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Practical Concurrent Wireless Charging Scheduling for Sensor Networks

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***Abstract*—In complex terrain where mobile chargers hardly move around, a feasible solution to charge wireless sensor networks (WSNs) is using multiple fixed chargers to charge WSNs concurrently with relative long distance. Due to the radio interference in the concurrent charging, it is needed to schedule the chargers so as to facilitate each sensor node to harvest sufficient energy quickly. The challenge lies that each charger's charging utility cannot be calculated (or even defined) independently due to the nonlinear superposition charging effect caused by the radio interference. In this paper, we model the concurrent radio charging, and formulate the concurrent charging scheduling problem (CCSP) whose objective is to design a scheduling algorithm for the chargers so as to minimize the time spent on charging each sensor node with at least energy E. We prove that CCSP is NP-hard, and propose a greedy algorithm based on submodular set cover problem. We also propose a genetic algorithm for CCSP. Simulation results show that the performance of the greedy CCSP algorithm is comparable to that of the genetic algorithm.**

***Index Terms*—Wireless Sensor Network (WSN), wireless charging, nonlinear superposition charging effect, scheduling, submodular set cover.**

I. Introduction

Recently many people are concerned with employing wireless charging technique to provide WSNs additional energy supply [1]. To obtain high charging efficiency, usually a mobile charger moves around in WSNs with a carefully designed route, and charges the sensor node nearby [2]. However, in complex terrain in many practical applications of WSNs, the mobile charger may not be able to move freely in WSNs.

People find that it is possible to charge sensor nodes in a relative long distance ($> 10m$ away) with multiple fixed chargers. However, to facilitate sensor nodes to harvest the energy of multiple chargers' radio signals, the chargers should constrain their radio signals' power spectral density (PSD) within a narrow spectrum band of sensor nodes' antenna. As a result, the chargers' PSD curves are largely overlapped with each other. We call these chargers are in-band. When more than one charger in-band transmits radio, there will be radio interference among the concurrent emitted radio waves [3], which may result in either constructive combination or destructive combination of the radio waves, thus leading to a typical *nonlinear superposition charging effect*.

We study how to optimally schedule the chargers so as to use the minimum time to charge each sensor node with at least energy E. We first model the concurrent charging, based on which we formulate the concurrent charging scheduling problem (CCSP). A specialty of CCSP is that *the charging utility of each charger cannot be defined or calculated separately* due to the nonlinear superposition charging effect in the concurrent charging, which brings some new challenges to the scheduling algorithm design. We propose two methods to solve the CCSP problem. One is a greedy algorithm based on submodular set cover problem, and another method is based on genetic algorithm.

II. The CCSP problem and solutions

A. Model

We model the power of compound radio signal at sensor s_j charged by a group of chargers C as:

$$P_j|_C = P \sum_{c_i \in C} \frac{1}{\hat{d_{ij}}^2} + P \sum_{c_i \in C} \sum_{\substack{c_m \in C \\ c_m \neq c_i}} \frac{1}{\hat{d_{ij}}\hat{d_{mj}}} \cos(2\pi \frac{d_{ij} - d_{mj}}{\lambda}) \tag{1}$$

where P is the radio power of each charger, d_{ij} is the distance between charger c_i and sensor node s_j, $\hat{d_{ij}} = \frac{4\pi d_{ij}}{\lambda}$, and λ is the wave length of the radio.

Hence, the concurrent charging model is as follows:

$$e_j|_{C,T} = \begin{cases} 0 & \text{if } P_j|_C < \delta, \\ \rho T(P_j|_C - \delta) & \text{otherwise.} \end{cases} \tag{2}$$

where $e_j|_{C,T}$ is the energy of s_j obtained from a group of chargers C during duration T, δ is a threshold for the radio harvesting power, and ρ is the transition coefficient.

B. Problem formulation

We schedule the chargers' active time with the unit of charging period Δ. The CCSP problem can be formulated as follows:

Given:

- $\mathcal{C} = \{c_i | 1 \le i \le N\}$, where c_i denotes the i^{th} charger.
- $\mathcal{S} = \{s_j | 1 \le j \le M\}$, where s_j denotes the j^{th} sensor node.
- $\{d_{ij} | 1 \le i \le N, 1 \le j \le M\}$, where d_{ij} is the distance between c_i and s_j.

Assume:

The energy capacity of each node is E, and the size of each charging period is Δ.

The problem is to find a family of active charger sets $S_1, \cdots, S_p$, ($S_k \subseteq \mathcal{C}$, $k = 1, \cdots, p$) with the corresponding number of charging periods $\gamma_1, \cdots, \gamma_p$ allocated for these sets such that:

- $\gamma_1 + \gamma_2 + \cdots + \gamma_p$ is minimized, while

subject to the following constraint:

- $\forall j = 1, \cdots, M$, $\sum_{k=1}^{p} \gamma_k u_j^k \geq E$, where u_j^k is the charging utility of S_k at sensor node s_j, i.e., $u_j^k = e_j|_{S_k,\Delta}$.

