Efficient Data Collection for Wireless Rechargeable Sensor Clusters in Harsh Terrains Using UAVs

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***Abstract*—Numerous applications of wireless sensor networks (WSNs) in harsh terrains are constrained by the sensors' battery-power and face the difficulties of data collection. In this paper, we propose to exploit wireless power transfer technology to replenish the energy of sensor clusters and develop an efficient data collection scheme for those wireless rechargeable senor clusters deployed in harsh terrains. In view of the harsh terrains, we employ unmanned aerial vehicles (UAVs) to travel to the sites of sensor clusters, collect data, and recharge the sensors in corresponding clusters. With joint consideration of data collection characteristics, wireless power transfer features and travel time, we mathematically formulate the data collection in rechargeable WSNs into an optimization problem with the objective of maximizing data collection utility. Based on the matching theory, we also develop a one side matching algorithm and a greedy algorithm to solve the problem in distributed manner. Through simulations, we show that UAVs are not always matched with nearest sensor clusters, the solution of the proposed greedy algorithm is optimal, and the sensed data can be efficiently collected.**

***Index Terms*—wireless power transfer, data collection, UAV, matching theory.**

I. Introduction

During the last decade, wireless sensor networks (WSNs) have attracted intensive attention due to its easy deployment and enormous application potential in battlefield surveillance, environmental monitoring, biomedical observation and other fields [1]–[4]. The advances in processing and computing designs can endow sensors with a multitude of sensing modalities (i.e., temperature, pressure, light, magnetometer, infrared, etc.) to support various applications, but the crawling development in battery technology imposes critical energy constraints on the battery-powered sensors. Besides, the WSN is usually required to provide *in situ* and unattended observations over a vast area. Although the sensors can easily be deployed, e.g., scattering sensors by aircraft over a vast area, it posts great challenges to keep the WSN alive and to efficiently collect the sensed data from the vast deployed areas, especially for harsh terrains (e.g., hot deserts, dense forests, snow mountains, etc.).

To avoid the sensors from draining up their energy, energy conservation [5], environmental energy harvesting [6], [7] and incremental deployment [8] approaches have been proposed in prior work. However, energy conservation schemes can only slow down energy consumption but not compensate energy depletion. Harvesting environmental energy, such as solar, wind and vibration, is subject to their availability which is often uncontrollable by people. The incremental deployment approach may not be environmentally friendly because deserted nodes can pollute the environment.

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Fig. 1. (a) unmanned aerial vehicle (UAV); (b) wireless charging system.

Fortunately, the recent breakthrough in the area of wireless power transfer technology [9] has provided a promising alternative for the energy replenishment of sensors in WSNs. Specifically, Xie et al. in [10] reviewed three wireless power transfer techniques, i.e., inductive coupling, electromagnetic radiation, and magnetic resonant coupling, and introduced their potential applications in WSNs. The National Aeronautics and Space Administration's (NASA) electromagnetic radiation experiment [11] proved the feasibility of long range power transmission at relatively high efficiencies, i.e., experiment at Goldstone sent 34,000 watts of power across a distance of 1.5 km at an efficiency of 82%. Kurs et al. in [9] showed that wireless power transfer is also insensitive to the neighboring environment and does not require a line of sight between the power charging and receiving nodes.

Together with more and more mature and inexpensive mobile unmanned vehicles, Xie et al. in [2], [12] employed a mobile vehicle carrying a power charging device to periodically visit each sensor/cluster of multiple sensors and charge it wirelessly, trying to make the WSN immortal. In [8], a proof-of-concept prototype of wireless mobile charging vehicle is established and experiments are conducted to evaluate its energy replenishment performance for WSNs. Although in those pioneer studies, energy of sensors has been replenished, there is still a huge amount of energy wasted for multi-

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hop fashioned data delivery from the sources to the sink in WSNs [13]. Moreover, for the sensor clusters (SCs) deployed in harsh terrains, if not impossible, it may take too much cost or time for the wireless charging vehicles to reach those areas and collect the sensed data.

