Low-Cost Collaborative Mobile Charging for Large-Scale Wireless Sensor Networks

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Abstract—In wireless rechargeable sensor networks (WRSNs), prior studies mainly focus on the optimization of power transfer efficiency. In this work, we consider the cost for building and operating WRSNs. In the network, sensor nodes can be charged by mobile chargers, that have limited energy which is used for charging and moving. We introduce a novel concept called "shuttling" and introduce an optimal charging algorithm, which is proven to achieve the minimum number of chargers in theory. We also point out the limitations of the optimal algorithm, which motivates the development of solutions named Push-Shuttle-Back (PSB). We formally prove that PSB achieves the minimum number of chargers and the optimal shuttling distance in a 1D scenario with negligible energy loss. When the loss in wireless charging is non-negligible, we propose to exploit detachable battery pack (DBP) and propose a DBP-PSB algorithm to avoid energy loss. We further extend the solution to 2D scenarios and introduce a new circle-based "shortcutting" scheme that improves charging efficiency and reduces the number of chargers needed to serve the sensor network. We carry out extensive simulations to demonstrate the performance of the proposed algorithms, and the results show the proposed algorithms achieve a low overall cost.

Index Terms—Collaborative mobile charging, wireless energy transfer, low-cost, wireless sensor networks

1 Introduction

While wireless sensor networks (WSNs) have a broad range of applications, it remains fundamentally challenging to achieve long operational lifetime due to the limited battery capacity of the sensor nodes. This has been widely recognized as a key hurdle that stunts the growth of WSNs.

Recently, the maturation of wireless energy transfer [1] with rechargeable lithium batteries [2] has created a new dimension for exploring effective solutions to the problem, as evidenced by several pioneering studies that apply wireless energy transfer to WSNs [3], [4], [5]. For example, charging devices can be carried by vehicles that move in the network to charge sensors within their proximity. This approach has been considered for such application settings as environmental sensing [6] and bridge monitoring [7].

In general, an efficient and practical wireless rechargeable sensor network (WRSNs) should meet the following requirements.

- (i) It should make full use of the energy-carrying capacity of each charger.
- (ii) It should reduce the number of chargers (NC), to minimize the cost of network building.
- (iii) It should reduce the chargers' traveling distances. A shorter traveling distance results in less energy consumption and accordingly lower cost for network operation.
- (iv) It should reduce the loss during wireless energy transfer to improve energy efficiency.

1.1 Challenges in Collaborative Mobile Charging for Large-Scale WSNs

To enable efficient wireless energy transfer and improve the network performance, recent studies have focused on how to reduce the charging delay [8], [9], achieve joint data collection and wireless charging [10], [11], minimize the traveling cost of chargers [12], [13], and support on-demand energy replenishment [14], [15].

However, the above approaches mostly assume that a mobile charger is equipped with unlimited energy to accomplish the charging task. When limited energy capacity is considered, the existing work often assumes only one charger or though there are multiple chargers, each of them works independently. In a larger network setting, such assumption may lead to substantial problems since the individual mobile chargers with limited energy can hardly reach to and charge all sensors. To this end, Zhang et al. [16] introduce a novel charging paradigm, i.e., *collaborative mobile charging*, where mobile chargers are allowed to transfer energy between themselves. The proposed PushWait algorithm achieves optimal energy usage effectiveness (EUE). Furthermore, the authors propose a ηPushWait scheduling algorithm for one-dimensional (1D) networks with energy loss and HηClusterCharging(β) scheduling algorithm for two-dimensional (2D) scenarios. The similar mobile charging algorithms also can be found in [17], [18].

The details of collaborative mobile charging can be found in [16]. Briefly, Fig. 1 shows the PushWait charging process in a 1D network. There are N sensors uniformly distributed along a straight line. The base station (BS) is located next to sensor node 1. Assume K chargers in the network, which all start from the BS with full energy. The 1D straight line is

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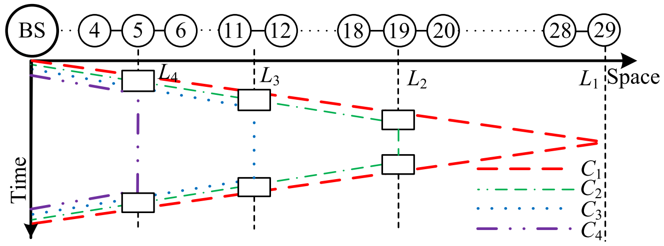


Fig. 1. Time-space view of PushWait.

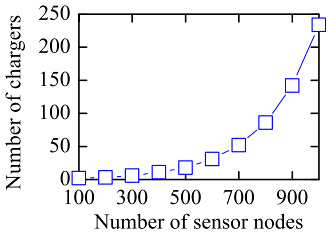


Fig. 2. Number of chargers required in PushWait. The battery capacity of a charger and a sensor is 2,000 and 10.8 KJ, respectively. The energy consumed by a charger to travel is 50 J/m. The distance between two adjacent sensors is 100 m.

divided into a number of segments, as marked by L_K, $L_{K-1}, \ldots, L_1$. The location of L_i is to be optimized by the algorithm. After charger C_i departs from the BS, it gets fully charged at locations $L_K, L_{K-1}, \ldots,$ and L_{i+1} by chargers C_K, $C_{K-1}, \ldots,$ and C_{i+1}, respectively, such that it can move further to reach out to remote sensors and to push other chargers forward. More specifically, C_i is responsible to fully charge sensors between L_{i+1} and L_i. When it arrives at L_i, it also fully charges $C_{i-1}, C_{i-2}, \ldots,$ and C_1. Then, C_i waits at L_i. When $C_1, C_2, \ldots,$ and C_{i-1} return to L_i, C_i evenly distributes its residual energy among these i chargers (including itself), to make them have just enough energy to return to L_{i+1}. When these i chargers arrive at L_{i+1}, they have zero remaining energy. Similarly, C_{i+1} evenly distributes its residual energy among them, so on and so forth. By this way, all chargers can get just enough energy to return to the BS.

