Characteristic Models and Algorithmic Methods for Efficient Electromagnetic Radiation Control in Wirelessly Powered Adhoc Communication Networks

Gabriel Filios
Computer Technology Institute and Press "Diophantus" (CTI) & University of Patras
Patras, Greece
filiosg@ceid.upatras.gr

Adelina Madhja
Department of Computer Engineering and Informatics, University of Patras
Patras, Greece
madia@ceid.upatras.gr

Sotiris Nikoletseas
Computer Technology Institute and Press "Diophantus" (CTI) & University of Patras
Patras, Greece
nikole@cti.gr

Christoforos Raptopoulos
Computer Technology Institute and Press "Diophantus" (CTI) & University of Patras
Patras, Greece
raptopox@ceid.upatras.gr

***Abstract*—This papers investigates the effective control of electromagnetic radiation (EMR) in wireless adhoc communication networks. In particular, we focus on networks with wireless provision of energy, via the emerging technology of wireless power transfer (WPT). Our aim is to propose algorithmic methods towards optimizing the trade-off among the (potentially high) radiation levels in the network and the efficiency of power transfer.**

After formally defining EMR and relevant performance metrics, we critically discuss selected abstract radiation models (such as a well-studied scalar model) and identify their strengths and limitations. In particular, we highlight a recent vectorial representation of wireless power, which allows a very precise management of radiation, as well as a peer to peer model of wireless power exchange with negligible radiation levels. Under these models, we present selected algorithmic methods and heuristics for effective radiation control, such as adaptive schemes for charger configuration in highly mobile systems, the precise phase management of the wireless power waves and the evaluation and handling of overlaps in the wireless power transmission.

I. Introduction

Effective energy management plays a fundamental role in rapidly evolving, power-critical wireless distributed systems and ad hoc wireless communication networks. However, the characteristic constraints and limitations of involved nodes (in terms of their form, size and cost) makes the efficient provisioning of energy a quite challenging task, with important consequences to crucial operational issues, such as the network lifetime and fault-tolerance, as well as the quality of service enjoyed by the network system users. In parallel, the rapidly evolving Wireless Power Transfer (WPT) technology offers new opportunities for convenient energy provisioning in modern wireless systems. Ongoing research and development is anticipating novel network models employing such technologies. In an abstract way, a WPT system includes two kinds of nodes: one (or more) wireless transmitter(s) equipped with a large pool of energy that transfers power in the network area via RF signals, and several receiver nodes equipped with an antenna that enables the energy harvesting from RF signals transmitted by the transmitters.

Despite significant technological process, the full potential and associated critical consequences of WPT in adhoc wireless communication systems have not been properly explored. A primary issue of concern is the fact that WPT introduces additional, potentially very strong sources of electromagnetic radiation (EMR) on top of several other wireless technologies that have been used extensively, such as Wi-Fi, Bluetooth, cellular etc. Uncontrolled exposure to high EMR may have important impact to human health. Thus, it is critical to understand and control EMR levels, without however sacrificing the quality of wireless communications offered to users. In this respect, our aim is to propose adaptive systems towards guaranteed, optimized trade-offs among radiation awareness and energy provisioning.

We address the emerging aspect of effective control of electromagnetic radiation (EMR) in wireless communication networks. Particularly, we focus on adhoc communication networks in which energy is provided by wireless power transfer (WPT) technology. Our overall aim is to investigate suitable formal models and to propose efficient methods for controlling EMR while at the same time achieving satisfactory

QoS levels offered to the users as well as high provisioning of power to the network. To this end, we first provide rigorous definitions and key performance metrics for EMR in wireless communication networks. In particular, we focus on wirelessly powered adhoc networks and examine the suitability and effectiveness of different WPT models for EMR control.

For the classic scalar model of wireless power (based on the well-known Friis equation), we discuss its strengths and limitations. Under this model, we propose an EMR control method for high, diverse node mobility, basically employing a dynamic, online adaptation of the charger's wireless range, in contrast to the usual fixed changing range which may incur unnecessarily high levels of radiation. Also, we present a novel method of peer-to-peer wireless power exchange among the network nodes, which does not necessitate any central charger stations, thus minimizing radiation to negligible levels.

Then we recommend a major modeling shift, via a vectorial representation of wireless power waves, enabling a much more precise handling of radiation, by effectively exploiting some non-trivial phenomena of cumulative as well as cancellative power reception. Such modelling allows us to provide effective algorithms which lead to satisfactory trade-offs among the efficiency of wireless power provision and the incurred radiation levels. Key ingredients of our algorithmic methods include a fine-tuned phase-configuration of the wireless signals as well as methods for modeling and controlling signal overlaps when studying the problem of choosing a low level radiation path for a mobile entity traversing the network area.

