2019 15th International Conference on Distributed Computing in Sensor Systems (DCOSS)

Placement Optimization in Wireless Charging Systems under the Vector Model

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***Abstract*—This paper addresses the optimization of power provisioning in systems of wireless energy transfer. In this context, a vectorial representation of wireless waves recently becomes a precious tool; being more reliable and precise than one-dimensional models, it enables an increased potential for power maximization and control that before seemed impossible.**

We study the deployment of nodes and chargers for power maximization, for the first time under the vector model. In particular, we present both offline and approximation protocols and provide an evaluation of their performance. The main idea of our approach is to take advantage of the high precision offered by the vector model of WPT waves, in order to fine-tune the exact positioning of wireless chargers. The results of the conducted simulations demonstrate the advantages of our approaches in terms of power maximization; interestingly our findings suggest that even some slight optimization in the exact placement of chargers can significantly improved received power.

***Index Terms*—Wireless Power Transfer, Vector Model, Ad-hoc Wireless Networks, Charger Placement**

I. Introduction

In general, energy harvesting is a very relevant process to prolong the lifetime of wireless sensor networks and IoT systems and also achieve perpetual operation. However, energy scavenging techniques also enable limitations and restrictions in the sense that the system should be deployed in an area where enough ambient energy source is provided. Hence, it is essential to adopt technologies that can decouple the installation location of such systems and the efficiency level of the harvested energy. Recent technological advancements have made wireless power transfer technology one that can satisfy the above requirements. In particular, efficiency, form, range, permeability and safety are the main properties that need to be considered towards the implementation of a wireless charging application scenario.

While in the state of the art there is a list of potential wireless power transfer technologies, here we study the one that makes use of RF radiation for charging. Efficiency keys and performance issues for RF energy harvesting, include the power transmission from the sources, the wavelength of the RF signals as well as the distance between the energy source and harvesting device. Regarding the RF charging process, there are different approaches and concepts that might be adopted. Firstly, we can deploy strong dedicated chargers that transmit energy in an area of interest with receiving nodes that run a specific task. Under this approach (which is the one that this paper discusses) we are able to provide stable power without the fear that unpredictable events may occur. Such chargers are already commercial products [1] and are able to transmit RF energy with 1 W or 3 W Effective Isotropic Radiated Power (EIRP) over 915 MHz band. In addition, it is equipped with an 8 dBi 60 degree beam directional antenna and no configuration options are available. Secondly, energy can also be harvested from ambient RF sources, such as surrounding mobile devices, TV, radio towers etc. For example, a dual-band rectenna that covers 1.8 GHz and 2.2 GHz can achieve a $\sim 50\%$ conversion efficiency [2], while for the broadband rectennas case (which in general can obtain a relatively low conversion efficiency ($< 20\%$) over a wide frequency bandwidth from 2 GHz to 6 GHz) a higher than 60% conversion efficiency [3] has been achieved. Although ambient RF energy is not intended for harvesting devices, it can provide sustaining power supply without any deployment cost. On the other hand, the unpredictable nature of the RF sources due to mobility, time-varying power transfer and intermittent transmission makes the whole process stochastic. Lastly, wireless communication devices can act as RF sources to power their neighboring devices, and combine both communication and energy harvesting functionality. This concept has enabled a very active research area under the topic of Simultaneous Wireless Information and Power Transfer (SWIPT), which based on time division, aims to perform both processes in the most efficient way by sharing the same antenna.

Recently, we witnessed a twist of the research activity by studying the complementary problem of electromagnetic radiation in the wireless charging context, since there is an urgent need to introduce this element in the study of purely wireless charging problems. This is due to the limited potentiality offered by the scalar or one-dimensional model which does not provide any description about non trivial phenomena that

This work was supported by the General Secretariat for Research and Technology (GSRT), the Hellenic Foundation for Research and Innovation (HFRI) and the EU Horizon 2020 Safestrip project.

2325-2944/19/$31.00 ©2019 IEEE
DOI 10.1109/DCOSS.2019.00093

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appear when electromagnetic sources are deployed in the same area. On the other hand, and despite the increased complexity, vector model enables a wide list of interesting problems and applications. Vector model is a different approach of modeling wireless power transfer process which is initially presented in [2]. The beginning was made by paper [4], where the vector model was for the first time algorithmically studied. Promising and impressive results were presented, which have led more researchers to deal with this particular new subject. For those who are not familiar with this model, we briefly mention that it is based upon laws of physics that describe the superposition of electromagnetic fields created by independent wireless energy sources. Vector model goes beyond the one-dimensional abstraction suggested by Friis' formula for the power received by one antenna under idealized conditions given another antenna some distance away. In subsection III-B we provide all the appropriate details and analysis of the model.