As formally proved in [16], PushWait achieves minimum total energy consumption in 1D networks under the assumption of loss-free wireless energy transfer. But at the same time, we observe that the total cost to enable collaborative mobile charging is in fact determined by two factors, the total energy consumption which is concerned in [16] and the total number of chargers required to run the system. While PushWait minimizes the former, it can lead to high cost due to the latter. For instance, Fig. 2 shows that, under PushWait, the number of chargers dramatically increases with the number of sensors. Such observation reveals that it would be impractical to solely minimize energy consumption in large-scale sensor networks.

Moreover, we discover that it is impossible to simultaneously minimize both the total energy consumption and the total number of chargers, as to be elaborated in Section 2. Given the seminal work [16] has investigated and optimized the former, we focus on the latter in this work. We aim to minimize the number of chargers for supporting collaborative mobile charging in large-scale sensor networks. Once the minimum set of chargers is identified, we further minimize the chargers' traveling distances, consequently achieving low energy consumption.

1.2 Contribution of This Work

In this work, we propose new efficient algorithms, aiming to minimize the number of chargers and to achieve low energy consumption. The efficiency of the proposed scheme lies in several novel ideas.

The first innovative contribution is the idea of "shuttling". It is motivated by an observation based on the PushWait algorithm. In PushWait, charger C_i stays at L_i to wait for C_{i-1}, $C_{i-2}, \ldots,$ and C_1 in order to subsequently charge them. The larger the number of sensors is, the longer time C_i waits at L_i. Therefore, the charger is not fully utilized. While this design minimizes the total energy consumption, it leads to undesired cost for a large number of chargers that must be employed to run the system. To this end, we propose a novel concept called "shuttling", which allows a charger to travel between its current and previous positions to carry more energy.

Based on this idea, we first introduce an optimal charging algorithm, and prove it achieves the minimum number of chargers in theory. We also point out the limitations of the optimal algorithm, which motivates the development of solutions named Push-Shuttle-Back (PSB) under the assumption of no waiting time during the push phase. We formally prove that PSB achieves the minimum number of chargers and the optimal shuttling distance in a 1D scenario with negligible energy loss. When the loss in wireless charging is non-negligible, we propose to exploit detachable battery pack (DBP). We introduce a DBP-PSB scheduling algorithm to efficiently exploit the detachable battery packs to avoid energy loss during energy transfer between chargers.

The second key contribution is a new "shortcutting" scheme under 2D settings. In a sharp contrast to the 1D scenario where a charger always moves along the same path for charging the sensors and for recharging the chargers, they must be decoupled in 2D. "Shortcutting" is critical to reduce the energy consumption and the number of chargers. We propose a new shortcutting scheme. During the "Push" phase, it adopts a "circle"-based approach that allows flexible shortcutting at any position on the moving path and performs an integrated calculation to simultaneously determine L_i $(1 \leq i \leq K)$ and corresponding shortcuts. During the "Back" phase, it employs a "Back with Shuttle" approach to ensure all chargers to return to the BS by the end of each recharging cycle. These techniques together effectively reduce the number of chargers needed to serve the network.

We carry out extensive simulations to demonstrate the performance of the proposed algorithms. While our primary objective is to minimize the number of chargers, our results show that the proposed algorithms also achieve a low overall cost by considering the expense for both energy consumption and for deploying the chargers.

The rest of this paper is organized as follows: Section 2 introduces the problem formulation. Section 3 proposes an optimal algorithm that achieves the minimum number of chargers in theory. Section 4 proposes the PSB algorithm for loss-free 1D networks. Section 5 presents the DBP-PSB algorithm for 1D scenario with energy loss. We extend our results to 2D scenario in Section 6. Section 7 shows simulation results. Finally, Section 8 concludes the paper.

2 Problem Formulation

In this section, we first introduce the network model and then present the problem formulation, followed by discussions on the non-triviality of the problem.

2.1 Network Model

Consider a network with a base station, N stationary sensor nodes, and a set of mobile chargers. A mobile charger can charge sensors wirelessly when it moves to their proximity. At the same time, a mobile charger can be charged at the BS or by other chargers. The number of chargers (denoted by K) is to be optimized by our algorithm. The battery capacities of a sensor and a charger are denoted by b and B, respectively. Typically, B is about hundreds times larger than that b. In energy loss scenario, one charger can only fully charge several to dozens of sensors. In addition, a charger with a full battery can travel a distance between dozens to hundreds sensors. All parameters of our algorithm examples in the next sections are the same as those used in [16], where $B = 80$ J, $b = 2$ J, and $c = 3$ J/m.

Once a sensor is fully charged, its lifetime can often last from several weeks to months [19], depending on its working load such as sensing rates. In contrast, the time for completing a round of recharging for a network of a few hundred nodes is usually no more than several days [20]. Thus, we assume the time consumed for a charging cycle is less than the battery lifetime of sensor nodes. In other words, the charging delay is not a major concern of this work. A similar assumption is adopted in [16].

