

Received July 11, 2018, accepted August 19, 2018, date of publication August 31, 2018, date of current version October 19, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2868223

Should Interference be Avoided? Charging WSNs With Efficient Placement of Wireless Chargers

PENG GUO¹, XUEFENG LIU¹⁰, MINGHUI CHEN¹, AND KUI ZHANG²

¹Department of Electronic Information and Communications, Huazhong University of Science and Technology, Wuhan 430074, China ²Department of Electrical Engineering, Mathematics and Computer Science, University of Twente, 7522 NB Enschede, The Netherlands

Corresponding author: Xuefeng Liu (lxfeng0527@hust.edu.cn)

The work presented in this paper was supported in part by the NSF of China under Grants 61572217, 61572218, and 61872410.

ABSTRACT Using multiple fixed chargers to remotely charge wireless sensor networks (WSNs) is a feasible way in harsh terrain. An interesting property is that, due to the radio interference, the charging efficiency with multiple chargers may not simply be the sum of that with single charger if the chargers have the same radio frequency. To avoid the interference, an alternative way is to employ chargers with diverse frequencies, which, however, occupies too much channel resources of WSNs. In this paper, we try to answer such an interesting question: to charge a given WSN, can unique-frequency chargers be comparable to diverse-frequency chargers? To answer this question, we formulate two problems targeting at minimizing the charger number and maximizing the minimum charging power at sensor nodes, respectively. Then, we propose corresponding greedy algorithms with proof of the approximation ratio. Extensive simulation results show that: 1) given threshold of radio power at sensor nodes, the number of unique-frequency chargers required is no more than 1.1 times of that of diverse-frequency chargers and 2) given the charger number, the minimum radio power provided by unique-frequency chargers can be up to 80% of that with diversefrequency chargers. This shows the quite competitive performance of unique-frequency chargers since they require only one channel instead of a group of channels required by diverse-frequency chargers. In addition, after appropriate placement, we find it needless to further schedule the unique-frequency chargers to improve the minimum charging power that they provide.

INDEX TERMS Circuits and systems, energy efficiency, wireless charging, radio interference, placement.

I. INTRODUCTION

Recently, as a promising energy harvesting technique, wireless charging circuit has attracted much attention in enhancing energy efficiency of wireless sensor networks (WSNs) [1]–[5]. Recent improvements in radio energy harvesting techniques have made it possible to charge sensor nodes in relative long distance (>10m away) [18]. It has been validated that sensor node could harvest radio energy with $6\mu W$ power when putting a charger with transmission power 4W about 12 meters away (the received radio power is $20\mu W$ and the transition efficiency is 30%) [18]. The longdistance charging can be free from the practical terrains, and it can charge multiple sensor nodes simultaneously. However, compared to the mobile charging [6], [7], the long-distance charging provides much weaker harvesting power (usually tens of μW -level) at sensor nodes. This may be sufficient for the ultra-low power signal processing circuits designed recently [8]. However, it is too low for the requirement of wireless communication (usually tens of mW-level) [9].

Since the chargers' power is strictly restricted by FCC (Federal Communications Commission), to accelerate the long-distance charging, we consider to employ multiple chargers located at different positions in WSNs to charge the sensor nodes concurrently. With the cooperation of the multiple chargers, the harvesting power at sensor nodes can be increased, and the charging range can be extended correspondingly.

In order to facilitate a sensor node to independently harvest the energy of the chargers' radios, the chargers need to work at different frequencies, which however will occupy too much channel resources. If the chargers fix their radios with unique frequency, interference between the radios surely occurs. The interference will lead to *nonlinear superposition charging effect* on sensor nodes [19]. Specifically, when the phase difference of two encountering radio waves is less than $\pi/2$, the waves will combine constructively, and the combined radio's power can be larger than the sum of each wave's power. However, if the phase difference of the encountering



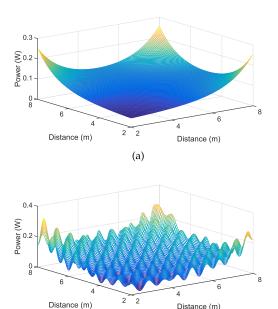


FIGURE 1. Distribution of radio power with three chargers. (a) div-chargers, (b) uni-chargers.

waves is over $\pi/2$, the waves will combine destructively, and the combined radio's power can be less than any one of the waves' power or even be close to zero.

(b)

To show this typical phenomenon, Fig. 1 gives a simple example with three chargers located at the corners of the area. We show the distribution of radio power in the area, based on the model in [21] and [22]. In Fig. 1(a), the chargers set their radios with diverse frequencies (called as div-chargers in this paper), while in Fig. 1(b) the radios are set with unique frequency (called as uni-chargers). It can be seen, the distribution of radio power in Fig. 1(b) is much uneven than that in Fig. 1(a). At some positions, the radio power in Fig. 1(b) can be much higher than that in Fig. 1(a), while it becomes much low at other positions. Hence, we are interested with such a question: given the locations of a group of sensor nodes, can uni-chargers be comparable to div-chargers on charging the WSN while using much less channel resources? To answer this question, we study the charger placement problem with different objectives. A specialty of the problem is that the charging utility of the uni-chargers cannot be defined or calculated independently due to the nonlinear superposition charging effect, which brings some challenges to the placement algorithm design.