Our contribution. Here we present the results of our work in an attempt of applying vector model in a placement concept for wireless power transfer systems. Thus, our work includes the following innovation items:

- This is the first work, to the best of our knowledge, that attempts to study deployment aspects in WPT with respect to the vector model [5], which is a new approach for power awareness in wireless settings.
- We provide an analysis about those hidden aspects and intuitions that arise regarding WPT placement problems.
- We design and propose algorithms and heuristics that solve the `PowerChargerPlacement` problem. In particular, our algorithms aim to fine-tune the exact positions of chargers so as to benefit of superadditive phenomena in received power, whose analysis is revealed by the accurate vectorial modelling of wireless waves.
- All the above approaches are evaluated through an extensive simulation process which demonstrates their performance properties. Interestingly, our findings imply that significant performance gains (in received power) are incurred, via carefully selecting the position of chargers; even a limited flexibility in charger positioning can introduce non-trivial performance.

Roadmap of the paper. The rest of this paper is organized as follows. Section II elaborates on the most recent related works in algorithmic approaches, designs and concepts. Our network and charging models are presented in Section III together with the problem definition. Section IV explains our algorithmic approach with the corresponding analysis and details. In Section V we present the outcomes of the evaluation of our design, while in the end we summarize the subject of the work and present our next steps for its further exploitation.

II. Related work

Research efforts in pure *Wireless Power Transfer* technology are mainly focused on topics such as exploitation of new more accurate models like vector model, study electromagnetic radiation as a WPT side effect, applications and implementations that include WPT etc.

Over the last two years, we have seen an intense activity in the use of new models in the field of wireless charging. Regarding the new model exploitation case, a subset of the authors ([5]) algorithmically study the *Power Maximization Problem* in WPT networks. In particular, solutions regarding the operational configuration of the chargers are proposed to maximize the total received power either by all the receivers or by a subset which is under-charged. They also present a formulation with respect to the vector model, as a quadratic program which succeeds in solving the above problems in the most efficient way. Then, other works also followed, such as [6], [7] and [8], with respect to the vector model. In particular, in [6] the authors present a novel use of the phase shift technique for a power maximization problem, while in [7] the authors formulate the concurrent charging scheduling problem (CCSP) with the objective that all the sensor nodes are quickly fully charged. Similarly, in the sense that a scheduling problem is considered, the authors in [8] study Fast Charging Scheduling problem (FCS), in which given a set of chargers and a set of devices, they examine how can the chargers be optimally scheduled over time to both minimize the total charging time and make sure that each receiver has at least a specific energy capacity. They prove that FCS is NP-complete and propose algorithms to solve the problem in 1D line and 2D plane respectively. In [9] wireless energy transfer scheduling is considered to minimize energy usage while meeting sensors' quality of service requirements in a network. The authors propose a distributed wireless charging scheduling to achieve the aforementioned objectives and evaluate it via a constrained stochastic game model to obtain a multi-policy constrained Nash equilibrium of wireless energy transfer request based on sensors' state. The recent work [10] studies the problem of finding a safe, radiation-aware path in a WPT network. In particular, given a start and end point, the objective is to find the path that a moving agent should travel, in order to achieve the least electromagnetic radiation exposure. This work is the first attempt that the radiation problem case has been studied under the vector model.

In [11] a comprehensive survey of the state-of-art techniques is presented, based on advances and open issues for simultaneous wireless information and power transfer (SWIPT) and WPT assisted technologies. More specifically, this paper identifies and provides a detailed description of various potential emerging technologies for the fifth generation communications with SWIPT/WPT. A unified theoretical approach is introduced in [12] that describes the wireless power transfer model either when the transmitter and the receiver are in the near-field or in the far-field region. Guidelines for the two configurations are discussed together with several practical examples, demonstrating predicted and experimental behavior of unconventional devices for both near-field and far-field power transfer usage. A simple adaptive 1-D frequency-scanning method is proposed in [13], for radiative wireless power transfer systems that fuel low-power wireless

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sensor networks. The authors show that using a frequency scanned antenna, a wider area than using a non-scanned directive antenna can be powered without additional expensive equipment. A protocol is described, showing that any sensor inside the network can potentially adjust to the optimum transmission channel in the 2.4-GHz band. This maximizes the WPT beaming efficiency and the transferred DC power. This procedure can perform periodically, which makes the system robust against channel state changes. In [14] the authors try to maintain energy balance for wireless-powered nodes when other ambient energy sources are unavailable, while in [15] an investigation is conducted regarding the practical realization of energy beamforming gains in the downlink wireless power transfer from a massive antenna radio frequency source to multiple single antenna energy harvesting users.