A mobile charger consumes its energy in several ways. First, its movement is powered by its battery. The energy consumed by a charger to travel one unit distance is denoted by c. Second, a charger consumes its energy to charge sensors' batteries. Since the charging efficiency is never 100 percent, partial energy will be lost during this process. Note that, none of the factors can dominate the energy consumption for charging. Let η_1 denote the wireless charging efficiency between a charger and a sensor. That means when a charger transfers one unit energy to a sensor, the sensor can receive η_1 unit of energy. Moreover, a charger may use its energy to charge other chargers. We let η_2 be the efficiency for energy transfer between chargers.

2.2 Problem Statement

As introduced in Section 1, the seminal work in [16] has achieved the minimum energy consumption by minimizing the moving distance of the mobile chargers. But at the same time, the number of chargers required by the scheme grows exponentially with the increase of the network size (as shown in Fig. 2). This is undesirable in some application settings, where the network is large and thus the cost to employ mobile chargers becomes excessively high.

In this work, we formulate the problem in a different way, aiming is to design a charging scheme to minimize the number of chargers. More formally, the *Minimum Charger Recharging Problem (MCRP)* is presented as follows.

Problem 1. *Given a WRSNs (N, B, b, and c), the objective is to find a charging scheme that employs a minimum number of chargers (i.e., minimum K) to charge all sensors, under the constraint of limited battery capacity for both chargers and sensors.*

Besides the above primary goal, we also have a secondary objective to minimize the energy consumption, when a minimum set of chargers are given.

Problem 2. *Given a minimum set of mobile chargers, the secondary objective is to find a charging scheme that minimizes the total energy consumption.*

In other words, our goal is twofold. First, we minimize the number of chargers. Then, based on the minimum set of chargers identified by our algorithm, we further minimize the total energy consumed for charging the sensors.

2.3 Non-Triviality of MCRP

We would like to point out that the MCRP problem in non-trivial. As to be elaborated next, a basic idea of the proposed scheme is to allow the mobile chargers to move back to a previous location or even the BS to get recharged. Thus the chargers can essentially carry more energy than their total battery capacities (i.e., KB), and accordingly reduce the number of chargers needed.

First, based on the basic idea, a naive question is why cannot we employ a single charger to charge all sensors? Whenever it depletes its battery energy for charging sensors, it can simply move back to the BS to get fully recharged and then go on to charge more sensors. This naive approach will fail because the changer can travel for a distance of up to B/c only, even it has a full battery and does not charge any sensors. Thus it will never be able to reach out to the sensors deployed beyond B/c from the BS. We need an efficient scheme that can use a minimum number of chargers to charge an arbitrarily large sensor network.

Second, we must point out that it is impossible to simultaneously minimize the number of chargers and the total energy consumption. For example, let's temporarily ignore the energy loss during wireless energy transfer (i.e., let η_1 and η_2 be 1). Let E^{pl} be the total energy required by the sensors during each recharging cycle, E^{tr} be the energy consumed by the chargers due to their movement, and E^{ch} be the total energy carried by the chargers in a recharging cycle. Note that, E^{ch} is not equivalent to B. For instance, if each charger departs twice from the BS with full energy in one recharging cycle, then $E^{ch} = 2B$. Then we have

$$K = \frac{E^{tr} + E^{pl}}{E^{ch}}. \quad (1)$$

To minimize K, one way is to increase E^{ch}, that means to let each charger carry more energy from the BS. However, if each charger returns to the BS more frequently to carry more energy in one recharging cycle, the total traveling distance of all chargers must be increased and thus E^{tr} is increased, accordingly resulting in higher energy consumption. Therefore, minimizing K and minimizing the total energy consumption are conflicting! As introduced earlier, our primary goal is to minimize the number of chargers, and then, based on the selected minimum set of chargers, we further minimize the total energy consumption.

3 Theoretical Optimal Solution

A key innovative contribution of this work is the idea of "shuttling". As discussed earlier, while the PushWait [16] achieves minimum energy consumption by minimizing the total traveling distances of the chargers, we observe that the chargers have substantial idle time. Therefore, the charger is not fully utilized. While this design minimizes the total energy consumption, it leads to undesired cost for a large number of chargers that must be employed to run the system. To this end, we introduce a novel concept called "shuttling", which allows a charger to travel between its current and previous positions to carry more energy.

In this section, we introduce an optimal charging algorithm based on shuttling, which is proven to achieve the minimum number of chargers in theory. We also point out the limitations of the optimal algorithm, which motivates the development of practical solutions to be introduced in the next section.

3.1 Minimum Charger Recharging Algorithm

In order to minimize the number of chargers, the charging coverage of each charger should be maximized. It indicates that C_i should move as far as possible. For simplicity, let's first consider a 1D senario. As to be discussed next, the results can be readily generalized to 2D networks. Similar to the PushWait algorithm [16], given K chargers, the 1D straight line is divided into K segments, as marked by L_K, $L_{K-1}, \dots, L_1$. All chargers start from the BS with a full battery. For each charger C_i, it gets fully charged at L_K, $L_{K-1}, \dots,$ and L_{i+1} by chargers C_K, C_{K-1}, ..., and C_{i+1}, respectively. C_i is responsible to charge sensors in its segment, i.e., between L_{i+1} and L_i. When it arrives at L_i, it also fully charges $C_{i-1}, C_{i-2}, \dots,$ and C_1.

