On Optimal Scheduling of Multiple Mobile Chargers in Wireless Sensor Networks

Richard Beigel, Jie Wu, and Huangyang Zheng
Department of Computer and Information Sciences
Temple University, USA
{rbeigel, jiewu, huanyang.zheng}@temple.edu

ABSTRACT

The limited battery capacities of sensor nodes have become the biggest impediment to the applications of wireless sensor networks (WSNs) over the years. Recent breakthroughs in wireless energy transfer-based rechargeable batteries provide a promising application of mobile vehicles in WSNs. These mobile vehicles act as mobile chargers to transfer energy wirelessly to static sensors in an efficient way. In this paper, we study the mobile charger coverage problem of sensor nodes distributed on a 1-dimensional line and ring. Each sensor needs to be recharged at a given frequency. A mobile charger can charge a sensor after it moves to the location of the sensor. We assume that the mobile charger has an unlimited charging capability, moves at a speed subject to a given limit, and that the charging time is negligible. An optimization problem is then presented on a time-space coverage of sensors so that none of them will run out of energy: (1) What is the minimum number of mobile chargers needed? (2) Given the minimum number of mobile chargers, how should these mobile chargers be scheduled in terms of trajectory planning? Given homogeneous sensors with the same recharging frequency, we provide an optimal solution with a linear complexity in finding the minimum number of charges, as well as the actual schedule. We then examine an extension to heterogeneous sensors and provide a greedy approach that has a constant ratio of 2 to the optimal solutions for a line and ring. Extensive simulations are conducted to verify the competitive performance of the proposed scheme.

Categories and Subject Descriptors

G.1.6 [**Approximation**]: Constrained optimization;
G.2.4 [**Graph algorithms**]: Network problems

General Terms

Algorithms, Design, Theory.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.
Copyright 20XX ACM X-XXXXX-XX-X/XX/XX ...$15.00.

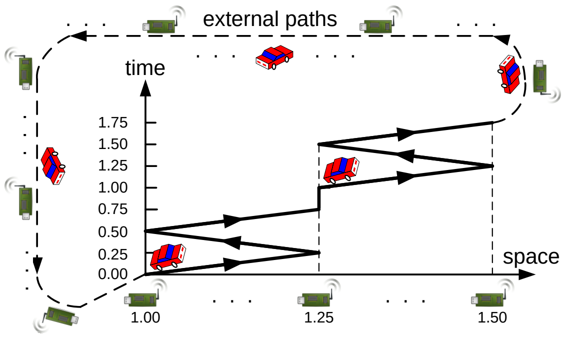


Figure 1: An example of the heterogeneous WSNs.

Keywords

Approximation ratio, mobile chargers, optimal solutions, wireless sensor networks (WSNs).

1. INTRODUCTION

Recent breakthroughs in rechargeable batteries, which support the wireless energy transfer, provide a promising application of mobile vehicles in wireless sensor networks (WSNs). These mobile vehicles act as either mobile sinks, mobile chargers, or combinations of both, to collect data from the sensors and/or transfer energy wirelessly to the sensors in an efficient way. Results show that significant energy and cost savings, as well as an extended life span of WSNs, can be achieved by placing mobile vehicles closer to the sensors for data collections and/or battery recharge [7].

In this paper, we study the mobile charger coverage problem for sensor nodes distributed on a 1-dimensional line and ring. In recent years, *linear WSNs* [4] have been proposed as a platform to perform various applications ranging from oil and water pipeline, monitoring of AC powerlines, to border monitoring. In such a network, each sensor needs to be recharged at a given frequency. A *mobile charger* (MC), a special mobile vehicle, can charge a sensor after it moves to the location of the sensor. We assume that the MC has an unlimited charging capability, moves at a speed subject to a given limit, and that the charging time is negligible. An optimization problem is then presented on a time-space coverage of sensors so that none of them will run out of energy: (1) What is the minimum number of MCs needed? (2) Given the minimum number of MCs, how should MCs be scheduled in terms of trajectory planning?

