Fast Interference-Aware Scheduling of Multiple Wireless Chargers

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Abstract—**Nowadays, breakthroughs in wireless power transfer make it possible to transfer energy over a long distance. Existing works mainly focused on maximizing network lifetime, optimizing charging efficiency, and optimizing charging quality. All these works use a charging model with the linear superposition, which may not be the most accurate in a real life situation. We use a concurrent charging model, which has a nonlinear superposition, and we consider the Fast Charging Scheduling problem (FCS): given multiple chargers and a group of sensor nodes, how can the chargers be optimally scheduled over the time dimension so that the total charging time is minimized and each sensor node has at least energy E? We prove that FCS is NP-complete and propose algorithms to solve the problem in 1D line and 2D plane respectively. Unlike other algorithms, our algorithm does not need to calculate the combined energy of every possible combination of chargers in advance, which greatly reduces the complexity. We obtain a bound in 2D cases when chargers and sensors are uniformly distributed. Extensive simulations demonstrate that the performance of our algorithm is almost as good as the optimal algorithm when the distribution of chargers is not very dense.**

Index Terms—**Wireless charging, Nonlinear Superposition, Efficient Scheduling, Interference-Awareness.**

I. INTRODUCTION

Wireless sensor networks (WSNs) have many applications: Shen et al. [1] proposed a cyber-physical design approach to monitor the indoor temperature. WSNs are also used to monitor structural health [2], measure biological parameters in cattle farm [3] and so on. However, sensors in WSNs are powered by small batteries and constrained energy supply limits the lifetime of WSNs. Wireless charging techniques have been proposed to provide additional energy supply to prolong the lifetime of WSNs [4, 5]. Recent breakthroughs in wireless power transfer (WPT) technology make it possible to charge sensors over a long distance.

However, long-distance charging brings a new problem: low transition efficiency, which means that the energy harvested by sensors is much lower than the energy sent by the chargers. As a result, it takes a much longer time to charge a WSN than expected. One way is to increase the chargers' power, but this may lead to electromagnetic radiation (EMR) pollution and harm humans [6]. By adding more chargers in WSNs and using multiple chargers to charge sensors at the same time, the combined power energy will be stronger and charging time will be shortened. To calculate the combined charging power, almost all previous studies assumed that the combined energy from multiple chargers is additive [6–12], but this may not
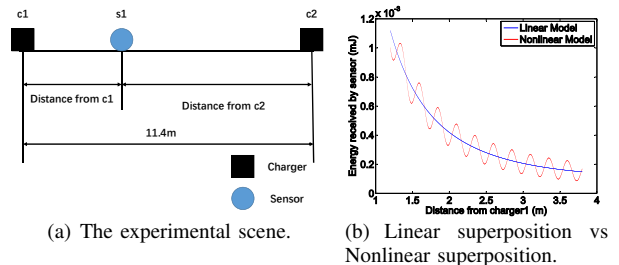

(a) The experimental scene.

(b) Linear superposition vs Nonlinear superposition.

Fig. 1. Difference between linear superposition and nonlinear superposition. There are two chargers placed in a line and they are $11.4m$ apart from each other. There is a sensor moving from c_1 to c_2. The x-axis of the figure represents the distance between the sensor and c_1, and the y-axis represents the energy received by this sensor from those two chargers. Blue line in (b) represents the combined energy of two chargers using linear superposition model, while red line represents the combined energy using nonlinear superposition model.

be the most accurate. Naderi et al. [13] points out that radio interference occurs when using multiple chargers to charge sensors at the same time.

Fig. 1 shows the difference between linear superposition model and nonlinear superposition model. We can see from Fig. 1(b) that when using nonlinear superposition charging model, chargers would strengthen each other in some places (which we call **strong areas**) but also weaken each other in other places (which we call **weak areas**). Based on this, Guo et al. [14] proposed a concurrent charging model and gave algorithms to solve the concurrent charging scheduling problem. The combined energy of two chargerps is not equal to the sum of these two chargers' energy. Multiple chargers may weaken or strengthen each other depending on different distances, therefore, we cannot know the combined energy at a sensor node unless we explicitly know the set of working chargers, their positions and phases. Guo et al. [14] calculates the charging energy of each charger set at each sensor node in advance, and algorithms were proposed based on these values. As a result of this preparatory process, the complexity of this step grows exponentially with the number of chargers.

However, we observe that, even though the combined energy is nonlinear superposition, it still has some properties. With these properties, we do not need to calculate the combined energy of each charger groups in advance, which reduces the complexity.

In this paper, we focus on FCS to prolong the lifetime of

WSNs. In our problem, multiple chargers can charge the same sensor at the same time, which may cause electromagnetic interference. To provide some intuitive insights into the structure of our problem, we first consider the scenario that all chargers and sensor nodes are distributed along a one-dimensional (1D) line. For this scenario, we propose an algorithm called FastPick. Then we investigate FCS in two-dimensional (2D) WSNs. We obtain a bound when chargers and sensors are uniformly distributed.

Our main contributions are summarized as follows:

- We apply a new charging model with nonlinear superposition into the FCS problem, which is proved to be NP-complete.
- We propose the FastPick algorithm to solve FCS in 1D scenario and get a bound of $2 - \epsilon$.
- We propose the RoundPick algorithm to solve FCS in 2D scenario and get a bound.
- Simulations are conducted to evaluate the proposed solutions. The results are shown from different perspectives to provide conclusions.