II. Formal Definition of Radiation

Consider a Wireless Communication Network $\mathcal{N}$ consisting of m *wireless chargers* (wireless power transmitters/devices) that operate within an area $\mathcal{A}$ (e.g. $\mathcal{A} \subseteq \mathbb{R}^2$). Due to the operation of the wireless chargers, 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 II.1. *Electromagnetic Radiation (EMR)*: Let $P_{\mathcal{N},\mathbf{x}}(t)$ denote the power caused by a network $\mathcal{N}$ of wireless devices to a point $\mathbf{x}$ within its area of deployment at time t. The Electromagnetic Radiation $\mathbf{x}$ is exposed to at t is

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

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 time. This assumption is crucial for some of the problems we study in this paper, since radiation is measured with respect to a moving individual (and thus its relative distance from power sources changes with time). We also note that, in the above definition $R_{\mathcal{N},\mathbf{x}}(t)$ 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 integrate as follows

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

Path radiation. The above definitions can be extended for trajectories within $\mathcal{A}$ traversed by an individual with *constant speed*: let $\mathcal{W}$ be a (finite, connected) route within $\mathcal{A}$. Denote by $\mathcal{W}[\tau_1,\tau_2]$ the part of $\mathcal{W}$ that the individual traverses from time τ_1 and τ_2 and let $\mathcal{W}_t$ be the location of the individual at t. The *path radiation that the individual walking on $\mathcal{W}$ is exposed to during* $[\tau_1,\tau_2]$ is

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

Observe that, by Definition II.1, in order to get a precise mathematical formula for $R_{\mathcal{N},\mathbf{x}}$, a precise mathematical formula for the power $P_{\mathcal{N},\mathbf{x}}$ is necessary. There are two prevalent approaches in the literature, which roughly correspond to *macroscopic* and *microscopic* study of electromagnetism.

A. The scalar model

In the scalar mode, we assume 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 (with respect to t) and equals

$$P_{u,\mathbf{x}}(t) = \frac{a \cdot r_u^2}{(1+\text{dist}(u,\mathbf{x}))^2}, \tag{4}$$

where r_u expresses the (unchanging) *operation level* of u, a is a constant determined by the environment and the hardware settings of u, and $\text{dist}(u,\mathbf{x})$ is the Euclidean distance between the position of u at t and point $\mathbf{x}$. Up to constant multipliers, equation (4) 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. We mention here that, in some cases studied 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. Furthermore, some authors use a cut-off bound D, meaning that the power created by u becomes 0 for points further than D from u.

The crucial assumption in the scalar model, which makes it easier to analyze 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

$$P_{\mathcal{S},\mathbf{x}}(t) = \sum_{u\in\mathcal{S}} P_{u,\mathbf{x}}(t). \tag{5}$$

Consequently, applying Definition II.1, the cumulative electromagnetic radiation $\mathbf{x}$ is exposed to at time t because of $\mathcal{N}$ is

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

We note that, even though the additive power assumption above may appear to be naive at first sight, nevertheless it provides quite good approximations, especially when distances

between wireless devices of the network and points of interest $\mathbf{x}$ are large compared to the wavelength of the electromagnetic wave generated by each wireless device (alternatively, the inverse of the frequency of operation of chargers). This is the reason why the scalar model can be used effectively in "macroscopic" studies studies of radiation.

B. The vector model

The vector model is a generalization of the single-dimensional scalar model and Friis' formula and provides a more detailed abstraction for the study of electromagnetic radiation. However, the latter comes at the cost of increased analytical difficulty compared to that of the scalar model. In particular, in the vector model, the *electric field* generated by a wireless device u, at some point $\mathbf{x}$ is a *2-dimensional vector* given by

$$\begin{aligned}\mathbf{E}_{u,\mathbf{x}} &\stackrel{\text{def}}{=} \beta \cdot \frac{1}{\text{dist}(u,\mathbf{x})} \cdot e^{-j\frac{2\pi}{\lambda}\text{dist}(u,\mathbf{x})} \\ &= \beta \cdot \frac{1}{d} \cdot \begin{bmatrix} \cos\left(\frac{2\pi}{\lambda}\text{dist}(u,\mathbf{x})\right) \\ -\sin\left(\frac{2\pi}{\lambda}\text{dist}(u,\mathbf{x})\right) \end{bmatrix}, \end{aligned} \quad (7)$$

where $\frac{1}{\lambda}$ equals the charger's frequency of operation, and β is a parameter that depending on the environment and on the hardware of the charger.[1]