Contributions of the paper are summarized as follows.

- To our best knowledge, this paper is the first work studying whether we should use uni-chargers or divchargers to charge a WSN concurrently. This helps us to efficiently charge WSNs with limited cost (including changer number and channel resources).
- To evaluate the two kinds of chargers, we study two charger placement problems whose objectives are to minimize charger number while guaranteeing the

- charging efficiency, and to maximize charging efficiency while restricting the charger number, respectively. Both of the two problems are NP-hard.
- We propose efficient greedy algorithms respectively for the two problems, as well as the approximation ratio. Extensive simulation results show the remarkable efficiency of the proposed iteration greedy algorithm when compared to the basic greedy algorithm directly designed for the problem.
- We find that, using uni-chargers usually achieves the performance much close to that using div-chargers, while occupying much less channel resources. In addition, after the placement of uni-chargers with the proposed algorithm, we find it needless to further schedule the radio interference.

The remainder of the paper is organized as follows. Section III reviews related works. Section III introduces the charging models, formulates the CCPP problem and CCPP-E problem, as well as the complexity analysis. In Section IV, we propose *Greedy CCPP* for CCPP and *Iter-Greedy CCPP* for CCPP-E, along with the approximation proof. Section V gives the simulation results for the two algorithms, as well as that of a basic greedy algorithm for CCPP-E for comparison. The conclusions are made in Section VI.

II. RELATED WORK

Wireless charging for WSNs has been widely studied in recent years. Electromagnetic radiation (EMR) is a cost-efficient way for sensor nodes to harvest the energy, and hence is often explored for charging WSNs [1], [23], [24]. Many people study using a mobile charger to move around in WSNs and charge sensor node when the charger is close to the node [25]–[28]. However, in many scenarios the mobile chargers may not move freely.

Recently, a series of works study the placement of multiple static chargers for the charging of WSNs. In [10], Zhang et al. studied the problem of charger placement and power allocation where chargers can be placed at a given set of points and the aggregate power supply of chargers is bounded by a power budget. Their goal is to maximize the overall charging utility. However, they ignore the interference between the chargers' radio. In [11], Wicaksono et al. considered the power interference when allocating frequency bands to adjacent stationary chargers. Similarly, in [12], He et al. studied efficient deployment of multiple fixed readers to concurrently charge the possible tags spread around (or say, just to cover the target area). However, the practical radio interference effect among the readers is ignored in their simulations. Some other works study the placement of static chargers with consideration of the EMR safety, i.e., no point on the considered 2-D area has EMR intensity exceeding a given threshold [13]–[15].

There are very few works studying concurrent charging of WSNs with considering the special charging effect caused by radio interference, except for [19]–[21]. Naderi *et al.* [21] noticed the radio interference effect among the in-band chargers, and propose RF-MAC protocol to cooperatively



charge an accessing sensor node. In our previous work [19], we study how to efficiently schedule the uni-chargers to fully charge the sensor nodes with minimum time. In [16], Katsidimas *et al.* presented a more realistic model for power harvesting by capturing the fundamental properties of the superposition of energy fields for wireless power transfer, and studied how to maximize the total power in the system.

In this paper, we study the concurrent charging with multiple static chargers with radio interference (corresponding to uni-chargers) or without radio interference (corresponding to div-chargers). In particular, we study the efficient placement of the chargers, and compare the performance with using these two kinds of chargers.

III. THE PROBLEMS

In this section, we first give the charging models for unichargers and div-chargers, respectively. Then, we formulate two placement problems and give the complexity analysis.

A. CHARGING MODELS

In scenario where chargers cannot move around, we have to employ multiple static chargers to cooperatively charge sensor nodes. For div-chargers, since there is no radio interference, the radio power at a sensor node s_j can be simply modeled as follows.

$$P_j|_C = P \sum_{c_i \in C} \frac{1}{\hat{d}_{ij}} \tag{1}$$

where P is the radio emitting power of each charger, C denotes a group of chargers, $\hat{d}_{ij} = \frac{4\pi d_{ij}}{\lambda}$, λ is the wave length and d_{ij} is the distance between charger c_i and sensor node s_j . α is the attenuation factor, and is regarded as 2 in this paper.

From Equation 1, more div-chargers always lead to higher radio power at a sensor node. However, for uni-chargers, as there is radio interference between the radio waves emitted by the chargers, the radio power at a sensor node s_j generally can be modeled as follows [23].

$$P_{j}|_{C} = P \sum_{c_{i} \in C} \frac{1}{\hat{d_{ij}}^{2}} + P \sum_{c_{i} \in C} \sum_{\substack{c_{m} \in C \\ c_{m} \neq c_{i}}} \frac{1}{\hat{d_{ij}} \hat{d_{mj}}} \cos(2\pi \frac{d_{ij} - d_{mj}}{\lambda})$$
(2)

The model in Equation 2 will lead to nonlinear superposition charging effect. The nonlinear superposition charging effect may significantly increase the charging power at some sensor nodes while seriously decrease the charging power at other nodes, as shown in Fig. 1(b). Hence, in order to efficiently charge each sensor node, it is needed to appropriately place the chargers.

