Energy Synchronized Task Assignment in Rechargeable Sensor Networks

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Abstract

Wireless rechargeable sensor networks have recently emerged as a promising platform that can effectively solve the power constraint problem suffered by traditional battery-powered systems. The problem of determining the best charging routes for maximizing charging efficiency has been studied extensively. However, the task assignment problem, which plays a crucial role in efficiently utilizing the harvested energy and thus minimize the charging delay, has received rather limited attention. In this paper, we study the problem of assigning a given set of tasks in a wireless rechargeable sensor network while maximizing the charger's velocity to minimize the charging delay. We first propose an online task assignment algorithm, namely Lower Bound assignment (LB), that yields a quantifiable lower bound on the charging velocity while guaranteeing a feasible assignment. This algorithm further enables the transformation of our considered task assignment problem into a variation of the classical multiple knapsack problem. We then present a fully polynomial-time approximation scheme with a $(2+\varepsilon)$-approximation ratio, namely ACT, that is built upon an existing greedy algorithm designed for the original knapsack problem. Extensive experimental results presented herein demonstrate that ACT is able to achieve near-optimal performance in most cases, and can achieve more than 15% performance improvement compared to the baseline algorithms.

1 Introduction

Wireless sensor networks (WSNs) have been widely adopted in a variety of application domains. In a typical scenario, sensors are deployed in a certain region for executing a large number of sensing, computing, and communication tasks. Unfortunately, stringent energy constraints posed by traditional battery-powered WSNs have become a critical bottleneck that impedes long-term operations of such systems.

Through recent advances in wireless recharging technologies [15], wireless rechargeable sensor networks (WRSNs) have emerged as a promising platform to effectively solve the energy constraint problem [6, 7, 9]. A WRSN often deploys one or more mobile chargers that traverse along an existing infrastructure and replenish the dissipated energy of sensor nodes [8, 7, 30]. For many practical applications of WRSNs, the charging delay is not negligible and plays a critical role in minimizing the system decision/operation cycle time [7, 30]. Prior works have focused on investigating the issue of determining the best traversing routes while assuming constant charger traversing velocity for minimizing the overall charging delay [7] and maximizing the network lifetime [30].

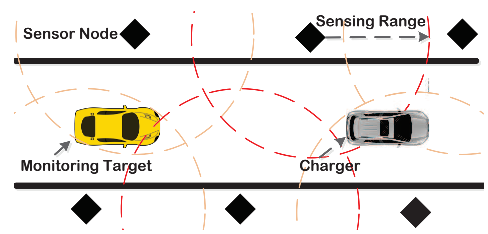


Figure 1: The charger wirelessly charges the sensor nodes along the road segment before each monitoring period.

While identifying the optimal or near-optimal routes is essential to minimize the charging delay, for many applications, such as warehouse and traffic monitoring [22, 17], the charger's traversing route is typically fixed due to geographical constraints. An example motivational scenario is vehicle monitoring along a road network [11], as illustrated in Fig. 1. Sensor nodes are deployed along the road and the sensing range of each sensor node covers part of the road segment. The road segment can be entirely covered by all the sensor nodes. A service vehicle carries wireless chargers and travel along the road network to power these sensor nodes. The monitoring task is composed by a set of sensing tasks utilizing sensors including image, magnetic, sound and radiation [11, 17]. During a monitoring period, due to the computational and energy capacity limitation, a single sensor node normally can not handle all tasks. Thus, different sensing tasks need to be assigned and distributed to different nodes for accomplishing the monitoring task collectively. These nodes gather different sensing data to be fused at the sink. In such scenarios with fixed traversing routes, identifying better routes becomes relatively easy. Rather, maximizing the charger's traversing velocity through optimally utilizing the charged energy on sensor nodes becomes critical in order to minimize the charging delay.

This problem of maximizing the charger's traversing velocity is challenging because sensor nodes in a WRSN need to be wireless charged to a degree such that they harvest enough energy for executing a given number of sensing and computing tasks, each of which possesses a specific energy requirement. This clearly conflicts with the objective of maximizing the charger's traversing velocity, where a faster charging velocity may cause reduced amount of energy harvested by sensor nodes (the detailed charging model is given in Sec. 2). Moreover, under a specific traversing velocity, the amount of energy harvested by different sensor nodes varies due to their different geographical locations. Our observation herein is that the strategy of assigning tasks to sensor nodes is critical in maximizing the traversing velocity. A judicious task assignment may lead to a reduced amount of energy that sensor nodes require to complete all given tasks and better utilize the energy harvested by each individual sensor, thus allowing an increased charging velocity. Motivate by this, we investigate in this paper the problem of maximizing the charger's traversing velocity (thus minimizing the charging delay) while guaranteeing a feasible task assignment.

Specifically, we consider the problem of assigning a given set of tasks in a WRSN while the charger travels along a fixed route charging sensor nodes. Our objective is to minimize the charging delay while ensuring that sensor nodes harvest enough energy for executing all tasks. To achieve this objective, we design novel online task assignment algorithms that seek to minimize the amount of required energy harvested by sensor nodes, thus yielding the maximum feasible charging velocity.

The major contributions of this paper are listed as follows:

- We propose a new task assignment algorithm, namely LB(Lower Bound) assignment, in WRSNs, which seeks to minimize the charging delay. LB is an online algorithm, meaning that tasks are assigned dynamically at runtime while the charger is traversing and charging the sensor nodes. LB yields an upper bound on the total amount of required energy that sensor nodes need to harvest in order to execute all given tasks. It thus yields a quantifiable lower bound on the charging velocity while guaranteeing a feasible assignment. We also analytically prove that the ratio of the charging velocity achieved by LB over an upper bound on the charging velocity is a constant factor that can be computed provided specific task and system parameters.
- Moreover, the LB algorithm is significant in the sense that it further enables us to formulate the task assignment problem as a multiple knapsack problem with variable capacity for each knapsack. Based upon this problem formulation, we present an improved polynomial time approximation scheme (ACT) with $(2+\varepsilon)$-approximation ratio. Our proposed ACT leverages a classical multiple knapsack solution and applies several efficient optimization techniques.
- We have conducted extensive experiments, which demonstrate that our proposed algorithms are able to achieve near-optimal performance compared to the optimal solution, and can achieve $>15\%$ performance improvement compared to a baseline algorithm.