Instead of using wireless charging vehicles, in this paper, we propose to employ unmanned aerial vehicles (UAVs) to carry the wireless power charger as shown in Fig. 1, and let the UAVs select the SCs, fly to the selected SCs, recharge the sensors within the selected SCs, and bring back the sensed data from those SCs to headquarters/sinks. Our salient contributions are summarized as follows.

- We propose to employ UAVs carrying wireless power transfer devices to collect sensed data of SCs deployed in harsh terrains while replenishing the energy of sensors within corresponding SCs.
- Based on distances from UAVs to SCs, data aggregated at the SC, the residual energy of sensors within the SC, we define the preference list of UAVs and SCs, and utility function of data collection. Furthermore, we mathematically formulate the data collection problem into the optimization with the objective of maximizing data collection utility.
- To solve the proposed problem, we develop two algorithm: one side matching algorithm and greedy matching algorithm, and prove the matching between UAVs and SCs by the proposed greedy algorithm can yield the optimal solution in terms of data collection utility.
- Through extensive simulations, we show that UAVs are not always matched with nearest SCs, and the sensed data can be efficiently collected.

The rest of this paper is organized as follows. In Section II, we introduces network configuration and corresponding models, and define the utility function of data collection. In Section III, based on those models, we present some concepts of matching theory and describe one side matching algorithm. We also develop another algorithm, the greedy matching algorithm, to further improve the data collection utility. We conduct the performance evaluation in Section IV and draw conclusion remarks in Section V.

II. Network Model

We consider there are some SCs deployed in harsh terrains for sensing/monitoring applications. Each cluster consists of a central sink node and a set of sensors, where the sensors periodically send their sensed data to the sink node. To compensate sensors's energy consumption and collect perceived data, one or multiple UAVs are employed to fly to the SCs, recharge the sensors within the SCs, collect the data from the sink nodes in corresponding SCs, and bring back the collected data from those SCs to headquarters/sinks.

We denote the set of SCs by $\mathcal{M} = \{1, 2, \cdots, j, \cdots, M\}$, the j-th SC by SC_j ($j \in \mathcal{M}$), the set of UAVs by $\mathcal{N} = \{1, 2, \cdots, i, \cdots, N\}$, the i-th UAV by UA_i ($i \in \mathcal{N}$), and all the perceived data of SC SC_j by C_j. Suppose sensor k in SC_j has a residual energy e_k^j and the full battery capacity for a sensor is $e_{\max}$.

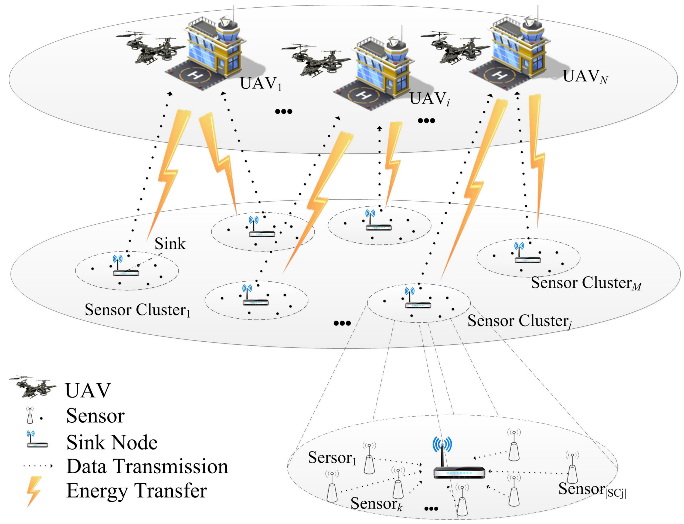


Fig. 2. Network Model.