B. PROBLEM FORMULATION

We formulate the concurrent charging placement problem (CCPP) as follows.

Given:

- *M* sensor nodes with their position information.
- \mathcal{N} candidate positions $\mathcal{P} = \{P_1, P_2, \cdot, P_{\mathcal{N}}\}$ for deploying wireless chargers.

The problem is to find a family of positions P_{pi} ($P_{pi} \in \mathcal{P}$, $i = 1, \dots, k$) for deploying k chargers such that:

• *k* is minimized.

subject to the following constraint:

• $\forall j = 1, \dots, M, P_i|_C \geq \Delta$.

We expect to solve this problem respectively with unichargers and with div-chargers, so as to see whether it is possible to use uni-chargers to achieve the similar charging performance as div-chargers or not.

Furthermore, we notice that, if gradually increasing the threshold Δ in CCPP till the optimal solution (i.e., the minimal number of chargers) tends to be k+1, we actually get the answer of such a problem (called as **CCPP-E**): Given k chargers, how to deploy them so as to maximize the minimal radio power at the sensor nodes? It can be seen, the deployment strategy for this problem and CCPP is the same, and the maximum value in this problem is the Δ who almost leads to the optimal solution of CCPP to be k+1.

C. COMPLEXITY ANALYSIS

Theorem 1: The CCPP is NP-hard.

Proof: We prove this by using the decision version of the problem: given a number of chargers k, does there exist a collection of candidate positions P_{pi} ($P_{pi} \in \mathcal{P}$, $i = 1, \dots, k$) to deploy k wireless chargers that satisfy the constraint above?

We prove this decision problem by reducing the Knapsack Problem (KP) [17], which is NP-hard. The decision version of the KP problem is as follows: given a set of items $\mathcal{U} = \{e_1, e_2, \cdot, e_m\}$, each with a weight and a value, and an integer k, does there exist a collection of these items so that the total weight is less than or equal to the limit W and the total value is V? Given an instance of the decision version of the KP, we construct an instance of CCPP as follows:

- For each element $e_j \in \mathcal{U}$, we construct a wireless charger c_i and its position P_{pi} in CCPP. The item's weight is w, and the value is the increment of the total *deserved* radio power at all the sensor nodes. Here, the *deserved* radio power at a sensor node denotes the radio power bounded in Δ . For knapsack's weight, we define k*w equal to W. For the given value V, we set $M*\Delta$ as the total value.
- After we pick a position P_{pi} for placing one wireless charger, we need to recalculate other position's value, because some sensor nodes may be sufficient to reach Δ. Moreover, for uni-chargers, the increment of total radio power is not simply addition of each position' value due to the nonlinear superposition effect. Therefore, we need to reduce or modify other position's value. And this complexity is the number of candidate positions.

Combining these elements, we get the following special case of the decision version of the CCPP problem: given a limited k*w and a candidate position set, does there exist a collection of candidate positions whose total size is less than or equal to k so that the radio power at each sensor node can be no less than Δ (total is $M*\Delta$)? It is not hard to see that the construction can be finished in polynomial time; thus,

54878 VOLUME 6, 2018



we reduce solving the NP-hard KP problem to a special case of CCPP, implying that CCPP is NP-hard. \Box

Similarly, we can prove the NP-hardness of CCPP-E. The proof is omitted for briefness.

IV. PROPOSED METHODS

In this section, based on submodular set cover problem (SSCP) [29], we first propose a greedy algorithm (called as *Greedy CCPP*) for the CCPP problem. Then, we extend the *Greedy CCPP* algorithm as *Iter-Greedy CCPP* for CCPP-E problem.

A. GREEDY CCPP ALGORITHM

We first assume the chargers are div-chargers, and transform CCPP to a SSCP problem by establishing a submodular set function f(*) as follows.

Since the constraint of CCPP is to guarantee the radio power at each sensor node to be no less than Δ , it is unnecessary to add more power to a sensor node where the radio power has already exceeded Δ . Hence, we define *necessary power* at sensor node s_j brought by charger c_k located at position P_{pk} as:

$$\sqcap_i^k = \min\{p_j|_k, \Delta - \min\{P_j, \Delta\}\}$$
 (3)

where $p_j|_k$ is the radio power at s_j brought by c_k , and P_j is the previous power at sensor node s_j before c_k is added. If the previous power at s_j is already over Δ , the *necessary power* at s_j with c_k is zero. For simpleness, we call a sensor node where the radio power exceeds Δ as a *full* node. In addition, we suppose each candidate charger in C_N can charge a sensor node with either zero power or at least power 1.

Lemma 1: Given a collection of K chargers C_K where each element c_k is located at position P_{pk} , define $f(C_K) = \sum_{k:c_k \in C_K} \sum_{j=1}^M \sqcap_j^k$. Then, $f(C_K)$ is a submodular set function.