The rest of the paper are organized as follows. Section II describes the concurrent charging model and formulates the problem. Section III analyzes the problem and proposes solutions. Section IV includes the simulation results. Section V surveys related works, and conclusions follow in section VI.

II. MODEL AND PROBLEM FORMULATION

In this section, we first propose our models, including network model, charging model and harvesting model. Different from previous works, our charging model is nonlinear superposition. Then we use these models to define FCS.

A. Network Model

We consider a set of N stationary sensor nodes $S = \{s_1, s_2, ..., s_n\}$ distributed over a two-dimensional area. The location of the ith node s_i is denoted as (x_i, y_i), and each node consumes energy for sensing, data reception, and transmission. There are also M chargers, defined as $C = \{c_1, c_2, \ldots, c_m\}$, distributed in this area. The location of the jth charger is denoted as (x_j, y_j). There is a set $\{d_{ij} | 1 \leq i \leq N, 1 \leq j \leq M\}$ of distance between c_i and s_j.

B. Charging Model and Harvesting Model

As we all know, chargers use electromagnetic waves to transmit energy. According to [14], we suppose that the amplitude of the frequency component ω_0 in the chargers' power spectral density (PSD) curve is A_0 and that the corresponding initial phase is φ_0. Therefore, the power density of each charger at ω_0 is $p_0 = \frac{A_0^2}{2}$. Since the charging powers from wireless chargers weaken nonlinearly with distance, we assume for simplicity, that the power attenuation factor is 2. The radio signal of the frequency component ω_0 arriving at the sensor node s_j from the charger c_i is expressed as :

$$a_{i0}(t) = \frac{A_0}{4\pi d_{ij}/\lambda} cos(\omega_0 t + \varphi_0 - 2\pi \frac{d_{ij}}{\lambda}) \qquad (1)$$

Based on this, Guo [14] proposed the compound radio signal of frequency component ω_0 at s_j from a group of chargers C is:

$$A_0^j(t) = \sum_{c_i \in C} a_{i0}(t) = \sum_{c_i \in C} \frac{A_0}{4\pi d_{ij}/\lambda} cos(\omega_0 t + \varphi_0 - 2\pi \frac{d_{ij}}{\lambda})$$
$$(2)$$

Then, we get the power of compound radio signal at sensor s_j from charger set C as follows:

$$P_{j|C} = \int \overline{[A_0^j(t)]^2} d_\omega$$
$$= P \sum_{c_i \in C} \frac{1}{d_{ij}^2} + P \sum_{c_i \in C} \sum_{\substack{c_m \in C \\ c_m \neq c_i}} \frac{1}{d_{ij} d_{mj}} cos(2\pi \frac{d_{ij} - d_{mj}}{\lambda})$$
$$(3)$$

where $P = \int p_i d_\omega$ is the radio power of each charger.

From this equation, we can see the nonlinear superposition charging effect in the concurrent charging. The equation above considers only distance and assumes that all sensors' initial phases are the same. With an adjustable initial phase, a new problem can be derived: how can the chargers initial phases be optimally controlled so that the total charging time is minimized? We leave this problem in our future work.

Denote $P_j^G|_c$ as the power that sensor s_j get from a group of chargers C. We assume $P_j^G|_c = \alpha * P_{j|C}$, where $\alpha(0 < \alpha < 1)$ is the transition coefficient. From the former research [15], we know that if the radio power is lower than a threshold, then the energy received by sensors is zero. Taking this into account, we present the harvesting model as follows:

$$e_j|_{C,t} = \begin{cases} 0 & if \ P_j|_C < \epsilon \\ \alpha t(P_j|_C - \epsilon) & otherwise \end{cases}$$

where $e_j|_{C,t}$ denotes the energy that s_j harvested from a set of chargers C during time t, and ϵ is the threshold of the radio power.

Each sensor also has an electric capacity. We set this capacity as E. So the energy harvesting model can be expanded as follows:

$$e_j|_{C,t} = \begin{cases} 0 & if \ P_j|_C < \epsilon \\ 0 & if \ P_j|_C > \epsilon \ and \ e_j' > E \\ \alpha t(P_j|_C - \epsilon) & otherwise \end{cases}$$

where e_j' denotes the energy s_j has now, and ϵ is the threshold of the radio power.

C. Problem Formulation

We use the vector $\boldsymbol{H_i}$ to denote i_{th} charging schedule. For example, $\boldsymbol{H_2}$=[1,0,1,0] means that in the second charging period, the first and the third charger are open while the second and the forth charger are closed. And we use Δ to represent

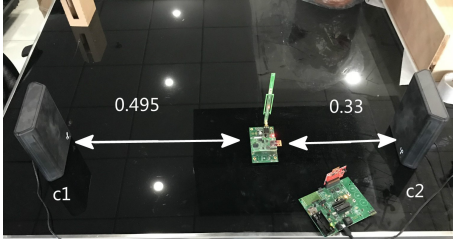Fig. 2. Experiment environment.

each charging duration, which are considered to be the same. Therefore, the main problem studied in this paper is:

Problem 1: Given a set C of chargers with fixed position, a set S of rechargeable sensors, a set $\{d_{ij} | 1 \leq i \leq N, 1 \leq j \leq M\}$ of distance between c_i and s_j, and an energy capacity E of each sensor, FCS is to find a set of multiple charging periods $\{H_1, H_2, ..., H_k\}$ to charge each sensor with energy no less than E, and k is minimized.

