. Specifically, they assumed a network consisting of static agents and multiple stationary chargers. They investigated which of the chargers should be active such that the EMR constraint is not violated and proposed algorithms with provable efficiency guarantees. Dai *et al.* [12] studied a variation of this problem where the power of each charger can be adjusted once at the beginning, and and it can be different compared to other chargers. Nikoletseas *et al.* [13] studied the low radiation efficient wireless charging as well. However, they defined a different charging model that takes into account hardware constraints for the chargers and the agents (i.e., the chargers have finite energy supplies and the agents have battery capacity constraints).

The last two papers are the most related to our problem, in the sense that the power of each charger is adjustable. However, observe that since the agents are static in both models considered in [12] and [43] each charger adjusts its power only once, at the beginning of the time horizon. In contrast, the power of the charger in our setting constantly changes over time, adaptively to the behavior of the mobile agents which is revealed in an online manner. Therefore, even though our setting and that of [12] and [43] are seemingly similar, they are fundamentally different and uncomparable to each other.

B. MODEL

Our network comprises of n mobile agents that move around in a bounded network area, and a single static charger that is positioned at the center of the area. For simplicity, we assume that the network area is represented as a rectangle defined by the points $(0, 0)$ and $(x_{\max}, y_{\max})$ on the Euclidean space.

In our model, we assume that the time horizon $T \in \mathbb{N}_{\geq 0}$ is discrete and consists of a number of distinct rounds. Each round runs for a constant period of time denotes as τ. Since the agents are mobile, their positions change at each round as they move around in the network area. At the beginning of round t, the position of every agent i is denoted by $p_i(t) = (x_i(t), y_i(t))$. However, for the charger, the parameter that changes at each round is its charging range. More specifically, at round t, its charging range is denoted by $R(t) \in [R_{\min}, R_{\max}]$. $R(t)$ is decided by the transmission

power of the charger and defines a circle of radius $R(t)$ around p_{charger}; let $\mathcal{C}_{R(t)}$ denote this circle on the plane. All agents that pass through $\mathcal{C}_{R(t)}$ during round t can get recharged (if they need to).

1) MOBILITY MODEL

We denote as $v_i(t)$ the velocity of node i at time t. We assume three different level of movements: slow, medium, and fast. Each kind of movement defines a range of possible speeds: $I_1 = [0, \frac{1}{4}v_{\max}]$, $I_2 = \left(\frac{1}{4}v_{\max}, \frac{1}{2}v_{\max}\right]$, and $I_3 = \left(\frac{1}{2}v_{\max}, v_{\max}\right]$, where $v_{\max}$ is the maximum possible velocity that any agent can have at any time.

The mobile agents perform a random walk. More specifically, each agent i, at round t, starts from position $p_i(t)$, and chooses randomly a new direction $\theta_i(t) \in [0, 2\pi)$ as well as a new velocity $v_i(t) \in I_{\mu_i(t)}$. The direction $\theta_i(t)$ together with $p_i(t)$, define a line along which the agent travels with the chosen velocity $v_i(t)$ until it reaches its final position at the end of the round, which is the position $p_i(t+1)$ at the beginning of the next round. If the selection of the velocity and direction lead to a position out of the network area, the movement is redefined accordingly.

2) ENERGY MODEL

Let $E_i(t)$ be the energy of agent i at the beginning of round t. All agents have the same battery capacity B, and they are initially fully charged.

During round t, each agent i consumes an amount of energy $E_i^c(t)$ for communication purposes. Following previous work (e.g., [31]), we assume that $E_i^c(t)$ follows a poisson probability distribution with expected value $\gamma_i \in [\gamma_{\min}^i, \gamma_{\max}^i]$. The energy of agent i at the beginning of the next round (assuming no recharging), is

$$E_i(t+1) := \max\left\{0, E_i(t) - E_i^c(t)\right\}.$$

We remark that the agents do not consume any energy due to movement as the necessary energy can be supplied by different sources.