To put the problem more formally, we consider an n-dimensional (n-D) space with two types of nodes: $S = \{s_i\}$ where s_i, called sensors, have fixed locations of x_i; $MC = \{MC_j\}$, where MC_j, called mobile chargers, are mobile with a given moving speed limit. Each s_i is required to be visited by MCs at frequency f_i. That is, the time between two adjacent visits to s_i (it can be visited by different MCs) is no more than $\frac{1}{f_i}$. Our questions become the following:

- What is the minimum $|MC|$ (called minimization problem)?
- Once minimum $|MC|$ is determined, how can we schedule MCs to meet the need of each s_i (called scheduling problem)?

Here, scheduling refers to the area coverage and the speed selection of each MC over the time domain. If f_i is identical, the problem is called the *homogeneous* mobile charging, otherwise, it is called the *heterogeneous* mobile charging.

Consider a circle track with circumference 8.75 that is densely covered with sensors having frequency 1, as shown in Figure 1. In addition, there are (1) a sensor with frequency 2 at position 1, (2) a sensor with frequency 4 at position 1.25, and (3) a sensor with frequency 2 at position 1.5. To simplify our discussion, we assume the maximum speed to be one unit distance per unit time for each MC (also called a car shown in the figure). It turns out that 10 cars are sufficient to ensure the coverage of all sensors of required frequencies. However, the optimal scheduling is more intriguing, as shown in Figure 1, as we have to select proper speeds for cars. Let us define $\frac{1}{4}$ as a mini-unit of a time step (or simply a mini-unit). One car enters location 1 at unit 0, and one more car enters the same location for every one additional time unit. Once having entered the region of [1, 1.5], each car in mini-units performs mini-steps as follows: (enters at mini-unit 0) at position 1, (1) 1.25, (2) 1, (3) 1.25, (4) 1.25, (5) 1.5, (6) 1.25, and (exits at 7) 1.5. In addition, another car is assigned at location 1.25 at time unit 0. This corresponds to its fourth mini-unit of the car, as to ensure that one car exits from the region of [1, 1.5] per time unit. In this optimal solution, the trajectories of cars are *overlapped*. When the trajectories of cars are disjointed, the corresponding solution is called *non-overlapped*.

Our study begins with homogeneous WSNs on a 1-D ring, where $f_i = 1$ and the moving speed is limited by 1 without loss of generality. We then extend our study to the heterogeneous WSNs and to the higher dimensional space. Our results are summarized as follows:

- An optimal solution to both minimization and scheduling problems is given in a homogeneous 1-D ring. Both solutions are linear with respect to $|S|$. This solution has either overlapped or non-overlapped trajectories.
- A greedy solution to both minimization and scheduling problems is given in a heterogeneous 1-D line and ring with an approximation ratio of 2. Again, this solution is linear with respect to $|S|$. Cars in this solution have non-overlapped trajectories.
- In the heterogeneous WSNs, simulations have been conducted to verify the closeness of the greedy approach to the optimal one.

The remainder of the paper is organized as follows. In Section II, some related works are reviewed. We point out that most of existing work focus on scheduling of one mobile charger. In Section III, an optimal scheduling in the homogeneous setting is given as well as a linear solution that finds the optimal result. In Section IV, a greedy scheduling in the heterogeneous setting is provided that has an approximation ratio of 2 compared to the optimal solution in a 1-D line and ring. In Section V, some simulation results are presented to show the difference between the greedy and optimal solutions. Finally, the conclusion is given in Section VI.

2. RELATED WORKS

The notion of MCs evolve from mobile sinks in WSNs, including data mules [8], and from message ferries [12] in delay tolerant networks (DTNs) for data collection. Another evolution comes from the recent wireless energy transfer technology (e.g., electromagnetic radiation [3] and magnetic resonant coupling [5] using MCs). MCs offer energy to sensors, and also consume energy due to their own movement.