CCSP can be proved to be NP-hardness, by reducing set cover problem. The proof is omitted for briefness.

III. Proposed Methods

In this section, we describe two methods to solve the CCSP, one is based on submodular set cover problem (SSCP) [4] and the other is based on the genetic algorithm.

A. A SSCP-based algorithm for the CCSP

In this section, we propose a method based on the SSCP. First, we enumerate all possible sets of chargers $C_{\mathcal{N}} = \{S_1, S_2, \cdots, S_{\mathcal{N}}\}$, and calculate the charging utility $\{u_1^i, u_2^i, \cdots, u_M^i\}$ of each set $S_i \in C_{\mathcal{N}}$ at each sensor node in advance. For convenience of computing, we suppose each candidate set in $C_{\mathcal{N}}$ can charge sensor nodes with either non energy or at least energy 1 during the charging period Δ.

Then, we establish a submodular set function $f(*)$ as follows. Considering the fact that: when the capacitor storing energy in the sensor node is full, the sensor node could not harvest energy any more. With this consideration, we define *harvesting utility* of sensor node s_j with the charger set S_k as follows.

$$\sqcap_j^k = \min\{u_j^k, E - er_j\} \tag{3}$$

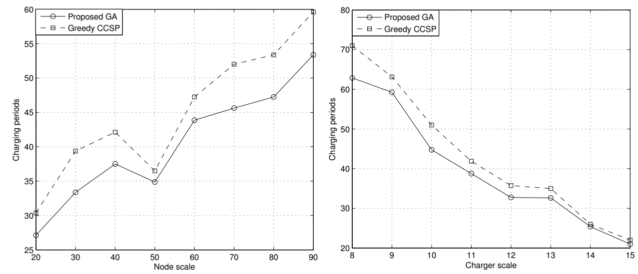
where er_j is the current energy stored in sensor node s_j. When the capacitor in s_j is full, i.e., $er_j = E$, the *harvesting utility* of s_j with S_k is zero. Hence, the total *harvesting utility* of a collection of chargers sets C_K, i.e., $f(C_K) = \sum_{k:S_k \in C_K} \sum_{j=1}^{M} \sqcap_j^k$ is a submodular set function.

Thus, we rewrite the CCSP in the form of SSCP as: *Given a submodular function $f(*)$ on $C_{\mathcal{N}}$, find the smallest set $C_K \subseteq C_{\mathcal{N}}$ such that $f(C_K) = f(C_{\mathcal{N}})$.* To solve this SSCP problem, we employ the classic greedy approximation algorithm for SSCP [4] which can be described as follows.

Algorithm 1 Greedy CCSP based on SSCP

```
Given: C_N and {u_1^i, ..., u_M^i | 1 ≤ i ≤ N}
C_K ← φ
while f(C_K) ≠ ME do
    find S_i ∈ C_N to maximize f(C_K ∪ {S_i}) − f(C_K)
    C_K ← C_K ∪ {S_i}
end while
```

According to the greedy SSCP, it's easy to prove that Algorithm 1 is a $(\ln ME + 1)$ approximation for CCSP.



(a) Different node Scale (b) Different charger Scale

Fig. 1: Performance evaluation.

B. The GA method for the CCSP

To design a Genetic Algorithm (GA) for CCSP, we devise the representation scheme as: $\hat{C}_N = \{S_1, S_2, \cdots, S_{\mathcal{K}}\}$, where S_i denotes the active charger set in the i^{th} charging period, and $\mathcal{K}$ is an upper bound of the number of charging periods. For each feasible solution $\hat{C}_N = \{S_1, S_2, \cdots, S_{\mathcal{K}}\}$, find the smallest value $m \leq \mathcal{K}$ satisfying that $\{S_1, S_2, \cdots, S_m\}$ is also a feasible solution, i.e., $\sum_{i=1}^{m} u_j^i \geq E$ for each $1 \leq j \leq M$. We define the fitness of $\hat{C}_N$ to be $1/m$, and regard $\{S_1, S_2, \cdots, S_m\}$ as $\hat{C}_N$'s output which takes m charging periods. With the definition of the representation scheme and the fitness function, the GA algorithm can be easily designed.

IV. Performance Evaluation

To test the effectiveness of the proposed methods, we conduct a series of simulations by randomly deploying a group of chargers and sensor nodes within $50m * 50m$ area. In the simulations, the sensor nodes are assumed to have the same capacity $E = 4m$J. The transmission power P of each charger is also the same and set to be $4W$. The transition efficiency ρ is set to be 0.25. The threshold of harvesting power is $\delta = 15\mu W$. We set the size of each charging period to be $\Delta = 20s$ and the wave length $\lambda = 3 * 10^8 m/915MHz \approx 0.33m$.

Fig. 1 shows the results at different scales of sensor nodes and chargers. It can be seen, the performance of the proposed greedy CCSP is comparable to that of GA.

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