Let S_i be the power transfer rate from UA_i to the sensors in SC_j. Then, the charging time for all the sensors in SC_j, i.e., T_{CH}^j, can be written as

$$T_{CH}^j = \frac{\sum_{k=1}^{|SC_j|}(e_{\max} - e_k^j)}{S_i}. \quad (1)$$

Let the distance between UA_i and its matched SC_j be d_{ij}, and the speed of UA_i be v_i. Due to the round trip of UAVs between the selected SCs and the headquarters [1], the travel time can be represented as

$$T_{TR}^{ij} = 2d_{ij}/v_i. \quad (2)$$

A. Utility function of UAVs

Based on the proposed models, we define the utility function of UAV as

$$U_{UA_i^j} = \frac{C_i}{T_{CH}^j + T_{TR}^{ij}}. \quad (3)$$

To achieve high utility, a UAV needs to consider the distance between UA_i and SC_j, the amount of data aggregated at the sink node of SC_j, and the residual energy of sensors in SC_j.

B. System utility

We let $\mathcal{X}$ be a $N \times M$ matrix, with the (i, j)-th element $x_{ij} = \{0, 1\}$, indicating matching in this paper. That is, if $x_{ij} = 1$, the i-th UAV is matched with the j-th SC. Otherwise, they are not matched with each other. Since each SC can only be matched with one UAV, we have the following constraint

$$\sum_{j \in \mathcal{M}} x_{ij} \le 1. \quad (4)$$

[1]Note that if a UAV is matched more than one SCs, in this paper, we assume the UAV has to collect the data from those SCs one by one. After collecting perceived information in the current SC, the UAV has to return to the headquarter for the data delivery before it flies to the next SC.

To efficiently collect the perceived data, we try to find the optimal matching pairs between SCs and UAVs to maximize data delivery rate from SCs to the UAVs, while guaranteeing the sensors recharged in those SCs. So, the efficient data collection for wireless rechargeable SCs can be represented as,

$$\max_{x_{ij}=\{0,1\}} \sum_{i\in\mathcal{N}} \sum_{j\in\mathcal{M}} U_{UA_i^j} \quad (5)$$
$$\text{s.t.}$$
$$\sum_{j\in\mathcal{M}} x_{ij} \leq 1.$$

III. Proposed Matching Algorithm

Based on the matching theory, in this section, we propose two algorithms to find the solutions to the formulated problem above in distributed manner. We first present the one side matching algorithm based on one-side preferences. Then, we extend the one side matching algorithm to the greedy algorithm based on Gale-Shapley algorithm [14].

A. Matching definition

Generally speaking, matching theory deals with allocating a set of indivisible goods among a set of applicants. Each applicant may have ordinal preferences. When there are no initial property rights, we obtain the “house allocation” problem as illustrated in [15]–[17]. Base on those matching concepts above, we can interpret our problem as follows.

An instance I comprises a set $\mathcal{N} = \{UA_1, ..., UA_n\}$ of UAVs and a set $\mathcal{M} = \{SC_1, ..., SC_M\}$ of SCs. The agents in I are the UAVs and SCs in $\mathcal{M} \cup \mathcal{N}$. There is a set $\mathcal{E} \subseteq \mathcal{N} \times \mathcal{M}$ of acceptable UAV-SC pairs. Each UAV $UA_i \in \mathcal{N}$ has an acceptable set of SCs $A(UA_i)$, where $A(UA_i) = \{SC_j \in \mathcal{M} : (UA_i, SC_j) \in \mathcal{E}\}$. Similarly each $SC_j \in \mathcal{M}$ has an acceptable set of applicants $A(SC_j)$, where $A(SC_j) = \{UA_i \in \mathcal{N} : (UA_i, SC_j) \in \mathcal{E}\}$. Here, we define a matching between UA_i and SC_j as follows.

***Definition** 1:* A matching Φ is a function: $\Phi(UA_i) \in \mathcal{M} \cup \{\varnothing\}$, and $|\Phi(UA_i)| \in \{0, 1, ...\}$; $\Phi(SC_j) \in \mathcal{N} \cup \{\varnothing\}$, and $|\Phi(SC_j)| \in \{0, 1\}$; where $\Phi(UA_i) = SC_j$ and $\Phi(SC_j) = UA_i$ ($i \in \mathcal{N}, j \in \mathcal{M}$).