The crucial assumption in the vector model, that distinguishes it from other, less realistic models, is that the following: the cumulative electric field generated by an entire wireless network $\mathcal{N}$ at some point $\mathbf{x}$ is the *vector-sum* of the individual electric fields vectors for all chargers in $\mathcal{N}$, that is

$$\mathbf{E}_{\mathcal{N},\mathbf{x}} \stackrel{\text{def}}{=} \sum_{\mathbf{u}\in\mathcal{N}} \mathbf{E}_{u,\mathbf{x}}. \quad (8)$$

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

$$P_{\mathcal{N},\mathbf{x}} = \delta \cdot \|\mathbf{E}_{\mathcal{N},\mathbf{x}}\|^2, \quad (9)$$

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. Observe that, by the above formulae, additivity holds for electric fields and, therefore, it does not hold for power.

It has been proved (both theoretically and experimentally) that the vector model is able to capture phenomena like the superposition of electromagnetic waves, which was not possible with other, single dimensional models (including the scalar model). In particular, cases of constructive (super-additive effect) and destructive (cancellation effect) interference have been successfully observed and studied using the vector model [2]–[4]. A simple example where we can observe the super-additive and cancellation effects is the following: To avoid tedious numerical calculations, without loss of generality we will set $\lambda = \beta = \gamma = 1$. Assume a network consisting of two wireless chargers C_1, C_2 placed so that their distance is 2; say for example that we place them at points 0 and 2 of the 1-dimensional line. We will consider two receivers R, R', the first one placed at the mid-point of the line segment connecting the two chargers (i.e. at point 1) and the second one placed at point 5/4. When only one of the two transmitters is operational, the power received by R is $P(C_1,R) = P(C_2,R) = \|\mathbf{E}(C_1,R)\|^2 = \|\mathbf{E}(C_2,R)\|^2 = \left(\frac{1}{\text{dist}(C_1,R)}\right)^2 = 1$. On the other hand, if both transmitters are operational, the power received by R is given by equation (8), that is $P(\{C_1,C_2\},R) = \|\mathbf{E}(C_1,R) + \mathbf{E}(C_2,R)\|^2$. Furthermore, since R is equidistant from either C_1 or C_2, the vectors $\mathbf{E}(C_1,R)$ and $\mathbf{E}(C_2,R)$ point to the same direction. Therefore, $P(\{C_1,C_2\},R) = 4P(C_1,R) = 2(P(C_1,R) + P(C_2,R)) = 4$, and we have the super-additive effect; in particular, the power received by R when both transmitters are operational is larger than the sum of the powers it receives when only one of the transmitters is operational (the latter being equal to 2). On the other hand, for receiver R', we have $\mathbf{E}(C_1,R') = \frac{4}{5}\cdot\begin{bmatrix}0\\1\end{bmatrix}$, and also $\mathbf{E}(C_2,R') = \frac{4}{3}\cdot\begin{bmatrix}0\\-1\end{bmatrix}$. By equation (8), the power received by R' when both transmitters are operational is $P(\{C_1,C_2\},R') = \left(\frac{8}{15}\right)^2 \approx 0.28$, which is much less than $\min\{P(C_1,R'),P(C_2,R')\} = \left(\frac{4}{5}\right)^2 \approx 0.64$; this is the so-called cancellation effect.

An additional deployment constraint. Upon closer inspection of equation (7), we notice that, the length of the vector of the electromagnetic field becomes arbitrarily large when we consider points $\mathbf{x}$ very close to u. In the scalar, 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 reason behind the above issue is that equation (7) only holds for points $\mathbf{x}$ for which $\text{dist}(u,\mathbf{x}) \geq \lambda$; 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, for most wireless devices, λ does not exceed a few centimeters, and thus the latter deployment constraints are not too restrictive.

III. Peer-to-Peer wireless power transfer

Peer to peer wireless power transfer is a recently proposed method that achieves an almost zero level radiation, emitted due to the corresponding wireless power transfer. In this new method, it is no longer required any special network entity with high energy supplies (i.e. the charger) that is responsible for recharging the network devices. In contrast, the network devices themselves, are responsible for charging each other (in a peer-to-peer manner). This charging takes

[1] The detailed formula given in [1] 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.

place when two devices come to close proximity, and interact to exchange energy (if required) and also, exchange other network information. In this model, the devices transfer energy over very small distances (and at specific direction) and thus, the corresponding EMR is almost nullified.