III. ALGORITHMIC DESIGN

In the first three subsections, we show that FCS is NP-complete, then we discuss the FCS in a 1D line and propose an algorithm for this problem. Once we prove that this algorithm has a bound of $2 - \epsilon$, we expand the 1D line to 2D network and propose an algorithm to solve FCS. We also get a bound in 2D plane.

A. Hardness Analysis

Theorem 1: The FCS is NP-complete.

Proof: We prove this by using the decision version of the problem: given a threshold k, does there exist a collection of charger sets $\{C_1, C_2, \ldots, C_h\}(C_i \subseteq C, i = 1, 2, \ldots, h)$ and a corresponding number of charging periods $H_1, \ldots, H_k$ that satisfy the constraint above and where h is equal or less than k?

We prove this decision problem by reduction from the k-napsack problem [16], which is NP-hard. The decision version of the knapsack problem is as follows: given a set of items $\mathbb{U} = \{e_1, e_2, \ldots, e_m\}$, 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 knapsack problem, we construct an instance of FCS as follows:

- For each element e_j in $\mathbb{U}$, we construct a charging period H_i in FCS.
- For the weight of the item, we construct the charging period duration in FCS, for the value of item, we construct the total energy harvested by the network in this period; we assume all charging periods' durations are equal to Δ.
- For the weight of knapsack, we use $k * \Delta$ to represent the limit. And for the given value V, we set $M * E$ as the value.

- After we pick a period H_i, we need to recalculate other periods' value, because while some sensors in this period may harvest energy, it is not sufficient to reach E. Therefore, we need to reduce other periods' value, as this complexity is the number of periods.

Combining these elements, we get the following special case of the decision version of the FCS problem: given a limited time $k * \Delta$ and a period set, does there exist a collection of periods whose total size is less than or equal to k so that all the sensors will harvest no less than E energy (total is ME)?

The construction can be finished in polynomial time; thus, we reduce solving the NP-hard knapsack problem to a special case of FCS, implying that FCS is NP-hard.

B. One-Dimensional Line

In this section, we first show how initial phases influence charging, then we propose an algorithm when phases and distances are considered at the same time.

1) Rationale: In this paper, we assume that the frequency of all chargers are the same. Then according to our observation, when the difference of phases between two chargers is less than $\lambda/4$, these two chargers will strengthen each other. And when the difference is between $\lambda/4$ and $\lambda/2$, two chargers will weaken each other, where λ represents the wavelength. As we can see from Fig. 3, the initial phases of chargers c_1 and c_2 are the same, and green lines represent the interaction areas of c_1 and c_2, and sensor s_2 is distributed in their strong area while s_3 lies in their weak area. If we increase the phase of c_1 by $\pi/2$, then the total size of their strong areas and weak areas remain the same, but the positions will change: original strong areas become weak and original weak areas become strong. Generally speaking, in 1D line, once the distance and initial phase are determined, then the strong and weak areas are determined. When we change initial phases to different values, these areas will move along the line. Based on these observations, we propose FastPick, a 2-approximation algorithm, to solve the FCS with adjustable initial phases in 1D line.

2) The FastPick Algorithm: FastPick is shown in Algorithm 1. Under the condition that the initial phases are adjustable, all chargers can be opened together and the initial phases of each charger are the only variable to be changed (line 1). Then we choose the sensor with the least energy (line 3). Next, we choose two chargers that are the closest to this sensor, and adjust their initial phases to make as many sensors as possible lie in their strong areas (lines 4-5). As we all know that areas will move parallel when initial phases change, so we can make all chargers strengthen each other in the same places by adjusting their phases (line 6). In line 8, we reverse the original weak and strong areas, make original weak areas become strong while strong areas become weak, this step ensures that our algorithm is 2-approximation. Algorithm 1 ends when all sensors are fully charged (line 2), and after each charging period, it will check whether a sensor is fully charged (lines 9-11).

Algorithm 1 FastPick (FP)

Input: C: Charger set, S: Sensor set, E: Energy capacity

Output: The i_{th} charging schedule: $\boldsymbol{H_i}$

1: Open all chargers together.
2: **while** $S \neq \emptyset$ **do**
3:    Find a sensor with the least energy.
4:    Choose two chargers that are the closest to this sensor.
5:    Adjust their phases to that make as many sensors as possible lie in their strong areas and record their phases in $\boldsymbol{H_i}$.
6:    Adjust the initial phases of other chargers to make their strong and weak areas overlap with the previous ones and record their phases in $\boldsymbol{H_i}$.
7:    Make all chargers work for time Δ.
8:    Change initial phases of all chargers and make original weak areas become strong while original strong areas become weak and record their phases in $\boldsymbol{H_i}$.
9:    Make all chargers work for time Δ.
10:    **for** every sensor in S **do**
11:       **if** s_i is fully charged **then**
12:          Remove s_i from S.

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3) Approximation Ratio Analysis: Now we show that Fast-Pick holds a bound of $2 - \epsilon$. First, we show a lower bound on the optimal charging time. Imagine that all chargers strengthen each other in all places (which cannot be achieved in reality); in this case, we can always open all chargers without interference. In doing so, we have a charging time T_a. Obviously, T_a is a lower bound on the optimal charging time.

Next, we show that the charging time achieved by our algorithm FastPick is at most 2 times longer than T_a.

