On-demand Mobile Charger Scheduling for Effective Coverage in Wireless Rechargeable Sensor Networks

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Abstract. In this paper, we consider the problem of scheduling mobile chargers(MCs) in an on-demand way to maximize the covering utility(CU) in wireless rechargeable sensor networks(WRSNs), while nearly all previous related works assume the MCs move along predefined paths with perfect priori information. And the CU is defined to quantify the effectiveness of event monitoring. We propose three heuristics for this problem after proving its NP-Completeness. Finally we evaluate our solutions through extensive trace-driven simulations.

Key words: On-demand charging; event monitoring.

1 Introduction

Many existing works [1–5] propose to use MCs to work in WRSNs with perfect priori information and predefined traveling path. On one hand, using MCs is much more energy efficient than deploying multiple static chargers. On the other hand, it is necessary to schedule the MCs to provide intensive charging power within a short distance.

In this paper, we consider the scenario where each MC responds the charging request in an on-demand way and recharges the requesting sensor via wireless to enable its continuous work.

The main contributions of this work are as follows.

- To the best of our knowledge, this is the first work considering the on-demand scheduling problem of MCs in WRSNs aiming to maximize the CU.
- We prove that the on-demand scheduling problem is NP-Complete and propose three algorithms by exploiting the spatial redundancy of WRSNs.
- We evaluate algorithms through extensive trace-driven simulations.

2 Related Work

The schemes proposed by [1–5] are based on the assumption of the availability of perfect priori knowledge. He *et al.* [6, 7] consider the on-demand schedule of mobile elements in a different scenario, i.e., data collection applications. There is an online-like mobile charging schedules [13] targeting on prolonging the lifetime in WRSNs, but it is constrained by specific setting and thus not general. In this paper, we relax the constraint they set and focus on the goal of maximizing the CU rather than purely elongate the lifetime of network.

3 Problem Statement

Assume that m sensors $V = \{v_1, v_2, \ldots, v_m\}$ are randomly distributed in a 2D area along with n Point of Interests(PoI) $O = \{o_1, o_2, \ldots, o_n\}$. The sensing range of every sensor is r. The events at a PoI emerge one after another, and the arrival of events at PoIs is spatially and temporally independent. Different sensors may cover some PoIs in common due to spatial redundancy [8]. Let O_i represent the set of PoIs covered by sensor v_i. Furthermore, we assume that all sensors work can communicate directly with the sink. Multiple sinks [9] might be deployed [10] in the field for fear that the coverage of a single sink is limited. A sensor only reports its data (with size of b bits) to the nearest sink directly once it senses an event, but its request for recharging can be relayed by the sinks to the mobile charger since the sinks are out of energy concern and cover the whole field collectively. For convenience of exposition, we divide the sensors into two subsets, the set of active sensors V_a and the set of sensors requesting recharging V_r.

An MC maintains a requesting queue for the recharging requests and we assume an $M/G/1$ queue in Kendall's Notation. All the recharging requests will be recorded and those sensors that send these requests will be kept in the requesting queue by the MC. For any sensor i, we assume the received power $P_c^{(i)} = \eta_i \cdot P_{MC}$, which is far greater than its working power P_i, where η_i denotes the charging efficiency of sensor i and P_{MC} is the working power of MCs.

The recharging time mainly depends on P_{MC}, η_i, and total battery capacity, W, of the sensor, i.e. $t_c^{(i)} = \frac{W}{\eta_i \cdot P_{MC}}$. In addition, for sensor i, the service time $t_s^{(i)}$ consists of the traveling time $t_t^{(i)}$ and the charging time $t_c^{(i)}$. As for sensor i, its working power P_i depends on the rate of event generating f_i and the unit energy consumption e_i, i.e. $P_i = f_i \cdot e_i \cdot b$. Notably, we adopt the energy consumption model used in [11, 12] to measure e_i. Hence, the average arrival rate (AAR) of the request λ can be estimated as $\lambda = \frac{\sum_{i=1}^{m} P_i}{(1-\alpha)\cdot W}$, where α denotes the recharging threshold factor. After finishing the service for the last request, the MC chooses the next target among the members in its requesting queue with its predefined rule and then moves for the target.

In order to define CU, we define *Global Effective Coverage*(GEC), the set of PoIs covered by actives sensors, at time t as $G(t) = \bigcup_{v_i \in V_a} O_i$ and *Global Coverage*(GC) as $M = \bigcup_{v_i \in V} O_i$. Intuitively, the **Covering Utility**(CU) denotes the ratio between above two as follow,

$$U(t) = |G(t)|/|M|. \tag{1}$$

We define *Incremental Effective Coverage*(IEC) as the set of PoIs that are going to be effectively covered. Formally, $I_j^{(i)} = \bigcup_{v_i \in V_a \bigcup \{j\}} O_i - \bigcup_{v_i \in V_a} O_i$ if sensor j is chosen before the MC makes its i-th selection.