Mobile charging can be modeled as the *travelling salesman problem* (TSP), where an MC constructs a tour of all sensors once and only once. In some cases, when an MC recharges energy to a node, it can also charge nodes in its neighborhood. This problem can be modeled as a *coverage salesman problem* (CSP) [1] to identify the least-cost tour of a subset of given cities (i.e., sensors in this paper) such that every city not on the tour is within some predetermined covering distance of a city that is on the tour. Usually, a predetermined distance corresponds to a 1-hop neighborhood, as used in CSP [1]. When neighborhood distance does not matter, CSP is similar to a connected dominating set-based tour construction [9]. Note that an MC does not have to be at a sensor for charging, and this corresponds to an extension of CSP in Qi-ferry [6].

Xie et al. [10] and Guo et al. [2] proposed several optimization models by considering an MC as both a data collector and an energy charger. Their focus is primarily on energy minimization using optimization and approximation on different scenarios of data collection and energy recharge; they focus less on scheduling of MCs, as only one MC is used.

Zhang et al. [11] studied collaborative mobile charging. In this model, a fixed charging location (i.e., base station, BS) provides a source of energy to MCs, which in turn are allowed to recharge each other while collaboratively charging sensors. The objective is to ensure sensor coverage while maximizing the ratio of payload energy (used to charge sensors) to overhead energy (used to move MCs from one location to another). An optimal scheduling scheme that can cover a 1-D homogeneous WSN with a infinite length is proposed. Several greedy scheduling solutions are also proposed for 1-D heterogeneous WSNs and 2-D WSNs, which are NP-hard.

3. OPTIMAL SOLUTION FOR THE HOMOGENEOUS WSNS

We assume the maximum speed to be one unit distance per unit time for each car. The circumference of the circle is L. The sensors are homogeneous (i.e., $f_i = 1$). Algorithm 1 is proposed for this scenario. In Algorithm 1, Method 1 is a scheduling policy where cars have overlapped trajectories. This methods assigns cars to move around the circle one

Algorithm 1 Optimal Schedule for the Homogeneous WSNs

Input: Locations of uncovered sensors $\{s_1, ..., s_n\}$;

1: **Method 1**: There are $k_1 = \lceil L \rceil$ cars moving continuously around the circle.

2: **Method 2**: There are k_2 cars moving inside fixed intervals of length $\frac{1}{2}$ so that all sensors are covered.

3: **Combined method**: It is either Method 1 or Method 2. That is, the combined solution uses $k = \min\{k_1, k_2\}$ cars.

by one (with the same direction). Meanwhile, Method 2 is a scheduling policy where cars move in non-overlapped intervals. This method assigns each car to go back and forth for a fixed interval. Then, the following theorem shows the optimality of Algorithm 1.

Theorem 1. *The combined method in Algorithm 1 is optimal in terms of the minimum number of cars used in the homogeneous WSNs.*

Proof: Assume that the optimal solution uses k MCs. If the circumference of the circle is not greater than k, Algorithm 1 obtains the optimal solution through Method 1. Therefore, we focus on the case that the circumference is larger than k. Now, let us define an MC's type as follows: (1) Type 1, the MC visits 2 sensors that are more than $\frac{1}{2}$ away from each other during the first time unit; (2) Type 2, all the other MCs.

Consider an optimal solution OPT that has the minimum possible number of type 1 MCs. If OPT does not have type 1 MCs, then Algorithm 1 obtains the optimal solution through Method 2. Therefore, we focus on the case that OPT has at least one MC of type 1. At this step, we convert OPT to an optimal solution that uses fewer MCs of type 1.

- Step 1: MCs never pass each other. If two MCs meet each other, we can always swap their velocities (speed and direction) to obtain a better solution.
- Step 2: During the first time unit, MCs travel in intervals that do not overlap, except possibly at their endpoints. Assign each point to the last MC that visited it during the first time unit (in case of a tie, assign it to both MCs). Instead of leaving its assigned interval, an MC will just wait at the endpoint for the amount of time that it would have traveled outside it.
- Step 3: We identify sensors by their coordinates on the circle. Choose an MC of type 1 with its interval to be $[a_0, b_0]$. Assume a_0 is located at the left (i.e., the counter-clockwise direction) of b_0, where $a_0 + \frac{1}{2} < b_0$ according to the definition of type 1. Without loss of generality, assume that this MC visits a_0 before it visits b_0. For each sensor located at x, define $p(x)$ to be the location of the first sensor that is strictly to the left of $x - \frac{1}{2}$. We number the MCs from right to left, so that the first MC to the left of MC_0 is MC_1, etc.