We know that sensors lie either in strong or weak areas. Sensors which lie in strong areas will get the most energy they can get from the chargers in this charging period. Sensors which lie in weak areas can hardly get energy in this period, but in the next period, weak and strong areas will reverse (line 8 in Algorithm 1), so these sensors will get most energy in the next period. If we put these two periods together to construct a big period, then each sensor will get a little more energy in this big period than in the hypothetical situation that all chargers strengthen each other in all places. So the total charging time is $2T_a - \epsilon$, which ensures $2OPT - \epsilon$. Therefore, Algorithm 1 holds a bound of $2 - \epsilon$.

4) Example in 1D: After computing, we get the combined energy of chargers which is showed in Table I. Then algorithm begins to select the sensor with the least energy; in the first iteration, all sensors have energy 0. Without loss of generality, we choose s_1, since s_1 does not distribute in any strong area, the algorithm adds c_1 in $\boldsymbol{H_1}$, then adds c_2, c_3 in $\boldsymbol{H_1}$. That is the first charging period schedule and after charging, the sensors' energy are $\{2, 2, 2, 0, 2\}$. In the second iteration, algorithm selects s_4 as the least energy sensor and adds c_3 in $\boldsymbol{H_2}$. Then algorithm adds c_1 only in $\boldsymbol{H_2}$, because if added c_2 then, the total energy harvested by all sensors would decrease.
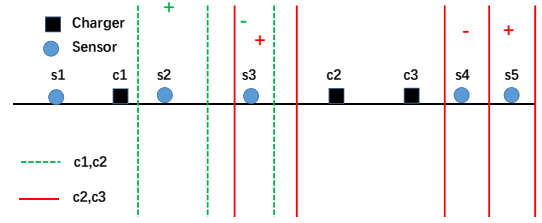

Fig. 3. One-dimensional strong and weak areas. Green lines represent the interactional areas of c_1 and c_2, and red lines represent the interactional areas of c_2 and c_3. c_1 and c_3 have no interactional area because they are too far away from each other.

After charging, the sensors' energy are $\{4, 4, 4, 2, 3\}$. In the third and forth iterations, the algorithm does the same

TABLE I
THE RECEIVING ENERGY OF SENSORS DURING ONE TIME DURATION IN 1D LINE.

	s_1	s_2	s_3	s_4	s_5
c_1	2	2	1	0	0
c_2	0	1	2	1	1
c_3	0	0	1	2	1
c_1, c_2	2	0	3	1	1
c_1, c_3	2	2	2	2	1
c_2, c_3	0	1	0	0	2
c_1, c_2, c_3	2	2	2	0	2

operation. After this, the sensors' energy are $\{8, 8, 8, 6, 5\}$. In the fifth iteration, the least energy sensor becomes s_5. and s_5 is distributed in the strong area of c_2 and c_3, so c_2, c_3 are added into $\boldsymbol{H_5}$. Then algorithm keeps adding c_1 in $\boldsymbol{H_5}$ because c_1, c_2, c_3 could provide more energy to all sensors than c_2, c_3. After charging, the sensors' energy are $\{10, 10, 10, 6, 7\}$ and s_1, s_2, s_3 are fully charged. Under this situation, c_1 becomes useless because it cannot charge s_4 and s_5. In the sixth iteration, the least energy sensor becomes s_4 and the algorithm adds c_3. After charging, sensors energy are $\{10, 10, 10, 8, 8\}$. In the seventh and eighth iterations, the sensor with least energy is s_4, so we add c_2 only, that allows the total charging periods of this example to be 8.

C. Two-Dimensional Plane

In this section, we propose an algorithm to solve FCS in 2D plane where initial phases of all chargers are the same. Then, we prove that under some conditions, our algorithm has a bound which is showed in the next section.

In 1D line, the strong and weak areas are line segments, and in 2D plane, the strong and weak areas are interspaces between some hyperbolas as showed in Fig. 4. Given any pair of chargers, we can find their strong and weak areas, and use the area information to make our schedule.

In order to reduce calculation, we propose a way to partition the WSN. After partition, we just need to focus on each slot independently. As we all know, the coverage areas of chargers would coincide in some place; with concurrent charging model, we cannot just look at one charger and leave other chargers
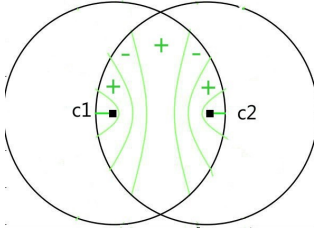
Fig. 4. Two-dimensional strong and weak areas. c_1 and c_2 represent chargers. '+' represents the strong areas of these two chargers, '-' represents the weak areas.

irrespective. We will show that our partition holds a bound, and this bound is related to the distribution of this WSN.

1) Partition: The partition should hold three conditions:

Condition 1: Every sensor in one slot should be covered by chargers in this slot.

Condition 2: There is at least one charger in a slot.

Condition 3: The length of slot side should be minimized, but no less than $2 * R$ (R is the charging radius).

After every charging period, we need to move the slot position by moving the slot towards the direction of the sensor with the least energy and condition 3 guarantee that after moving, two chargers, which cause the overlap, will be in the same slot.

With these three conditions, we can find a bound of our algorithm. The worst case of the partition is that we can only get one slot, which means we do not make any partition. The best case of the partition is that every slot has exactly one charger.