In this subsection we will focus on distributed networks which consist of computationally weak devices that should distributively form a star network structure and converge to a targeted energy distribution.

A. Problem

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. $\binom{m}{2}$ edges.

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:

$$\delta_t^s(\mathbb{G}, G(t)) \stackrel{def}{=} \min_{G \sim G(t)} H(\mathbb{G}, G), \tag{10}$$

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 [5], [6]. 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:

$$\delta_t^e(\mathbb{E}, \mathcal{E}(t)) \stackrel{def}{=} \min_{\sigma \in S_m} \frac{1}{2} \sum_{i=1}^{m} |\mathbb{E}_i - \mathcal{E}_{\sigma(u_i)}(t)|, \tag{11}$$

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

Definition III.1. *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) $E_{loss} = \sum_u E_u(0) - \sum_u E_u(t) \leq \theta$.

As described above, our goal is to construct a star network where one agent should become the central node and all other should become peripherals. In addition, all peripheral nodes should be connected to solely one node, the central one. In star networks, all information generated by the nodes is forwarded to the central node and thus, its energy consumption is much higher. Motivated by this, the proposed energy distribution defines that 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 $\frac{E_{total}(t)}{2(m-1)}$.

B. Interaction Protocols

In this subsection we will provide a description of two interaction protocols that achieve the star network structure and try to converge to the targeted energy distributions. These protocols are designed for devices with extremely low computational power and memory and thus, we minimize the required power, while maintaining high performance.

In this model, there is a probabilistic scheduler that selects at each time, a pair of nodes to interact. At each interaction, the corresponding nodes can update their state (central/peripheral), modify the values on their registers, add/remove the connection between them and exchange energy. In both protocols, the set of possible states of each agent is $\mathcal{Q} = \{c, p\}$.

Full Transfer Protocol: This protocol assumes that 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.

- *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.
- *Both agents are peripherals:* If a connection exists between them, it is removed.
- *One agent is peripheral and the other one is central:* If there is no connection between them, it is established.

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 achieves to both create the star and converge to an energy distribution in a quite small number of steps. The main interaction cases are the following.

- *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.
- *Both agents are peripherals:* If a connection exists between them, it is removed.
- *One agent is peripheral and the other one is central:* If there is no connection between them, it is established.

IV. Adaptive wireless power transfer

Another method that has been recently proposed in [7], is to select a different charging range for the charger at any time, adaptively to network devices characteristics. This method, aims to reduce the emitted EMR due to wireless power transfer while maintaining a high quality of service. This method can be applied 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 use (and prolong the network lifetime) and reduce the emitted radiation while in parallel, the network is operational with a high QoS.

Prior to this novel charging method, authors in [8] had studied a variation, where the power of each charger can be adjusted just once at the beginning of time and it can be different compared to other chargers. Also, in [9] authors investigated the low radiation efficient wireless charging problem as well, but 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). Observe that since the agents are static in both models considered in [8], [9] each charger adjusts its power only once, at the beginning of the time horizon. In contrast, in the method that we present here, the charging power changes constantly over time, adaptively to the behavior of the mobile agents which is revealed in an online manner.

A. Model

The 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. The mobile agents perform a random walk. More specifically, at each round, they change their positions by randomly selecting a new velocity and direction. In contrast, the static charger, at each round, changes its charging power, indicating a different charging range. Each charging range value defines a circle of radius equal to charging range, around of the position of the charger. At each time, all agents that pass through the circle that is defined based on the current charging range, can get recharged (if they need to).

Regarding the energy model, agents consume energy for communication purposes. Following previous work (e.g., [10]), the energy consumption follows a Poisson probability distribution with expected value $\gamma_i \in [\gamma^i_{\min}, \gamma^i_{\max}]$.

In this model, the total available energy is finite, which necessitates even more its careful management. Regarding the charging model, each agent receives energy according to a simplified version of the well-known Friis transmission equation. In particular, at time t, each agent i receives an amount of energy equal to:

$$E^r_i(t) = \frac{\alpha \cdot R(t)^2 \cdot T^{\text{in}}_i(t)}{(||p_{\text{charger}} - f_i(t)||_2 + \beta)^2}, \tag{12}$$

where α and β are environmental and technological constants, p_{charger} is the position of the charger, $R(t)$ is the charging range at time t, $f_i(t)$ is the first position where agent i gets inside the circle and gets recharged. Finally, $T^{\text{in}}_i(t)$ is the time that agent i spends in range and is estimated as follows:

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

where $\ell_i(t)$ is the least position of the agent inside the range and $v_i(t)$ is the selected velocity of agent i at time t.