Proof: According to the definition of *necessary power* \sqcap_j^k in Equation 3, as long as there is no *full* node, we have $f(C_K) + f(\{c_i\}) = f(C_K \cup \{c_i\})$, where c_i is any element in $C_N - C_K$. However, if C_K has resulted in at least one *full* node, the *necessary power* of c_i at the *full* node is zero according to Equation 3. Thus, for this case, we have $f(C_K) + f(\{c_i\}) > f(C_K \cup \{c_i\})$, i.e., $f(C_K \cup \{c_i\}) - f(C_K) < f(\{c_i\})$. Since C_K can potentially lead to more *full* nodes than $C_{K'} \subseteq C_K$, we have $f(C_K \cup \{c_i\}) - f(C_K) \le f(C_{K'} \cup \{c_i\}) - f(C_{K'})$, i.e., function f(*) has the property of *decreasing marginal utility*. Therefore, f(*) is a submodular set function. □

With establishing the submodular set function f(*), we rewrite the CCPP in the form of SSCP as: Given a submodular function f(*) on C_N , find the smallest set $C_K \subseteq C_N$ such that $f(C_K) = f(C_N)$. To solve this SSCP problem, we employ the classic greedy approximation algorithm for SSCP [29] which can be described with Algorithm 1.

Theorem 1: Algorithm 1 is a $(\ln M \Delta + 1)$ approximation for CCPP.

Proof: According to the definition of f(*), $f(C_N) = M\Delta$. Let x_i denote the amount of *necessary power* brought

Algorithm 1 Greedy CCPP Based on SSCP

- 1: **Given:** $C_{\mathcal{N}}$
- 2: $C_K \leftarrow \phi$
- 3: **while** $f(C_K) \neq M \Delta$ **do**
- 4: find $c_i \in C_N$ to maximize $f(C_K \cup \{c_i\}) f(C_K)$
- 5: $C_K \leftarrow C_K \cup \{c_i\}$
- 6: end while

by the i^{th} charger that Algorithm 1 picks. Let $z_i = M\Delta - \sum_{j=1}^{i} x_i$, which means the amount of remaining power required by the sensor nodes after i steps of Algorithm 1. According to the notations, $Z_0 = M\Delta$.

Suppose that the optimal solution uses k chargers to charge each node with power at least Δ , i.e., the total *necessary power* is $M\Delta$, we have: there exists at least one charger in C_N that must charge the nodes with at least 1/k fraction of the total *necessary power* $M\Delta$. Since Algorithm 1 always selects the set with the largest total *necessary power* at each step, we have $x_1 \geq \frac{z_0}{k}$. Furthermore, since there exists a solution that uses only k chargers to charge the nodes with total energy $M\Delta$, for the remaining energy $z_i \leq z_0 = M\Delta$ after the i^{th} step of Algorithm 1, there must also exist a solution that uses only k chargers to charge the nodes with total *necessary power* z_i (due to the monotone of the submodular set function). Thus, there exists at least one charger that must charge the nodes with at least total *necessary power* $\frac{z_i}{k}$. Hence, according to Algorithm 1, we have $x_{i+1} \geq \frac{z_i}{k}$.

Based on the result above, we have:

$$z_{i+1} = z_i - x_{i+1}$$

$$\leq z_i - \frac{z_i}{k} = z_i (1 - \frac{1}{k})$$

$$\leq z_{i-1} (1 - \frac{1}{k})^2 \leq \cdots$$

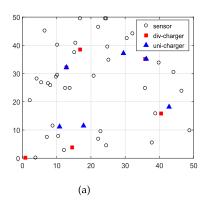
$$\leq z_0 (1 - \frac{1}{k})^{i+1} = (1 - \frac{1}{k})^{i+1} * M\Delta$$
 (4)

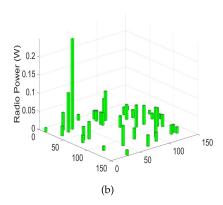
Hence, after $i = k \lceil \ln \frac{M\Delta}{k} \rceil$ steps of Algorithm 1, we have:

$$z_{i} \leq (1 - \frac{1}{k})^{k \lceil \ln \frac{M\Delta}{k} \rceil} * M\Delta = [(1 - \frac{1}{k})^{k}]^{\lceil \ln \frac{M\Delta}{k} \rceil} * M\Delta$$
$$\leq (\frac{1}{e})^{\ln \frac{M\Delta}{k}} * M\Delta = \frac{k}{M\Delta} * M\Delta = k \tag{5}$$

Thus, after $i = k \lceil \ln \frac{M\Delta}{k} \rceil$ steps, there are no more than k remaining *necessary power* that the sensor nodes need. Since each candidate charger in C_N can charge sensor nodes with at least total *necessary power* 1, at most k more steps, Algorithm 1 can finish. Therefore, the total number of steps of Algorithm 1 is less than $k \lceil \ln \frac{M\Delta}{k} \rceil + k \le k(\ln M\Delta + 1)$, i.e., Algorithm 1 is a $(\ln M\Delta + 1)$ approximation for CCPP.