The rest of this paper is organized as follows. Sec. 2 describes our system model and problem formulation. In Sec. 3, we present the LB assignment and the resulting lower bound on the charger velocity. Then in Sec. 4, we present a PTAS with an approximation ratio of $2+\varepsilon$ that yields a faster charger velocity. We evaluate our design in Sec. 5. We discuss related works in Sec. 6 and conclude in Sec. 7.

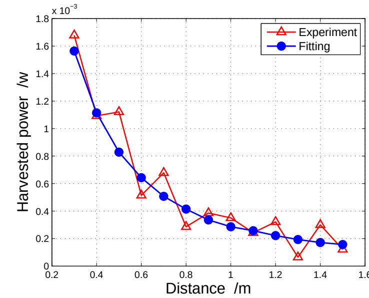


Figure 2: Charged Power vs. Distance

2 Preliminaries

In this section, we present models used for the wireless charging and the task assignment problem in wireless rechargeable sensor network.

2.1 Mobile Wireless Charging Model

Wireless recharging has become a promising technology to address sustainable problem for battery-powered devices. Much recent work [18, 20, 24] has shown that rechargeable sensor nodes can harvest energy from ambient radio frequency signals. Wireless Identification and Sensing Platform (WISP) [25], developed by Intel Research, is one of the most representative wireless rechargeable sensor node platform for many sensing applications such as Passive Data Logger (PDL) [32] and daily activity recognition [1].

To model the wireless charging power, He *et al.* [9] propose a wireless recharging model based on the *Friis'* free space equation as follows:

$$P_r = \frac{G_s G_r \eta}{L_p} \left(\frac{\lambda}{4\pi(d+\beta)}\right)^2 P_0, \tag{1}$$

where d is the distance between the sensor node and charger. All other parameters are constant based on the environment and device settings. P_0 is the source power, G_s is the source antenna gain, G_r is the receive antenna gain, L_p is polarization loss, λ is the wavelength, η is rectifier efficiency, and β is a parameter to adjust the *Friis'* free space equation for short distance transmission. This model has been widely used in prior work [7, 9, 27]. We have also validated this model by conducting measurements-based experiments, which study the relationship between the charged power and the distance between a charger and a sensor node. The experiments were conducted on WISP and the measured results are shown in Fig. 2.

According to Eq. (1), the only variable that affects the charged power of a sensor node is its distance from the charger within a given environment. Thus, for readability, we abbreviate the charging model in Eq. (1) as:

$$P = \kappa(d). \tag{2}$$

Based on this charging model, we calculate the charging

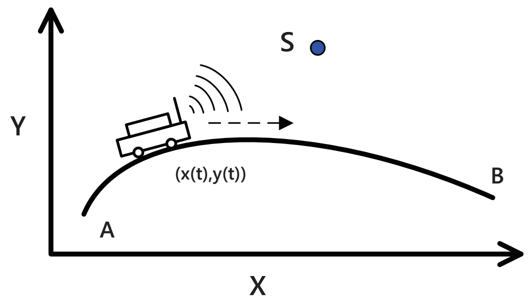


Figure 3: Mobile Charging Model

power for a mobile charger. In Fig. 3, the charger travels along a trajectory AB, charging the sensor node s continuously. The charger's location is a function of time t, which can be denoted as $(x(t), y(t))$, and the coordinates of sensor node s is denoted (x_s, y_s). Therefore, the distance between the sensor node s and the charger can be computed as follow:

$$f_d(t) = \sqrt{(x(t)-x_s)^2 + (y(t)-y_s)^2}. \quad (3)$$

Then based on Eqs. (2) and (3), the charging power at time t for the sensor node s is $\kappa(f_d(t))$ and the total amount of charged energy $E_s(v)$ on sensor node s can be denoted as:

$$E_s(v) = \int_0^{\frac{L}{v}} \kappa(f_d(t))dt, \quad (4)$$

where v is the charger's velocity and L is the length of AB. From Eq. (4), we can see that given a fixed travel trajectory of the charger, the total amount of charged energy on the sensor s, $E_s(v)$, only depends on the charger's travel velocity.

2.2 Problem Statement

We consider a wireless rechargeable sensor network with a set $S = \{s_1, s_2, s_3, \ldots, s_m\}$ of m stationary sensor nodes, which need to execute a set $T = \{T_1, T_2, T_3, \ldots, T_n\}$ of n tasks.[1]

Each task T_i requires e_i amount of energy for execution. e_i equals to the sensing power of s_i multiplied by the monitoring period. The locations of individual nodes can be obtained with solutions proposed in [27] and represented as (x_j, y_j) for node j. Given the location of each node and the charger velocity v along a trajectory, we can estimate the charged energy on a node s_j, denoted $E_j(v)$, using Eq. (4). Therefore, the total amount of charged energy on all sensor nodes, denoted E_{total}, is:

$$E_{total} = \sum_{j=1}^{m} E_j(v) \quad (5)$$

Since $E_j(v)$ is a monotonically decreasing function of v according to Eq. (4), E_{total} is also a monotonically decreasing function of v. Consequently, our objective is to find the maximum velocity v_{max} for the charger, while guaranteeing that all the tasks can be completed.

