

Prolonging WSN Lifetime with an Actual Charging Model

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Abstract—Recent breakthroughs in wireless power transfer make it possible to charge sensors over a long distance. Existing works have mainly focused on maximizing network lifetime, optimizing charging efficiency, and optimizing charging quality. All these works use a linear superposition charging model, which may not be accurate in real life situations. We use the actual charging model, which has a nonlinear super-position and we consider the charging scheduling problem (CSP): given multiple chargers and a group of sensor nodes, how can the chargers be optimally scheduled so that the total charging time is minimized and each sensor node has at least energy E ? We prove that CSP is NP-hard, and propose a weight-greedy algorithm to solve the problem. Unlike the algorithm proposed before, ours does not need to calculate all charger groups utility in advance, which reduces the complexity. Extensive simulations demonstrate that the performance of our algorithm with sparse network is almost as good as the optimal algorithm. In general cases, our algorithm outperforms the random algorithm. Furthermore, our algorithm obtains the best solution in two special cases.

Index Terms—Wireless charging, nonlinear superposition, weight and minimum coverage set, sparse network.

I. INTRODUCTION

Nowadays, Wireless sensor networks and mobile computing applications are well discussed [1–4]. Wireless sensor networks (WSNs) are powered by small batteries, and a constrained energy supply limits the lifetime of a WSN. Wireless charging techniques have been proposed to provide WSNs an additional energy supply that can prolong their lifetime [5, 6]. The Wireless Power Consortium (WPC), established in 2008, has more than 200 members now, including IT leaders such as Apple and Microsoft. As we can see, wireless power transfer (WPT) is a promising technology to charge WSNs in the future.

With recent breakthroughs in wireless power transfer, it is possible to charge sensors over a long distance with a fixed charger. However, long-distance charging leads to low charging efficiency, which means that the energy harvested by sensors is much less than the energy delivered by the charger. To accelerate long-distance charging, the charger’s power can be increased, but this may lead to electromagnetic radiation (EMR) pollution and harm humans [7]. Another method is adding more chargers at different positions in the WSNs to charge sensors at the same time. This way, the power harvested by sensors increases. To calculate the combined charging power, almost all researchers just add them together. However, this assumption may not be the most accurate. Naderi et al. [8]

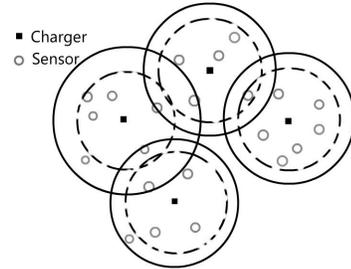


Fig. 1. Scenario of charging with multiple chargers and sensors.

point out that there will be radio interference between charging waves, so the aggregate power is not additive. Based on this discovery, Guo et al. [9] proposed a concurrent charging model and designed three algorithms to solve the concurrent charging scheduling problem (CCSP). However, since each charger’s charging utility cannot be calculated independently, Guo et al. [9] have to calculate the charging utility of each charger set at every sensor node in advance. As a result, the complexity of this step grows exponentially with the number of chargers, making it much more complex than previously thought. 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 set in advance, which reduces the complexity.

This paper focuses on CSP to prolong the lifetime of WSNs. The scenario, which involves multiple chargers and a group of sensor nodes, is shown in Fig. 1. Chargers and sensor nodes are deployed in a common area. The chargers transmit energy with certain power level, which results in multiple charging radii [10]. Due to radio interference, multiple chargers’ aggregate charging effect is a nonlinear superposition. In this paper, we are concerned with the problem: given multiple chargers and a group of sensor nodes, how can chargers be optimally scheduled so that the total charging time is minimized and each sensor node has at least energy E ?