In [16] the problem of maximizing the transmitted wireless power to receivers subject to the safety constraints is considered. Particularly, a dual ascent-like distributed charging algorithm is introduced, where energy transmitters communicate only with the sensors in their power transmission range to obtain their measurements, perform simple computation steps to adjust their power levels and at the same time satisfy safety constraints by having local network knowledge. In [17], [18] the authors aim to maximize the wireless power transfer to remote devices, while maintaining a safe level of electromagnetic radiation (EMR) for humans that are in the vicinity of the energy transmitters. To address this problem in [17] they propose a self-adaptive charging system named TESSA that keeps the charging network safe even when it is perturbed by environmental dynamics. It's shown that TESSA can reach, on average, up to 85% of the theoretical optimal maximum total transmitted power (calculated using centralized solution) while satisfying the EMR safety constraints.

Concerning placement solutions, given a set of candidate locations for placing chargers, [19] finds a charger placement and a corresponding power allocation to maximize the charging quality of the network devices, subject to a power budget. In [21], given a number of heterogeneous rechargeable devices and chargers, distributed on a 2D plane where obstacles exist, the authors propose solutions to determine the chargers' positions and orientations, so that the rechargeable devices achieve maximized charging utility. In [22] a challenge of cooperatively deploying minimum number of chargers and sink stations in wireless rechargeable sensor networks has been addressed. Particularly, they try to minimize the total deployment cost of both chargers and sink stations and determine their locations from randomly deployed candidate sets, while sustaining the sensing and communication demands of each sensor node. In [23], the authors study a placement and radiation problem in which wireless charger placement scheme guarantees electromagnetic radiation safety for every location on the plane. [24] highlights the fact that only a few nodes can remarkably benefit from the transmitter power emission. Thus, they organize the nodes in clusters and propose an efficient localized algorithm as well as a centralized one to compute the charger position such that the cluster lifetime is maximized. Finally, [20] studies the problem of maximizing the power at certain points of the plane, using directional chargers.

III. Model and Problem Definition

A. Network Model

Our network is a typical wireless power network that consists of a set of chargers $\mathcal{C}$ and a set of receivers $\mathcal{R}$. An RF wireless charger is equipped with an omnidirectional antenna which generates a time-varying electromagnetic field, and transmits power uniformly for the horizontal plane to all directions across free space to potential receiver devices. Similarly, RF devices are equipped with omnidirectional antennas that receive RF signals and convert them to electricity. We deploy uniformly at random both the chargers and the devices. Regarding the chargers, each one of them defines a circular area in which it can be redeployed and better adjust its position to achieve a better performance in terms of received power by the receivers' set. The center of this circular area is the spot that the charger is initially located, while the radius is small to satisfy the cause that was deployed there at first. An example of such a network is demonstrated in Figure 1.

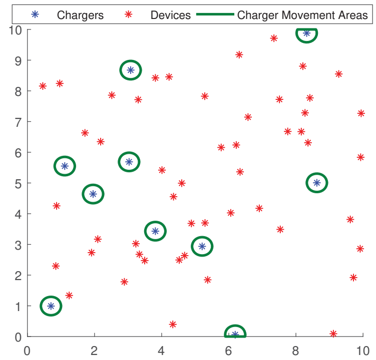

Fig. 1. Example of a system showing the charger's movement areas.

B. Charging Model

The *electric field* created by an energy transmitter C, to a receiver r at distance $d = \text{dist}(C, r)$ is a 2-dimensional vector given by

$$\mathbf{E}(C,r) \stackrel{def}{=} \beta \cdot \frac{1}{d} \cdot e^{-j\frac{2\pi}{\lambda}d} = \beta \cdot \frac{1}{d} \cdot \begin{bmatrix} \cos\left(\frac{2\pi}{\lambda}d\right) \\ -\sin\left(\frac{2\pi}{\lambda}d\right) \end{bmatrix}, \quad (1)$$

where λ is the wavelength at which the chargers transmit, and β is a constant that depends both on the charger's hardware and the environment.[1]

[1]In fact, the exact formula used in [5] for the electric field is $\mathbf{E}(C,r) \stackrel{def}{=} \sqrt{\frac{Z_0 G_C P_C}{4\pi d^2}} \cdot e^{-j\frac{2\pi}{\lambda}d}$, where Z_0 is a physical constant indicating the wave-impedance of a plane wave in free space, G_C is the gain and P_C is the output power of the transmitter. In this paper, without loss of generality of our algorithmic solutions, we assume that all wireless transmitters and devices are identical, thus the aforementioned parameters are the same for each charger.