3) CHARGING MODEL

The total available energy is finite and equal to the charger's battery capacity C. Let $E_{\text{charger}}(t)$ denote the energy of the charger at the beginning of round t.

As described above, the charging range defines a circle and all nodes that are travel through it are being recharged, if the charger has the required amount of energy. Let $f_i(t)$ and $\ell_i(t)$ be the first and last position of agent i in range. These may or may not be defined depending on whether the agent travels or not through $\mathcal{C}_{R(t)}$. Hence, the time that agent i spends in range is

$$T_i^{\text{in}}(t) = \begin{cases} \dfrac{||f_i(t) - \ell_i(t)||_2}{v_i(t)}, & \text{if } f_i(t) \neq \ell_i(t),\ v_i(t) \neq 0 \\ \tau, & \text{if } f_i(t) = \ell_i(t),\ v_i(t) = 0 \\ 0, & \text{otherwise.} \end{cases}$$

We assume that agent i receives energy according to a simplified version of the scalar model. In particular,

$$E_i^r(t) = \frac{\alpha \cdot R(t)^2 \cdot T_i^{\text{in}}(t)}{(||p_{\text{charger}} - f_i(t)||_2 + \beta)^2}, \tag{24}$$

where α and β are environmental and technological constants. The energy of agent i at the beginning of the next round (taking into account both energy consumption and possible recharging), is

$$E_i(t+1) := \min\left\{B, \max\{0, E_i(t) - E_i^c(t) + E_i^r(t)\right\}\}.$$

In parallel, the energy of the charger is decreased accordingly.

C. OPTIMIZATION PROBLEMS

We now discuss two simplified offline optimization problems with different objective goals: the number of charges performed by the charger, and the number of rounds during which the network is active.

1) MAXIMIZING THE NUMBER OF CHARGES

In this problem, all information about the movement and energy consumption characteristics of the agents during all rounds $t \in [T]$ is given as input, where T is a given *finite* time horizon. Moreover, the charger has initial energy C and we can choose its charging range from a set of k distinct values $\{R_1, ..., R_k\}$ such that $0 \leq R_1 < ... < R_k$. All non-fully charged agents in the specified charging range receive energy according to equation (24) with $\alpha = 1$ and $\beta = 0$. The goal is to set the range $R(t)$ of the charger, for every $t \in [T]$, to maximize the total number of recharges until the charger is left out of energy.

Theorem 4: The MAXIMIZING THE NUMBER OF CHARGES problem is NP-hard.

2) MAXIMIZING THE NETWORK LIFETIME

In this optimization problem the goal is to maximize the network lifetime. In particular, we are given all movement and energy consumption characteristics of the agents, during a time horizon T. The charger has initial energy C and its charging range is selected from a set of k distinct values $\{R_1, ..., R_k\}$ such that $0 \leq R_1 < ... < R_k$. All non-fully charged agents in the specified charging range receive energy according to equation (24) with $\alpha = 1$ and $\beta = 0$. The goal is to set the range $R(t)$ of the charger, for every $t \in [T]$, to maximize the total rounds during which there exists at least one agent with strictly positive energy.

Theorem 5: The MAXIMIZING THE NETWORK LIFETIME problem is NP-hard.

D. ADAPTIVE ALGORITHMS

We now present three adaptive algorithms, which differ on the knowledge they require in order to select the appropriate charging range during any round t. In particular, the first one only uses information about the positions of the agents at the beginning of each round. The second one needs extra

information about the positions both at the beginning and at the end of each round, as well as the energy levels of the agents at the beginning of each round. Finally, the third algorithm uses all information about the positions and the energy levels of all agents at the beginning and at the end of each round.

a: LEAST DISTANT AGENT OR MAXIMUM RANGE (LdMax)

At the beginning of each roung t, the LdMax algorithm sets

$$R(t) := \max\{R_{\min}, \min_{i:p_i(t)\in\mathcal{C}_{R_{\max}}} ||p_{\text{charger}} - p_i(t)||_2\}$$

with some probability $q \in [0, 1]$, and $R(t) := R_{\max}$ otherwise (with probability $1 - q$).