Due to the nonlinear superposition, it is impossible to calculate the combined charging power of all the groups of chargers at a sensor node in polynomial complexity. Fig. 2 illustrates why we cannot simply add all the charging utilities together. Suppose that radio waves λ sent by two chargers c_1 and c_2 have the same phase. The phases of the two waves arriving at s_1 are always the same, so the waves combine

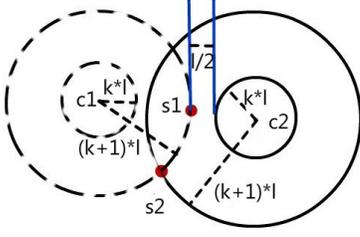


Fig. 2. Concurrent charging using two chargers. c_1 and c_2 are chargers; s_1 and s_2 are two sensors. l represents the length of radio wave.

constructively. However, the phases arriving at s_2 are different from each other, and the difference is $\lambda/2$. Therefore, the two waves combine negatively at s_2 , and the total energy is almost zero. The actual charging model brings challenges to the scheduling algorithm design. Unlike the previous work [9], we do not calculate all charger combinations utilities in advance. Finding an algorithm to minimize charging time with all the constraints mentioned above is challenging.

Our main contributions are summarized as follows:

- We apply a new charging model with nonlinear superposition into the CSP problem, which is proved to be NP-hard.
- We propose a weight-greedy scheduling algorithm to solve CSP, which performs nearly as well as the optimal algorithm in sparse network.
- Simulations are conducted to evaluate the proposed solutions. The results are shown from different perspectives.

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

II. RELATED WORK

In the past decade, wireless charging for WSNs has been widely studied. Some works focused on fixed chargers. He et al. [11] and Pang et al. [12] investigated the energy provision problem of finding the minimum number of RFID readers to cover a given WSN. Dai et al. also focused on charger location problem but took safety into account and provided a near optimal solution to find the maximum electromagnetic radiation point (MEP) in the network [10, 13]. Zhang et al. jointly determined charger placement and power allocation to improve the charging quality [6]. Soon after, mobile charger began to attract much attention. Zhang et al. proposed a scheduling algorithm called Pushwait to cover a one-dimensional WSN of infinite length [14]. To prolong the lifetime of a WSN, Peng et al. optimized the charging sequence for network lifetime maximization [15]. All the algorithms above are based on an assumption that the power received by one device from multiple chargers is additive[11]. However, this assumption may not be the most accurate.

In 2010 [15], Peng designed and implemented a wireless charging system for sensor networks; they further built a proof-of-concept prototype to evaluate its feasibility and performance in small-scale networks. In 2011 [16], the joint routing and charging scheme was proposed by Li to proactively guide the routing activities of the network and to deliver energy to where it was needed. In 2013 [11], He et al. studied how to deploy readers in a network to ensure that the wireless identification and sensing platform(WISP) tags could harvest sufficient energy for continuous operation.

Naderi et al. [8] pointed 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. [9] proposed three algorithms to solve CCSP based on the nonlinear superposition charging model [9]. 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.

III. 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 CSP.

A. Charging Model

We consider a set of M stationary rechargeable devices $S=\{s_1, s_2, \dots, s_m\}$ distributed in a two-dimensional plane. There are also N chargers $C=\{c_1, c_2, \dots, c_n\}$ distributed in this scenario. We also use d_{ij} to denote the Euclidean distance between the charger c_i and the sensor s_j . According to [9], 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 are nonlinear 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 :

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

Based on this, Guo [9] proposed the power of compound radio signal at sensor s_i :

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

where $P=\int p_i d\omega$

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 use this model as our charging model to solve CSP.

B. Harvesting Model

Denote $P_j^G|_C$ as the harvesting power of sensor s_j charged by a group of chargers C . We assume $P_j^G|_C = \alpha * P_j|_C$, where α ($0 < \alpha < 1$) is the transition coefficient. From the previous work [11], 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:

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

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 , which is the energy we set in the problem. So the energy harvesting model can be expanded as follows:

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

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

C. Problem Formulation

We use H_i to denote i_{th} charging period. Although different periods' durations Δ can be different, in this paper, we only consider the same charging duration. 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, CSP is to find a set of multiple charging periods $\{H_1, H_2, \dots, H_k\}$ to charge each sensor with energy no less than E , and k is minimized.

IV. SOLUTION

In this section we first show that CSP is NP-complete, and then we propose an algorithm to solve it.

A. Hardness Analysis

Theorem 1: The CSP is NP-complete.

Proof: We prove this by using the decision version of the problem: given a number of charging periods k , does there exist a collection of charger sets $\{C_1, C_2, \dots, C_h\}$ ($C_i \subseteq C, i = 1, 2, \dots, h$) and a corresponding number of charging

periods H_1, \dots, H_k that satisfy the constraint above and h is equal or less than k ?