Assume C_i has been fully charged at L_{i+1}. The maximum distance of C_i be able to travel is B/c. To ensure it can move back to L_{i+1}, the theoretical farthest point that C_i can reach from L_{i+1} is $L_{i+1} + B/2c$. However, if C_i would move to $L_{i+1} + B/2c$, it would have no extra energy to charge C_{i-1}, $C_{i-2}, \dots,$ and C_1. Denote by ϵ an infinitesimal value. We let C_i move to $L_i = L_{i+1} + B/2c - \epsilon$, such that it has $2c\epsilon$ J remaining energy. Accordingly, C_i can use the remaining energy to charge the $i-1$ chargers in order to push them further. Apparently, $2c\epsilon$ can be extremely small, given that ϵ is an infinitesimal value. Therefore, C_i is unlikely to complete the charging task in one round. Here is where shuttling comes in handy. After it uses its $2c\epsilon$ J energy to partially charge the $i-1$ chargers, it always returns to L_{i+1} and gets fully charged by C_{i+1}, and then come back again to charge other chargers. It essentially carries $2c\epsilon$ J energy in each round, and repeats as many round as necessary to fully charge the $i-1$ chargers. Let NS_i^{push} denote the number of shuttling rounds C_i needs to push C_{i-1}, C_{i-2}, ..., and C_1.

Similarly, C_i can perform shuttling to carry energy to charge the sensors between L_{i+1} and L_i. Finally, when C_{i-1}, $C_{i-2}, \dots,$ and C_1 finish their charging task and return to L_i with 0 J residual energy, C_i should provide enough energy to the $i-1$ chargers again, so that they can move back to L_{i+1}. We assume C_i shuttles NS_i^{sensor} and NS_i^{back} rounds, respectively, for charging sensors and charging the chargers on the back trip.

We name the above approach the Infinite-Shuttle Charging (ISC) algorithm, since the number of shuttling rounds can be as high as infinity when ϵ is infinitesimally small. Next, we prove that, despite its obvious limitation, this simple approach minimizes the number of chargers.

Lemma 1. *In given K chargers in the network, the theoretical farthest distance that each charger can move away from the BS is:*

$$L_i = (K - i + 1) \cdot (B/2c - \epsilon).$$

Proof. For each charger C_i, it departs from L_{i+1} with a full battery B. The maximum distance of C_i be able to travel is B/c. To enable C_i moves back to L_{i+1} and it has extra energy to push other chargers, the theoretical farthest distance that C_i moves from L_{i+1} is $L_{i+1} + B/2c - \epsilon$. By deduction, the theorem is proven. □

Obviously, the charging coverage of every charger is equal. Further, assume there are N sensors in the 1D network and the distance between two adjacent sensors is one unit. To ensure that all sensors can be charged, the theoretical minimum number of chargers can be obtained: $K = N/(B/2c - \epsilon)$.

Theorem 1. *ISC minimizes the number of chargers.*

Proof. Denote by $L_i(alg)$ the farthest distance that C_i travels away from the BS in a scheduling algorithm alg. We further denote $COV_i(alg)$ the charging coverage of each charger C_i, $COV_i(alg) = L_i(alg) - L_{i+1}(alg)$. Obviously, we can prove ISC achieves the minimum K by showing the charging coverage of each charger is the largest.

Suppose that ISC is not optimal, and the optimal scheduling algorithm is A. This indicates for A, there is at least one charger C_i such that $COV_i(A) > COV_i(ISC)$ is true. To enable C_i moves back to $L_{i+1}(A)$ from $L_i(A)$ and C_i has extra energy to charge sensors, $COV_i(A) < B/2c$. However, we have proven $COV_i(ISC) = B/2c - \epsilon$ in Lemma 1. Note that, ϵ is an infinitesimal value. This means $COV_i(A) \leq COV_i(ISC)$. However, since the hypothesis is that A is optimal and $COV_i(A) > COV_i(ISC)$: a contradiction! Therefore, no such A exists and ISC is optimal. □

Furthermore, we discuss the theoretical optimal solution in 2D networks. We denote by s_f the sensor farthest away from the BS, and $d(BS, s_f)$ the distance between BS and s_f. In the 2D-ISC algorithm, every sensor is charged individually by a separate charging round. Therefore, minimize K is to minimize the number of chargers required in the longest charging round. We can obtain the minimum K by applying ISC to charge s_f, $K = d(BS, s_f)/(B/2c - \epsilon)$.

3.2 Observations

The ISC minimizes the number of chargers at the cost of extremely long total shuttling distance. Formally, we have the following theorem that gives the number of shuttling rounds for each charger.

Lemma 2. *In one charging cycle, let NS_i^{total} be the total number of times that C_i shuttles between L_{i+1} and L_i. Then, NS_i^{total} can be calculated as follows:*

$$\begin{cases} NS_i^{total} = \left\lceil \frac{b\cdot(B/2c-\epsilon)}{2c\epsilon} \right\rceil + 2\left\lceil \frac{(i-1)c\cdot(B/2c-\epsilon)}{2c\epsilon}\right\rceil \\ \qquad + \left\lceil \frac{NS_{i-1}^{total}}{2c\epsilon}\right\rceil, \\ NS_1^{total} = \left\lceil \frac{b\cdot(B/2c-\epsilon)}{2c\epsilon}\right\rceil. \end{cases}$$

Proof. For charger C_1, it is only responsible to fully charge sensors between L_2 and L_1. Since the distance between L_2 and L_1 is $B/2c-\epsilon$ can be calculated by Lemma 1, C_1 transfers $2c\epsilon J$ energy to the sensors by once shuttle. Then, $NS_1^{total} = \left\lceil \frac{b\cdot(B/2c-\epsilon)}{2c\epsilon}\right\rceil$ can be obtained.

Similarly, for each charger C_i, it shuttles $NS_i^{sensor} = \left\lceil \frac{b\cdot(B/2c-\epsilon)}{2c\epsilon}\right\rceil$ times to fully charge the sensors between L_{i+1} and L_i.