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Thus, the total electric field created by a family of energy transmitters $\mathcal{C}$ at a receiver r is the *superposition* of the individual electric fields, that is

$$\mathbf{E}(\mathcal{C}, r) \stackrel{def}{=} \sum_{\mathbf{C}\in\mathcal{C}} \mathbf{E}(C, r). \tag{2}$$

Regarding the total *power* at the receiver r, this is given by

$$P(\mathcal{C}, r) = \gamma \cdot \|\mathbf{E}(\mathcal{C}, r)\|^2, \tag{3}$$

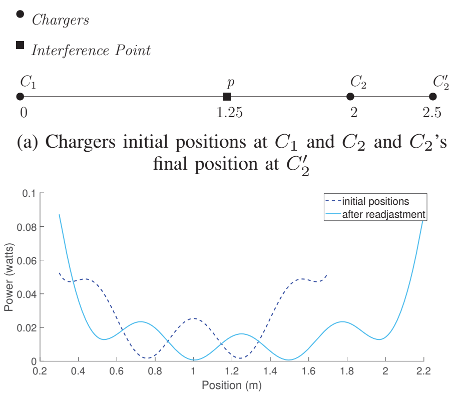
where $\|\cdot\|$ denotes the length (2-norm) of the vector. The constant γ depends on the hardware of the transmitter and the hardware of the receiver. Finally, we calculate the cumulative received power by a set of devices by the following equation:

$$\mathcal{P} = \sum_{r\in\mathcal{R}} P(\mathcal{C}, r) \tag{4}$$

C. Problem Definition

Consider a system consisting of a family $\mathcal{C} = \{C_1, C_2, \ldots, C_m\}$ of m identical wireless chargers and a family $\mathcal{R} = \{R_1, R_2, \ldots, R_n\}$ of n identical wireless receivers. The family of chargers $\mathcal{C}$ defines a set of areas $\mathcal{A}_\mathcal{C}$. Assume that $\mathcal{A}_\mathcal{C}$ is a set of m circular areas having the initial location of the chargers as center and radius $\rho_\mathcal{C}$. Observe that, by the definition of the vector model described in equation (1), different location for each charger can give different values for the cumulative power $P(\mathcal{C}, \mathcal{R})$. In fact, the change in the cumulative power as a result of changing from a placement configuration $\mathbf{\Psi}$ to another configuration $\mathbf{\Psi}'$ can be significant, as shown in the evaluation section.

Figure 3 gives an example of these interesting effects. Two chargers C_1 and C_2 are placed at points (0,0) and (2,0) respectively. We observe that if a device is placed at p = (1.25,0), moving C_2 away from it, to (2.5,0), the final power the device receives is significantly increased, since the initially destructive interference at point p, was converted to constructive.



(a) Chargers initial positions at C_1 and C_2 and C_2's final position at C_2'

(b) Power distribution before and after moving C_2

Fig. 2. Example with two chargers C_1 and C_2, showing that moving C_2 away from some points, to the point C_2', can increase their received power. The point p is one of them.

Based on the above observation, we assume here that location can be adjusted for each charger inside a specific area so that improved quality of service is provided. In this paper, in particular, we study the following problem:

Definition III.1. Power maximization with chargers placement (`PowerChargerPlacement`)

Given a system consisting of a set of chargers $\mathcal{C}$ and a set of receivers $\mathcal{R}$, that satisfy the placement constraints [2], find a placement reconfiguration for the chargers based on their initial location that maximizes the total cumulative power from $\mathcal{C}$ to $\mathcal{R}$. That is, find $\mathbf{\Psi}^*$ such that

$$\mathbf{\Psi}^* \in \arg\max_{\mathbf{\Psi}\in\mathcal{A}_\mathcal{C}} P_\mathbf{\Psi}(\mathcal{C}, \mathcal{R}). \tag{5}$$

IV. Algorithmic Design

The main difference between the vector model and the scalar one lies in the fact that the former takes into account the interference among radio waves transmitted by different chargers. If the phase difference between two interfering waves equ $\frac{\pi}{2}$ at a point p, then the waves are combined destructively and the power at p is reduced, whereas in the case where the phase difference is 0, then superadditive interference occurs and the power is increased. In particular, the phase difference is 0, when the term $\frac{2\pi}{\lambda}d$ in equation 1 is equal to $2k\pi$, where $k \in \mathbb{N}$. That happens when d, which defines the difference between the distances of the device to the two chargers, is a multiple of λ.

Although points where superadditive interference occurs show high power concentration, it is not necessary that they are the points where a local maxima of the power function occurs. In the following example we study such a case.