b: MAINTAIN WORKING AGENTS (MWA)

The MWA algorithm uses a parameter $\mu \in [n]$ and, for each round t, sets $R(t)$ in order to guarantee that there are at least μ agents that either have positive energy at the beginning of the round or get recharged during it, called working agents. To compute $R(t)$ it first counts the number $k_1(t)$ of agents that are in the circle $\mathcal{C}_{R_{\max}}$ and have positive energy at the beginning of the round. If $k_1(t) \geq \mu$, then $R(t) := R_{\min}$. Otherwise, it counts the number $k_2(t)$ of agents with zero energy at the beginning of the round and either $p_i(t) \in \mathcal{C}_{R_{\max}}$ or $p_i(t+1) \in \mathcal{C}_{R_{\max}}$. If $k_1(t)+k_2(t) < \mu$, then $R(t) := R_{\max}$. Otherwise, it it sets $R(t) := R^*$, where R^* is the smallest range value such that $\mathcal{C}_{R^*}$ covers at least $\mu - k_1(t)$ agents.

c: MAXIMIZE CHARGES OVER ENERGY RATIO (MCER)

Let $\mathcal{R}$ be a set of range values in $[R_{\min}, R_{\max}]$. Let $\nu_j(t)$ be the number of agents that would get recharged if the charger had range equal to $R_j \in \mathcal{R}$ during round t, and let $\varepsilon_j(t)$ be the total given energy in this case. The MCER algorithm uses a parameter $\lambda \geq 1$ and sets

$$R(t) := \arg\max_{R_j\in\mathcal{R}} \frac{\nu_j(t)^\lambda}{\varepsilon_j(t)}.$$

Observe that MCER needs to perform many heavy computations as, in order to select the best possible range, it needs to simulate the whole recharging process repeatedly.

E. PERFORMANCE EVALUATION

1) SIMULATION SETUP

For evaluating the performance of the three described algorithms, we conducted simulations in Matlab R2016a. We consider a simulation setup with $n = 100$ agents that move around in a 25×25 network area. The charger is positioned at the center of the network area, has initial energy $C = 10^5$, and its range can take values in $[1, 5]$. Each agent has battery $B = 1000$, maximum velocity $v_{\max} = 3$. Also, the agents are randomly partitioned into 4 groups, namely, (S_1, S_2, S_3, S_4) of expected sizes $\left(\frac{n}{2}, \frac{n}{4}, \frac{n}{8}, \frac{n}{8}\right)$. Then, agent i consumes energy following a poisson distribution with randomly chosen expected value γ_i such that

$$\gamma_i \in [0, 10 \cdot 2^{j-1}] \quad \text{if } i \in S_j. \tag{25}$$

We remark that the expected values are chosen non-uniformly from the corresponding intervals so that there is heterogeneous energy consumption among the agents.

For the mobility behavior of the agents we consider three different randomized scenarios:

(S1) All agents randomly move around in the network area.
(S2) Choose $R \in [R_{\min}, \frac{1}{2}R_{\max}]$ uniformly at random do not allow the agents to enter circle $\mathcal{C}_R$.
(S3) Choose $\delta \in \left[\lfloor \frac{n}{10} \rfloor\right]$, $R_\ell \in \left[R_{\min}, \frac{1}{4}(R_{\min} + R_{\max})\right)$ and $R_h \in \left[\frac{1}{4}(R_{\min} + R_{\max}), R_{\max}\right]$ uniformly at random. Then, choose δ agents to move around only within the ring $\mathcal{C}_{R_h} \setminus \mathcal{C}_{R_\ell}$, while the remaining $(n - \delta)$ agents randomly move around in the whole network area.

For statistical smoothness, we repeated our simulation 100 times, and in each of them we equiprobably selected a different scenario (from the ones described above). Due to the many different random choices that have to be made, many different instantiations can arise.