This definition implies that if the input of the function is a SC_j, Φ is a one-to-one matching. On the other hand, if the input of the function is a UA_i, Φ is a many-to-one matching.

In matching theory, agents, i.e., UAVs and SCs in our problem, need a preference list to start matching process. So, in our problem, before selecting SCs for energy replenishment and data collection, each UA_i will form a descending order preference list according to UA_i's utility over all the SCs.

B. Proposed matching algorithm with one-side preferences

As summarized in Alg. 1, the one side matching algorithm has two stages. At the first stage, UAVs' utility functions are calculated. Then, the descending order preference list $\mathcal{U}ALIST_i$ is constructed. It also constructs a set of the unmatched SCs as $\mathcal{U}NMATCH$. The second stage will conduct the matching based on the preference list $\mathcal{U}ALIST_i$. UA_i proposes to the highest unmatched SC_j in $\mathcal{U}ALIST_i$ and removes SC_j from $\mathcal{U}NMATCH$. If $\mathcal{U}NMATCH \neq \varnothing$, the algorithm goes back to the beginning of step 2. The algorithm iteratively conducts matching process until $\mathcal{U}NMATCH$ is an empty set.

Algorithm 1 One Side Matching Algorithm

Input: $e_{\max}$, e_k^j, d_{ij}, v_i.
Output: $U_{UA_i^j}$

1.Initialization;
Construct the preference list of UAVs, $\mathcal{U}ALIST_i = \{SC_j\}_{j=1}^M$;
Construct the set of SCs that are not matched, $\mathcal{U}NMATCH$;
2.Matching;
for each $UA_i, i \in \mathcal{N}$ **do**
    Propose to highest SC_j has never rejected it before;
    if $SC_j \in \mathcal{U}NMATCH$ **then**
        Keep matched pair (SC_j,UA_i);
        Remove SC_j from $\mathcal{U}NMATCH$;
    else
        Reject applied UA_i;
    end if
end for
if $\mathcal{U}NMATCH \neq \varnothing$ **then**
    Go to Step 2;
else
    Go to Step 3;
end if
3.End of algorithm;

C. Proposed matching algorithm with two-side preferences

In pervious subsection, we present the proposed matching algorithm with one-side preferences from the perspective of UAVs. To further improve the system utility, we conduct the matching with two-side preferences, i.e., from the perspectives of the UAVs and SCs, respectively. According to utility function $U_{UA_i^j}$, which is

$$U_{UA_i^j} = \frac{C_i}{T_{CH}^j + T_{TR}^{ij}},$$

SCs can also build their own preference lists. Then, each $UA_i \in \mathcal{N}$ or each $SC_j \in \mathcal{M}$ has a different preference list in a strict order.

Gale and Shapley proposed a program known as the Gale-Shapley algorithm, which always finds a stable matching [14]. Based on the Gale-Shapley algorithm, we develop a greedy algorithm. At the first stage, it calculates both UAVs' and SCs' utility functions. Then, it constructs descending order preference lists $\mathcal{U}ALIST_i$ and $\mathcal{S}CLIST_j$. It also constructs a set of the unmatched SCs as $\mathcal{U}NMATCH$. Based on the preference list, $\mathcal{U}ALIST_i$, UA_i proposes to the highest SC_j in $\mathcal{U}ALIST_i$, which has never rejected it before. If SC_j has not been matched, pair (UA_i,SC_j) is kept. If SC_j has been matched, SC_j will check the ranking of new applied $UA_{i'}$ and UA_i from previous iteration. SC_j matches with the higher ranking one in its $\mathcal{SCLIST}_i$ and rejects the other one. The rejected SC_j is added to the $\mathcal{UNMATCH}$ and waits for the next round of matching process. The algorithm goes back to the step 2 if $\mathcal{UNMATCH} \neq \varnothing$. Even if $\mathcal{UNMATCH} = \varnothing$, and UA_i has not finished proposing to all $SC_j (j \in \mathcal{M})$, the algorithm goes back to the Step 2. Until $\mathcal{UNMATCH} = \varnothing$ and every UAV has proposed to all $SC_j, j \in \mathcal{M}$, the algorithm terminates. The greedy algorithm is summarized in Alg. 2.