B. Optimization Problems

In the subsections below we will define two simplified offline optimization problems with different objective goals. The hardness of these problems is only indicative of the hardness of the actual online multi-objective problem.

Maximizing the Number of Charges (MNC): 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 (12) 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.

Maximizing the Network Lifetime (MNL): 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 (12) 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 1. *The* MNC *problem and the* MNL *problem are NP-hard.*

The interested readers may find the proofs of both theorems in [7] which use reduction from KNAPSACK [11].

C. 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.

Least Distant Agent or Maximum Range (LdMax): At the beginning of each round t, the LdMax algorithm sets the range equal to

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

with some probability $q \in [0, 1]$, and $R(t) := R_{\max}$ otherwise (with probability $1 - q$), where $p_i(t)$ is the current position

of agent i, $R_{\min}$ and $R_{\max}$ are the minimum and maximum charging ranges (based on minimum an maximum transmission power of the charger) and $\mathcal{C}_{R_{\max}}$ is the circle of maximum range. The goal is to capture worst case scenarios, where no agent get close to charger. This algorithm, requires knowledge only about the positions of the agents.

Maintain Working Agents (MWA): The MWA algorithm uses a parameter $\mu \in [n]$ and, for each round, sets the charging range appropriately 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. MWA requires knowledge about the positions of the agents and the energy level of the agents.

Maximize Charges over Energy Ratio (MCER): Let $\mathcal{R}$ be a set of charging ranges in $[R_{\min}, R_{\max}]$. Let $\nu_j(t)$ be the number of agents that would get recharged if the charger had selected a charging 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 the charging range as follows:

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

Note that MCER has to simulate the entire charging process at each round in order to select the appropriate charging range.

V. Minimizing Path Radiation

In this section, we wish to briefly highlight the first study [12] (and the only one so far) for electromagnetic radiation concept in WPT networks, with respect to vector model. So far, the use of the vector model has shown significant and intriguing results. We below provide the problem definition and the different approaches to address it.

Definition V.1. *The Minimum Radiation Path Problem:* Given a set of chargers $\mathcal{C}$ and a mobile entity *r* that wants to move from point *S* to point *T*, find a route *P* from *S* to *T* that minimizes the radiation exposure of *r* during its travel with respect to travel distance.

We assume that the moving entity can travel at least λ distance from a charger. In a different case, it receives high level of radiation which does not comply with this model as it has also been presented in [13].

Hence, two algorithms are presented for this problem. For the first one (*Surf*), the mobile entity interacts with the inside a communication radius and exchange information regarding the chargers' position. The algorithm aims to find the points that have low radiation levels, and at the same time drive the mobile entity to the target end point. The second, offline algorithm (*Graph*), has a global view of the radiation pattern inside the area and creates a graph containing low radiation points as vertices and weighted edges depending on the radiation and length. Finally, it succeeds in proposing a low radiation route, by using a shortest path algorithm.

A. Algorithms

Different patterns and intensity of power or radiation can be formed depending on both the number and the topology of the chargers. It is evident that there are points close to the transmitters where power drops due to the destructive interference, while instead there are points at distance of transmitters which show high harvested power owing to the constructive interference. Thus, our algorithm *SURF*, tries to catch a "low radiation wave" and drive the mobile agent at his destination through it.

***Surf* Algorithm:** The algorithm's main target is to provide those positions where destructive effects take place and include them in the mobile agent's travel. In the case of two transmitters, these positions have the property that the absolute difference of their distances to the two transmitters is an odd multiple of $\lambda/4$. That means that they are part of the conic section of hyperbola. If c is half the distance between two chargers, $n = \left\lfloor \frac{c}{\lambda/2} \right\rfloor$ is the number of hyperbolas formed between them. The foci of these hyperbolas are the positions of the two chargers and their center is in the middle of the line segment formed by the chargers. The vertices are placed, on the same line segment, at distance a_k from the center equal to odd multiples of $\lambda/4$. That means $a_k = k \cdot \lambda/4$, where $1 \leq k \leq n$.