Energy is an essential constraint for the task assignment problem. A node can not execute a task if the required amount of energy for executing the task is more than the harvested energy. Formally, let A denote a task assignment, where $x_{i,j}$ is a binary decision variable. Let $x_{i,j}$ be 1, if T_i is assigned to sensor node s_j, and 0 otherwise. In order to execute all assigned tasks on s_j, the amount of charged energy on s_j should be more than the required amount of energy, i.e.,

$$\sum_{i=1}^{n} x_{i,j} e_i \le E_j(v). \quad (6)$$

A task assignment is *feasible* under a charger's traversing velocity v if under this assignment, all sensors have enough charged energy for executing their assigned tasks.

If both Eq. (6) and $\sum_{i=1}^{n}\sum_{j=1}^{m} x_{i,j} = n$ hold, then the charged energy on m nodes is sufficient to execute all n tasks. Therefore, we can formulate our problem as the following integer linear programming (ILP):

$$\max \quad v \quad (7)$$

$$\text{subject to}: \quad \sum_{j=1}^{m} x_{ij} \le 1 \quad (8)$$

$$\sum_{i=1}^{n} x_{ij} \times e_i \le E_j(v) \quad (9)$$

$$\sum_{i=1}^{n}\sum_{j=1}^{m} x_{i,j} = n \quad (10)$$

$$x_{i,j} = \{0,1\} \quad (11)$$

3 A Feasible Lower Bound on Velocity

Although solving the above ILP guarantees an optimal solution, it takes exponential time to search the solution space, which is not practical. In this section, we present the LB algorithm, which is an online task assignment algorithm that yields an upper bound on the total amount of required energy that sensor nodes need to harvest in order to execute all given tasks (Theorem 1). Thus, LB yields a quantifiable lower bound on the charging velocity while guaranteeing a feasible assignment. Before describing the algorithm, we first give necessary definitions.

DEFINITION 1. *Let $E_1, E_2, \ldots, E_m$ denote the amount of charged energy on sensor nodes $s_1, s_2, \ldots, s_m$, when the charger travels with speed v_{act} along its trajectory. Let e_{sum} denote $\sum_{i=1}^{n} e_i$. We index tasks such that $e_i \le e_j$ holds if $i \le j$. For conciseness, let T_{sub} denote $\{T_1, T_2, \ldots, T_m\}$ with m tasks.*

THEOREM 1. *A feasible traveling velocity v_{lb} for the charger yields a total charged energy $E(v_{lb}) = \max\left\{\sum_{k=m+1}^{n} e_k + (m-1)\cdot e_n, \sum_{k=1}^{n} e_k + (m-1)\cdot e_m\right\}$, which guarantees that*

[1] Note that we assume that tasks can be assigned to and executed on any sensor node. This is a reasonable assumption that can be seen in many application scenarios, in particular many state-of-the-art sensor systems that apply the compressive sensing technique [2, 5]. The compressive sensing technique allows an arbitrary subset of the sensor nodes in the system to execute the required tasks, while still guaranteeing that all needed information, which is expected to be provided by the entire sensor system, can be obtained. For example, the container-keepers distribute sensor nodes in the seaport containers in order to monitor the temperature. Traditionally, every sensor node needs to execute the temperature sensing task and return the results to the monitoring system. This may cause significant but necessary energy loss [2, 5, 14]. By applying the compressive sensing technique, only an arbitrary subset of the sensor nodes need to execute such temperature sensing tasks. Based upon the obtained results, the complete temperature data can be reconstructed accurately [14].

there exists a feasible task assignment.

Proof. We prove Theorem 1 by showing that our proposed LB algorithm guarantees to yield a feasible task assignment under v_{act}. The LB algorithm is a 2-Stage process (described next) and the order of these 2 stages can not be inverted. **Stage 1 of LB:** Assign $\{T_{m+1}, T_{m+2}, \ldots, T_n\}$ to sensor nodes in order. Before assigning $T_{m+i}(1 \leq i \leq n-m)$, we denote the total amount of remaining energy on all sensor nodes as E_r and it holds that:

$$\begin{aligned}
E_r &= E(v_{lb}) - \sum_{j=m+1}^{m+i-1} e_j \\
&= \max\{ \sum_{k=m+1}^{n} e_k + (m-1)\cdot e_n - \sum_{j=m+1}^{m+i-1} e_j, \\
&\qquad \sum_{k=1}^{n} e_k + (m-1)\cdot e_m - \sum_{j=m+1}^{m+i-1} e_j \} \\
&\geq \sum_{k=m+1}^{n} e_k + (m-1)\cdot e_n - \sum_{j=m+1}^{m+i-1} e_j \\
&\geq \sum_{k=m+i}^{n} e_k + (m-1)\cdot e_n \\
&\geq m \cdot e_{m+i}.
\end{aligned} \tag{12}$$

Since $E_r \geq m \cdot e_{m+i}$, the average amount of remaining energy on each sensor node is no less than e_{m+i}. Thus, we can always find a sensor node with an amount of remaining energy no less than e_{m+i}. Then, we assign T_{m+i} to this sensor node. By applying this argument inductively on i, we are able to find sensor nodes to which $T_{m+1}, T_{m+2}, \ldots, T_n$ can be assigned. **Stage 2 of LB:** Assign tasks in T_{sub} to sensor nodes. After **Stage 1**, we denote the total amount of remaining energy on all sensors as E_{tr} and it holds that:

$$\begin{aligned}
E_{tr} &= E(v_{lb}) - \sum_{j=m+1}^{n} e_j \\
&= \max\{ \sum_{k=m+1}^{n} e_k + (m-1)\cdot e_n - \sum_{j=m+1}^{n} e_j, \\
&\qquad \sum_{k=1}^{n} e_k + (m-1)\cdot e_m - \sum_{j=m+1}^{n} e_j \} \\
&\geq \sum_{k=1}^{n} e_k + (m-1)\cdot e_m - \sum_{j=m+1}^{n} e_j \\
&= \sum_{k=1}^{m} e_k + (m-1)\cdot e_m \\
&= \sum_{k=1}^{m-1} e_k + m \cdot e_m,
\end{aligned} \tag{13}$$

Since $E_{tr} \geq \sum_{k=1}^{m-1} e_k + m \cdot e_m$, there exists at least one sensor node s_x that has a remaining energy greater than e_1. Thus, we can assign T_1 to s_x. Similarly, if we assign tasks in T_{sub} in order, then after assigning T_{i-1} $(2 \leq i \leq m)$, the total amount of remaining energy on all sensor nodes is at least $\sum_{k=1}^{m-1} e_i + m \cdot e_m - \sum_{j=1}^{i-1} e_j = \sum_{k=i}^{m} e_k + (m-1)\cdot e_m$. Thus, we can always find a sensor node s_y whose remaining energy is no less than e_m. We can assign T_i to s_y.

