# Maximizing Charging Throughput in Rechargeable Sensor Networks

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***Abstract*—Energy is one of the most critical optimization objectives in wireless sensor networks. Compared with renewable energy harvesting technology, wireless energy transfer based on magnetic resonant coupling is able to provide more reliable energy supplies for sensors in wireless rechargeable sensor networks. The adoption of wireless mobile chargers (mobile vehicles) to replenish sensors' energy has attracted much attention recently by the research community. Most existing studies assume that the energy consumption rates of sensors in the entire network lifetime are fixed or given in advance, and no constraint is imposed on the mobile charger (e.g., its travel distance per tour). In this paper, we consider the dynamic sensing and transmission behaviors of sensors, by providing a novel charging paradigm and proposing efficient sensor charging algorithms. Specifically, we first formulate a charging throughput maximization problem. Since the problem is NP-hard, we then devise an offline approximation algorithm and online heuristics for it. We finally conduct extensive experimental simulations to evaluate the performance of the proposed algorithms. Experimental results demonstrate that the proposed algorithms are efficient.**

## I. Introduction

Energy is by far one of the most critical design hurdles that hinders the deployment of wireless sensor networks. The lifetime of traditional battery-powered sensor networks is limited by the capacities of batteries. Even many energy conservation schemes were proposed to address this constraint, the network lifetime still is inherently restrained, as the consumed energy cannot be replenished on time. Fully addressing this issue requires energy to be replenished quite often. An ideal solution is to enable sensors to harvest energy from their surroundings [5], [10], [13], [17], [18], [19]. However, energy harvesting unfortunately is not stable and the amount of energy harvested is hardly predictable. For example, the harvested solar energy is usually affected by many factors including time (whether exposed under the sun), weather, and season. This poses a great challenge in design of energy-efficient protocols for wireless sensor networks to maintain them operational.

The recent breakthrough in wireless energy transfer technology provides a promising alternative solution to power sensors. Particularly, employing two strongly coupled magnetic resonant objects, Kurs *et al.* [11] exploited the resonant magnetic technique to transfer energy from one storage device to another without any plugs or wires. They empirically demonstrated that a wireless illumination of a 60 watts light bulb from 2 meters away achieved a 40% energy transfer efficiency. What makes such wireless energy transfer technology particularly attractive is that it does not require line-of-sight (LOS) or any alignment (i.e. omnidirectional). This promising technique will provide a controllable and perpetual energy source to recharge sensors if needed.

### A. Related Work

Armed with the wireless energy transfer technology, several studies on employing mobile vehicles with high volume batteries as mobile chargers to recharge energy for sensors have been conducted [1], [4], [6], [8], [12], [16], [20], [21], [22], [27], [26]. For example, Shi *et al.* [20], [25] applied this technology for a wireless sensor network, where the sensing rates of sensors are fixed and given in advance, and sensing data is forwarded to a stationary base station through multi-hop relays. They formulated a joint optimization problem of data flow routing and energy recharging, and showed that each sensor will not run out of its energy by having a mobile charger charges it periodically. Xie *et al.* [23] extended this solution by allowing the charger to charge multiple sensors simultaneously. Li *et al.* [12] analyzed the possibility of practical and efficient joint routing and charging schemes, where each sensor sends data hop-by-hop to the sink periodically using the Collection Tree Protocol. They showed that the network lifetime is prolonged by a mobile charger which mostly moves along energy-minimum paths, where an energy-minimum path is defined as the path with the minimum total energy consumption in delivering a packet from a source to a destination. Xie *et al.* [22], [24] applied this technology for a wireless sensor network where a mobile station is employed for both data collection and energy charging. They formulated an optimization problem that jointly considers the traveling path, the charger stopping locations, sensor charging schedule and data flow routing, and developed a provably near-optimal solution. Zhao *et al.* [27] considered a joint optimization of mobile data collection and energy charging. They devised an adaptive solution that jointly selects sensors to be charged and finds the optimal data gathering scheme. Wang *et al.* [21] studied wireless energy charging in event detection scenarios and proposed a solution including stochastic charging and adaptive sensor activation. Most of these mentioned studies assumed that both the sensing rate and the energy consumption rate of each sensor are fixed and given in advance. However, in terms of different application scenarios (e.g. event detections), both the sensing and energy consumption rates of each sensor vary

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over time. Thus, these existing solutions are not applicable in such dynamic energy consumption and sensing rate application scenarios.