2) Approximation Ratio Analysis: We take uniform distribution as an example and show the relation between bound and distribution. Hypothesis model is that all chargers strengthen each other to every sensor, so the schedule is to open all chargers together. This charging time is less than the optimal way. Under these three conditions, errors between neighbouring slots depend on the number of sensor sets in overlap areas. Suppose that sensors and chargers are uniformly distributed, then the most overlap areas of a slot are 4, and the sensors in these overlaps are half of sensors in this slot. If chargers in other slots will strengthen these overlaps, we just ignore them. If chargers will weaken the overlaps, the worst case is that half the sensors would get less energy. But after every period, we do the movement operation, which will make sensors in weak areas in a new slot without charging conflict with other slot. But one operation of movement can only make one direction in 2D plane becomes conflict-free, which means that we should do another movement to make another direction become conflict-free. In every charging period, we first choose a pair of chargers that can charge the most energy, then a new charger can be added if only if this charger has the same strong area with the first two chargers. So in every charging period, we can make sure that half sensors charge the most energy. Since half of them are influenced by other slots, eventually, only $1/4$ sensors get the most energy. The bound is $\alpha * (N_d + 1) - \epsilon$, where α is the charging ability

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Algorithm 2 RoundPick (RP)

Input: C: Charger set, S: Sensor set, E: Energy capacity
Output: The charging schedule: H_1, H_2, H_3, ...

1: Choose a charger say c_i that can charge the most sensors.
2: **for** every sensors in the coverage of c_i **do**
3:   **if** s_j has the farthest distance to c_i on x or y axis **then**
4:     Record s_j.
5: Use these two sensors as the border to partition the WSN
6: **while** partition is not under three conditions **do**
7:   Add a new charger in this slot that has the least side length.
8: **while** $S \neq \emptyset$ **do**
9:   **for** every slot **do**
10:     Compute each two chargers' strong area, called St.
11:     Choose a sensor s_j with the least energy, do **SP** (s_j).
12:     Make chargers in H_i work for time Δ.
13:     Choose a sensor s_j that has the lowest energy and lies in a overlap.
14:     Compute the distance L between the s_b and the charger c_d that cause the overlap.
15:     Move slot to the direction of s_b-c_d with distance L.
16:   **for** every sensor in S **do**
17:     **if** s_i is fully charged **then**
18:       Remove s_i from S.

Algorithm 3 sub-procedure SinglePick (SP)

Input: C: Charger set, S: Sensor set, E: Energy capacity
Output: The i_{th} charging schedule: H_i

1: **for** every area in St **do**
2:   **if** s_j is in this area **then**
3:     Add these two charger in H_i and **break**.
4: **if** H_i is empty **then**
5:   Add the charger that can charge most energy to s.
6: **for** every charger in C **do**
7:   **if** adding will charge more energy to the WSN **then**
8:     Add this charger in H_i.
9: **return** H_i
10: **return** Se as the FCS schedule plan.

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compared with OPT in each slot, N_d is the influenced direction in slot ($N_d = \{1, 2\}$), and 1 represents the original slot, while ϵ is the error related to the actual charging condition. In uniform distribution, the upper bound is $(2 - \epsilon) * (2 + 1) - \epsilon = 6 - 4\epsilon$.

3) The RoundPick Algorithm: In lines 1-7, the Algorithm 2 partitions the whole WSN. After partitioning, algorithm circularly pick chargers during each iteration to decide each charging schedule (lines 8-12). The iteration terminates when all the sensors are fully charged, which means that harvest energy is at least E ($S = \emptyset$ line 8). In each iteration, algorithm first computes each two chargers strong areas in each slot, called St (line 10), then algorithm chooses a sensor with the least energy and uses Algorithm 2 to select chargers (line 11). Then, the chargers opening in this charging period are selected. After charging, we need to move slot so that the sensors lied
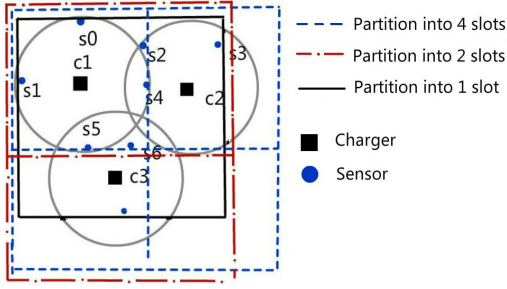
Fig. 5. An example of the partition of a WSN. Blue lines represent the partition that each slot has at most one charger; Red lines represent the partition that each slot has at most two chargers; Black lines represent the partition that all chargers lie in the same slot.

TABLE II
THE RECEIVING ENERGY OF SENSORS DURING ONE TIME DURATION IN 2D PLANE.

	s_0	s_1	s_2	s_3	s_4	s_5	s_6	s_7
c_1	2	2	0	0	2	2	0	0
c_2	0	0	2	2	3	0	0	0
c_3	0	0	0	0	0	3	3	3
c_1, c_2	2	2	2	2	0	2	0	0
c_1, c_3	2	2	0	0	2	5	2	2
c_2, c_3	0	0	2	2	3	3	3	3
c_1, c_2, c_3	2	2	2	2	0	5	2	2

in overlaps no longer lies in the overlap (lines 13-15). In this iteration, we still need to remove sensors with full energy, which means they already got E energy (lines 16-18).

The complexity of Algorithm 2 is O(M^3N). The total number of charging period is O(N), we can make this by increasing each charging period. The complexity to partition is O(M), because once we confirm a slot, others can be expanded, and the maximum number of chargers in a slot is M. During every charging period, the complexity of picking chargers is O(M^3); it is composed by two parts; the number of slot and chargers in slot. The most combination is M^3 mathematically. So, the total complexity is O(M^3N).