We know that $p(b_0)$ is between a_0 and b_0 since the interval length of MC_0 is greater than $\frac{1}{2}$. Define t_0 to be the last time prior to time 1 that MC_0 is at $p(b_0)$. Since $p(b_0)$ is more than $\frac{1}{2}$ away from b_0, MC_0 cannot return to $p(b_0)$ by time $t_0 + 1$. Hence, MC_1 must reach $p(b_0)$ by time $t_0 + 1$.

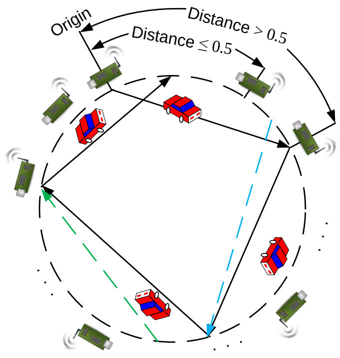


Figure 2: A directed interval graph.

Therefore, at time t_0, the position of MC_1 must be larger than $p(b_0) - 1$.

Suppose that MC_1 starts at a_1. If $p(b_0) - a_1 \leq \frac{1}{2}$ then we can assign MC_1 to the interval $[a_1, p(b_0)]$ and MC_0 to the interval $(p(b_0), b_0]$, where both of those MCs will be type 1. For this case, Algorithm 1 determines the optimal solution through Method 2. Hence, assume that $p(b_0) - a_1 > \frac{1}{2}$. Then, $p(p(b_0))$ is between a_1 and $p(b_0)$ so that MC_1 visits $p(p(b_0))$ during the first time unit, but cannot return to $p(p(b_0))$ in time to serve it after visiting $p(b_0)$. Therefore, MC_2 must visit $p(p(b_0))$ within one time unit after MC_1 visits $p(p(b_0))$. Traveling at a full speed, MC_2 would in principle be able to reach $p(b_0)$ one time unit after MC_1 reaches $p(b_0)$, i.e., at time $t_0 + 2$. Therefore, at time t_0, the position of MC_2 must be $\geq p(b_0) - 2$. Continuing this way, we find that for every i, the position of MC_i must be $\geq p(b_0) - i$ at time 0.

Finally, there must be an MC_k whose position is no less than $p(b_0) - k$ at time 0. MC_k cannot be the same as MC_0 because the circle circumference is larger than k. Therefore, there are $k + 1$ MCs, which is a contradiction. □

Method 2 requires scheduling, i.e., an appropriate break point to convert a circle to a line. Once a line is given (labeled from left to right starting from location 0 in an increasing order of distance), a simple greedy approach will follow. A naive approach will work that breaks the circle at each sensor. Method 2 for each given line requires $\min\{|S|, L\}$ steps. Therefore, the overall complexity is $|S| \times \min\{|S|, L\}$. In the following, we provide a linear scheduling with respect to $|S|$.

Start from location 0 (i.e., the leftmost point), the greedy approach, which follows Method 2, always places the right endpoint of an interval as far to the right as possible, except for the very last interval. We generate a *directed interval graph*, where each directed link points from the start to the end of an interval (i.e., the first sensor to the right of the interval of length $\frac{1}{2}$) as shown in Figure 2. Clearly, each interval can be covered by one car. In this directed graph, each node has exactly one outgoing link (but one or more incoming links).