In this paper, we consider a heterogenous sensor network in which sensors have significant variations in samplings and energy consumptions. A typical example is that a sensor network deployed for ecological study consists of sensors of different modalities including humidity, temperature, video, etc. The sensing rates of different sensors vary, depending on their physical phenomena. Under this setting we investigate an on-demand wireless sensor charging paradigm. That is, sensors send their recharging requests to the base station according to their residual energy statuses. The base station then dispatches the wireless mobile charger to start a charging tour to recharge these requested sensors. He *et. al.* [8] also studied an on-demand mobile charging problem. The essential difference between their work and ours is that they did not put any constraint on the mobile charger in consideration, while we consider the tour time constraint on the mobile charger.

### B. Contributions

The contributions of this paper are summarized as follows.

- We first study an on-demand energy replenishment in rechargeable sensor networks by employing a wireless mobile charger and formulating an optimization problem with an objective of maximizing the number of sensors charged (charging throughput) per tour.
- We then devise an offline approximation algorithm which runs in quasi-polynomial time by reducing the problem to the orienteering problem with time windows. We also provide online heuristics where recharging requests arrive one by one without the future arrival knowledge.
- We finally conduct extensive simulations to study the efficiency of the proposed algorithms in both small-scale and large-scale networks. Experimental results demonstrate that the proposed algorithms are very efficient in terms of charging throughput.

### C. Paper Organization

The rest of the paper is organized as follows. Section II introduces the network model and problem definition. Section III proposes an offline approximation algorithm and two online heuristics, respectively. Section IV presents the simulation results, and Section V concludes the paper.

## II. Modeling and Formulation

### A. Network Model

We consider a sensor network consisting a set $V$ of heterogenous sensors and a stationary base station $v_0$ deployed over a rectangle region. Each sensor $v_i \in V$ is equipped with a rechargeable battery of capacity $B_i$ and consumes energy on sensing and data transmission activities. Each sensor $v_i$ will send a recharging request $c_i = (v_i, RE_i, r_i)$ to the base station or a mobile charger once its residual energy $RE_i$ falls below a pre-defined threshold $M_i = \alpha \cdot B_i$, where $RE_i$ is the residual energy of $v_i$ at the moment of issuing this request, $r_i$ is the release time and $\alpha$ is a constant with $0 < \alpha < 1$.

A mobile charger is a moving vehicle equipped with a powerful wireless charger and it can keep information synchronized with the base station via a long range radio [12]. It starts from the base station and will recharge sensors based on the recharging requests received. Since the mobile charger consumes petrol or electricity either on moving or charging, we then assume that each charging tour of the mobile charger is bounded by a pre-defined time period $T$. That is, the mobile charger must finally return to the base station within time period $T$ to be serviced (e.g., refueling, preforming maintenance service). For simplicity, we assume that a mobile charger per tour has enough energy to charge all sensors [8], [20]. In our charging model the charging is performed from points to points, i.e., only one sensor can be fully charged at each time by the mobile charger when the sensor is in the vicinity of the mobile charger so that the charging process has the maximum efficiency. Given battery material breakthroughs for ultra-fast charging [9], we further assume that the charging time at each sensor is a constant $C$ [8]. We also assume that the mobile charger travels at a constant speed $S$. An example of this charging paradigm is illustrated in Fig. 1, where sensors will send their requests to either the base station or the mobile charger anytime if their residual energy levels are below their given thresholds. The mobile charger then starts a charging tour from the base station and travels around the deployment field to charge sensors. When the mobile charger is traveling, it may still receive new charging requests from sensors as well. Finally it will returns to the base station within time period $T$ so that it can be maintained and prepared for the next charging tour.

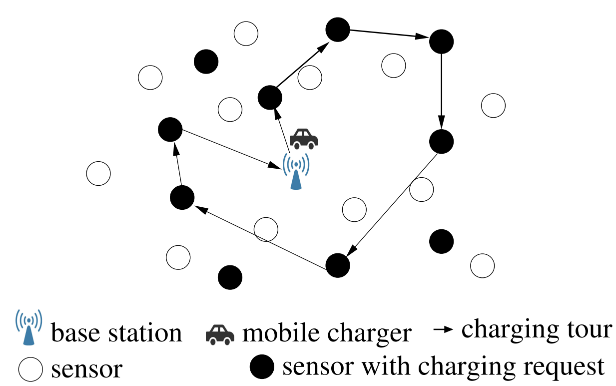



Fig. 1. An example of charging paradigm.