Algorithm 2 Greedy Algorithm

Input: $e_{\max}$, e_k^j, d_{ij}, v_i.
Output: $U_{UA_i^j}$

1.Initialization;
Construct the preference list of UAVs,
$\mathcal{UALIST}_i = \{SC_j\}_{j=1}^{M}$;
Construct the preference list of SCs,
$\mathcal{SCLIST}_j = \{UA_i\}_{i=1}^{N}$;
Construct the set of SCs that are not matched,
$\mathcal{UNMATCH}$;
2.Matching;
for each $UA_i, i \in \mathcal{N}$ **do**
  Propose to highest SC_j that has never rejected it before;
  if $SC_j \in \mathcal{UNMATCH}$ **then**
    Keep matched pair (SC_j,UA_i);
    Remove SC_j from $\mathcal{UNMATCH}$;
  else
    Compare the $Rank(i')$ of new $UA_{i'}$ and the $Rank(i')$ of assigned UA_i in $\mathcal{SCLIST}_j$;
    if $Rank(i) > Rank(i')$ **then**
      Reject new applied $UA_{i'}$;
    else
      Keep new matched pair (SC_j,$UA_{i'}$);
      Reject former applied UA_i;
    end if
  end if
end for
if $\mathcal{UNMATCH} \neq \varnothing$ **then**
  Go to Step 2;
end if
if $\mathcal{UNMATCH} = \varnothing$ and each UA_i not propose to all SCs **then**
  Go to Step 2;
end if
3.End of algorithm;

D. Theoretically algorithm analysis

First, we define what is the "optimal matching".

***Definition** 2:* **Optimal Matching**: If in a matching Φ, $\sum_{i \in \mathcal{N}} \sum_{j \in \mathcal{M}} U_{UA_i^j}$ is maximized under the constraint $\sum_{j \in \mathcal{M}} x_{ij} \leq 1$, we claim matching Φ is optimal.

Based on this optimal matching definition, we have the following theorem,

***Theorem** 1:* Matching Φ_g obtained by the greedy algorithm is optimal.

Proof: If $\sum_{i \in \mathcal{N}} \sum_{j \in \mathcal{M}} U_{UA_i^j}$ is maximized under the constraint $\sum_{j \in \mathcal{M}} x_{ij} \leq 1$ in matching Φ, each SC_j must match with the top UA_i in its preference list, which is denoted as UA_f^j.

Now, we assume matching Φ' is optimal, but at least one SC_j does not match with its UA_f^j. According to the greedy algorithm, in the first round, SC_j matches with UA_i who proposes to it and ranks highest, denoted as UA_{rh}^j. In the next rounds, if the new proposed ${UA_{rh}^j}'$ ranks higher than UA_{rh}^j, SC_j will be matched with ${UA_{rh}^j}'$ and UA_{rh}^j will be rejected. Consequently, we find that SC_j always matches with the UAV who ranks the highest in the UAVs, who proposed to SC_j. Each UA_i has a preference list including all SC_j $(j \in \mathcal{M})$, which means all UAVs will propose to each SC_j. As a result, each SC_j matches with its UA_f^j, which is contradictory to at least one SC_j does not match with its UA_f^j. Therefore, the matching Φ_g obtained by the greedy algorithm is optimal. ■