After completing this 2-Stage process, we have assigned all n tasks to sensor nodes with a total charged energy of $E(v_{lb})$. The theorem thus follows. □

Intuitively, since $\sum_{k=1}^{n} e_k$ denotes the total amount of energy required to execute the n tasks, Theorem 1 shows that the amount of redundant energy is related to the number of sensor nodes. Note that in order to guarantee a feasible task assignment, the above-mentioned 2-Stage LB algorithm only relies on the total amount of harvested energy on all sensor nodes. Thus, it can be executed online, which implies that sensor charging, task assignment, and task execution can be operated at the same time regardless of the amount of harvested energy on each individual sensor node. While the charger is traveling and charging the sensor nodes, tasks can be assigned to sensor nodes that harvest enough energy. All n tasks are guaranteed to be assigned after the 2-Stage process (i.e., when the total amount of harvested energy on all sensor nodes reaches $E(v_{lb})$).

Example. We use an example to illustrate the 2-Stage task assignment, as shown in Fig. 4. In this figure, notation $s_i(j)$ denotes the amount of remaining energy on sensor node s_i and the number shown in the task block denotes the amount of energy required by that task. For this system, the task set is $\{T_1, T_2, T_3\}$ and the sensor set is $\{s_1, s_2\}$. According to Theorem 1, $E_o = \max\{e_{sum} + e_2,\ e_{sum} + (e_3 - e_1)\} = 13$. Fig. 4(b) shows the amount of harvested energy increasing with time t for s_1 and s_2, when the charger travels with v_{lb} and finally the total amount of harvested energy on s_1 and s_2 is 13. Since the 2 stages in Theorem 1 can not be inverted, we has to assign T_3 first to guarantee a feasible task assignment. In Fig. 4(b), we observe that the amount of harvested energy on s_2 is 5 at time t_1. Therefore, we assign T_3 to s_2 at t_1. After assigning T_3, the algorithm enters **Stage 2**, we start to assign T_{sub}. At time t_1, the amount of harvested energy on s_1 is 4.5, which is larger than e_1. Thus we also assign T_1 to s_1 at t_1. Fig. 4(c) shows the system status after assigning T_3 and T_1. In Fig. 4(b), we can see that the total amount of harvested energy on s_1 is 5 at t_2. So after executing T_1, the amount of remaining energy is enough to execute T_2. T_2 can thus be assigned to s_1 at t_2. Fig. 4(d) shows the final task assignment.

Approximation Ratio of LB. The LB algorithm yields a feasible velocity v_{lb}. We now derive the approximation ratio between v_{lb} and the maximum possible velocity v_{max}.

According to Eq. (5), the total amount of harvested energy on all sensor nodes E is a monotonically decreasing function of the charger's traveling velocity v, therefore, the inverse function for v can be described as:

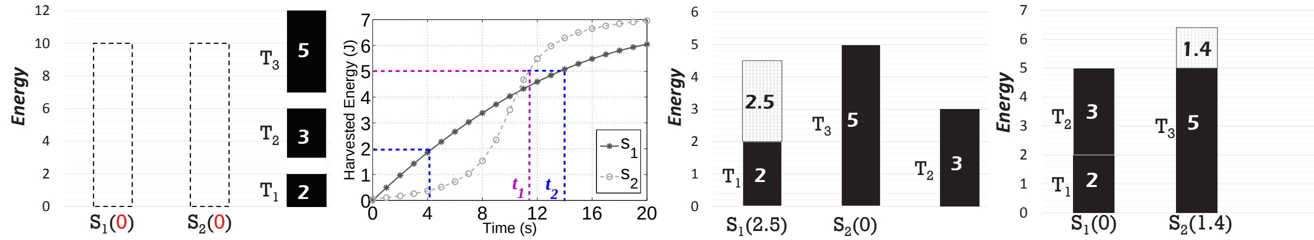
$$v = E^{-1}(E_{total}), \tag{14}$$

where E_{total} is the total amount of harvested energy on all sensors. v is also a monotonically decreasing function of E_{total}.

THEOREM 2.

$$\frac{E^{-1}(E(v_{lb}))}{E^{-1}(e_{sum})} \leq \frac{v_{lb}}{v_{max}} \leq 1. \tag{15}$$

Proof. Assuming when the charger travels with v_{max}, the total amount of harvested energy on all sensor nodes is



(a) Assign T_1, T_2, T_3 to s_1, s_2 (b) Harvested Energy VS. Time (c) Task Assignment at t_1 (d) Task Assignment at t_2

Figure 4: Example for 2-Stage Process

$E(v_{max})$. Since $E(v_{max})$ must yield a feasible task assignment to accomplish all tasks, it is clear that $E(v_{max}) \geq e_{sum}$ must hold (e_{sum} is defined in Def. 1. Since v is a monotonically decreasing function of $E^{-1}(E_{total})$, $E^{-1}(E(v_{max})) \leq E^{-1}(e_{sum})$. Therefore, $\frac{v_{lb}}{v_{max}} = \frac{E^{-1}(E(v_{lb}))}{E^{-1}(E(v_{max}))} \geq \frac{E^{-1}(E(v_{lb}))}{E^{-1}(e_{sum})}$. Since $v_{lb} \leq v_{max}$, $\frac{v_{lb}}{v_{max}} \leq 1$. Hence, the theorem follows. □