### B. Charging Throughput

In order to measure the contribution of the mobile charger, we introduce *the charging throughput* concept. If a sensor runs out of energy, it will stop functioning. We thus expect that none of the sensors will run out of its energy, or it will be recharged prior to its energy expiration. Ideally, we define the charging throughput of the mobile charger to be the average functioning time of sensors during a charging tour. However, due to the dynamic nature of sensor activities, it is hard to predict the sensors' functioning time. To be practical, we here use the total number of sensors getting charged during a charging tour to represent the charging throughput of the charging tour. For an instance, in Fig. 1, there are 10 sensors waiting for charging, and the mobile charger charges 8 of them before it returns to the base station. Thus, the charging throughput of this charging tour is 8. Note that the rest 2 uncharged sensors will keep staying in the waiting charging list, and the mobile charger will take them into consideration in its future charging tours until they are charged.

### C. Problem Statement

Given a time period $T$ per tour by the mobile charger, the base station may receive many recharging requests from different sensors, depending on the network scale and energy statuses of sensors. Let $Q_c$ be the queue of recharging requests and $V_c$ the set of sensors to be charged which is updated dynamically as recharging requests arrive one by one. Since the mobile charger takes time when it travels in the monitoring region, sometimes it may not be possible to charge all requested sensors per tour within time period $T$. The *charging throughput maximization problem* thus is to find a close tour for the mobile charger, such that the charging throughput is maximized, subject to the amount of time per tour being bounded by $T$. Specifically, assuming that the queue of all recharging requests from sensors $Q_c = \{(v_j, RE_j, r_j) \mid v_j \in V_c\}$ are given in advance, the *offline charging throughput maximization problem* can be defined as follows.

Given a set $V_c \subseteq V$ of sensors to be recharged, a tour $P = \{(v_j, t_j)\}_{j=0}^{m}$ is a sequence of pairs $(v_j, t_j)$, where $v_j \in V_c \cup \{v_0\}$ and $t_j$ is the arrival time when a mobile charger visits $v_j$. Noticing that $v_0$ is the depot of the mobile charger, the feasibility constraint for a tour is

$$t_0 = 0 \quad (1)$$

$$t_1 = t_0 + l(v_0, v_1) \quad (2)$$

$$t_{j+1} = t_j + C + l(v_j, v_{j+1}),\ 1 \leq j < m \quad (3)$$

$$t_j \geq r_j,\ 1 \leq j < m \quad (4)$$

$$t_m + C + l(v_m, v_0) \leq T \quad (5)$$

where $l(v_j, v_{j+1})$ is the travel time of the mobile charger from $v_j$ to $v_{j+1}$, $C$ is a constant charging time, and $T$ is a given finite horizon time period. Constraint (4) ensures that a sensor should be charged only after it sends a request. Constraint (5) ensures that the mobile charger will return to $v_0$ ultimately. The goal is to find a tour with the maximum charging throughput.

*Theorem 1:* The offline charging throughput maximization problem is NP-hard.

**Proof** We show the claim by a reduction from a well-known NP-hard problem - the orienteering problem [7] which is defined as follows. Given $n$ nodes in the Euclidean plane labeled from 1 to $n$ and each with a score, find a route of the maximum score through these nodes beginning at 1 and ending at $n$ of length (or duration) no greater than a given budget. Clearly, assuming that each recharging request is released at the beginning of the given time period $T$, it is easy to verify that this special case of the offline charging throughput maximization problem is equivalent to the defined orienteering problem. Hence, the offline charging throughput maximization problem is NP-hard too. □

## III. Algorithms

In this section, we first deal with the charging throughput maximization problem by devising an offline approximation algorithm. We then propose two online heuristics for it.

### A. Offline Approximation Algorithm

In this subsection, we devise an approximation algorithm for the charging throughput maximization problem by assuming that all recharging requests in a given time period $T$ are known in advance. We reduce the problem to the orienteering problem with time windows. The solution to the latter in turn returns an approximate solution to the former.

The orienteering problem with time windows is defined as follows. Given a directed arc weighted graph $G' = (V', A', l')$ with $l'(u, v)$ denoting the length of arc $(u, v) \in A'$ from $u$ to $v$ and each node $v' \in V'$ having a time window $[R(v'), D(v')]$ during which it can only be visited no earlier than $R(v')$ and no later than $D(v')$ with $R(v') \leq D(v')$, two nodes $s, t \in V'$ and an integer budget $B > 0$, find an $s - t$ walk of length at most $B$ to maximize the number of vertices covered. Chekuri et al. [3] proposed a recursive greedy algorithm for the orienteering problem.