For uni-chargers, we still apply Algorithm 1 for the deployment. In consideration of the *nonlinear superposition charging effect* brought by uni-chargers, the function f(*) may not be submodular set function now. However, we notice that the trend of total *necessary power* generally exhibits the





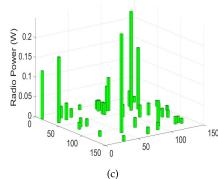


FIGURE 2. An example of CCPP: using minimal chargers to charge each of 50 nodes with at least 12mW power. (a) The placement with Greedy CCPP. (b) Radio power at nodes using uni-chargers. (c) Radio power at nodes using div-chargers.

submodular characteristic. Thus, in view of selecting several chargers at a time, the total *necessary power* brought by this charger set could exhibit the submodular characteristic. Hence, Algorithm 1 with uni-chargers generally has the similar approximation above.

B. ITER-GREEDY CCPP ALGORITHM

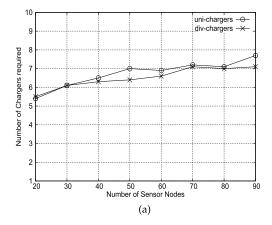
We notice that, if gradually increasing the threshold Δ in CCPP till the minimal number of chargers tends to be k+1, we actually get the answer of such a problem (called as CCPP-E): how to deploy k chargers so as to maximize the minimal radio power at the sensor nodes? It can be seen, the deployment strategy for this problem is the same as that for CCPP, and the maximum value of this problem is the current Δ in CCPP.

Based on the analysis above, we propose *Iter-Greedy CCPP* algorithm for CCPP-E problem with Algorithm 2. *Iter-Greedy CCPP* is an iteration version of *Greedy CCPP*. It iteratively executes *Greedy CCPP* by gradually adjusting the threshold Δ . To accelerate *Iter-Greedy CCPP*, the step size in each iteration round can actually be adjusted with binary search.

Algorithm 2 *Iter-Greedy CCPP*: Iterating *Greedy CCPP* for CCPP-E

- 1: **Given:** C_N and k chargers
- 2: $\Delta \leftarrow \delta$
- 3: **while** i < k + 1 **do**
- 4: Apply Algorithm 1.
- 5: i = number of chargers in solution with Algorithm 1.
- 6: $\Delta + +$.
- 7: end while

Besides *Iter-Greedy CCPP*, we notice that there is actually a simple greedy algorithm for CCPP-E, which directly keeps selecting the charger's position that leads to the maximal minimum radio power at sensor nodes. We call this simple algorithm as *Greedy CCPP-E*. In next section, we'll compare the performance of *Iter-Greedy CCPP* with that of *Greedy CCPP-E*.



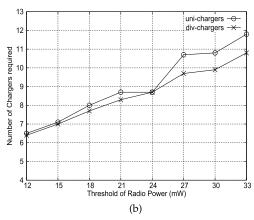


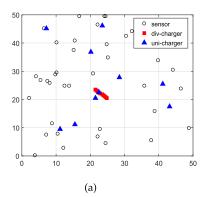
FIGURE 3. Simulation results for CCPP with different scales of sensor nodes and required threshold of radio power. (a) The threshold of radio power is 12*mW*. (b) The number of sensor nodes is 40.

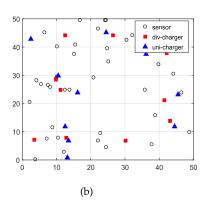
V. PERFORMANCE EVALUATION

To evaluate the performance of the proposed methods, we conduct a series of simulations with Matlab tool, by generating a series of random deployments of sensor nodes within $L \ast L$ area. In the simulations, we employed the charging models present in Section III. With the deployments and the charging models, the radio power at each sensor node charged by a set of chargers placed at certain positions can be calculated, and thus the proposed algorithms can be directly

54880 VOLUME 6, 2018







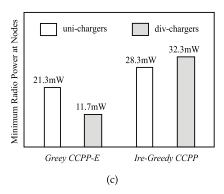


FIGURE 4. An example of CCPP-E: using 10 chargers to charge 50 nodes with maximal minimum radio power. (a) The placement with *Greedy CCPP-E*. (b) The placement with *Iter-Greedy CCPP*. (c) Comparison of the minimum radio power.

executed in Matlab. Without loss of generality, we assumed in the simulations that all the transmission power P of each charger is the same and set to be one unit of Watt. The wave length λ is set to be one unit of meter (corresponding to 300MHz radio wave), and the size of deployment area L is set to be 50.

A. SIMULATIONS FOR CCPP

Fig. 2 gives an example of charging task which requires to provide at least 12mW power to each of the 50 sensor nodes randomly deployed in 50m*50m area. Fig. 2 (a) shows the placement results of the proposed *Greedy CCPP* with uni-chargers and div-chargers, respectively. It can be seen, to fulfill the charging task, 6 uni-chargers are needed, which is very close to the number (i.e., 5) of div-chargers. However, the 6 uni-chargers occupy only one channel, while the div-chargers occupy five channels. Fig. 2 (b)(c) further show the radio power at each sensor node with uni-chargers and div-chargers, respectively. It can be seen, the radio power at each node exceeds 12mW.