Additionally, we assume a greedy strategy in order to maximize the overall CU. The MC tries to choose the next to-be-served sensor by updating the i-th *Piecewise Covering Utility*(PCU) with maximum of the average CU during the service time of the promising sensor j each time the MC finishes the last service.

$$U^{(i)} = \max_j \{ \frac{1}{t_s^{(j)}} \int_{t_{i-1}}^{t_{i-1}+t_s^{(j)}} U(t)dt \}. \tag{2}$$

To sum up, we formally formulate our problem as follows.

$$\begin{array}{ll} \textbf{Maximize} & \frac{1}{N} \sum_{i=1}^{N} U^{(i)} \\ \textbf{s.t.} & (1)(2), \end{array}$$

where N denotes the number of the requests.

4 Theoretical Analysis and Solution

By similar analysis of [13], we can reduce the Geometric TSP problem to the problem and show its NP-completeness. Since it is NP-Complete, we resort to greedy algorithms. In the following parts, we will propose three greedy heuristics. Due to space limit, we just sketch these algorithms.

4.1 Maximal Next Coverage Utility First(MNCUF) Algorithm

MNCUF requires that the MC choose the current maximal IEC to serve. In other words, MC checks the requesting queue and chooses the sensor with maximum IEC currently as the next to-be-served sensor, which can be regarded as a specific instance for the strategy of maximizing PCU(2).

4.2 Maximal Average Coverage Utility First(MACUF) Algorithm

MACUF takes the trade-off between the travel time and IEC of every service into consideration and greedily selects the target with the following formulation.

$$U_j^{(i)} = \frac{|G(t_{i-1})| \cdot t_t^{(j)} + |G(t_{i-1}) + I_j^{(i)}| t_c^{(j)}}{t_s^{(j)} \cdot |M|} \tag{3}$$

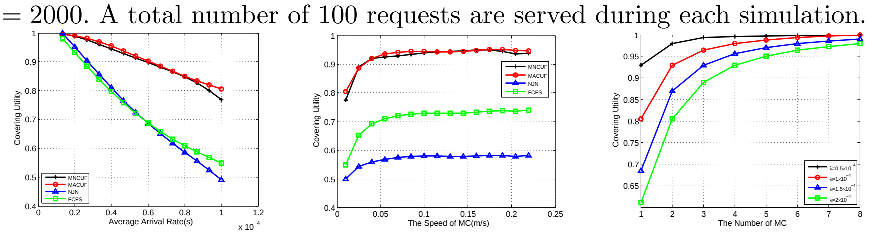
where $U_j^{(i)}$ performs as the approximation candidate for PCU, which substitutes the right hand side of (2).

4.3 MACUF Algorithm with Multi-MCs

Suppose that there are n MCs in total, and they are numbered sequentially, $\{0, 1, \ldots, n-1\}$. Intuitively, although every MC receives and records the information of all the requests within the WRSNs, the i-th MC only serves the $(kn+i)$-th requests, where $k \in N$, with MACUF discipline.

5 Performance Evaluation

We utilize the same value setting of η, W and P_c as in our previous works [4]. In our scenario, the sensing field is a 100×100 m^2 square with 100 randomly distribute sensors, 300 PoIs and 10 sinks. Furthermore, we set the sensing range $r = 15m$, the threshold factor $\alpha = 20\%$ and the message size is $2Kbits$, i.e., $b = 2000$. A total number of 100 requests are served during each simulation.



(a) CU vs. AAR (b) CU vs. Speed (c) CU vs. Multiple

Fig. 1. Performance Comparisons from different perspectives

To the best of our knowledge, there are no existing works designed to maximize CU based on on-demand mobile charging in WRSNs. To exhibit the system performance of our algorithms, we tailor two on-demand mobile data collection disciplines, NJN [6] and FCFS [7], to adapt to the scenario we consider.

1) *Evaluation of different rates of event generation*: we vary the rate of event generation, proportion to the Average Arrival Rate(AAR), and compare the CU of all four algorithms. In Fig.1(a), the speed of MC v is set to $0.01m/s$, which makes the traveling time essential. As can be seen, both of our algorithms outperform the existing ones in terms of CU.

2) *Evaluation of different speeds of MC*: we continue to focus on the CU of all of the algorithms influenced by varied speed v. In this evaluation, $\lambda = 1 \times 10^{-4}$. Intuitively, with the speed increasing, the traveling overhead goes down, so as the response delay to the charging requests, which may lead to a higher CU. We plot the fact in the Fig.1(b).

We deploy different numbers of MCs (n=1, 2, . . . , 8) in the sensing field and compare the CU with the varying AAR λ together. Fig.1(c) shows that the larger number of MCs we choose, the higher overall CU we obtain.

6 Conclusion

In this paper, we consider the on-demand mobile charger scheduling problem to maximize the CU of event monitoring in WRSNs. Due to the NP-completeness of this problem, we propose three heuristic algorithms. We evaluate the proposed algorithms through extensive trace-driven simulations.

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