In the following we reduce the problem of concern to the orienteering problem with time windows. Given a set $V_c$ of sensors to be recharged, we construct a directed graph $G_c = (V'_c \cup \{v_0\}, A_c, l)$ with the budget $T > 0$, where the base station $v_0$ with a time window $[0, T]$ corresponds to the node $s$, the base station $v_0$ also corresponds to the node $t$. For each node $v_i \in V_c$, there are two corresponding nodes $v'_i$ with a time window $[r_i, T]$ and $v''_i$ with a time window $[r_i + C, T]$ in $V'_c$, and an arc from $v'_i$ to $v''_i$ with $l(v'_i, v''_i) = C$, where $r_i$ is the charging request release time of $v_i$ and $C$ is the charging time on $v_i$. Recall that $l(v_i, v_j)$ is the travel time of the mobile charger from $v_i \in V_c \cup \{v_0\}$ to $v_j \in V_c \cup \{v_0\}$. We then add an arc from $v_0$ to each node $v'_i \in V'_c$ and let $l(v_0, v'_i) = l(v_0, v_i)$. We also add an arc from each node $v''_i \in V'_c$ to $v_0$ and let $l(v''_i, v_0) = l(v_i, v_0)$. We finally add an arc from each node $v''_i \in V'_c$ to each different node $v'_j \in V'_c - \{v'_i\}$ and let $l(v''_i, v'_j) = l(v_i, v_j)$. As a result, $G_c = (V'_c \cup \{v_0\}, A_c, l)$ is obtained, where $l(u, v)$ is the length of arc $(u, v)$.

The proposed approximation algorithm is as follows: It first guesses the middle node $v_m$ in a tour of the mobile charger and the amount of time consumed $T_m$ within the time budget $T$ by the mobile charger from $v_0$ to $v_m$ assuming that $T$ is an integer. The guessing step is implemented by enumerating all candidate nodes as the middle node $v_m$ as well as the possible value of $T_m$, $1 \leq T_m < T$. Notice that we can use the standard scaling and rounding techniques to ensure that all values within the total time budget $T$ are integers and polynomially bounded. It then recursively finds a tour $P_{left}$ from $v_0$ to $v_m$ with budget $T_m$, which means a tour $P_{left}$ starts at $v_0$ at time 0 and has to reach $v_m$ with no later than time $T_m$. It also finds another tour $P_{right}$ starting from $v_m$ and ending at $v_0$ with the budget $T - T_m$ to augment the nodes that are not covered by $P_{left}$, which means a tour $P_{right}$ starts at $v_m$ with no earlier than time $T_m$ and has to reach $v_0$ at time $T$. It finally outputs the tour by concatenating $P_{left}$ and $P_{right}$. Let procedure Offline_Appro$(v_s, v_e, t_s, t_e, V'_c, r)$ be used to implement the recursive greedy algorithm mentioned above, where $v_s$ is the start node with starting time $t_s$, $v_e$ is the end node with ending time $t_e$, and $r$ indicates the depth of the recursion allowed. Note that $v_s$ and $v_e$ can be the same which implies a close tour. The algorithm details are described in **Algorithm** 1.

**Algorithm 1** `Offline_Appro`$(v_s, v_e, t_s, t_e, V'_c, r)$

**Input:** A directed arc weighted graph $G_c = (V_c \cup \{v_0, t_c\}, A_c, l)$ and a given time budget $T$.
**Output:** A tour $P$ starts from $v_0$.

**if** $l(v_s, v_e) > t_e - t_s$ **then**
  /* It implies that the time budget is not enough even the mobile charger goes directly from $v_s$ to $v_e$ */
  **return** Infeasible;
**end if**;
$P \leftarrow < v_s, v_e >$;
**if** $r == 0$ **then**
  /* The recursive limit works*/
  **return** P;
**end if**;
/* $m(P)$ calculates the number of nodes covered by $P$ */
$max \leftarrow m(P)$;
**for** each $v \in V_c$ **do**
  /* Guessing the middle node visited */
  $v_m \leftarrow v$;
  **for** $1 \leq T' \leq (t_e - t_s)$ **do**
    /* Guessing the time budget used */
    $T_m \leftarrow T'$;
    $P_{left} \leftarrow$ Offlice_Appro$(v_s, v_m, t_s, t_s{+}T_m, V'_c, r{-}1)$;
    $P_{right} \leftarrow$ Offline_Appro$(v_m, v_e, t_s + T_m, t_e, V'_c - V(P_{left}), r-1)$;
    **if** $m(P_{left} \cdot P_{right}) > max$ **then**
      /* Concatenation of the two separate tours*/
      $P \leftarrow P_{left} \cdot P_{right}$;
      $max \leftarrow m(P_{left} \cdot P_{right})$;
    **end if**;
  **end for**;
**end for**;
**return** $P$.