The equation that describes them is as follows:

$$\frac{x_h^2}{a_k^2} - \frac{y_h^2}{b_k^2} = 1 \tag{13}$$

$$x_h = (x - x_{cen}) \cdot \cos\theta + (y - y_{cen}) \cdot \sin\theta$$

$$y_h = -(x - x_{cen}) \cdot \sin\theta + (y - y_{cen}) \cdot \cos\theta$$

where $\theta = atan2((y_{C_2} - y_{C_1}), (x_{C_2} - x_{C_1}))$, C_1 is the first charger, C_2 is the second charger, cen is the center and θ is the angle between C_1, C_2. With x_h and y_h we apply the rotation of the hyperbola by angle θ and the center modification. Note that $b_k = c^2 - a_k$.

Therefore, we aim to avoid the radiation caused by a couple of chargers each time. For more than two chargers, these hyperbolas are few and scattered on the plane as the pattern begins to have a bigger complexity.

In our algorithm we choose to use only the hyperbolas closest to the center of each pair of chargers ($k = 1$), in order to reduce complexity but also because their radiation is lower, as the distance from the power sources is higher.

Let x be our current position, which initially is at S. As long as x is not at the target point T, we iteratively perform the following. Firstly, we check the number of chargers inside agent's communication range at x and add them to a set $\mathcal{C}_x$.

If $\mathcal{C}_x$ is empty, we move one step towards T. If there is only one charger C_j in $\mathcal{C}_x$, we move on the circle with center the position of C_j and radius equal to a radius threshold (slightly smaller than the communication range). Then we check whether the distance of the new point to T is less than its distance to the center of the circle, and whether T is inside the circle. If so, we move to T. Lastly, given that the new point is on a tangent line to the circle that crosses T, and T is outside the circle, we move out of the circle.

In the case of two or more chargers in $\mathcal{C}_x$, we create each of the $\binom{N}{2}$ possible pairs of chargers. For every pair, we calculate the equation of their hyperbola. Then, we find the projection points of x to the hyperbola and choose the closest one to x. The distance between x and the chosen point is calculated ($distHypePos$). We do the same for T ($distHypeT$). Additionally, we take into consideration the mean distance of x to the two chargers ($distPos\_ij$). The pair with the smallest sum including these three parameters, that are multiplied by some weight constants (v, w, u respectively), is the pair we choose. That means, we select a pair that not only is near to our position but also traversing its hyperbola will bring us closer to T than other pairs' hyperbolas would. In case both chargers of a pair are over or below the line that connects x with T and their distance to this line is higher than $z = communication\ range/2$, we ignore them. If no pair is chosen, we walk one step towards T.

Let p be the selected pair and p_{old} be the previous pair chosen, providing that there is one. Let also, H_p and $H_{p_{old}}$ be their hyperbolas respectively. If we currently are on $H_{p_{old}}$ and want to move to H_p, we first check for intersection points between the two. If there are any, we check if their distance to the centers of $H_{p_{old}}$ and H_p is less than d (d is a parameter depending on the density of the network). If so, we move on $H_{p_{old}}$ until we find the closest one to our position. Then we make a step on H_p. Unless there are intersection points, we find the closest point, q, to our position on H_p, that is at distance equal to 1 to H_p's center (so that we don't walk on the pair of chargers). In the case p_{old} is empty, meaning we are not on a hyperbola, we move to the point q described above. Lastly, if p equals p_{old} we just make one more step on H_p towards T. Generally, every time we get onto a new hyperbola, we have to make enough steps on it, so we get past the two chargers. Unless that's true we do not search for a new pair, given we don't find new chargers at distance less than z. In addition, we have to notice that we only move on the branch of the hyperbola (each one has two branches) that we chose first.

After any of the described steps, we check whether the distance of the new point to T is less than 1. If so, we move straight to T.

***Graph* Algorithm:** This approach aims to create offline a graph $G = (V, E)$ in the following way. At first we tessellate the $x - y$ axis plane A into n^2 squares. Then, for every hyperbola H_k of the $\left\lfloor \frac{c}{\lambda/2} \right\rfloor$ (except the ones closest to the chargers) formed between each pair of chargers, we examine at which points they intersect with other hyperbolas. The vertex set V of the graph consists of these intersection points but also of points where the hyperbolas cross the limits of the plane. More formally, if H_l is one of the hyperbolas which intersects with H_k, and $H_k(x) = 0$, $H_l(x) = 0$ are the equations of the two hyperbolas, then the points p_{int} are the points described above. Given that, the vertex set is $V = \{p_{int} = (x_{int}, y_{int}) \mid ((H_k(x_{int}) = y_{int}) \cap (H_l(x_{int}) = y_{int})) \cup (x_{int} = startx \cup y_{int} = starty \cup x_{int} = stopx \cup y_{int} = stopy)\}$, where $startx$, $starty$, $stopx$ and $stopy$ are the limits of the plane.