Counterexample: Two identical chargers C_1 and C_2, working at $P_C = 1,\ G_C = 1,\ \lambda = 0.3$, are placed at points $(0, 0)$ and $(4, 0)$ respectively. A device r is placed at $p_1 = (0.35, 0)$. Its distances to the two chargers C_1 and C_2 equal to $R_1 = 0.35$ and $R_2 = 3.65$ respectively. The phase difference of the two signals coming from C_1 and C_2 to r depends on their relative position to r. The difference $d = |R_1 - R_2| = 3 \cdot \lambda$, that means that r is on superadditive interference. We calculate its power and find out it's $P(\mathcal{C}, d) = 5.58mW$. Then, we slightly move the device towards C_1 to the point $p_2 = (0.349, 0)$, so the new difference equals to $d = |R_1 - R_2| 3 \cdot \lambda + 0.002$. The point p_2 is not on a superadditive interference. Surprisingly, the power at the new point is greater than the one at p_1, being equal to $P(\mathcal{C}, d) = 5.61mW$. With this simple example, where the device is very close to a charger, we show that moving it slightly away from the superadditive interference, towards the charger, can increase the incoming power, meaning that the local maxima was not there. Nevertheless, since the power difference between the local maximas and the superadditive interference points is slight, our algorithmic approaches assume superadditive interference points show the highest power concentration.

[2]Chargers and receivers need to be at distance at least λ for the vector model to be in force.

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When trying to find a solution to a power maximization problem, the most practiced and realistic way (based on current commercial products) in order to modify the phase difference of two waves at the position of a device, is by adjusting the corresponding chargers' positions. The chargers should be placed in a way that the difference of the distances between the device and the two chargers is a multiple of λ. Having found such a placement for the two chargers, we can move one of them by λ towards or away from the device. It is obvious, that the difference of the distances will still be a multiple of λ and the device will be on a superadditive interference.

The two distributed algorithms below, are based on these observations. The first one, is an approach where the charger can move on a line of small length, reducing this way the search space and achieving good results presented in section V. Communication with the devices is necessary in order to get their power level information. The second approach is a geometric one, in which the charger can be placed at any point inside the movement area. It only needs to know the positions of the chargers and devices.

A. Algorithm 1

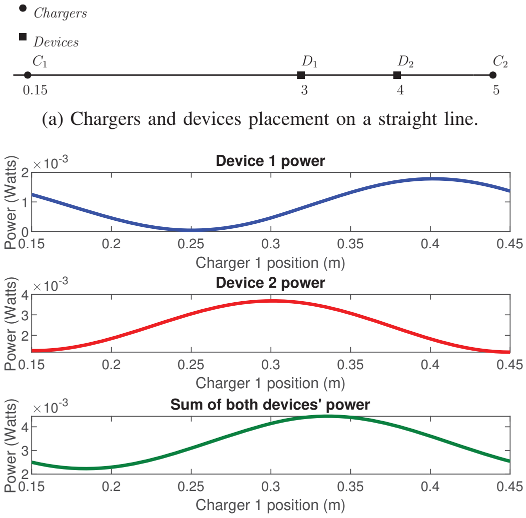
This algorithm adjusts the positions of the chargers multiple times in order to achieve convergence to a state where no movement can increase the cumulative device power.

Firstly, a random charger is selected. The charger can move on the horizontal line segment $\mathcal{L}$ of length λ, with center the initial charger's position, x_{init}. The charger communicates with every device in its communication range, in order to get information about the power $E(\mathcal{C}, r)$ each device r receives from the set of chargers. Then, the charger calculates the point x^* on $\mathcal{L}$ that will maximize the function of the cumulative power of every device, $P_{\mathbf{x}}(\mathcal{C}, \mathcal{D}_{r_i})$. This is done by adding the sinusoids of the power of every device, with respect to the position of the charger and then finding the maxima of the sum. After that, a random charger will be selected, and so on.

Note that when there are no communication bounds, moving one charger can't decrease the cumulative power, since every charger tries to increase the power of all the devices in the network. If it can't increase it, then it won't move. This is confirmed in the evaluation section, V.

Figure 3 gives an insight into the idea of the algorithm, by showing a simple topology with two chargers and two devices placed on a line. While moving C_1 from (0.15, 0) to (0.45, 0), distance equal to λ, exactly one point of local maxima and local minima exists for any device. This is visible in the first two plots of 3b. In this example the charger will be placed at the point where the sum of the two sinusoids (third plot) is maximized, (0.34, 0).

Extending this process for more devices and chargers, the number of sinusoids that are added will be increased to the new number of devices but the procedure stays the same. This is repeated many times until there is no change in the total network power.