*Theorem 2:* Given a set $V_c$ of sensors to be charged within a time period $T$ in the defined rechargeable sensor network, there is an approximation algorithm `offline_Appro` for the offline charging throughput maximization problem with approximation ratio of $O(\log |V_c|)$, which takes $O((|V_c| \cdot T)^{\log |V_c|})$ time.

**Proof** Following the classical results in [3], the theorem follows, omitted. □

### B. Online Heuristic

So for we have provided an offline approximation algorithm for the problem by assuming that all recharging requests are given in advance. In reality, it is impossible to know the requests in advance until they are actually received. In the following we develop an online algorithm, where the recharging requests arrive over time. In other words, it is very likely that new recharging requests will be received when the mobile charger moves towards its next charging sensor or is charging the current sensor.

For this online version of the problem, a naive approach is to construct the tour of the mobile charger iteratively. That is, within each iteration, a new recharging request is added to the tour and the mobile charger will serve it. The sum of the traveling time and charging time of charging a sensor can be treated as the processing time of serving a recharging request. This will lead to an online algorithm `Online_SPT` [15]: choose one sensor with the shortest processing time from all available recharging requests. Specifically, assume that the mobile charger currently stays at the location of sensor $v_i$ and finishes its charging. Recall that $l(v_i, v_j)$ is the travel time of the mobile charger from $v_i$ to $v_j$, and $C$ is the constant charging time. The amount of time for serving the recharging request $c_j$ of sensor $v_j$ is $l(v_i, v_j) + C + l(v_j, v_0) - l(v_i, v_0)$, where $v_0$ is the depot of the mobile charger. We thus choose a sensor to charge if its recharging request incurs the minimum amount of serving time. This procedure continues until the tour time constraint $T$ is no longer met.

Notice that once the mobile charger visits and charges a sensor, the serving time cost of the mobile charger changes due to the change of its location. Thus, the solution delivered by algorithm `Online_SPT` is sub-optimal, which can be illustrated by an example in Figure 2.

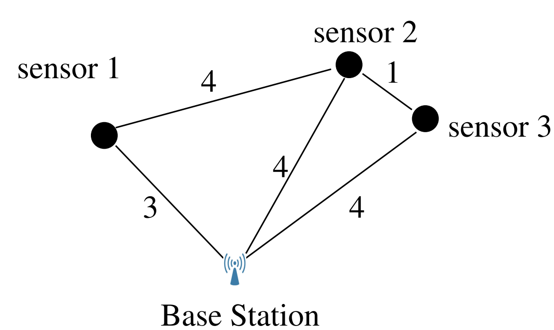



Fig. 2. An example scenario where the time constraint $T$ is 11, the constant charging time $C$ is 1 and the travel time between nodes is as labeled.

In this example, all three sensors are waiting for charging, the SPT-rule based solution is: Base→1→Base, where only sensor 1 is charged. Notice that although sensor 2 requires longer serving time than sensor 1, it is much closer to sensor 3. Hence it is easy to verify a better solution: Base→2→3→Base, where both sensor 2 and 3 will be charged.

### C. Improved Online Heuristic

Inspired by the illustrated example, we here propose a clustering-based algorithm, which takes both the serving time and sensor location information into consideration. In general, the proposed algorithm proceeds iteratively. The mobile charger makes its next charging decision only when it finishes recharging the currently chosen sensors already. Within each iteration, it will charge a set of sensors instead of a single sensor. To this end, it first groups recharging requests into different 'clusters' according to the locations of requesting sensors, and then identifies a group as its next charging target with maximizing a metric to defined later.

Recall that $V_c$ is the set of sensors to be charged which is updated dynamically. Specifically, within each iteration, for a given integer $K \leq |V_c|$, we first group all sensors to be charged based on their geographical locations, by adopting a well-known $K$-means clustering algorithm – Lloyd's algorithm [14], which aims to partition $|V_c|$ nodes into $K$ clusters such that each node belongs to the cluster with the nearest mean. Let $V_1, V_2, ...V_K$ be the $K$ clusters formed, where $V_1 \cup V_2 \cup ...V_K = V_c$. Assuming the mobile charger currently stays at the location of sensor $v_a$, for each cluster obtained, we then find a charging path for the mobile charger that starts from $v_a$, visits every node in the cluster exactly once and finally returns to the base station $v_0$ by adopting a MST heuristic for the Traveling Salesman Problem (TSP) [2]. A cluster $V_i$ is a *feasible charging cluster* if the time spent on all previous charging and traveling $T'$, plus the time spent for charging this cluster $|V_i| \cdot C$, and the relevant traveling time $l(V_i)$ is no more than $T$, i.e., $T' + |V_i| \cdot C + l(V_i) \leq T$, where $l(V_i)$ is the travel time to finish the relevant path from $v_a$ to $v_0$. If no feasible charging cluster can be found, it implies that the value of $K$ needs to be adjusted. We then change the value of $K$ iteratively by setting $K = \min\{\lfloor \beta \cdot K \rfloor, |V_c|\}$ and re-partition the set $V_c$ until a feasible charging cluster is found, where $\beta = 2$ is the adjusting rate which can also be set as any real number larger than 1. Denote by $\Delta gain(V_i) = \frac{|V_i|}{l(V_i) - l(v_a, v_0) + |V_i| \cdot C}$ the charging gain of cluster $V_i$. We finally choose a cluster with the maximum charging gain from all feasible charging clusters as the next charging cluster.