2) SIMULATION RESULTS

After extensive fine-tuning of the parameters used by our adaptive algorithms, we have concluded that setting $q = 0.9$, $\mu = 15$ and $\lambda = 2$ are the best values for the particular simulation setup that we consider here.

Figure 11 depicts the performance of the adaptive algorithms as well as that of the fixed $R_{\max}$ value algorithm over time, with respect to various metrics: the charging range (Figure 11a); the charger's energy (Figure 11b); the number of charges (Figure 11c); the number of working agents (Figure 11d); the number of agents with adequate energy (Figure 11e); the charging frequency of the agents (Figure 11f).

We will present a brief analysis on how MWA and MCER respond to the behavior of the agents by inspecting Figure 11a which displays the evolution of the charging range over time depending on the algorithm. As observed, during the early rounds, most of the agents are considered working because they are initially fully charged. Thus, the MWA algorithm's requirement of maintaining 15 working agents is trivially satisfied and it selects the minimum charging range. In parallel, as shown in Figure 11b it has high amount of energy stored for future rounds. In contrast, MCER initially chooses a higher charging range such that to perform more charges while giving away little energy because agents already have energy supplies due to initial charging. However, as the time progresses, the agents spend energy and thus their energy level drops. This means that they need to be recharged higher amount of energy. As a result, MWA is forced to increase the range in order to keep satisfying the requirement of maintaining 15 working agents, while MCER decreases its range as the cost per charge has increased substantially.

VII. FUTURE CHALLENGES

As wireless technology pervades everyday life, users are somehow skeptical about the potential consequences of using