(a) Chargers and devices placement on a straight line.

(b) The power at the devices when moving C_1 from $(0.15, 0)$ to $(0.45, 0)$.

Fig. 3. Example showing the power of two devices when moving one charger.

TABLE I. Notations

Symbol	Meaning
$\mathcal{C}$	set of Chargers
$\mathcal{C}_p$	set of already placed Chargers
$\mathcal{D}$	set of Devices
$\mathcal{D}_{r_i}$	set of Devices in range of charger i
$\mathcal{D}_u$	set of Devices checked for intersection points
r_{c_i}	range of charger c_i
$\rho_{\mathcal{C}}$	charger's movement area radius
$\mathcal{S}_{d_i}$	set of circles for device d_i
$\mathcal{X}$	intersection points between two sets of circles
$\mathbf{x}^*$	charger's new position

Input : $\lambda, \mathcal{C}, \mathcal{D}$
Output: $\mathcal{C}_{\mathbf{placement}}$
begin
  for *given number of repetitions* **do**
    c = *random charger*
    x_{init} = *x coordinate of c*
    $\mathcal{L} = [x_{init} - \lambda/2,\ x_{init} + \lambda/2]$
    $\mathbf{x}^* \in \arg\max_{\mathbf{x}\in\mathcal{L}} P_{\mathbf{x}}(\mathcal{C}, \mathcal{D}_{r_c})$.
  end
  return $\mathcal{C}_{\mathbf{placement}}$
end

Algorithm 1: *Algorithm* 1 *heuristic*

B. Algorithm 2

Given a charger of stable position at each step, this algorithm tries to find all points where a second charger should be placed, so that superadditive interference occurs at the devices' positions.

Firstly, a random charger is selected. It is placed on the centroid of a polygon, each vertex of which is the point of the movement area circle closest to a device, in the charger's communication range.

Then, the nearest charger to the first one is chosen. For

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the new charger, we try to find all the points, inside the charger's movement area, where the charger should be placed so that the devices that are in both chargers' range will be on superadditive interference points. For each device, these points are circles for which it is true that the difference of the distances from the device to the first charger, and the device to the points of the circles, is a multiple of λ. A set of such concentric circles is formed for each device, and the difference between their radii is clearly also a multiple of λ. The size of each set is $\lfloor 2r/\lambda \rfloor$ where r is the radius of the charger's movement area.

Figure 4 demonstrates a simple example with two chargers and two devices, where we can see the two sets of circles for the two devices and their intersection points inside the charger's movement area.

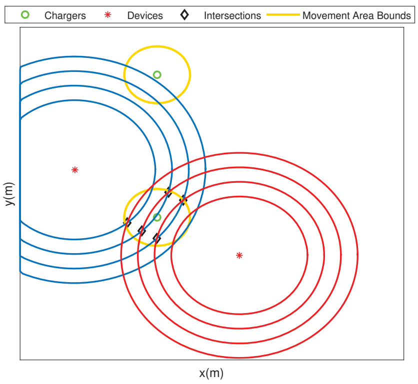

Fig. 4. Simple example with two chargers and two devices, showing the intersections between the sets of circles for the two devices. If the charger is set at any of the intersection points, both devices will be on a superadditive interference point.

After finding the concentric circles for every device in the range of both chargers, we present four different approaches for finding the placement point for the charger, that are described below and will be evaluated in section V.

1) Approach A.: We calculate the intersection points between the two sets of circles of the closest two devices to the chargers. If we set the charger on one of these intersection points, the two devices will be on superadditive interference. But if there are more devices, we want them to have benefit too. Thus, for every extra device, we calculate the distance of every found intersection point to the circles of the set of circles of the device. The point where the most circles have distance less than $\lambda/5$ is the placement point of the new charger. Note that the distance between a destructive and superadditive extremum is $\lambda/4$. Thus, in this case, $\lambda/5$ is chosen as a threshold so that the devices are close to the superadditive interference maxima.

2) Approach B.: Approach B is the same as A, but the two devices of which the intersection points are found, are chosen randomly.

3) Approach C.: The approaches above try to find a placement position for the charger so that superadditive interference will occur on, or very close to the devices. These approaches don't take into account the distance of the charger to the devices. On the contrary, the third one considers this distance by calculating the centroid described in the beginning of the algorithm's presentation. Then, it finds the intersection point closest to it, which is the new charger's position.

4) Approach D.: The last approach calculates every intersection point of every possible pair of devices, finds the one that maximizes the total power of the devices and sets the charger there. This is the optimal approach for this algorithm and is used as an upper bound for comparison purposes.

When the new charger is set, the closest charger to the first two is chosen and so on.