Example. Since $v = E^{-1}(E_{total})$ is an inverse function of Eq. (5), we can quantitatively calculate the approximation ratio $\frac{E^{-1}(E(v_{lb}))}{E^{-1}(e_{sum})}$ of LB with given system parameters. Consider one of the settings used in our experiments for example, which is given in Sec. 5. Specifically, we set $\frac{G_s G_r \eta}{L_p}(\frac{\lambda}{4\pi})^2 P_0 = 36$ and $\beta = 30$ for the charging model given in Eq. (1). Assume that 5000 tasks are randomly generated with power assumption parameters given in Table. 1 and the system contains 100 sensor nodes, we can calculate $E(v_{lb}) = 5.25KJ$ and $e_{sum} = 5.12KJ$ according to Theorem 1 and the definition of e_{sum}. Thus, the lower bound on the velocity yielded by LB is $v_{lb} = E^{-1}(E(v_{lb})) = 0.65m/s$ and the upper bound on the velocity is $v_{max} = E^{-1}(e_{sum}) = 0.5m/s$. (Note that we omitted the detailed calculation steps due to space constraints.) Therefore, the approximation ratio of LB for this example system is given by $0.5/0.65 \approx 76\%$.

Let v_{ub} denote $E^{-1}(e_{sum})$. According to Theorem 2, $v_{lb} \leq v_{max} \leq v_{ub}$. In the following sections, we introduce a binary search algorithm to find v_{max}.

4 Practical Binary Compression

In the previous section, we have shown that the LB algorithm yields a lower bound v_{lb} (Theorem 1) and an upper bound v_{ub} (Theorem 2) on the feasible velocity for the charger. This implies that for any velocity $\leq v_{lb}$, we can always find a corresponding feasible task assignment, and for any velocity $> v_{ub}$, we can not find a feasible task assignment. Thus, the optimal velocity v_{max} falls in the interval $[v_{lb}, v_{ub}]$. According to Theorem 2, $[v_{lb}, v_{ub}]$ is expected to yield a rather limited solution space in most cases. In this section, we present novel techniques that find v_{ub} by compressing the limited solution space of $[v_{lb}, v_{ub}]$.

4.1 Task Scheduling for A Given Energy Distribution

According to the mobile charging model in Sec.2, we know that the amount of harvested energy on each sensor node only depends on the charger's traveling speed v. In other words, each $v \in [v_{lb}, v_{ub}]$ corresponds to an energy distribution on these sensor nodes. Our key observation is that since the amount of harvested energy on each sensor node decreases monotonously when the charger's velocity increases, we can apply the binary search algorithm to reduce the searching space efficiently.

In the rest of this section, we investigate how to derive a feasible task assignment under a given v using the binary search algorithm. For any given v, the amount of harvested energy on each sensor node is fixed. Our objective is thus changed to determine whether all tasks can be completed by sensor nodes with fixed energy distributions.

The Task Assignment Problem (TAP) can be formulated by the following ILP:

$$\max \quad z = \sum_{i=1}^{n} \sum_{j=1}^{k} x_{ij} \tag{16}$$

$$\text{subject to :} \quad \sum_{j=1}^{k} x_{ij} \leq 1 \tag{17}$$

$$\sum_{i=1}^{n} x_{ij} \times e_i \leq E_j(v) \tag{18}$$

$$x = \{0, 1\} \tag{19}$$

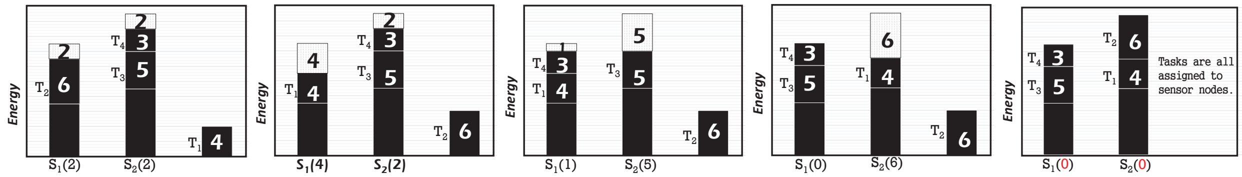
where z denotes the number of tasks executed by the rechargeable sensor nodes, when the charger travels with speed v. If $z = n$, then the corresponding v guarantees that all n tasks can be assigned.

4.2 Multiple Knapsack Problem

According to the above formulation, we observe that TAP has many similarities with the Multiple Knapsack Problem (MKP). MKP can be defined as follows: given a set of n items and a set of m knapsacks ($m \leq n$) such that each item i has a profit p_i and size s_i, and each knapsack j has a capacity c_j, how to select m disjoint subsets of items such that the total profit of the selected items is maximized while satisfying the constraint that each subset can only be assigned to a knapsack whose capacity is no less than the total size of items in the subset.

For TAP, the amount of charged energy to each sensor node corresponds to the capacity of each knapsack; the consumed energy to accomplish each task corresponds to the size of each item. Our objective is to assign tasks to these sensor nodes as many as possible while guaranteeing that all sensor nodes have enough charged energy to execute the assigned tasks.

Therefore, TAP is a special case of MKP, where the profit for each item equals 1. The solutions proposed to tackle MKP can also be used to solve TAP.



(a) Greedy (b) Swapping (c) Moving (d) Exchange (e) ACT

Figure 5: Example task assignments illustrating the three optimization techniques.

4.3 Our Proposed PTAS Algorithm.

MKP is a nature extension of the single knapsack problem, which has been studied extensively [12, 19, 3]. MKP is NP- hard [12]. Many solutions were proposed to seek the optimal profit for MKP [10] [13] [3]. In [3], a polynomial time greedy scheme is designed, which yields a $(2+\varepsilon)-approximation$ algorithm. The time complexity of this algorithm is $O(mn\log(1/\varepsilon)+m/\varepsilon^4)$, using the results of Lawler [16] for the knapsack problem.