For every hyperbola, we connect with edges all the vertices that belong to it, in order, from end to end, creating this way the edge set, E. With this method we save memory compared to other implementations, because the Vertex set contains only the intersection points between the hyperbolas and not all the points of the plane.

After the graph is created, the problem can be reduced to the problem of finding a minimum weight path between vertices S and T. If S or T are not on a vertex, we use the closest vertices to them and then move on a straight line to them. For each edge, we calculate the cumulative radiation r of the respective hyperbola's section and its length d. We use the linear combination of these quantities as edge weight. We adjust the weights properly in order to satisfy our constraints about radiation and distance. Then we apply Dijkstra's algorithm to find the shortest path.

VI. FUTURE PERSPECTIVES (PHASE MANAGEMENT OF WIRELESS WAVES)

Vector model enables a wide list of potential approaches for RF wireless charging research filed. The interest that it has as a model goes in hand with the inherent difficulty and complexity that appears when it is applied. Thus, researchers try to both set configurations and algorithms that make use of different parameters of the model to further achieve better performance, that previously was limited by one dimension approaches. This challenge can be addressed in two different ways. As you can see, the phase of the charger's power formula is affected by the distance parameter d to the receiving node. Calibrating accordingly either the chargers' or the nodes' positions can further improve our objectives. For the second approach we introduce initial phase, which similarly affects the phase configuration of the charger. In particular, as it appears in formula 14 we can move one step further and include the initial phase parameter since the model describes electromagnetic waves and follows general laws of physics science. Therefore, equation 7 can be rewritten as follows:

$$\mathbf{E}_{\phi_C}(C, R) \stackrel{\text{def}}{=} \beta \cdot \frac{1}{d} \cdot e^{-j\frac{2\pi}{\lambda}d + \phi_C} = \beta \cdot \frac{1}{d} \cdot \begin{bmatrix} \cos\left(\frac{2\pi}{\lambda}d + \phi_C\right) \\ -\sin\left(\frac{2\pi}{\lambda}d + \phi_C\right) \end{bmatrix}, \tag{14}$$

where ϕ_C corresponds to the initial phase of each charging device. Now, the non-linear superposition charging effect can be easily manipulated by configuring different values of ϕ_C. Thus, a more effective radiation management can take place,

and significantly increase power in a set of nodes, while for some others we can decrease radiation.

The aforementioned approach, concerning initial phase is currently in an early stage as it is introduced in WPT concept during the last two years. However, although in [14] the authors use initial phase in their formulation, it is not mainly used to solve the fast charging problem. On the other hand, in [15] we observe an effective but simple use of initial phase parameter by assigning a configuration alongside with a scheduling technique that aims to both prolong network lifetime and minimise charging time.

In general, the idea is that the charging entities can be coordinated in a such way that benefits specific nodes of interests. This chargers' cooperation can be dynamically and online be implemented so that different tasks can be achieved in a period of time. That includes either radiation or power needs, as well as energy balance issues that now seem to be more realistic to solve. Now, that we are not restricted by chargers or nodes positions we are closer to address even more efficiently energy or power balance.

Thus, we seek for more sophisticated solutions by taking into advantage initial phase parameter in the WPT paradigm. Such an approach is presented in [16], in which the authors present mechanisms that provide a near optimal configuration regarding the initial phase of the chargers. In particular, the authors consider the vector model for WPT adapted to phase-shifting, where chargers are initiated at different times. They present a maximization problem, called PowerShift, for finding the phase shift configuration that maximizes the total power fueled in a WPT network at the set of the receivers.

Besides power and charging efficiency that initial phase can potentially offer, it supports the decoupling of power/radiation management from previous restrictions. For example, to reduce/increase electromagnetic radiation level in a point of interest either charger should reduce/increase its transmitting power or change position. Hence, initial phase configuration feature, further upgrades power management and control, for a list of WPT applications and problems.

VII. Conclusion

We studied the problem of how to efficiently control electromagnetic radiation in wirelessly powered communication networks. We provided a diverse set of algorithmic design approaches to fine-tune the trade-off among the level of radiation in the network area and the efficiency of wireless power provisioning. Our methods include the dynamic adaptation of the charging configuration under high mobility, the direct peer to peer wireless energy transfer, the delicate management of the phase of wireless waves and the management of wireless charging overlaps.