To find all cycles, we first construct a breadth-first search (BFS) forest on the directed interval graph. Then, each backward link in that forest determines a cycle, since each sensor has only one outgoing link. A backward link from level j (a larger BFS level) to level i (a smaller BFS level)

Algorithm 2 Greedy Algorithm for the Heterogeneous WSNs

Input: Locations $\{x_1, ..., x_n\}$ and frequencies $\{f_1, ..., f_n\}$ of uncovered sensors $\{s_1, ..., s_n\}$;

1: **if** $n = 0$ **then return**;

2: Generate a car that goes back and forth as far as possible at a full speed to cover sensors at $\{x_1, ..., x_{i-1}\}$;

3: Recursively call Algorithm 2 for $\{s_i, ..., s_n\}$;

determines a cycle of length $j-i+1$. Since each link is visited only once, we can find all of the cycles and determine the shortest cycle in a linear time (i.e., $O(|S|)$). In addition, the correctness of algorithm follows from two facts: (1) all greedy solutions differ in cost (i.e., cycle length) by at most 1; (2) If there are two greedy solutions whose costs are k and $k+1$, then there is a cycle of length k.

4. GREEDY SOLUTION FOR THE HETEROGENEOUS WSNS

As shown in the example of Figure 1, the challenge of scheduling in the heterogeneous WSNs is not only the trajectory of each car, but also the speed of each car along time. We consider a greedy algorithm where all cars go back and forth at full speeds in disjoint intervals. The greedy algorithm (shown in Algorithm 2) produces a result that has an approximation ratio of 2 compared with the optimal ones. For a line, the algorithm starts from the leftmost sensor (s_1) to the rightmost one (s_n). For a ring, it is converted to a line by arbitrarily selecting a breakpoint.

Theorem 2. *Algorithm 2 has a factor of 2 of the optimal ones for sensors on a line and ring.*

Proof: Consider an optimal solution OPT that uses k cars in total. Without loss of generality, we assume that cars do not meet or pass each other, otherwise, switching the velocity (both speed and direction) of the crossed cars will lead to the same or a better solution.

Consider each subset (in terms of car composition in the subset) of the OPT as a color. Let us color each sensor with the set of cars that serve it infinitely often. For example, in Figure 3, the first area is served by car 1, which is colored by red; the second area is served by cars 1 and 2, which are colored by green. Now, we show that this coloring scheme partitions the sensors into at most $2k-1$ monochromatic intervals as follows. The $2k$ endpoints of these k intervals partition the line into $2k-1$ bounded intervals (colors 1 to 5 in Figure 3) and 2 unbounded intervals (black and gray in Figure 3), each of which must be monochromatic. The unbounded intervals contain no sensors.

We now show that each color can be served by a single car moving back and forth at a full speed. Consider any of those intervals $[a, b]$ and a sensor in it, which is located at x ($a \leq x \leq b$) with frequency f. We call a and b being at the left side and right side of x, respectively. Consider the rightmost car (in the geographical sense) that serves this sensor. When the rightmost car serves x, all the other cars that serve this sensor should be at the left side of the rightmost car, due to the fact that cars do not pass each other. Therefore, when the rightmost car leaves x and runs toward a, it should be the first car that comes back to x, among all the cars that serve this sensor. Moving from x to a and then back to x

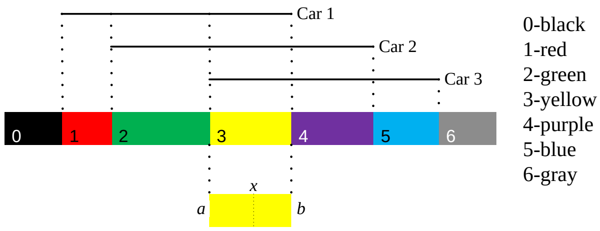


Figure 3: A partition of a line into $2k-1$ segments of different colors.

takes at least $2(x-a)$ time, as the actual speed of the car may not be full. Therefore, $2(x-a)f \leq 1$. Similarly, we can get $2(b-x)f \leq 1$ by considering the leftmost car. Overall, $2(x-a)f \leq 1$ and $2(b-x)f \leq 1$ imply that this sensor can be served by a single car that moves back and forth at a full speed in the interval $[a, b]$.