Our proposed algorithm is built upon this greedy scheme [3], while preserving the theoretical property of the $(2+\varepsilon)$ approximation ratio.[2] For brevity, we denote this greedy scheme as "GREEDY". Under GREEDY, the sensor nodes are considered as independent components. Each sensor is considered in turn and tasks are assigned to each considered sensor by applying the PTAS [26] designed for the single knapsack problem on the remaining tasks. Thus, GREEDY seeks to maximize the number of tasks assigned to each individual sensor. However, our key observation herein is that maximizing the number of tasks assigned to each sensor may not maximize the total number of tasks assigned to all sensor nodes. Thus, based upon GREEDY, we present an improved algorithm by globally exploring the correlations among sensor nodes in order to maximize the total number of assigned tasks, as described next.

Assuming a feasible solution given by [3] is F_i $(i = 1,2,...,m)$, where F_i is the set of tasks assigned to s_i. First we give necessary definitions.

DEFINITION 2. *Let $P = \bigcup_{i=1}^{m} F_i$ and $R = T - P$, where T is the task set $\{T_1, T_2, \ldots, T_n\}$, P is the set of tasks that have already been assigned, and R is the set of remaining tasks that cannot be assigned under GREEDY. Let z_i denote the total number of assigned tasks on s_i and c_i denote the current reminder energy on s_i. Let g_j denote the index of the sensor where T_j is assigned.*

Our algorithm applies the following three optimization techniques on the task assignment obtained by GREEDY. As demonstrated by the experiments presented later, these optimization techniques are effective in practice for increasing the number of assigned tasks. After executing the GREEDY algorithm, no sensor has enough remaining energy to execute tasks in R in the resulting task assignment. Thus, the idea behind these optimization techniques is to increase the remaining energy on sensor nodes in order to allow more tasks to be assigned. Note that the order of applying these optimization techniques can be arbitrarily determined. Although different orderings may yield different performance, they are incomparable in general and the resulting performance heavily depends on the task and system parameters.

Task Swapping. This optimization technique increases the remaining energy on sensor nodes by swapping the assigned tasks with the unassigned tasks. The swapping process can be described as follows: for each T_i $(T_i \in R)$, search P to find the minimum k which satisfies $e_i < e_k$. Then swap T_i for T_k such that the remaining energy is increased on sensor node g_k while the total number of assigned tasks does not decrease. This process ends until $R = \phi$, or for each $T_i (T_i \in R)$, we can not find a T_k $(T_k \in P)$ that satisfies $e_i < e_k$.

Fig. 5 presents an example illustrating this swapping process. After executing the Greedy algorithm, task T_1 is not assigned, and $e_1 = 4$, as illustrated in Fig. 5(a). T_2 $(e_2 = 6)$ is assigned on s_1. If we swap T_2 for T_1 on s_1, the total number of assigned tasks on sensor nodes is not decreased and the amount of remaining energy on s_1 is increased. So we swap T_2 for T_1. Fig. 5(b) shows the task assignment after swapping. The complexity of this process is $O(n^2)$.

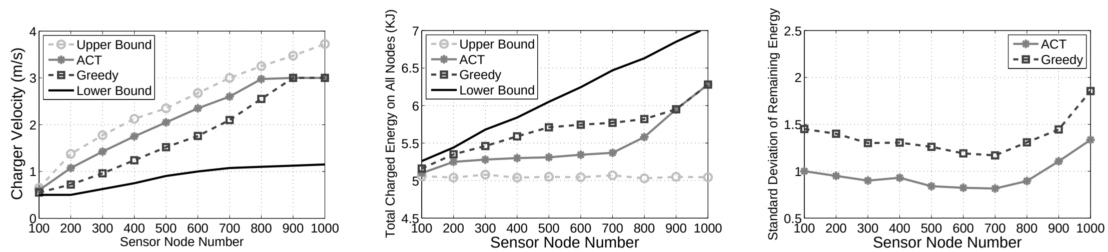
Task Moving. This optimization technique seeks to increase the remaining energy on sensor nodes by moving tasks from one sensor node to another. The moving process can be described as follows: for each sensor node s_i $(1 \leq i \leq m)$, search P to find the minimum k which satisfies $c_i \geq e_k$ and $c_i < c_{g_k} - e_k$. Then move T_k from s_{g_k} to s_i such that the remaining energy on s_{g_k} is increased up to c_i. The process ends until all sensor nodes are tested.

As shown in Fig. 5(b), after swapping, if T_4 $(with e_4 = 3)$ is moved from s_2 to s_1, then the amount of remaining energy on s_2 becomes 5, which is larger than $c_1 = 4$. Therefore, we move T_4 to s_1. Fig. 5(c) shows the assignment after the moving step. The complexity of this moving step is $O(m \times n^2)$.

Task Exchanging. This optimization technique increases the amount of remaining energy on sensor nodes by exchanging the assigned tasks on different sensor nodes. For each T_i $(T_i \in P)$, we exchange T_i with T_k $(T_k \in P)$ if any task T_j $(T_j \in R)$ can be assigned to sensor g_i or sensor g_k after this exchange process. This exchanging step is executed on all pairs of tasks.

An illustrating example is shown in Fig. 5. After the moving step (Fig.5(c)), the amount of remaining energy on s_2 is 5. If we exchange T_3 $(with e_3 = 5)$ and T_1 $(with e_1 = 4)$, the

[2] We would like to emphasize here that LB is a key enabler of this problem transformation process and leverage prior methods designed for the original MKP. MKP requires that each knapsack has a fixed capacity. However, for our task assignment problem, the capacity of each knapsack (which corresponds to the charged energy of each sensor node) may vary if the charger's velocity changes. Thus, TAP can be transformed to a MKP with variable knapsack capacity. In order to efficiently leverage prior methods such as GREEDY, we have to have a limited variation range for the knapsack capacity, which is determined by the solution space of the charger's velocity. Clearly this is enabled by the lower bound on the charger's velocity provided by LB as shown in Theorems 1 and 2.