C_i is also responsible to push charger $C_{i-1}, C_{i-2}, \ldots, C_1$ at L_i. The total energy that the $i-1$ chargers need to be charged is $(i-1)c\cdot(B/2c-\epsilon)J$. Thus, to push the $i-1$ chargers, the number of times that C_i shuttles between L_{i+1} and L_i is $NS_i^{push} = \left\lceil \frac{(i-1)c\cdot(B/2c-\epsilon)}{2c\epsilon}\right\rceil$.

When charger $C_{i-1}, C_{i-2}, \ldots, C_1$ return to L_i, they need to be replenished enough energy to moves back to L_{i+1}. C_i shuttles $NS_i^{back} = \left\lceil \frac{(i-1)c\cdot(B/2c-\epsilon)}{2c\epsilon}\right\rceil$ times to transfer sufficient energy to the $i-1$ chargers.

In addition, C_i is responsible to provide sufficient energy to C_{i-1} during the C_{i-1}' shuttle process. Therefore, C_i shuttles $NS_i^{shuttle} = \left\lceil \frac{NS_{i-1}^{total}}{2c\epsilon}\right\rceil$ times to support the shuttle process of C_{i-1}.

Sum the shuttle times NS_i^{sensor}, NS_i^{push}, NS_i^{back}, and $NS_i^{shuttle}$ together, we can obtain the total shuttle times of C_i. Consequently, the theorem is proven. □

In ISC algorithm, the minimum number of chargers is achieved when $\epsilon \to 0$. Based on the above results, the number of shuttling rounds NS_i^{total} goes to infinity. In 2D networks, if $d(BS, s_f) \geq B/2c - \epsilon$, the number of shuttling round goes to infinity too. Consequently, both the energy consumption E^{tr} and the charge period become extremely high, rendering it infeasible in practical network settings, where a charging cycle is always finite. Moreover, in order to efficiently charge the sensors, we always initiate the charging process when a charging cycle approaches the end; otherwise, most sensors would still have substantial energy, resulting in inefficient charging. Therefore, after the chargers depart from the BS, they must continuously move forward (without idling time except for charging) until they reach their farthest location (i.e., L_i). This constraint is also adopted in [16]. Based on the constraint, we propose our charging algorithm in the next section.

4 Charging with Loss-Free in 1D Networks

In this section, we propose our solution to the MCRP problem, named Push-Shuttle-Back. For a lucid presentation, we first introduce the PSB algorithm in a one-dimensional network setting with no energy loss during charging. The more general scenarios are to be discussed in the next sections.

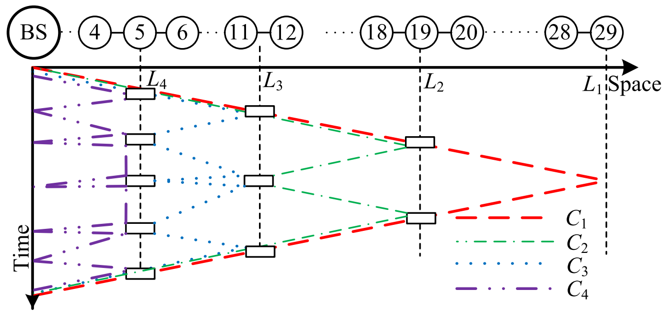


Fig. 3. Time-space view of PSB.

4.1 Push-Shuttle-Back

We consider a sensor network with N sensor nodes distributed along a 1D straight line to the east of the BS (see Fig. 3). For simplicity, we assume the distance between two adjacent sensors is one unit, but the proposed algorithm can be readily generalized to an arbitrary non-uniform distribution of the sensors, as along as their deployment is known. The sensors are labelled from s_1 to s_N.

We intend to discover the minimum number of chargers. To achieve the optimization, we first assume there are K chargers and then derive the minimum value of K. We denote C_i the ith mobile charger, and L_i the farthest distance that C_i moves away from the BS. In order to minimize K, we must let each charger cover as many sensors as possible. In other words, we want the chargers to be able to move as far as possible such that a minimum number of chargers will cover all sensor nodes. This observation motivates the proposed PSB algorithm as outlined below, including three phases Push, Shuttle, and Back.

(i) During the "Push" phase, each charger, e.g., C_i, starts from the BS with a full battery. It will also get charged at $L_K, L_{K-1}, \ldots,$ and L_{i+1} by chargers $C_K, C_{K-1}, \ldots,$ and C_{i+1}, respectively.

It begins to offer charging service when it reaches L_{i+1}. First, it is responsible to charge the sensors between L_{i+1} and L_i. Note that, to keep its energy load balanced during its "Push" and "Back" trip, C_i only half-charges sensors between L_{i+1} and L_i during "Push", and leave the remaining half for the "Back" phase to be discussed later. In the next Section 4.2, we further prove that PSB could achieve the minimum K, only when C_i half-charges sensors in the "Push" phase. Moreover, when it arrives at L_i, it also fully charges other chargers that travel along with it, including $C_{i-1}, C_{i-2}, \ldots,$ and C_1, such that they can move further to reach their target segments. Now, the residual energy of C_i should be just enough to return to L_{i+1}.

Clearly, it is critical to determine the optimal positions of L_i, $1 \leq i \leq K$, in support of maximum coverage of the chargers. We formally give such positions in the following lemma.