4) Example in 2D: In this section, we give an example to show our algorithm. A simple example is shown in Fig. 5 and Table II shows the actual charging energy.

Suppose the energy capacity of each node $E = 10$. According to algorithm, we first partition the WSN and find the charger that can cover the most sensors. Then, we choose c_1, and use it as the division criterion to partition the whole WSN. Next, we get 4 slots, as shown in Fig. 5, with green lines. Afterwards, we check whether this partition follows our three conditions. Obviously, s_2 belongs to slot 1, but since it is not covered by c_1, this partition is incorrect. Then, we add one charger to c_2, without loss of generality, we add c_2, and we use a new length of slot to partition the WSN, which is shown in Fig. 5 with red lines. After partition, we get 2 slots, and we check it again. s_6 lies in slot 1 but is not covered by c_1 and c_2, which means this partition is wrong, so we add c_3, and make the whole WSN as a slot, which is shown in Fig. 5 with black lines. This is the worst case, because we do not partition the WSN actually. After partition, Algorithm 2 selects a sensor with the least energy; in the first iteration, all sensors have energy 0. Without loss of generality, we choose s_0 and add c_1 in H_1. According to Algorithm 2, we add c_3 into H_1. That is the first charging period schedule. After this charging period, the sensors energy are {2, 2, 0, 0, 4, 5, 3, 3}. In the second iteration, we select s_2 and choose c_2 into H_2; then, we add c_3 into H_2. After this charging period, the sensors energy are {2, 2, 2, 2, 8, 8, 6, 6}. In the third period, we choose c_1, c_3. Because s_4 and s_5 have an energy of 8 now, the energy harvested by them is at most 2 due to our harvest

model in Section III. So, we can add c_2 into H_3 too. After this charging period, the sensors energy are {4, 4, 4, 4, 8, 10, 9, 9}. In the forth iteration, we choose $c_1, c_2.c_3$, and sensors energy after charging are {6, 6, 6, 6 ,8, 10, 10, 10}. In the fifth period, we choose c_1, c_2, and sensors energy are {8, 8, 8, 8, 8, 10, 10, 10}. In the sixth period, we choose c_1, c_2, and sensors energy after charging are {10, 10, 10, 10, 8, 10, 10, 10}. In the seventh period, we choose c_1 only. Therefore, the total charging periods of our algorithm is 7.

Our algorithm would obtain the optimal solution in two extreme cases. The first is when all chargers strengthen each other. Obviously, the optimal method is to turn on all the chargers, which is the same answer that our algorithm gives. The other case is when all chargers do not affect others. In this case, The partition are the chargers themselves, and the optimal way to charge is opening all chargers together, which is the way our algorithm gives.

D. Summary

When initial phases of all chargers are the same, we propose 2 algorithms to solve FCS in 1D line and 2D plane respectively. In 1D line, we propose the FP algorithm to solve FCS and obtain a bound of $2 - \epsilon$ under conditions mentioned in section III-B. When it comes to 2D plane, we propose the RP algorithm to solve FCS and also obtain a bound of $6 - 4\epsilon$ under conditions mentioned in section III-C.

Our algorithms still have some limitations. In this paper, we set the duration of each charging period to be the same. But in reality, different charging periods can have different charging durations. And with adjustable charging duration of each charging period, a new problem can be presented: given multiple chargers and sensors, how can we make decide the opening duration and time of each charger, so that the total charging time is minimized and each sensor node has at least energy E? we also leave this problem in our future works.

We know from section III-C that interaction areas in 2D plane are interspaces between some hyperbolas, which are irregular. So we cannot make all chargers strengthen or weaken each other in the same strong or weak areas respectively. Given a number of chargers, we have to adjust the initial phases of each charger to achieve a better schedule. But there are too many combinations of chargers, and adding or removing any charger may produce a great influence to the charging

schedule. We have to try all combinations of these chargers and the number of combinations grows exponentially with the number of chargers. FCS is more complex in 2D plane and carelessly initial phases changing may not get a better charging plan. Changing initial phases in 2D plane makes interaction areas still irregular and we have to exhaust almost all combinations of chargers to get a relatively better schedule. We will leave this problem in our future works.

IV. EXPERIMENTS

In this section, we conduct a series of simulations with Matlab tool to evaluate the performance of the proposed algorithm.

A. Experimental Settings

We assume wireless devices and chargers are randomly distributed over a $50m \times 50m$ area. In the simulations, we employed the energy harvesting model present in Section III. For the deployments and the harvesting model, the time is calculated and the procedures for the proposed algorithm are executed in Matlab. Fig. 2 shows our experiment equipments. We use the powercast TX91501-915 MHz to transmit energy. Moreover, we set the charger' power to be 915 MHz, which makes the wave length to be $\lambda = 0.33m$. We set the threshold of harvesting power as $\epsilon = 15\mu W$, transition efficiency as $\alpha = 0.25$ and each charging period as $\Delta = 20s$.

Based on these parameters, we calculate the distance threshold, $0.25 * 4/(4\pi*d)^2 = 0.015mW(watt)$. Then we calculate that $d \approx 6.78m$, which means that when the distance between a sensor and a charger is over $6.78m$; the sensor will harvest no energy from that charger. In this simulation, the default number of chargers is $N = 12$. The default number of sensors is $M = 50$, and the default energy capacity is $E = 4mJ$. Fig. 6(a) gives an example of the default placement. 6(b) illustrates the partition that the algorithm finds in the first iteration.