IV. Performance Evaluation

A. Simulation setup

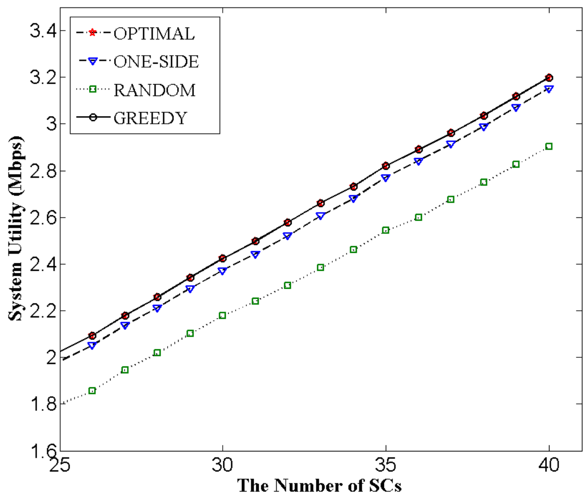
We conduct simulations with UAVs and SCs deployed within a 10km × 10km area. The full battery capacity is $e_{max} = 70$J and the residual energy of sensor nodes in SC_j is $e_k^j \in [60, 65]$J. The number of sensors in each SC is $|SC_j| \in [50, 100]$. The transmission power is $S_i = 1.2$W and the speed of UAVs is set to be 120km/h. For the other parameters, data rates of sensors are randomly generated within [1, 10]kb/s. The simulations are conducted in the grid and random topology, respectively.

B. Results and analysis

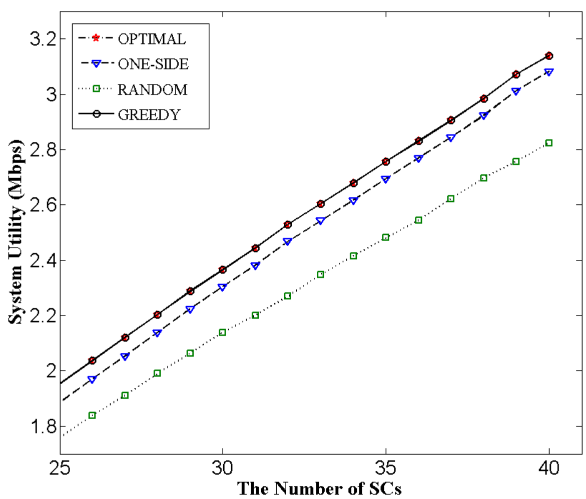
To evaluate the performances of the proposed algorithms, we compare the greedy algorithm with the one side matching algorithm as well as the random matching algorithm.

Figure 3 shows simulation results with a fixed number of UAVs, the number of SCs from 25 to 40, and the SCs deployed in grid topology and random topology, respectively. We find that the performance of the one side matching algorithm is much better than that of randomly matching $UA_i(i \in \mathcal{N})$ and $SC_j(j \in \mathcal{M})$. Since the one side matching algorithm considers the preference lists of UAVs, each $UA_i(i \in \mathcal{N})$ has the chance to propose to the highest SC_j in its preference list $\mathcal{UALIST}_i$. So, the one side matching algorithm is superior to the random matching algorithm. Furthermore, the performance of the greedy algorithm is better than that of the one side matching algorithm. As for the greedy algorithm, SCs use the same utility function with UAVs to build the preference lists, which are employed for their decisions. SC_j can reject UA_i who has proposed to it and choose an better one, which explicitly increases the system utility.