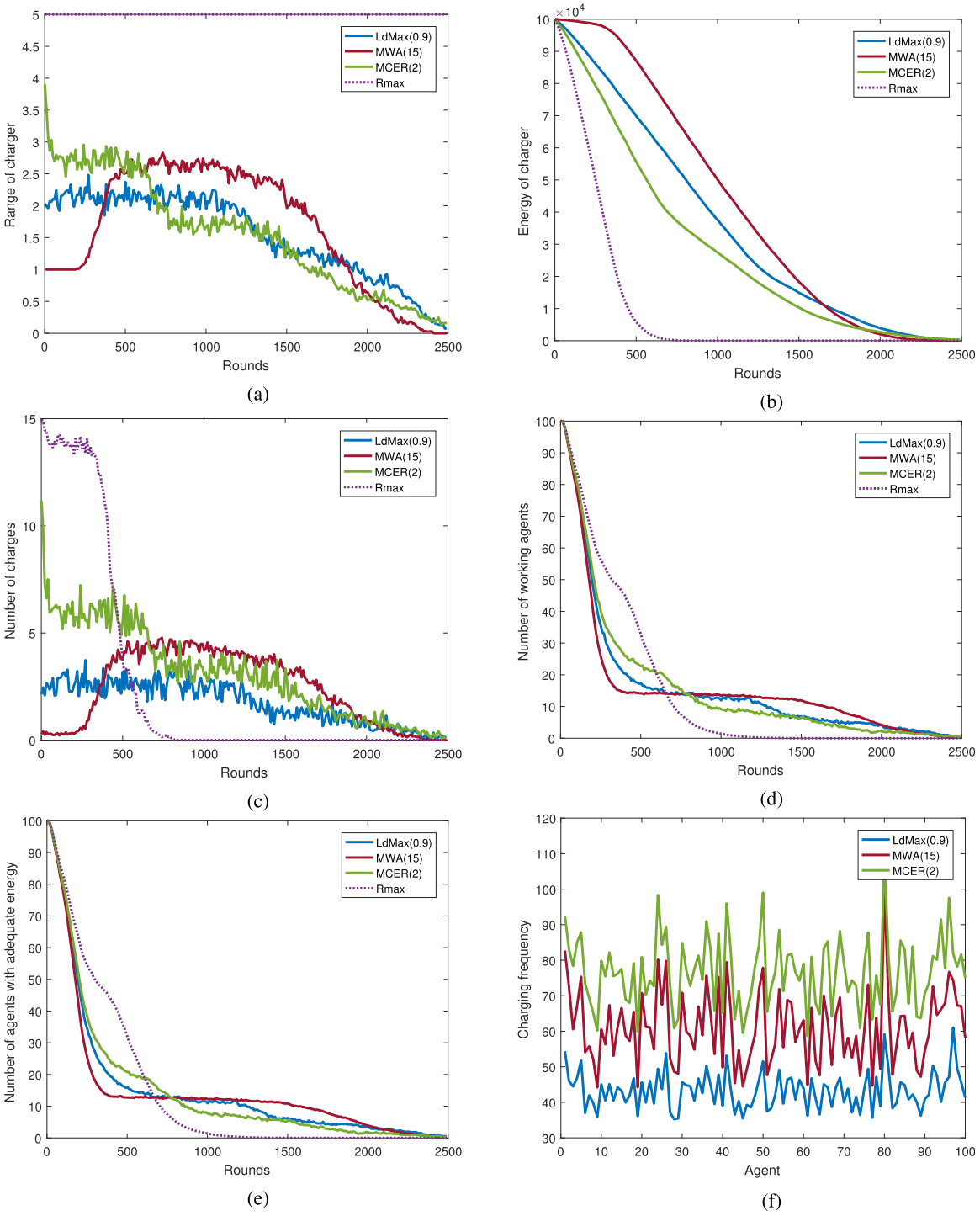


FIGURE 11. Comparison between the three adaptive algorithms LdMax(0.9), MWA(15), MCER(2), and the fixed R_{max} value algorithm. Figure (a) depicts the evolution of the charging range over time. Figure (b) depicts the decrease of the charger's energy. Figure (c) depicts the number of charges that were performed. Figure (d) depicts the number of working agents. Figure (e) depicts the number of agents with adequate energy. Figure (f) depicts the charging frequency of the agents.

WPT technology, such as electromagnetic radiation. There are recent studies that have previously addressed this subject in a very explicit, inefficient and inconvenient way, but now, new possibilities and intuition are emerging through more precise abstractions, such as the vector model, towards establishing safe and efficient wireless charging.

In this direction, a recent work [29] studies the problem of finding a safe, radiation-aware path. In particular, the concept

is the following; given a starting point and a point of termination, find the path that a moving agent should follow, with the smallest exposure to electromagnetic radiation. Regarding the moving agent, mind that it could be a human being or even a nano-device sensitive to electromagnetic waves. Notice also that, rules like ''the further away you are from an electromagnetic radiation source, the less radiation you receive'' are not realistic (as we have shown above). This work is the first attempt for the radiation problem being studied under the vector model and provides interesting results. Therefore, our aim and vision is to further study radiation phenomena with greater precision, especially when they include the human factor.

Notice that the quality of service must go hand in hand with protection from electromagnetic radiation in such applications. Significant results and knowledge are expected from the study of the vector model for a number of problems in the field of wireless power transfer, that were previously studied based under a more basic, less precise model. At the same time, another aspect of this technology remains the provision of better services. The vector model also enables to study problems and find solutions and mechanisms that incur better results than most of the solutions proposed in the state-of-the-art.

Based on this, issues such as efficient placement of chargers and receivers become a new challenge for the field. Apart from geometry and topology matters, we may also address other problems such as scheduling the chargers operation time since, as we have seen, the functionality of one can affect the operation of another at a point of interest.

Finally, vector model enables a set of technologies that are not inherently related to wireless charging, such as phase shifting. Even though the technology for phase shifting already exists, yet it could not adapt to the wireless technology in order to exploit the new opportunities that arise. As a result, not enough work has been done in this direction. In our view, the vector model can implement such a technology, like phase shifting, and achieve both efficient control of power and radiation distribution in a system, as well as energy balance. Hence, effective power management can be studied and discussed under a new basis compatible with the vector model.

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