A key recommendation we wish to convey is the necessity to adopt a complementary set of abstract models for wireless power transfer, with different strengths and weaknesses each. In particular, we emphasize a recent vectorial model of wireless waves, towards a more accurate handling of radiation, and demonstrate how to best exploit its appealing features.

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References

[1] M. Y. Naderi, K. R. Chowdhury, and S. Basagni, "Wireless sensor networks with rf energy harvesting: Energy models and analysis," in *2015 IEEE Wireless Communications and Networking Conference (WCNC)*, March 2015, pp. 1494–1499.

[2] S. He, J. Chen, F. Jiang, D. Yau, G. Xing, and Y. Sun, "Energy provisioning in wireless rechargeable sensor networks," *Mobile Computing, IEEE Transactions on*, vol. 12, no. 10, pp. 1931–1942, Oct 2013.

[3] Y. Li, L. Fu, M. Chen, K. Chi, and Y. H. Zhu, "Rf-based charger placement for duty cycle guarantee in battery-free sensor networks," *IEEE Communications Letters*, vol. 19, no. 10, pp. 1802–1805, Oct 2015.

[4] M. Y. Naderi, K. R. Chowdhury, S. Basagni, W. Heinzelman, S. De, and S. Jana, "Experimental study of concurrent data and wireless energy transfer for sensor networks," in *2014 IEEE Global Communications Conference*, Dec 2014, pp. 2543–2549.

[5] D. Aldous and J. A. Fill, "Reversible markov chains and random walks on graphs," 2002.

[6] D. A. Levin, Y. Peres, and E. L. Wilmer, *Markov chains and mixing times*, 2006.

[7] A. Madhja, S. E. Nikoletseas, and A. A. Voudouris, "Mobility-aware, adaptive algorithms for wireless power transfer in ad hoc networks," in *Algorithms for Sensor Systems - 14th International Symposium on Algorithms and Experiments for Wireless Sensor Networks, ALGOSENSORS*, 2018, pp. 145–158.

[8] H. Dai, Y. Liu, G. Chen, X. Wu, T. He, A. X. Liu, and Y. Zhao, "SCAPE: safe charging with adjustable power," *IEEE/ACM Transactions on Networking*, vol. 26, no. 1, pp. 520–533, 2018.

[9] S. E. Nikoletseas, T. P. Raptis, and C. Raptopoulos, "Radiation-constrained algorithms for wireless energy transfer in ad hoc networks," *Computer Networks*, vol. 124, pp. 1–10, 2017.

[10] C. M. Angelopoulos, J. Buwaya, O. Evangelatos, and J. D. P. Rolim, "Traversal strategies for wireless power transfer in mobile ad-hoc networks," in *Proceedings of the 18th ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems (MSWiM)*, 2015, pp. 31–40.

[11] M. R. Garey and D. S. Johnson, *Computers and intractability: A guide to the theory of NP-completeness*. W. H. Freeman, 1979.

[12] I. Katsidimas, E. Kerimakis, and S. Nikoletseas, "Radiation aware mobility paths in wirelessly powered communication networks," in *2018 Global Information Infrastructure and Networking Symposium (GIIS)*.

[13] I. Katsidimas, S. Nikoletseas, T. P. Raptis, and C. Raptopoulos, "Efficient algorithms for power maximization in the vector model for wireless energy transfer," in *Proceedings of the 18th International Conference on Distributed Computing and Networking*. New York, NY, USA: ACM, 2017, pp. 30:1–30:10. [Online]. Available: http://doi.acm.org/10.1145/3007748.3007749

[14] P. Guo, X. Liu, S. Tang, and J. Cao, "Concurrently wireless charging sensor networks with efficient scheduling," *IEEE Transactions on Mobile Computing*, vol. 16, no. 9, pp. 2450–2463, Sep. 2017.

[15] Z. Ma, J. Wu, S. Zhang, and S. Lu, "Fast interference-aware scheduling of multiple wireless chargers," in *2018 IEEE 15th International Conference on Mobile Ad Hoc and Sensor Systems (MASS)*, Oct 2018, pp. 344–352.

[16] I. Katsidimas, S. Nikoletseas, and C. Raptopoulos, "Power efficient algorithms for wireless charging under phase shift in the vector model," in *15th International Conference on Distributed Computing in Sensor Systems (DCOSS), 2019*.