(a) Velocity VS. Sensor Node Number (b) Total Energy VS. Sensor Node Number (c) Standard Deviation VS. Node Number

Figure 6: Impact of the Sensor Node Number

Table 1: Executing Power for Sensing Modules

Model	Consumed Power
Temperature: TI TMP175	$0.275mW$
General Purpose ADC: MAX 1363	$1.5696mW$
Humidity: Sensirion SHT15	$3mW$
Accelerometer: ST Micro LISL02DQ	$3.6mW$
Light: TSL 2651	$5.5mW$
Processor(TELOSB): TI MSP430	$0.726mW$
Processor(MicaZ): ATmega 128L	$44mW$
GPS: LS20033	$180mW$
Gyroscope: ADIS16266	$205mW$

amount of remaining energy on s_2 becomes 6, which allows T_2 to be assigned to s_2. We thus exchange T_3 and T_1, and the resulting task assignment is shown in Fig. 5(d)(d). We then assign $T_2 \in R$ to s_2. Fig. 5(d)(e) shows the final task assignment after applying all the three optimization techniques. As seen, applying these techniques enables all the tasks in this example system to be successfully assigned. The complexity of the exchanging process is also $O(n^2)$. Note that this process ends when the sum of the remaining energy on any two sensors is smaller than the energy required by the unassigned task that consumes the minimum energy among all unassigned tasks.

5 Evaluation

To evaluate our proposed task assignment algorithms, we have conducted extensive experiments assuming different network settings and different trajectories for the mobile charger.

5.1 Experiment Setup

We simulated a network consisting of 500 wireless rechargeable nodes randomly deployed in an area of $100m \times 100m$ two-dimensional square. Regarding the charging model as given in Eq. (1), we set $\frac{G_s G_r \eta}{L_p}(\frac{\lambda}{4\pi})^2 P_0 = 36$ and $\beta = 30$. A total number of 5000 tasks are generated for each experiment. We simulate an application scenario where 9 categories of tasks need to be performed, as shown in Table. 1. The power consumption values listed in this table are obtained from the corresponding sensors' data sheet. The executing time of a task is randomly selected from $[1s, 10s]$.

5.2 Baseline Settings

Since the literature on investigating the task assignment problem in RWSNs is limited, we set the greedy algorithm [3] discussed in Sec.4 as the baseline for comparison purposes. We also compare our proposed approach with two other methods: the lower bound v_{act} and the upper bound v_{max}, as discussed in Sec.3.

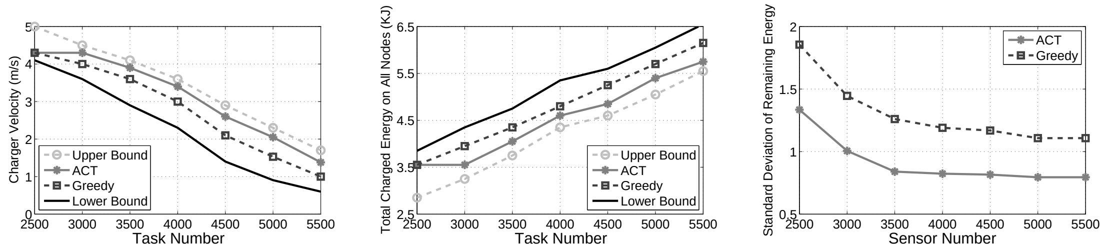
Results. We investigate the performance of our algorithm with different system parameters including the number of wireless rechargeable nodes, the number of tasks and different kinds of traveling trajectories.

5.3 Impact of Sensor Node Number

We explore the scalability of our design and investigate the impact of the number of nodes on the feasible charger velocity, as shown in Fig.6(a). In the experiment, the number of sensor nodes is varied from 100 to 1000. We can see that ACT yields near optimal velocity, which is close to the upper bound v_s. Another observation is that both ACT and the greedy algorithms yield better performance when more sensors are involved in the system. This is because the density of sensor nodes in the square increases when the number of sensors increases, which implies that the charger may charge more sensor nodes at the same time and the total harvested energy thus increases. This further implies that the charger can travel with a faster velocity. However, when the number of sensor nodes is more than 900, ACT and the greedy algorithm achieve similar performance. Also the charger's velocity stops increasing. The reason is because the sensor on which the assigned tasks require the maximum amount of energy gives an upper bound of the charger's velocity. Thus, whenever this sensor has been charged with enough energy under a certain velocity, the velocity cannot increase any further. Fig.6(b) shows the total amount of charged energy under difference approaches. As seen in this figure, ACT also performs quite close to the upper bound v_s under all cases. Fig. 6(c) shows the standard deviation of remaining energy on sensors with the sensor numbers varying from 100 to 500. Our algorithm yields smaller deviations under all cases, which implies that the amount of remaining energy on sensors under our algorithm is more balanced.