To evaluate the performance of the two kinds of chargers comprehensively, we conduct more simulations with different parameters on the scale of sensor nodes and the required threshold of radio power at the nodes. For each parameter set, 20 simulations are performed and the average result is calculated. Fig. 3(a) shows the results at different scales of sensor nodes while the threshold of radio power is fixed to be 12mW. It can be seen, with the increment of sensor nodes' scale, generally more chargers are required. The number of uni-chargers always keeps much close to that of divchargers (the gap is no more than 10%), showing much comparable performances. Fig. 3(b) shows the results at different thresholds of radio power while the scale of sensor nodes is fixed to be 40. It can be seen, with the increment of the radio power threshold, still more chargers are required, and the performance of uni-chargers is also much close to that of div-chargers.

B. SIMULATIONS FOR CCPP-E

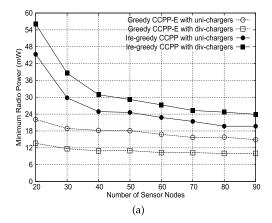
In this subsection, we evaluate the efficiency of the proposed *Greedy CCPP* algorithm. To this end, we compare the

performance of the extension of *Greedy CCPP*, i.e., *Iter-Greedy CCPP*, with that of *Greedy CCPP-E*.

Fig. 4 gives an example of using 10 chargers to appropriately charge 50 sensor nodes randomly deployed in 50m * 50m area. Fig. 4 (a) shows the placements with the simple Greedy CCPP-E for uni-chargers and div-chargers, respectively. The positions of 10 div-chargers with Greedy CCPP-E are much close to each other. This is because that, during the placement of div-chargers, the addition of radio power for each placement is independent of the former placement, thus making Greedy CCPP-E always select the similar positions for placement. The minimum radio power with the 10 unichargers and the 10 div-chargers is respectively 21.3mW and 11.7mW (as shown in Fig. 4 (c)). It can be seen, there is a big gap between the performance of uni-chargers and div-chargers with Greedy CCPP-E. And, uni-chargers surprisedly far outperform div-chargers.

Fig. 4 (b) shows the placements with the proposed *Iter-Greedy CCPP* for uni-chargers and div-chargers, respectively. The minimum radio power with 10 uni-chargers and 10 div-frequency chargers is respectively 28.3mW and 32.3mW, which are much close to each other and are both much higher than those with *Greedy CCPP-E*.

To evaluate the performance with two algorithms comprehensively, we conduct more simulations with different parameters on the scales of sensor nodes and chargers. For each parameter set, 20 simulations are performed and the average result is calculated. Fig. 5(a) shows the results at different scales of sensor nodes while the number of chargers is fixed to be 10. It can be seen, the minimum radio power at the sensor nodes decreases with the sensor nodes' scale, which is as expected. Fig. 5(b) shows the results at different scales of chargers while the number of sensor nodes is fixed to be 40. It can be seen, the minimum radio power at the sensor nodes increases with the chargers' scale, which is also in accordance with expectation. From both Fig. 5(a) and Fig. 5(b), the minimum radio power with *Iter-Greedy CCPP* usually remarkably exceeds that with Greedy CCPP-E by more than 30%, and the power provided by uni-chargers can generally be up to 80% of that by div-chargers. Hence, though



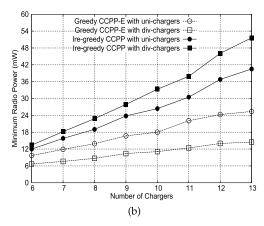


FIGURE 5. Simulation results for CCPP-E with different scales of sensor nodes and chargers. (a) The number of chargers is 10. (b) The number of sensor nodes is 40.

uni-chargers bring radio interference, appropriate placement of them can achieve quite competitive performance, thus making them much worthy to be placed in practice, especially for channel-limited applications of WSNs.

C. SIMULATIONS FOR CCPP-E WITH SCHEDULING

In this subsection, we expect to study whether it is possible to further improve the performance of uni-chargers through appropriately scheduling the radio interference among them. To this end, we apply the scheduling scheme in our previous work [19] to uni-chargers after the appropriate placement.

The basic idea of the scheduling in [19] is also greedy, i.e., keeping activating the charger set who can maximize the current minimum radio power at sensor nodes. We assume that the uni-chargers are firstly placed with *Iter-Greedy CCPP*, and then the uni-chargers work in turn according to the scheduling. The average radio power in the turns at the sensor nodes stands for the performance.

Table 1 shows the results of the scheduling with different parameters on the scale of sensor nodes and chargers, which are normalized by the corresponding performance of unichargers without scheduling. It can be seen, after efficient placement of uni-chargers, the scheduling could hardly further improve the charging performance for the sensor nodes.

TABLE 1. Normalized performance with scheduled uni-chargers.