Lemma 3. *Given K chargers in the network, the farthest distance that each charger can move away from the BS is*

$$\begin{cases} L_K = \frac{B}{(K+1)c+b/2}, \\ L_i = \sum_{j=i}^{K} \frac{B}{(j+1)c+b/2}, \\ L_1 = \sum_{j=2}^{K} \frac{B}{(j+1)c+b/2} + \frac{B}{2c+b}. \end{cases} \tag{2}$$

Proof. In the "Push" trip, each charger C_i gets fully charged at L_{i+1} by C_{i+1}. When C_i arrives at L_i, its energy consumption includes: (1) the energy C_i used to travel from L_{i+1} to L_i; (2) the energy C_i used to fully charge C_1, $C_2, \ldots,$ C_{i-1} at L_i; (3) the energy C_i used to half-charge sensors from L_{i+1} to L_i. Because the energy consumption for each C_i to travel from L_{i+1} to L_i is equal and C_i should retain enough energy to return to L_{i+1}, we have

$$\begin{cases} B = 2c(L_1 - L_2) + b(L_1 - L_2), \\ B = (1+i)c(L_i - L_{i+1}) + (b/2)(L_i - L_{i+1}), \\ B \geq (1+K)c(L_K - 0) + (b/2)(L_K - 0). \end{cases} \tag{3}$$

The theorem is proven by solving the linear equations. □

(ii) The "Shuttle" phase begins after C_i charges C_{i-1}, $C_{i-2}, \ldots,$ and C_1 at L_i. Recall that in PushWait [16], C_i will wait there, in order to minimize the traveling distance.

In the proposed scheme, C_i moves back to L_{i+1} to get recharged by C_{i+1}, aiming to fully utilize the charger to carry more energy and therefore minimize the number of chargers. Note that, since C_{i+1} has consumed some energy for traveling from L_{i+2} to L_{i+1}, it may not be able to fully charge C_i at one time. Therefore, C_{i+1} will return to L_{i+2} to get fully charge by C_{i+2}, and then it moves to L_{i+1} to further charge C_i. This process can repeat multiple times until C_i is fully charged. After C_{i+1} full charges C_i, it moves to L_{i+2} only when there is just enough residual energy to return to L_{i+2}.

Lemma 4. *In the "Shuttle" phase, let NS_i be the number of times that C_i shuttles between L_{i+1} and L_i. Then, NS_i can be calculated as follows:*

$$\begin{cases} NS_1 = 0, \\ NS_2 = 1, \\ NS_i = \left\lceil \dfrac{NS_{i-1} \cdot B}{B - 2c(L_i - L_{i+1})} \right\rceil + 1, \quad 2 < i < K \\ NS_K = \left\lceil \dfrac{NS_{K-1} \cdot B}{B - 2cL_K} \right\rceil + 1. \end{cases}$$

Proof. Obviously, C_1 does not have a "Shuttle" phase. It only need to return to L_2 after finishing charging sensors from L_2 to L_1. For C_2, because C_1 does not have a "Shuttle" phase, it only needs to shuttle between L_3 and L_2 once to transfer enough energy to C_1 at L_2 for C_1 to move back to L_3. For C_i, during the "Shuttle" phase, the total energy obtained at L_{i+1} is consumed in four ways: (1) the energy consumed for C_i shuttling between L_{i+1} and L_i; (2) the total energy that C_{i-1} needs to obtain at L_i during its "Shuttle" phase; (3) the sufficient energy for $C_1, C_2, \ldots,$ and C_{i-1} to move back to L_{i+1} from L_i; and (4) the energy for C_i to half-charge sensors from L_i to L_{i+1}. We then have: $NS_i \cdot B = NS_i \cdot 2c(L_i - L_{i+1}) + NS_{i-1} \cdot B + (i-1)c(L_i - L_{i+1}) + (b/2)(L_i - L_{i+1})$. Thus, we can get: $NS_i = \left\lceil \frac{NS_{i-1} \cdot B}{B - 2c(L_i - L_{i+1})} + \frac{((i-1)c + b/2) \cdot (L_i - L_{i+1})}{B - 2c(L_i - L_{i+1})} \right\rceil$. Since we have proved $B = (1+i)c(L_i - L_{i+1}) + (b/2)(L_i - L_{i+1})$ in Lemma 3, $NS_i = \left\lceil \frac{NS_{i-1} \cdot B}{B - 2c(L_i - L_{i+1})} \right\rceil + 1$ can be obtained. By deduction, the theorem is proven. □

(iii) During the "Back" trip, C_i gets charged at locations L_{i+1}, $L_{i+2}, \ldots,$ and L_K on its way back to the BS, which enables it to have enough energy to return to the BS. C_i also half-charges sensor nodes between L_{i+1} and L_i.

In summary, the "Push" phase enables each charger to push other chargers to move further to reach out to remote sensors; "Shuttling" means that each charger C_i (except C_1) travels between L_{i+1} and L_i to obtain sufficient energy to charge C_{i-1}; and during the "Back" phase, each charger have enough energy to move back to the BS.

Fig. 3 shows the result of PSB. The coverage of four chargers is 29 sensors. The shuttle times of each charger is: $NS_1 = 0$, $NS_2 = 1$, $NS_3 = 3$ and $NS_4 = 5$.

4.2 Properties of PSB

We now show two highly desired properties of PSB. More specifically, it achieves the minimum K as proven in Theorem 2. Moreover, for the given K, it also minimizes the shuttling distance and consequently achieves minimum energy consumption, as shown in Theorem 3.

Theorem 2. *PSB achieves the minimum K in 1D loss-free networks.*

Proof. Without loss of generality, we assume that the energy transfer to sensors must occur in the "departure from BS" trip or "back to BS" trip. Denote by $L_i(alg)$ the farthest distance that C_i travels away from the BS in a scheduling algorithm alg. Obviously, we can prove PSB achieves the minimum K by showing $L_1(PSB)$ is the largest. Suppose there are K mobile chargers in the network. We prove the theorem by mathematical induction on K.