Figure 4 shows the change of system utilities over the network size. With the network size increasing, the system



(a) Grid topology



(b) Random topology

Fig. 3. Performance comparison of different algorithms

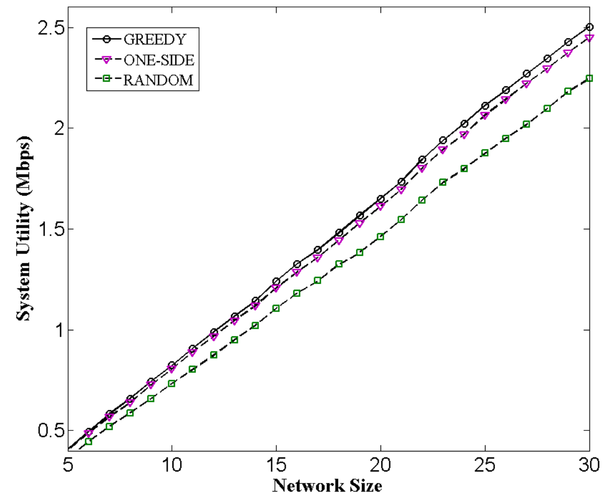


Fig. 4. System utilities as the network size varies.

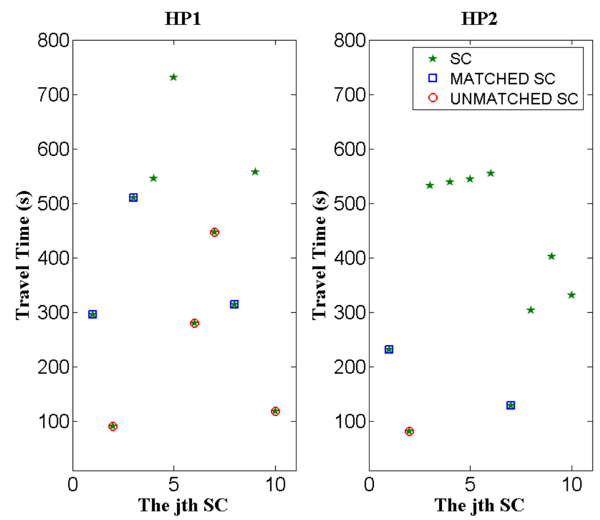


Fig. 5. Relation between the matching decision and the travel time.

utilities increase. Besides, we find that the gap of system utilities between the greedy algorithm and the one side matching algorithm or the random matching algorithm becomes larger as network size is bigger. That indicates when the number and locations of UAVs are fixed, the proposed greedy algorithm are more suitable for a large WSN than the one side matching algorithm and the random matching algorithm. Along with network size increasing, the number of popular SCs is growing (We define the SCs which occupy the high positions in all UAVs' preference lists as the popular SCs.). In either the one side matching or the random matching algorithm, popular SCs cannot have their preference lists. Therefore, there is a high probability for the SCs to make improper decisions which may decease the system utility.

Figure 5 shows the relation between the matching decision and the travel time[2]. Here, we use the greedy algorithm to match UAVs with SCs. The stars represent the time for UAVs to travel to each SC, the squares indicate the travel time to SC_j which is matched with UA_i, and the circles represent the travel time to the unmatched SC_j, which is shorter than at least one matched SC_j. In Fig. 5, we find although some SCs are close to the UAVs, they are not matched with any UAVs. The reason is that the matching decisions rely on not only the travel time, but also the charing time and the data amount of SCs. The matching may not only occur between closest UAVs and SCs.

In addition, in Fig. 3, we also observe that the line of the optimal scheme coincides with the line of the greedy algorithm. Through simulations, it confirms our claims in

[2]For illustrative purposes, we use only 2 UAVs here.

Section III, i.e., the matching by the greedy algorithm is optimal.

V. Conclusion

In this paper, we have investigated how to use UAVs to efficiently collect sensed data in wireless rechargeable SCs deployed in harsh terrains. Considering the features of wireless power transfer, we have formulated the efficient data collection into a matching optimization under multiple constraints, i.e., the distance between UAVs to SCs, the amount of data aggregated at sink nodes in SCs, and the residual energy of sensors in SCs. To maximize the system utility of the formulated problem, we have developed two matching theory based distributed algorithms: a one side matching algorithm and a greedy algorithm, and proved the greedy algorithm is optimal. Through simulations, we have verified our theoretical results and shown that the proposed algorithm can efficiently collect perceived data while recharging SCs in harsh terrains.

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