B. Baseline Setup

Currently there is only one algorithm available for FCS with an actual charging model. The algorithms proposed in [14] calculate all the charger groups' charging abilities in advance, and the performance of the Genetic Algorithm (GA) they proposed is almost as good as the brute force algorithm. We consider the GA as the optimal algorithm (OPT).

We also introduce a Random Algorithm (RA) for comparison. In addition, we compare our simulation with the random algorithm that consists of two phases. The first phase is removing k chargers(which cannot charge any sensor, because some sensors may be fully charged after some periods from C. The second phase is to randomly selecting $\beta(N - k)(0 < \beta < 1)$ chargers in each period. In this simulation, we set β to be 0.8.

C. Evaluation Results

In general, RP achieves a near optimal solution and outperforms the random algorithm.

In Fig. 7(a), the total charging periods decreases as the number of chargers grows. This is obvious, because with more

(a) The placement with 12 chargers and 50 sensors.

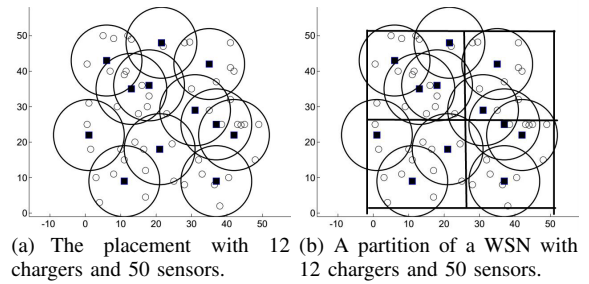(b) A partition of a WSN with 12 chargers and 50 sensors.

Fig. 6. An example of the partition.

chargers, more sufficient energy will be supplied in the same duration, thereby reducing the charging time. According to the algorithms, the performance of RP is close to OPT when the number of chargers is small, and as the number of chargers increases, the operation performance of RP is gradually withdrawn by OPT. This is because when the number of chargers is small, the electromagnetic interference will be limited and will tend to select all the chargers.

In Fig. 7(b), the total charging time grows with the growth of the number of sensors, there is a very good explanation, because with more sensors, interference will become more common, so the total charging length is increased. From each of the algorithms, the performance of RP is close to OPT when the number of sensors is small, and as the number of sensors increases, the performance of RP is worse than OPT. This is because when the number of sensors is small, the electromagnetic interference caused by the sensor will be small, and the overall charging power of the network will be higher than that of a single sensor.

In Fig. 7(c), when the energy capacity goes up, the total charging time grows with the growth of the capacitance, it is obvious, because the total harvesting grows, thereby increasing the charging time. This is due to the fact that the electromagnetic interference is not large in the case of an hour of electrical capacity, but as the capacitance increases, the influence of electromagnetic interference on the charging will be amplified.

In Fig. 7(a) and Fig. 7(b), when the number of sensors or chargers decreases, the chance of charging interferences goes down. As a result, the total charging periods our algorithm calculates is close to the optimal one. However when the number of sensors or chargers goes up, the performance of our algorithm is bad because the interference becomes more common and is hard to be controlled. The only way to make the best choice is calculate each group of chargers when interference occurs.

As for the time complexity, it can be seen from Fig. 7(d-f); the running times of the RP and RA is much lower than the optimal algorithm. As we said before, the complexity of OPT algorithm grows exponentially with the number of chargers. The running times of these three algorithms all increase with the charger scale, sensor scale, and energy capacity, which is as expected.
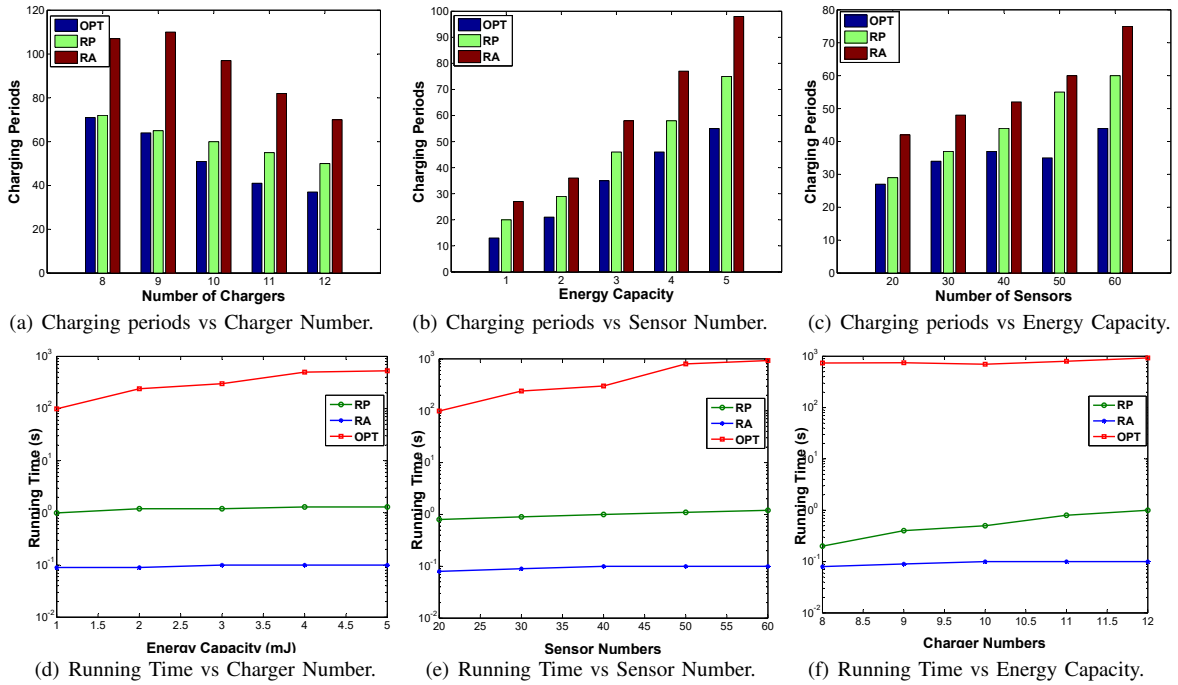
In summary, the proposed algorithm RP performs very