$K = 1$. We have only one charger in this case. Suppose that PSB is not optimal, and the optimal scheduling algorithm is A_1. This means $L_1(A_1) > L_1(PSB)$. Assume $L_1(A_1) = L_1(PSB) + x$. Multiply both sides by $(2c+b)$, we have $(2c+b)L_1(A_1) = (2c+b)L_1(PSB) + (2c+b)x$. However, we have proved $L_1(PSB) = B/(2c+b)$ in Lemma 3. Since C_1 departs from the BS with full battery B in both algorithms, we arrive at $B = B + (2c+b)x$. Therefore, x must be 0 and accordingly PSB is optimal.

$K = 2$. Suppose that PSB is not optimal, and A_2 is the optimal scheduling algorithm. This means $L_1(A_2) > L_1(PSB)$. For A_2, assume C_2 transfers $y \cdot bJ (0 \leq y \leq 1)$ energy to each sensor which is located between the BS and $L_2(A_2)$. In addition, assume C_2 transfers $z \cdot cL_2(A_2)(0 \leq z \leq 1)J$ energy to C_1. The total energy consumption of C_2 during the "Push" trip includes the energy for C_2 to move from the BS to $L_2(A_2)$, to return to the BS, to transfer $yb \cdot L_2(A_2)J(0 \leq y \leq 1)$ energy to sensors, and to transfer $z \cdot cL_2(A_2)J(0 \leq z \leq 1)$ energy to C_1, thus we have

$$B = (2c + yb + zc) \cdot L_2(A_2). \tag{4}$$

When C_1 moves back to $L_2(A_2)$, the residual energy is 0 J, so C_1 must get enough energy from C_2 to go back to the BS. C_2 starts from the BS with full energy, thus for the "Back" trip of C_2, we have

$$B = (2c + (1-y)b + c) \cdot L_2(A_2). \tag{5}$$

From Equations (4) and (5), we can get

$$L_2(A_2) = B/(5c + b + zc). \tag{6}$$

Since C_2 transfers $z \cdot cL_1(A_2)(0 \le z \le 1)J$ energy to C_1, when C_1 starts from $L_2(A_2)$ the residual energy is $B - (1-z)L_2(A_2)J$. The energy consumption of C_1 includes move from $L_2(A_2)$ to $L_1(A_2)$, to return to the $L_2(A_2)$, to transfer $b \cdot (L_1(A_2) - L_2(A_2))J$ to sensors, thus we have

$$B - (1-z)c \cdot L_2(A_2) = (2c + b) \cdot (L_1(A_2) - L_2(A_2)). \tag{7}$$

From Equations (6) and (7), we can get

$$L_1(A_2) = \frac{B}{2c+b} + \frac{2B \cdot (c + b + zc)}{(2c+b)(5c+b+zc)}. \tag{8}$$

Then, we find the derivative of $L_1(A_2)$ with respect to z

$$L_1(A_2)' = \frac{8Bc^2}{(2c+b)(ec+b+zc)^2}. \tag{9}$$

Obviously, when $z = 1$, $L_1(A_2)$ gets the maximum value, $L_1(A_2) = B/(2c+b) + B/(3c+b/2)$. Further, from Equations (4) and (5), we can get $y = 0.5$, so $L_2(A_2) = B/(3c + b/2)$.

However, in Lemma 3, we have proved $L_2(PSB) = B/(3c+b/2)$ and $L_1(PSB) = B/(3c+b/2) + B/(2c+b)$, which means $L_2(A_2) = L_2(PSB)$ and $L_1(A_2) = L_1(PSB)$. However, since the hypothesis is that A_2 is optimal, it must satisfy $L_1(A_2) > L_1(PSB)$: a contradiction! Therefore, no such A_2 exists, and PSB is optimal.

I.H.: PSB is optimal for any $K < n$.

$K = n$. Suppose that PSB is not optimal, and A_n is the optimal scheduling algorithm. According to our hypothesis, PSB is optimal when $K = n-1$, thus $L_1(A_n) - L_n(A_n)$ must equal $L_1(PSB) - L_n(PSB)$. Because A_n is optimal, this implies $L_n(A_n) > L_n(PSB)$. For A_n, assume C_n transfers $y \cdot bJ(0 \le y \le 1)$ energy to each sensor which is located between the BS and $L_n(A_2)$, and transfers $z \cdot cL_n(A_n)J(0 \le z \le 1)$ energy to each charger. Then, we have

$$\begin{cases} B = (2c + yb + z(n-1)c) \cdot L_n(A_n), \\ B = (2c + (1-y)b + (n-1)c) \cdot L_n(A_n). \end{cases} \tag{10}$$

Note that, PSB is optimal when $K = n-1$. Thus we can get the farthest distance of the $n-1$ chargers travel from the $L_n(A_n)$

$$L_1(A_n) - L_n(A_n) = \sum_{j=2}^{n-1} \frac{B - (1-z)L_n(A_n)}{(j+1)c + b/2} + \frac{B - (1-z)L_n(A_n)}{2c+b}. \tag{11}$$

By finding the derivative of $L_1(A_n)$ with respect to z, we can get that when $z = 1$, $L_1(A_n)$ gets the maximum value. The detail of the result is omitted due to its complexity. Further, from Equation (10), we can get $y = 0.5$. Thus, $B = ((n+1)c + b/2)L_n(A_n)$. Lemma 3 has proven $L_n(PSB) = B/((n+1)c + b/2)$, which means $L_n(A_n) = L_n(PSB)$. However, since we have assumed A_n be optimal, it must satisfy $L_n(A_n) > L_n(PSB)$. Thus, no such A_n exists and PSB is optimal. □

Theorem 3. *In the 1D scenario with given K, each charger shuttles the minimum number of rounds in PSB.*

Proof. Suppose there are K mobile chargers in the network, and let $NS_i(alg)$ denote the times charger C_i shuttles under an algorithm alg. We prove the theorem by mathematical induction on K.