We prove this decision problem by reduction from the Knapsack Problem [17], which is NP-hard. The decision version of the knapsack problem is as follows: given a set of items $\mathbb{U} = \{e_1, e_2, \dots, e_m\}$, 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 T and the total value is V ? Given an instance of the decision version of the knapsack, we construct an instance of CSP as follows:

- For each element e_j in \mathbb{U} , we construct a charging period H_i in CSP. The item's weight is the charging period's duration, and the value is the total energy harvested by the network in this period; we assume all charging periods' durations are the same and are equal to Δ . For knapsack's weight, we define $k * \Delta$ equal to T . For the given value V , we set $M * E$ as the total 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. And this complexity is the number of periods.

Combining these elements, we get the following special case of the decision version of the CSP 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)?

It is not hard to see that the construction can be finished in polynomial time; thus, we reduce solving the NP-hard knapsack problem to a special case of CSP, implying that CSP is NP-hard.

B. Algorithmic Design

In this subsection, we propose a weight-greedy algorithm to solve the CSP. Then we show that our greedy algorithm performs well in sparse networks and is the optimal solution in two extreme cases.

Our goal is to use the minimal time to charge each sensor with at least E energy, therefore, the energy charged in each period should be maximized. Some sensors can only be charged by one or two chargers, so it takes them a longer time to fully charged than those sensors that can harvest energy from multiple chargers at the same time. Consequently, the number of chargers that are able to charge a sensor should be taken into account when designing an algorithm. In this paper, we only discuss instances where the charging periods are the same.

In order to balance sensors received energy and the network's total harvesting energy, we give each sensor a weight w which set to be E'/r , where E' is the remaining energy that is not charged yet ($E - e_j$) and r is the number of chargers that can charge this sensor. We also give each charger a weight w which set to be the sum of the weights of the sensors that can be charged by this charger.

The main idea of our algorithm is shown as follows: we find a maximum unique covering set (MCS) first and then

Algorithm 1 Weight-Greedy Picking (WGP)

Input: C : Charger set, S : Sensor set, E : Energy capacity**Output:** The time schedule

- 1: Initialize W , and set W'_1 to be 1, $i=1$.
 - 2: **while** $S \neq \emptyset$ **do**
 - 3: Find a MCS, and divide chargers into two groups H_i , C' .
 - 4: **while** W'_1 is over 0 **do**
 - 5: **for** each charger c_i in C' **do**
 - 6: Compute the w'_i .
 - 7: sort from largest to smallest in W' .
 - 8: **if** W'_1 is over 0 **then**
 - 9: Add C'_1 in H_i .
 - 10: Make chargers in H_i work for time Δ .
 - 11: **for** every sensor in S **do**
 - 12: **if** s_i is fully charged **then**
 - 13: remove s_i from S .
 - 14: $i++$, $W'_1=1$, compute W ;
-

expand this set by adding more chargers. Maximum unique coverage means every item can be covered at most once, and total weight of the set is maximized. As we all know, MCS is a NP-complete problem [18] and there is not a polynomial way to solve it. We propose a weight-greedy way to find a MCS. We give each charger a weight defined above. Every time we pick or add a charger, we pick or add the charger with the maximum weight.

We show why using the weight we designed to select charger can balance both individual and overall energy. Supposing sensor s_i can be charged only by one charger named c_k while s_j can be charged by 4 chargers, and c_k weakens other chargers. It is obvious that c_k should be opened for $E/p(c_k)$ time so that s_j can be fully charged. By setting sensors' weight as E'/r , s_j 's weight is divided into 4 parts while s_i 's weight remains the same. So the priority to select c_k is increased. After we select a charger, we need to remove covered sensors from the universal set and also remove chargers that can charge these covered sensors. As a result, every sensor is covered by at most one charger. Then we need to calculate every charger's weight again. The complexity to find a MCS is $O(NM)$.

In order to be clearer, we define $C' = C - H$, and we use W' to denote chargers weight in C' , which means the positive effect to the whole network when adding this charger.