M	20	30	40	50	60	70	80	90
Δ	0.93	0.89	0.90	0.90	0.89	0.89	0.89	0.90
N	6	7	8	9	10	11	12	13

In other words, we do not need to further scheduling the unichargers after appropriately placing them.

VI. CONCLUSIONS

In this paper, we study the appropriate placement of wireless chargers to concurrently charge a given WSNs. Concurrent charging with unique frequency leads to radio interference which significantly influences the radio power at sensor nodes. To avoid the interference, the chargers need to work at different frequencies, which however occupies too much channel resources. Hence, we address an interesting question: to efficiently charging WSNs, should we avoid interference by using channel-costly div-chargers or bear it with using channel-efficient uni-chargers? With proposing a boundguaranteed algorithm for the charger placement, we find that: i) given number of chargers (either div-chargers or unichargers), the minimum radio power with the proposed algorithm can usually exceed that of the basic greedy algorithm by more than 30%; ii) the minimum radio power provided by unique-frequency chargers can usually be up to 80% of that with the same number of diverse-frequency chargers; iii) to provide a given minimum radio power at sensor nodes, the number of unique-frequency chargers required slightly exceeds that of diverse-frequency chargers by no more than 10%; iv) it is needless to further schedule the unichargers after appropriate placement to increase the average radio power at sensor nodes.

REFERENCES

- [1] S. Basagni, M. Y. Naderi, C. Petrioli, and D. Spenza, "Wireless sensor networks with energy harvesting," in *Mobile Ad Hoc Networking: Cutting Edge Directions*, Hoboken, NJ, USA: Wiley, Mar. 2013, ch. 20, pp. 703–736.
- [2] W. Ouyang, C. W. Yu, C. Huang, and T. H. Peng, "Optimum partition for distant charging in wireless sensor networks," in *Proc. 7th Int. Conf. Mobile Ad-Hoc Sensor Netw. (MSN)*, Dec. 2011, pp. 413–417.
- [3] Y.-J. Hong, J. Kang, S. J. Kim, S. J. Kim, and U.-K. Kwon, "Ultra-low power sensor platform with wireless charging system," in *Proc. IEEE Int. Symp. Circuits Syst. (ISCAS)*, May 2012, pp. 978–981.
- [4] Z. Li, Y. Peng, D. Qiao, and W. Zhang, "Joint charging and rate allocation for utility maximization in sustainable sensor networks," in *Proc. 11th Annu. IEEE Int. Conf. Sens., Commun., Netw. (SECON)*, Jun./Jul. 2014, pp. 459–467
- [5] C. Wang, J. Li, F. Ye, and Y. Yang, "Improve charging capability for wireless rechargeable sensor networks using resonant repeaters," in *Proc. 35th Int. Conf. Distrib. Comput. Syst. (ICDCS)*, Jun./Jul. 2015, pp. 133–142.
- [6] K. Li, H. Luan, and C.-C. Shen, "Qi-ferry: Energy-constrained wireless charging in wireless sensor networks," in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*, Apr. 2012, pp. 2515–2520.
- [7] L. He, L. Kong, Y. Gu, J. Pan, and T. Zhu, "Evaluating the on-demand mobile charging in wireless sensor networks," *IEEE Trans. Mobile Com*put., vol. 14, no. 9, pp. 1861–1875, Sep. 2015.