(a) Charging periods vs Charger Number.

(b) Charging periods vs Sensor Number.

(c) Charging periods vs Energy Capacity.

(d) Running Time vs Charger Number.

(e) Running Time vs Sensor Number.

(f) Running Time vs Energy Capacity.

Fig. 7. Simulation Results.

similarly to GA (which is considered as OPT) in sparse network and outperforms the random algorithm.

V. RELATED WORK

In the past decade, wireless charging for WSNs has been widely studied, and some works focused on fixed chargers.

He et al. [15] proposed how to deploy readers in a network to ensure that the WISP tags can harvest sufficient energy for continuous operation. They investigated the energy provision problem of finding the minimum number of RFID readers to cover a given WSN, and they showed that their algorithm can greatly reduce the number of readers compared with those assuming traditional coverage models.Pang et al. [17] investigated the minimum charging coverage problem, which aims to recharge a set of sensors in a given area with the minimum number of wireless chargers. They introduced a partition algorithm to address this charging coverage challenge, and through theoretical analysis, they proved that the proposed algorithm can develop a solution close to the optimal one with guarantees approximation ratio. Dai et al. [7] also focused on charger location problem but took safety into account. They proposed PESA, a wireless charger Placement scheme that guarantees EMR safety for every location on the plane. Their experimental results showed that in terms of charging utility, their algorithm outperforms the prior art by up to 45.7%. Zhang et al. [5] jointly considers charger placement and power allocation to improve the charging quality. They proved the problem is NP-complete then proposed an approximation algorithm. Extensive simulations demonstrate that the gap between their design and the optimal algorithm is within 4.5%, validating their theoretical results.

There are also some works focused mobile chargers. Gao et al. [10] proposed a new framework that can jointly schedule sensor activity and recharging to save the traveling energy of Recharging Vehicles (RVs). They proposed two schemes to manage sensor activity: balanced clustering and distributed sensor activation schemes. Based on schemes, they further introduced a new metric so that the energy demand in each cluster can be managed. Then they formulated the recharging problem into a Traveling Salesman Problem with Profits and proposed two algorithms to reduce travelling distance. The experiments results show that their algorithms can save travelling distances of RVs by 41% and 16% respectively. Shi et al. [18] investigated the operation of a sensor network under this new enabling energy transfer technology. They considered the scenario of a mobile charging vehicle periodically traveling inside the sensor network and charging the battery of each sensor node wirelessly. They introduced the concept of renewable energy cycle and offer both necessary and sufficient conditions. Zhang et al. [19] proposed a scheduling algorithm called Pushwait to cover a one-dimensional WSN of infinite length, and they proved that Pushwait is the optimal algorithm in a 1D scenario. Li et al. [4] proposed J-RoC — a practical and efficient Joint Routing and Charging scheme. They used proactives to guide the routing activities in the network and deliver energy to where it is needed. Evaluation results demonstrated that J-RoC significantly elongates the network lifetime compared to existing wireless charging based schemes. Sangare et al. [20] developed a hardware platform using off-the-shelf radio frequency energy transfer hardware equipments to evaluate the practical performance of wireless sensor networks powered by radio frequency energy transfer.

Based on the developed platform, they established an empirical model and used the empirical model to jointly optimize path planning and mobile charge scheduling for wireless-powered sensor networks. Numerical results showed that their derived policy significantly improves the performance of wireless sensor networks in different practical scenarios.

However, all the works above are based on an assumption that the power received by one device from multiple chargers is linear additive, but this assumption may not be entirely accurate.

Naderi et al. [13] point out that radio interference occurs when multiple chargers are used to charge one device, even if all the chargers transfer energy with high power. Interference may result in higher or lower levels of energy cancellation. Guo et al. [14] proposed three algorithms to solve concurrent charging scheduling problem based on the nonlinear super-position charging model. To the best of our knowledge, it is the first time that the nonlinear superposition charging model has been used. However, their algorithms had to calculate all charger sets utilities in advance. The complexity would grow exponentially with the number of chargers. Therefore, we propose an algorithm to solve FCS without calculations beforehand.

VI. Conclusion

In this paper, we study the fast charging schedule problem (FCS), addressing the nonlinear superposition charging effect caused by radio interference. We prove that this problem is NP-complete by reduction from the set cover problem. To solve this problem, we propose the RP algorithm, which has a bound of $6 - 4\epsilon$ in 2D plane, and ϵ is the error related to the actual charging condition. The simulation results show that the RP can achieve a good performance that is close to that of OPT at sparse network.

VII. Acknowledgments

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