According to Algorithm 1, we first initialize W as a set of all chargers weights in line 1. we also set the remaining charger set's weight W'_1 to be positive because we need to use it to start our iteration. The algorithm iteratively decides each charging schedule (line 2 to 14). The iteration terminates when all the sensors are fully charged, which means that harvest energy at least E ($S \neq \emptyset$ line 2). In each iteration, the algorithm finds a minimum coverage set (MCS) and then puts chargers in H_i during this charging period. When W'_1 is over 0, which means a new charger can be added, we use Equ. (2) to recalculate

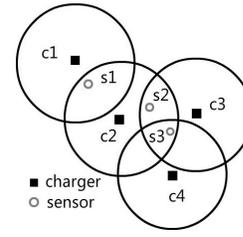


Fig. 3. Example of the placement of 4 chargers and 3 sensor nodes.

TABLE I
EXAMPLE OF THE CHARGING UTILITIES OF 4 CHARGER SETS AT 3 SENSOR NODES.

	s_1	s_2	s_3
c_1	3	0	0
c_2	2	3	2
c_3	0	3	3
c_4	0	0	2
c_2, c_3	2	0	1
c_3, c_4	0	3	5
c_1, c_2	4	3	2
c_2, c_4	4	3	0
c_2, c_3, c_4	2	0	2

every charger's increasing energy for the whole network, and we sort the energies from large to small. When W'_1 is over 0, we put the first charger in H_i . After adding a charger, the algorithm recalculates W because of the changing interference. This operation continues until no chargers are able to be added; which means adding any charger would have negative effect on the whole network (line 4-9). The algorithm makes the chargers in H_i charge for Δ time (line 10). After each charging period, the algorithm removes the fully charged sensors from S (line 11 to 13). Finally, we reset W'_1 to be 1 and increase 1 to i (line 14).

C. Example and Analysis

In this subsection, a simple example of the algorithm is shown in Fig. 3, and Table 1 shows the actual charging energy. Suppose the energy capacity of each node $E = 10$.

According to Algorithm 1, we first find a MCS which is c_2 , then we add other chargers if the total energy harvested by the network increases after adding this charger. So we add c_1 and this iteration ends. After charging, the current energy harvested in the node is $\{4, 3, 2\}$. In the next period, we first check if any sensor is fully charged. Then, we continue this operation. Obviously, c_1 and c_2 will be picked in the next two periods. The current energy of each sensor increases to be $\{10, 9, 6\}$. Now, sensor s_1 is fully charged, and we remove it and find MCS again, which is c_2 or c_3 . Suppose we choose c_3 ; then c_4 will be added. After this charging period, all sensors are fully charged. The total charging period is 4.

Our algorithm would obtain the optimal solution in two extreme cases. The first is when all chargers strengthen each

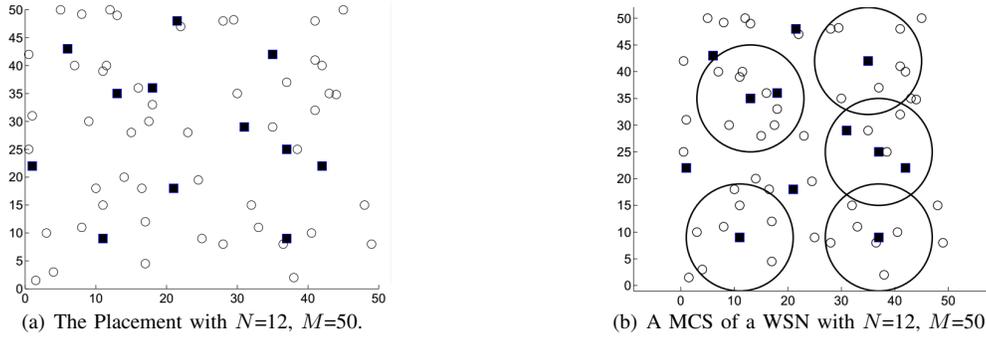


Fig. 4. A WSN with $N=12$, $M=50$.

other. Obviously, the optimal method is to turn on all the chargers, which is the same answer that our algorithm would give. The other case is when all chargers weaken each other. In this case, we should make the interference the smallest possible in each period. The answer is the MCS, which is also the same answer that our algorithm gives.