In summary, the algorithm proceeds iteratively. Initially, the mobile charger starts from the base station. Within each iteration, the mobile charger chooses a feasible charging cluster of sensors with the maximum charging gain among the $K$ clusters to charge. Once no feasible cluster is found, the value of $K$ is then self-adjusted and re-evaluated iteratively until a feasible cluster is found. This procedure continues until the tour time constraint $T$ is no longer met. The detailed algorithm `Online_K_Cluster` is described in **Algorithm** 2.

*Theorem 3:* Given a time period $T$ per tour and an integer $K$ in a rechargeable sensor network, there is an online algorithm `Online_K_Cluster` for the charging throughput maximization problem, which takes $O(|V|^2 \cdot \log |V| \cdot T)$ time, where $|V|$ is the total number of sensors.

**Algorithm 2** `Online_K_Cluster`

**Input:** A set $V_c$ of sensors to be charged which varies over time, a given time period $T$, and a specified constant $K$.
**Output:** A tour $P$ starts from base station $v_0$.

$P \leftarrow < v_0 >$;
$K_{init} \leftarrow K$;
/* the current location of the mobile charger */
$v_a \leftarrow v_0$;
/* the current time */
$t \leftarrow 0$;
**while** $t \leq T$ **do**
  Apply a $K$-means clustering algorithm to partition $V_c$ into $K$ clusters: $V_1, V_2, ...V_K$;
  For each cluster, find a path from $v_a$ that visits every node within this cluster and finally returns to $v_0$ by adopting a MST heuristic for TSP problem;
  Once no feasible cluster is found, then adjust $K$ by setting $K = \min\{2K, |V_c|\}$ and repartition.
  **if** $K == |V_c|$ and no feasible cluster found **then**
    /* the mobile charger return to $v_0$ */
    Break;
  **end if**;
  Calculate charging gain for each feasible cluster;
  /* Assuming cluster $V_i$ has maximum charging gain, the mobile charger then goes to charge sensors in this cluster by following the found path */
  Add the charged sensors in $P$;
  Update sensor set $V_c$, $v_a$ and $t$ accordingly;
  /* reset $K$ for next iteration */
  $K \leftarrow K_{init}$;
**end while**;
**return** $P$.

**Proof** Clearly, algorithm `Online_K_Cluster` yields a feasible solution to the charging throughput maximization problem. We now analyze the time complexity of algorithm `Online_K_Cluster` in the following.

Within each iteration, applying Lloyd's algorithm takes $O(|V_c| \cdot K \cdot l)$ time, where $V_c$ is the set of sensors to be charged and $l$ represents the number of iterations inside Lloyd's algorithm. Calculating the charging gain for a cluster takes $O(|V_c|^2)$. As the value of $K$ may need to be adjusted by setting $K = \min\{2K, |V_c|\}$ and $l$ can be bounded by a predefined constant, finding a feasible cluster with the maximum charging gain takes $O(|V_c|^2 \cdot \log |V_c|)$ time. It is easy to verify that the number of iterations is bounded by $T$. The algorithm thus takes $O(|V_c|^2 \cdot \log |V_c| \cdot T) = O(|V|^2 \cdot \log |V| \cdot T)$ time since $|V_c| \leq |V|$. □

## IV. PERFORMANCE EVALUATION

In this section, we evaluate the performance of the proposed algorithms through experimental simulation. We also study the impact of the cluster parameter $K$ on algorithm performance.