54882 VOLUME 6, 2018



- [8] C. Wang et al., "Near-threshold energy- and area-efficient reconfigurable DWPT/DWT processor for healthcare-monitoring applications," IEEE Trans. Circuits Syst., II, Exp. Briefs, vol. 62, no. 1, pp. 70–74, Jan. 2015.
- [9] J. Zhou, C. Huang, C. Wang, T. T.-H. Kim, and Y. Lian, "Energy-efficient digital and wireless IC design for wireless smart sensing," *J. Semiconduc*tors, vol. 38, no. 10, p. 105005, 2017.
- [10] S. Zhang, Z. Qian, F. Kong, J. Wu, and S. Lu, "P³: Joint optimization of charger placement and power allocation for wireless power transfer," in Proc. IEEE INFOCOM, Apr. 2015, pp. 2344–2352.
- [11] R. P. Wicaksono, G. K. Tran, K. Sakaguchi, and K. Araki, "Wireless grid: Enabling ubiquitous sensor networks with wireless energy supply," in *Proc. IEEE Veh. Technol. Conf. (VTC Spring)*, May 2011, pp. 1–5.
- [12] S. He, J. Chen, F. Jiang, D. K. Y. Yau, G. Xing, and Y. Sun, "Energy provisioning in wireless rechargeable sensor networks," *IEEE Trans. Mobile Comput.*, vol. 12, no. 10, pp. 1931–1942, Oct. 2013.
- [13] H. Dai, H. Ma, A. X. Liu, and G. Chen, "Radiation constrained scheduling of wireless charging tasks," *IEEE/ACM Trans. Netw.*, vol. 26, no. 1, pp. 314–327, Feb. 2018.
- [14] H. Dai, X. Wang, A. X. Liu, H. Ma, and G. Chen, "Optimizing wireless charger placement for directional charging," in *Proc. IEEE INFOCOM*, May 2017, pp. 1–9.
- [15] H. Dai et al., "SCAPE: Safe charging with adjustable power," IEEE/ACM Trans. Netw., vol. 26, no. 1, pp. 520–533, Feb. 2018.
- [16] I. Katsidimas, S. Nikoletseas, T. P. Raptis, and C. Raptopoulos, "Efficient algorithms for power maximization in the vector model for wireless energy transfer," in *Proc. ACM ICDCN*, Hyderabad, India, 2017, Art. no. 30.
- [17] S. Martello, D. Pisinger, and P. Toth, "New trends in exact algorithms for the 0–1 knapsack problem," Eur. J. Oper. Res., vol. 123, no. 2, pp. 325–332, 2000.
- [18] P. Nintanavongsa et al., "Design optimization and implementation for RF energy harvesting circuits," *IEEE J. Emerg. Sel. Topics Circuits Syst.*, vol. 2, no. 1, pp. 24–33, Mar. 2012.
- [19] P. Guo, X. Liu, S. Tang, and J. Cao, "Concurrently wireless charging sensor networks with efficient scheduling," *IEEE Trans. Mobile Comput.*, vol. 16, no. 9, pp. 2450–2463, Sep. 2017.
- [20] M. Y. Naderi, K. R. Chowdhury, and S. Basagni, "Wireless sensor networks with RF energy harvesting: Energy models and analysis," in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*, New Orleans, LA, USA, Mar. 2015, pp. 1494–1499.
- [21] M. Y. Naderi, P. Nintanavongsa, and K. R. Chowdhury, "RF-MAC: A medium access control protocol for re-chargeable sensor networks powered by wireless energy harvesting," *IEEE Trans. Wireless Commun.*, vol. 13, no. 7, pp. 3926–3937, Jul. 2014.
- [22] 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 *Proc. IEEE GLOBECOM*, Austin, TX, USA, Dec. 2014, pp. 2543–2549.
- [23] Y. Peng, Z. Li, G. Wang, W. Zhang, and D. Qiao, "Prolonging sensor network lifetime through wireless charging," in *Proc. IEEE RTSS*, San Diego, CA, USA, Nov./Dec. 2010, pp. 129–139.
- [24] B. Tong, Z. Li, G. Wang, and W. Zhang, "How wireless power charging technology affects sensor network deployment and routing," in *Proc. IEEE ICDCS*, Genoa, Italy, Jun. 2010, pp. 438–447.
- [25] L. Jiang, H. Dai, X. Wu, and G. Chen, "On-demand mobile charger scheduling for effective coverage in wireless rechargeable sensor networks," *Mobile Netw. Appl.*, vol. 19, no. 4, pp. 543–551, 2014.
- [26] H. Dai, G. Chen, C. Wang, S. Wang, X. Wu, and F. Wu, "Quality of energy provisioning for wireless power transfer," *IEEE Trans. Parallel Distrib.* Syst., vol. 26, no. 2, pp. 527–537, Feb. 2014.
- [27] A. Madhja, S. Nikoletseas, and T. P. Raptis, "Hierarchical, collaborative wireless charging in sensor networks," in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*, Mar. 2015, pp. 1285–1290.

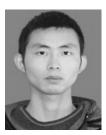
- [28] L. Xie, Y. Shi, Y. T. Hou, W. Lou, H. D. Sherali, and S. F. Midkiff, "Multinode wireless energy charging in sensor networks," *IEEE/ACM Trans. Netw.*, vol. 23, no. 2, pp. 437–450, Apr. 2015.
- [29] V. V. Vazirani, Approximation Algorithms. Berlin, Germany: Springer, 2003.



PENG GUO received the M.S. and Ph.D. degrees from the Huazhong University of Science and Technology, Wuhan, China, in 2003 and 2008, respectively. He is currently an Associate Professor with the School of Electronic Information and Communications, Huazhong University of Science and Technology. His research interests include wireless sensor networks, distributed computing, and in-network processing. He has served as a reviewer for several international journals/conference proceedings.



XUEFENG LIU received the M.S. degree from the Beijing Institute of Technology, China, in 2003, and the Ph.D. degree from the University of Bristol, U.K., in 2008. He is currently an Associate Professor with the School of Electronic Information and Communications, Huazhong University of Science and Technology. His research interests include wireless sensor networks and in-network processing. He has served as a reviewer for several international journals/conference proceedings.



MINGHUI CHEN received the B.S. degree from the University of Suzhou, China, in 2017. He is currently pursuing the master's degree with the Huazhong University of Science and Technology. His research interests include wireless sensor networks and in-network processing.



KUI ZHANG received the B.S. and M.S. degrees from the Huazhong University of Science and Technology, Wuhan, China, in 2007 and 2009, respectively, and the Ph.D. degree from the University of Twente, The Netherlands, in 2015. He currently holds a post-doctoral position with the University of Twente. His research interests include wireless sensor networks and pervasive computing.