Input : $\lambda, \mathcal{C}, \mathcal{D}$
Output: $\mathcal{C}_{\mathbf{placement}}$
begin
  $\mathcal{C}_p \leftarrow \emptyset$; c := *random charger*
  place c on the centroid of the polygon with vertices
  the points of the circle closest to the devices in its range
  $\mathcal{C}_p \leftarrow \mathcal{C}_p \cup c$
  while $\mathcal{C}_p \neq \mathcal{C}$ **do**
    $\{c, c_p\} := \arg\min_{c \in \mathcal{C} - \{\mathcal{C}_p\}} \arg\min_{c_p \in \mathcal{C}_p} dist(c, c_p));$
    $\mathcal{D}_{r_{\{c,c_p\}}} \leftarrow \{d_i \in \mathcal{D} | \; dist(d_i, c) < r_c \cap dist(d_i, c_p) < r_{c_p}\}$
    $\mathcal{X} \leftarrow \emptyset$; $\mathcal{D}_u \leftarrow \emptyset$
    while $\mathcal{X} == \emptyset$ **do**
      $d_1 := d_1 \in \mathcal{D}_{r_{\{c,c_p\}}} \cap \; d_1 \notin \mathcal{D}_u \cap$
      $\cap \; arg \min_{d_1} (dist(d_1, c) + dist(d_1, c_p))$
      $d_2 := d_2 \in \mathcal{D}_{r_{\{c,c_p\}}} - \{d_1\} \cap \; d_2 \notin \mathcal{D}_u \cap$
      $\cap \; arg \min_{d_2} (dist(d_2, c) + dist(d_2, c_p))$
      $\mathcal{D}_u \leftarrow \mathcal{D}_u \cup \{d_1, d_2\}$
      $\mathcal{X} \leftarrow \{x_j | \; x_j \in \{\mathcal{S}_{d_1}, \mathcal{S}_{d_2}\} \cap dist(x_j, c) < \rho_C\}$
    end
    $\mathbf{x}^* := \arg\max_{x_j \in \mathcal{X}} \{|K| : K = \bigcup_{d_i \in \mathcal{D}, dist(C_{d_i}, x_j) < \lambda/5} d_i\}$
    $\mathcal{C}_p \leftarrow \mathcal{C}_p \cup c$
  end
  return $\mathcal{C}_{\mathbf{placement}}$
end

Algorithm 2: *Algorithm* 2, *Approach A heuristic*

V. Evaluation

Simulations were executed using Matlab R2018a, in order to assess the proposed methods and reveal insights of their performance. The system set-up considered for the evaluation consists of 10 chargers and 50 devices deployed on a 10 m^2 plane with the chargers' wavelength λ set at 30 cm. The chargers' movement area radius was $\lambda/2$ for *Algorithm* 1 and $2 \cdot \lambda$ for *Algorithm* 2.

Starting with *Algorithm* 1, in Figure 5 we see the cumulative power at the devices during a random execution (of 90 rounds), varying the communication range of the chargers. It is easy to notice that extending the communication range gives better results. On the contrary, when the range is small, there are times when moving a charger, decreases the cumulative power. Figure 6 shows the confidence intervals for the mean of the cumulative power of each round, after 100 executions. It is clear that after a few rounds, the algorithm converges and thus the corresponding confidence intervals are small.

Figure 7 depicts the cumulative power for *Algorithm* 1 and for each approach of *Algorithm* 2 after executing the

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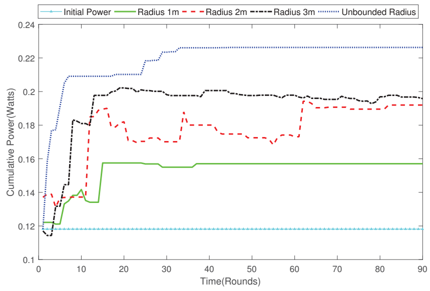

Fig. 5. The cumulative system power during a random execution of the first algorithm for different communication ranges of the chargers.

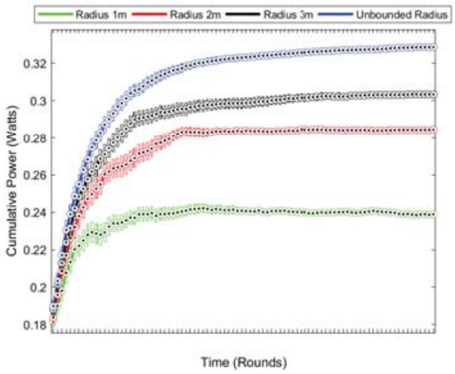

Fig. 6. Confidence intervals for the mean of the cumulative power of the devices for different communication ranges during 100 executions of the first algorithm.