### A. Simulation environment

TABLE I
DEFAULT PARAMETERS SETTING

| Parameter | Value |
|---|---|
| Network Size (Small Scale) | 10 - 30 |
| Sensing Field (Small Scale) | 50m × 50m |
| Given Time Period T (Small Scale) | 30s |
| Network Size (Large Scale) | 100 - 1,000 |
| Sensing Field (Large Scale) | 500m × 500m |
| Given Time Period T (Large Scale) | 1,800s, 3,600s |
| Constant Charging Time | 2s |
| Charging Moving Speed | 8m/s |
| Adjust Rate $\beta$ | 2 |

As listed in Table I, two different scale networks are considered in our experiments. One is a small-scale network consisting of 10 to 30 sensors randomly deployed in a $50m \times 50m$ square area, and another is a large-scale network consisting of 100 to $1,000$ sensors randomly deployed in a $500m \times 500m$ square area. The base station (the depot of the mobile charger) is located at one corner of the monitoring area. Due to the dynamic nature of sensing activity, each sensor randomly sends its recharging requests within a given time period $T$. That is, for each sensor there is a corresponding recharging request with the value of release time randomly chosen within $[0, T]$. Without loss of generality, we here set $T = 30s$ for a small scale network, and also set the time period for a large scale network at $T = 1,800s$ and $T = 3,600s$, respectively. We further assume that the default constant charging time for each sensor is $2s$, and the mobile charger travels at a constant speed $8m/s$. Each value in figures is the mean of the results by applying each mentioned algorithm to 30 different network topologies of the same network size.

### B. Performance evaluation of both offline approximation and online heuristic algorithms

We first evaluate the performance of the offline approximation algorithm `Offline_Appro` as well as two proposed online heuristics `Online_SPT` and `Online_K_Cluster` in small-scale networks, by varying the network size from 10 to 30 and setting the cluster parameter $K = 3$, while the time period $T$ is fixed at $30s$.

Fig. 3 clearly shows that the offline algorithm `Offline_Appro` outperforms the two online heuristics `Online_SPT` and `Online_K_Cluster` significantly. With the increase on network size, the performance gap between them becomes larger. The reason behind is that the offline algorithm has all request information, and use a nearly exhaustive search method. Obviously, when there is small-scale recharging requests workload and the global knowledge is available (e.g. by prediction), the offline algorithm is the best choice. However, the offline algorithm is very computationally expensive, which makes it impractical for large-scale networks.

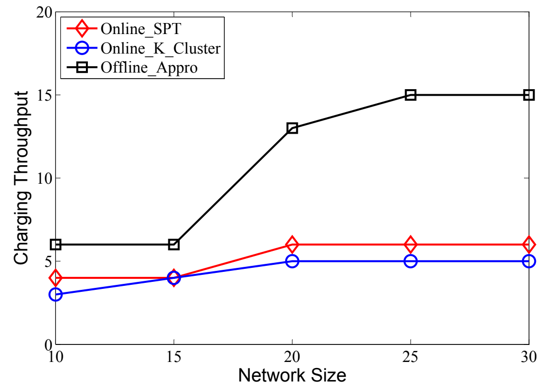



Fig. 3. The charging throughput performance of both offline approximation and online heuristic algorithms.

### C. Performance evaluation of online heuristic algorithms

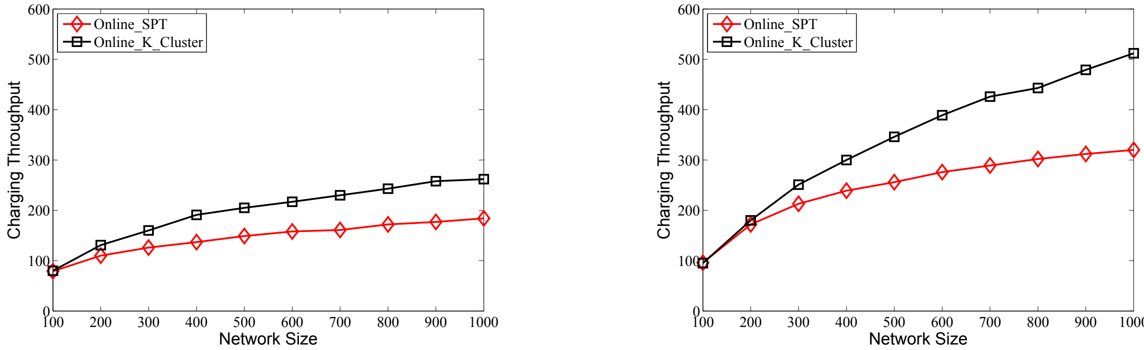
We then investigate the performance of two online heuristics `Online_SPT` and `Online_K_Cluster` in large-scale networks by varying the network size from 100 to $1,000$ and setting the cluster parameter $K$ at 5, while the time period $T$ is fixed at $1,800s$ and $3,600s$, respectively.