The drawback of this algorithm is how it finds a MCS. The MCS itself may have many negative effects in bad situations, and we cannot limit this drawback to a bound. However, in sparse networks, our algorithm operates well because interferences are rare and our way to choose a MCS is almost optimal.

The complexity of this algorithm is $O(M^2N^2)$. The while-loop runs at most $O(M)$ iterations, we can make this by increasing the charging time of each period. In each iteration, while-loop runs at most N times and for-loop runs at most $O(N)$ times because the complexity of calculating the weight w' of one charger is $O(MN)$. The complexity of finding a MCS is $O(MN)$. The total complexity is $O(M^2N^2)$.

V. EXPERIMENTS

In this section, we conduct a series of simulations with Matlab tool to evaluate the performance of the proposed algorithm. After presenting the setup and parameters, the results are shown from different perspectives to provide insightful conclusions.

A. Experiment Setup

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. We set the threshold of harvesting power as $\epsilon = 15\mu W$, transition efficiency as $\alpha = 0.25$, each charging period as $\Delta = 20s$, and the wave length as $\lambda = 0.33m$.

Based on these parameters, we calculate the distance threshold, $0.25 * 4 / (4\pi * d)^2 = 0.015mW(watt)$. Then we calculate that $d \approx 6.78$, 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. 4(a) gives an example of the default placement. Fig. 4(b) illustrates the MCS that the algorithm finds in the first iteration.

B. Baseline Setup

Currently there is only one algorithm available for CSP with an actual charging model. The algorithms proposed in [9] 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. 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. Performance Comparison

In general, WGP achieves a near optimal solution and outperforms the random algorithm. In Fig. 5(a), when the number of chargers goes up, the number of charging periods goes down. It is obvious that with more chargers, the total charging energy in the same duration increases. In Fig. 5(b), when the number of sensors goes up, interference will become more common and as a result, charging periods lengthen. In Fig. 5(c), when the energy capacity goes up, the number of charging periods goes up; it is obvious that the total harvesting energy grows.

In Fig. 5(a) and Fig. 5(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 approaches 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.

In summary, the proposed algorithm WGP performs very similarly to GA (which is considered as OPT) in sparse network, and outperforms the random algorithm.

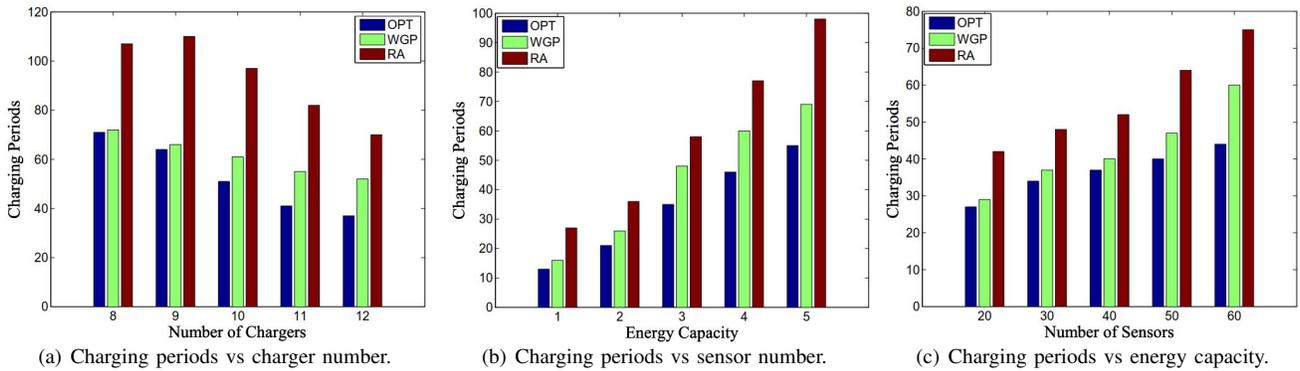


Fig. 5. Simulation Results.

VI. CONCLUSION

In this paper, we study the charging schedule problem (CSP), addressing the nonlinear super-position charging effect caused by radio interference. We prove that this problem is NP-hard by reduction from the knapsack problem. To solve this problem, we propose a near weight-greedy algorithm. The simulation results show that the WGA can achieve a good performance that is close to that of GA at sparse network and that outperforms the random algorithm.

VII. ACKNOWLEDGEMENT

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