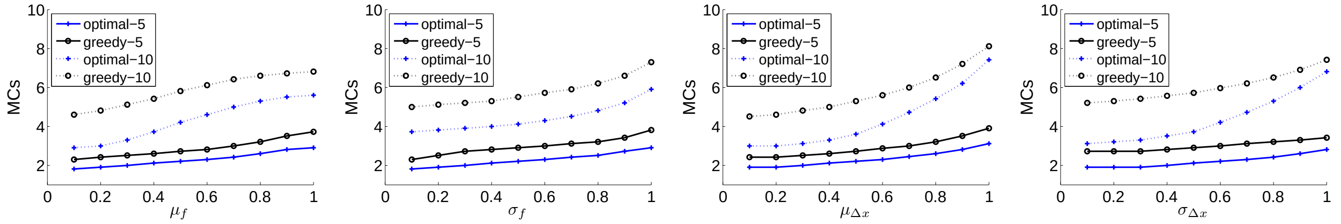
Since Algorithm 2 is optimal under the constraint that all cars go back and forth at a full speed in disjoint intervals, it generates a solution that uses fewer than $2k-1$ cars. Therefore, it is within a factor of 2 of the optimal solution on a line. For a ring, one extra car may be introduced when it is converted into a line (as discussed in the linear scheduling in Section III). $(2k-1)+1$ reseats in the same approximation ratio of 2. $\square$

Note that for any solution, the speed of an MC can be replaced by either zero (which is minimum), or the maximum given speed without increasing the number of MCs.

5. SIMULATION

In this section, we conduct simulations to evaluate the gap between the proposed greedy algorithm and the optimal solution for the heterogeneous WSNs on a ring. The results for a line follow similar trends and are omitted due to the space limitation. The optimal solution is obtained through an exhaustive search with discrete time steps. Due to the exponential time complexity of the exhaustive search, we focus on small-scale scenarios, i.e., scheduling results for 5 and 10 sensors, respectively, on a line.

In our simulations, the frequencies of sensors (f) follow normal distribution, i.e., $N(\mu_f, \sigma_f^2)$, where μ and σ are mean and variance, respectively. Meanwhile, the distances between adjacent sensors (Δx) also follow normal distribution $N(\mu_{\Delta x}, \sigma_{\Delta x}^2)$. To match the physical meaning, only positive f and Δx are used. The speeds of MCs are either zero or one unit (i.e. the maximum speed). The average value of the frequencies and distances are represented by μ_f and $\mu_{\Delta x}$, respectively, while σ_f and $\sigma_{\Delta x}$ indicate their fluctuation. Since the maximum MC speed is one unit, cases where $\mu_f > 1$ and $\mu_{\Delta x} > 1$ are not considered as they will lead to trivial solutions, where one static MC is assigned to a sensor. Cases where $\mu_f = 0$ and $\mu_{\Delta x} = 0$ are also ignored, since the former means that the corresponding sensor is free of recharge, and the latter one means that all sensors are in the same location. In our simulations, we fix three parameters at a time among μ_f, $\mu_{\Delta x}$, σ_f, $\sigma_{\Delta x}$ to be 0.5, and tune the remaining one parameter to observe its influence. Each simulation is repeated until the confidence interval of the average result is sufficiently small ($\pm 1\%$ percent for 90% probability).



(a) Tune μ_f (b) Tune σ_f (c) Tune $\mu_{\Delta x}$ (d) Tune $\sigma_{\Delta x}$

Figure 4: Simulation results. The last numbers of the labels indicate the number of sensors in the simulation, e.g., optimal-5 represent the optimal result in a WSN of 5 sensors. Three parameters among μ_f, $\mu_{\Delta x}$, σ_f, $\sigma_{\Delta x}$ are fixed to be 0.5, while the remaining one is tunable.

The simulation results are shown in Figure 4. It can be seen that larger μ_f and $\mu_{\Delta x}$ bring more demands on MCs, i.e., more MCs are needed to cover these sensors. Larger frequencies and distances post higher requirements for an MC to serve more sensors. Meanwhile, larger σ_f and $\sigma_{\Delta x}$ also call for more MCs. A sensor with a high frequency requires a designed MC; likewise, a large distance between two adjacent sensors indicates that they have to be served by different MCs. Overall, simulations show the approximation ratios at around 1.5.