Fig. 4 demonstrates that the charging throughput of algorithm `Online_K_Cluster` outperforms that of `Online_SPT` with the increase of the network size. For example, in Fig. 4(a), when the network size is greater than 100 and $T$ is 1,800s, the charging throughput of `Online_K_Cluster` is at least 20% more than that of `Online_SPT`. When the network size becomes larger, the performance gap between them also increases upto around 47%. Similarly, in Fig. 4(b), when the network size is greater than 200 and $T$ is 3,600s, the charging throughput of `Online_K_Cluster` is at least 19% more than that of `Online_SPT`. It also can be noticed that with a larger time period $T$, the charging throughput of both `Online_SPT` and `Online_K_Cluster` is increased, as the mobile charger has more time available to serve the recharging requests.

### D. The impact of cluster parameter $K$ on charging throughput performance

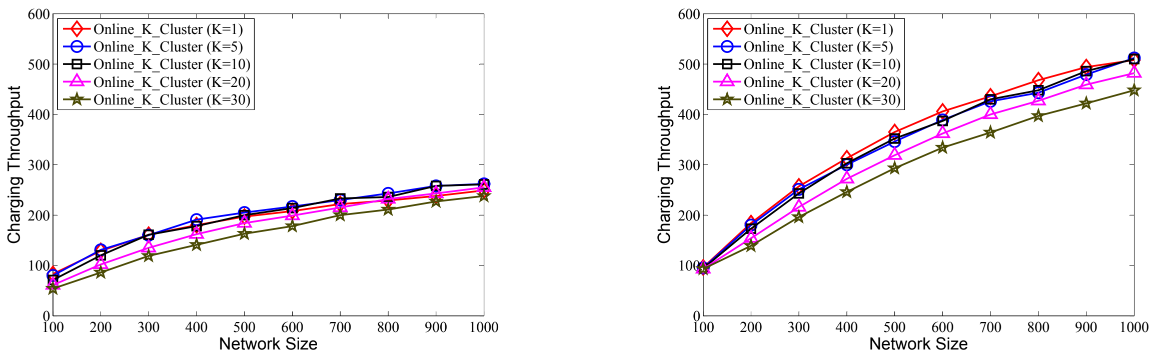
We finally study the impact of the cluster parameter $K$ on the performance of algorithm `Online_K_Cluster` by setting $K$ at 1, 5, 10, 20, and 30, while the network size varies from 100 to 1,000 and the time period $T$ is fixed at $1,800s$ and $3,600s$, respectively.

From Fig. 5, it can be seen that the charging throughput of algorithm `Online_K_Cluster` with $K = 30$ delivers the worst performance. With the growth of the network size, the performance gap between them becomes smaller. Specifically, in Fig. 5(a), the charging throughput of algorithm




(a) $T = 1,800s$ (b) $T = 3,600s$

Fig. 4. The charging throughput performance of online algorithms by varying the network size and setting the given time period $T$ at 1,800s and 3,600s.




(a) $T = 1,800s$ (b) $T = 3,600s$

Fig. 5. The impact of cluster parameter $K$ by varying the network size $n$ and setting the tolerant delay $T$ at 1,800s and 3,600s.

`Online_K_Cluster` with $K = 5$ outperforms that of algorithm `Online_K_Cluster` with $K = 1$ and $K = 10$ slightly, and is more than at least 25% and 19% compared with that of algorithm `Online_K_Cluster` with $K = 20$ and $K = 30$ when the network size is less than 800, respectively. Fig. 5(b) also exhibits the similar performance behavior in which algorithm `Online_K_Cluster` with $K = 1$ outperform algorithm `Online_K_Cluster` with $K = 5, 10$ slightly, omitted. In general, the charging throughput of algorithm `Online_K_Cluster` decreases when the $K$ value is sufficiently large. In order to achieve a best charging throughput, a proper $K$ should be assigned according to the network size and the tour time bound.

## V. Conclusion

In this paper we have studied the problem of finding an optimal close trajectory for a mobile charger in wireless rechargeable sensor networks, subject to the time duration constraint of the mobile charger per tour. We formulated the problem as the charging throughput maximization problem with an aim of maximizing the number of sensors charged per tour. Due to the NP-hardness of the problem, we then proposed an offline approximation algorithm and two online heuristics. Finally, we evaluated the performance of the proposed algorithms through experimental simulation, and provided numerical results to validate the efficiency of the proposed algorithms. Nevertheless, our work mainly focuses on maximizing the number of sensors charged, which may result in biased charging behaviors in some extreme cases, where some sensors that are far from the base station or sparsely located, and they will have fewer opportunities to be charged forever. We will extend our work in future by considering this fairness issue as well.

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