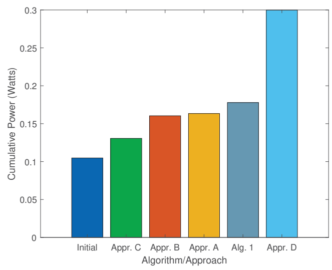

Fig. 7. Mean cumulative device power after executing each approach for 100 different network topologies.

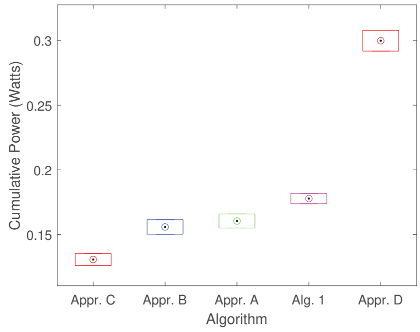

Fig. 8. Confidence intervals for the mean of the cumulative device power after executing each approach for 100 different network topologies.

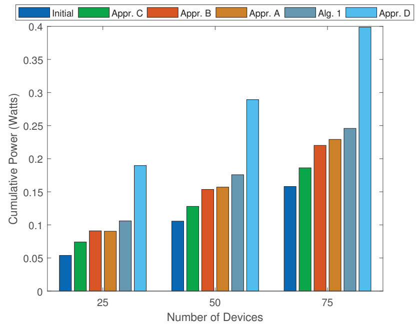

Fig. 9. Mean cumulative device power after executing the algorithms for different number of devices.

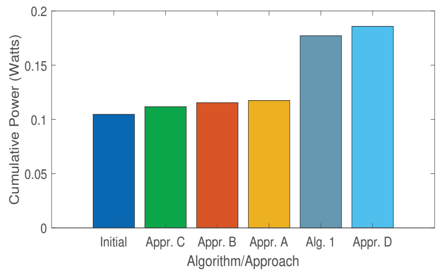

Fig. 10. Mean cumulative device power after executing each approach for 100 different network topologies, with movement area radius equal to $\lambda/2$ for every algorithm.

algorithms for 100 different network topologies. Approach A and $Algorithm$ 1 achieve similar results, while Approach D shows the optimal performance for $Algorithm$ 2. Choosing the devices' intersection points randomly (Approach B) gives a little worse results than A. The approach that sets the chargers at intersection points near the centroid (C) has the lowest performance. This is because it tries to set the charger to a point that will benefit only two devices regarding superadditive interference. Generally, the two algorithms increase the power by at least 60%. In Figure 8, we can see the confidence intervals for the mean of the cumulative power for the different approaches. The confidence intervals are small, indicating that there is not much deviation from the mean.

Figure 9 demonstrates the cumulative power, varying number of devices. The relative performance between the approaches doesn't change when the number of devices is modified.

Finally, in Figure 10 we see the mean power received by the devices after executing the algorithms for 100 different chargers and devices placements, but this time setting the movement area radius to $\lambda/2$ for each algorithm. It is obvious that the performance of the second Algorithm is significantly declined.

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This is caused by the fact that this algorithm tries to find intersection points between set of circles defined above. When the movement area is small, the intersection points are few, leading to bad performance. On the other hand, $Algorithm\ 1$ gives results almost equal to Approach D, showing that there is not much difference whether the movement area is a circle or a line, given that its width is λ. Therefore, comparing the two algorithms, we see that $Algorithm\ 1$ doesn't need a wide area in order to perform well, given that there is communication with the devices, whereas $Algorithm\ 2$ needs a wide area, but its total overhead is low.

CONCLUSION AND FUTURE WORK

Vector model is now an emerging model that aims to dominate wireless charging research field versus other one-dimensional models. This potentiality comes by the fact that it can describe more accurately the wireless power transfer technology and at the same time enables phenomena such as supperadditive and cancellation effects. Based on that, this paper further exploits vector model and addresses the charger placement problem in WPT networks in order to maximize the total received power. This approach seems to be easier and more realistic to be applied in current simple power maximization WPT set-ups rather than others more sophisticated approaches.

This study results two different approaches which are presented in detail and evaluated via an extended numerical simulation. A basic high level technical recommendation is the quite positive impact on received power of carefully adapting the positions of chargers, towards taking advantage of interesting superadditive phenomena of wireless waves revealed by their vectorial representation. In the future we opt to investigate more problems than previously were studied under the scalar model, but also further explore the vector model and its potential in different WPT concepts. Finally, we also wish to add more restrictions and parameters in our approach and solve problems that also address efficient charging alongside EMR safety.

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