A more intriguing result is that our greedy algorithm has a lower (i.e., better) ratio of the optimal solution, when μ_f, $\mu_{\Delta x}$, σ_f, $\sigma_{\Delta x}$ are larger. Smaller frequencies and distances bring more possible routes for an MC in an optimal soluton, since it can serve more sensors. Therefore, MC mobilities can be utilized more efficiently in these scenarios, leading to a higher (i.e., worse) optimal ratio of our greedy solution.

6. CONCLUSION

In this paper, scheduling of multiple mobile chargers (M-Cs) is studied to meet the recharge frequency of each sensor in a 1-D line and ring of wireless sensor networks (WSNs). The objective is to use the minimum number of MCs. We provide an optimal solution when sensor recharge frequency is uniform. For a WSN with non-uniform frequency, we provide a greedy solution with an approximation ratio of 2 comparing with the optimal solutions in a 1-D line and ring. Simulation results show the closeness of the greedy solution to the optimal one in various heterogeneous settings. In future work, we will focus on optimal solutions with a fixed set of recharge frequencies. We will also explore solutions with good approximation ratios in a higher dimensional space.

Acknowledgment

This work was supported in part by NSF CCF 1301774, ECCS 1231461, CNS 1156574, ECCS 1128209, and CNS 1065444.

References

[1] J. R. Current and D. A. Schilling. The covering salesman problem. *Transportation Science*, 23(3):208–213, 1989.

[2] S. Guo, C. Wang, and Y. Yang. Mobile data gathering with wireless energy replenishment in rechargeable sensor networks. In *Proc. of IEEE INFOCOM 2013*, pages 1932–1940.

[3] S. He, J. Chen, F. Jiang, D. K. Yau, G. Xing, and Y. Sun. Energy provisioning in wireless rechargeable sensor networks. In *Proc. of IEEE INFOCOM 2011*, pages 2006–2014.

[4] I. Jawhar, M. Ammar, S. Zhang, J. Wu, and N. Mohamed. Ferry-based linear wireless sensor networks. In *Proc. of IEEE Globecom 2013*, accepted to appear.

[5] A. Kurs, A. Karalis, R. Moffatt, J. D. Joannopoulos, P. Fisher, and M. Soljačić. Wireless power transfer via strongly coupled magnetic resonances. *Science*, 317(5834):83–86, July 2007.

[6] K. Li, H. Luan, and C.-C. Shen. Qi-ferry: Energy-constrained wireless charging in wireless sensor networks. In *Proc. of IEEE WCNC 2012*, pages 2515–2520.

[7] J. Luo and J.-P. Hubaux. Joint sink mobility and routing to maximize the lifetime of wireless sensor networks: The case of constrained mobility. *IEEE/ACM Transactions on Networking*, 18(3):871–884, 2010.

[8] R. C. Shah, S. Roy, S. Jain, and W. Brunette. Data mules: Modeling a three-tier architecture for sparse sensor networks. In *Proc. of IEEE SNPA Workshop 2003*, pages 30–41.

[9] A. Srinivasan and J. Wu. Track: A novel connected dominating set based sink mobility model for WSNs. In *Proc. of IEEE ICCCN 2008*, pages 1–8.

[10] L. Xie, Y. Shi, Y. T. Hou, W. Lou, H. D. Sherali, and S. F. Midkiff. Bundling mobile base station and wireless energy transfer modeling and optimization. In *Proc. of IEEE INFOCOM 2013*, pages 109–118.

[11] S. Zhang, J. Wu, and S. Lu. Collaborative mobile charging for sensor networks. In *Proc. of IEEE MASS 2012*, pages 84–92.

[12] W. Zhao, M. Ammar, and E. Zegura. A message ferrying approach for data delivery in sparse mobile ad hoc networks. In *Proc. of ACM MobiHoc 2004*, pages 187–198.