5.4 Impact of Task Number

Fig. 7 shows the experimental results investigating the impact due to different number of tasks. In the experiment the number of tasks is varied from 2500 to 5500. Intuitively, with a larger number of tasks and a fixed number of sensors, it is more likely that sensors need to harvest more energy in order to execute all of the tasks. This in turn implies that the charger may need to decrease its speed. This observation is verified in Fig. 7(a) and Fig. 7(b), where a clear decreasing trend for the charger's velocity and a clear increasing trend for the total amount of charged energy on all sensors can be

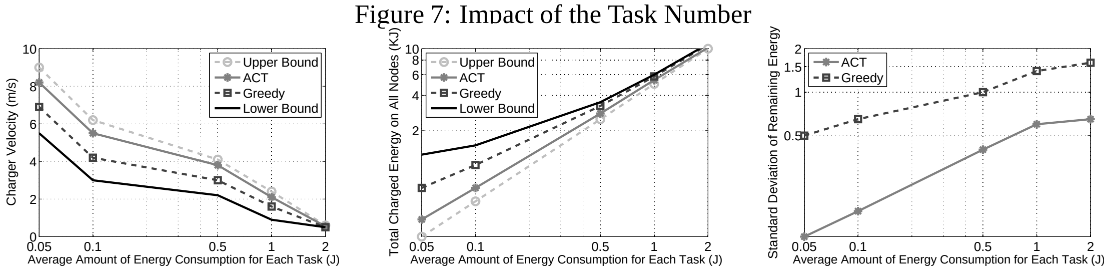


(a) Velocity VS. Task Number

(b) Total Energy VS. Task Number

(c) Standard Deviation of Remaining Energy VS. Task Number

Figure 7: Impact of the Task Number



(a) Velocity VS. Average Energy

(b) Total Energy VS. Average Energy

(c) Standard Deviation of Remaining Energy VS. Average Energy

Figure 8: Impact of the Task Average Energy

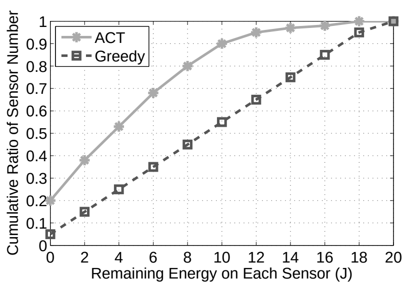


Figure 9: CDF

observed, respectively. As seen in Fig.7(a), ACT achieves quite close performance to the upper bound, yielding a faster speed than the greedy algorithm. The corresponding results on the total amount of harvested energy under the four tested algorithms are shown in Fig.7(b). Fig. 7(c) shows the standard deviation of the amount of remaining energy on sensors with the task number varying from 2500 to 5500 under ACT and the greedy algorithm. ACT gets smaller deviations under all cases, which means that the amount of remaining energy on sensor nodes for ACT is more balanced, regardless of the number of tasks.

5.5 Impact of the Task Average Energy

In this experiment, we study the impact due to different distributions of the energy consumption of tasks by varying the average energy consumption of tasks from $0.05J$ to $2J$, and the results are shown in Fig. 8. In Fig. 8(a), we can see that the charger's velocity decreases as the average energy consumption of tasks increases. This is because with a larger average energy consumption, tasks need more energy, thus the charger needs to travel with a lower speed to charge more energy on these sensors. An increasing trend of the amount of harvested energy on all sensor nodes is observed in Fig. 8(b) when the average energy consumption of tasks increases.

5.6 System Insight

In order to reveal the insight about why our proposed algorithm ACT can significantly reduce charging delay, we conduct an experiment to observe the amount of remaining energy on each sensor node while the harvested energy can accomplish all tasks with ACT. For comparison, we also show the results under the greedy algorithm [26] with the same system settings. Intuitively, an algorithm becomes more efficient when the amount of remaining energy on each sensor node is small after accomplishing all the tasks (all the sensor nodes use up their harvested energy is the best case). Fig.9 shows the cumulative distribution of sensor node number when the amount of remaining energy varies from 0 J to 20 J. The cumulative ratio of sensor number associated with the remaining energy J represents the number of sensors with remaining energy less than J. As seen in this figure, for each remaining energy value, ACT is able to achieve a higher cumulative ratio of sensor number than the greedy algorithm. This implies that ACT is able to better utilize the harvest energy, leaving a smaller number of sensors with large remaining energy after assigning all tasks. Given that the same set of tasks is tested under both algorithm, the greedy algorithm fails to assign as many tasks as ACT because it yields a greater remaining energy.

6 Related Work

Recently, the research problem of improving charging efficiency in wireless rechargeable sensor networks has received much attention [15, 28, 31, 4, 23]. Many pioneer work has focused on hardware design to improve charging efficiency [15, 28]. Kurs *et al.* [15] improve the overall output efficiency of charging multiple devices. Sample *et al.* [28] design a scheme of analog circuitry for WISP node to obtain an efficient conversion of the incoming RF energy. From the view of networks, some recent work has investigated the network charging coordination to improve charging performance. He *et al.* [9] consider the static reader deployment in a wireless rechargeable sensor networks so that the nodes can harvest enough energy for continuous operation. In [30], Xie *et al.* consider the joint design of traveling path of mobile wireless charging vehicle (WCV), flow routing among the network, and charging time of WCV at each stopping point, and propose a near-optimal solution with guaranteed accuracy. The authors in [21] build a proof-of-concept prototype of wireless charging system for sensor networks and conduct experiments to evaluate its feasibility and performance in small-scale networks. Bin *et al.* [29] investigate how to minimize charging cost by reducing energy consumption rate and improving recharging efficiency.

To the best of our knowledge, none of the prior work co-considers the task assignment problem along with the charging delay minimization problem. We consider the problem of finding the maximum charging velocity and a corresponding feasible task assignment such that each sensor has enough charged energy to execute the assigned tasks. This distinguishes this paper from the prior work.

7 Conclusion

In this paper, we study a general scenario of randomly deployed rechargeable wireless sensor network, where a charger travels along a fixed trajectory to charge energy on the sensor nodes that need to execute a set of tasks. Our objective is to find the maximum velocity for the mobile charger while ensuring a corresponding feasible task assignment. We first propose an online task assignment algorithm LB that yields a quantifiable lower bound on the charging velocity while guaranteeing a feasible assignment. LB further enables us to transform the considered task assignment problem into a variation of the classical multiple knapsack problem. We then present an improved task assignment algorithm, namely ACT, that built upon an existing greedy algorithm designed for the original knapsack problem. The effectiveness of our proposed algorithm has been demonstrated by extensive experiments. In the future work, it would be interesting to explore the proposed techniques to address the problem of minimizing the overall system delay including both the charging delay and the task execution delay.

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