For C_1: $NS_1(PSB) = 0$ has been proved in Lemma 4, so C_1 shuttles the minimum times.

For C_2: Suppose that $NS_2(PSB)$ is not optimal, and B_2 is the optimal scheduling algorithm. Since $NS_2(PSB) = 1$, $NS_2(B_2)$ must equal 0. This implies C_2 doesn't have "Shuttle" phase in scheduling algorithm B_2. So, for B_2, after C_2 fully charges C_1 at L_2, C_2 will stay at L_2. When C_1 returns to L_2, C_1 has 0 J energy and C_2 has $B - 2c \cdot (L_2 - L_3) - (b/2) \cdot (L_2 - L_3)J$ energy. According to Lemma 3, $B = (3c + b/2) \cdot (L_2 - L_3)$ can be obtained, the residual energy of C_2 is $c \cdot (L_2 - L_3)J$. However, C_1 and C_2 return to L_3 need $2c \cdot (L_2 - L_3)J$ energy. So, if $NS_2(B2) = 0$, C_1 and C_2 cannot return to L_3! Thus, no such B_2 exists, and $NS_2(PSB) = 1$ is optimal for C_2.

I.H.: For C_{K-1}, $NS_{K-1}(PSB)$ is optimal.

For C_K: Suppose that $NS_K(PSB)$ is not optimal, and B_K is the optimal algorithm. According to our hypothesis, $NS_{K-1}(PSB)$ is optimal. Because $NS_K(B_K) < NS_K(PSB)$, the maximum value of $NS_K(B_K)$ is $\left\lceil \frac{NS_{K-1}(PSB) \cdot B}{B - 2c \cdot L_K} \right\rceil$. Then, the maximum energy that C_K can transfer to other chargers is $\left\lceil \frac{NS_{K-1}(PSB) \cdot B}{B - 2c \cdot L_K} \right\rceil \cdot (B - 2cL_K)J$. In the "Shuttle" phase, C_{K-1} need $NS_{K-1}(PSB) \cdot BJ$ energy, then after C_K charges C_{K-1}, the residual energy of C_K must be in the interval $[0, B - 2cL_K)$. In the "Back" trip, when C_{K-1}, $C_{K-2}, \ldots$, and C_1 move back to L_K, they need $(K-1)c \cdot L_K J$ energy to return to the BS. However, it is obvious that after C_K charges C_{K-1} in the "Shuttle" phase, the residual energy of C_K cannot ensure to bring all chargers return to the BS. So, it can be seen that no such B_K exists, and PSB is optimal. □

The above theorem shows that for the given K, the proposed algorithm minimizes the shuttling distance and consequently achieves minimum energy consumption.

5 Practical Charging with Energy Loss in 1D Networks

5.1 Observations

In practical application settings, energy loss is inevitable in wireless energy transfer between chargers and between charger and sensor. Giving $\eta_1 = 0.25$ and $\eta_2 = 0.5$ in PSB with energy loss, the coverage of four chargers is reduced from 29 to 16 sensors (compared with the loss-less scenario shown in Fig. 3). Further, NS_3 is increased to 4 and NS_4 to 11.

In this section, we consider the scenario with energy loss and introduce a scheme based on detachable battery pack to address the problem. More specifically, we propose to equip each charger with DBP. The Alkaline rechargeable battery pack on each charger is made up of a number of batteries with energy p. We assume that the charger consumes energy battery by battery, i.e., one detachable battery after another. Every battery is detachable and installable to other chargers. Therefore, the chargers can exchange detachable batteries to achieve loss-free energy transfer between each other.

Recent researches in the field of intelligent robots have investigated mechanisms to exchange detachable batteries [21], [22], [23]. For example, Wu et al. [22] have devised an automatic battery exchange system for home robots. It can be installed on the front of remote control car and complete battery exchange operations in an average time of 84.2 seconds. However, this system always consists of loading and unloading mechanism, shifting mechanism, and locking device. Thus, the battery exchange systems are applicable to chargers only, but not sensors due to cost concerns.

In this section, we consider the scenario where mobile chargers can exchange detachable batteries for loss-free energy transfer, while the energy transfer to sensors is still subject to energy loss.

5.2 Proposed Solution: DBP-PSB

Our basic idea is to employ a scheme similar to PSB, but when C_i charges C_{i-1}, it calculates the number of batteries detached from C_i and installs them to C_{i-1}. In this process, energy loss will not occur. However, given every detachable battery has p energy, the energy that C_{i-1} needs is often not an integral multiple of p. Therefore, after installing a number of batteries to C_{i-1}, C_i needs to further charge C_{i-1} by wireless energy transfer.

We assume $E^{pl}_{C_{i-1}}$ is the amount of energy C_{i-1} needs to be replenished and $E^{provide}_{C_i}$ is the maximum amount of energy that C_i can provide to C_{i-1}. For example, charger C_i has 30 J residual energy at L_i, and it will consume 9 J energy to return to L_{i+1}, then $E^{provide}_{C_i}$ is 21 J. The process for C_i to charge C_{i-1} is falls into the following situations:

(i) If $E^{provide}_{C_i} < E^{pl}_{C_{i-1}}$, C_i first detaches $\lfloor E^{provide}_{C_i}/p \rfloor$ number of full batteries and exchanges them for $\lfloor E^{provide}_{C_i}/p \rfloor$ empty batteries of C_{i-1}. Then, C_i wireless transfers $E^{provide}_{C_i} - \lfloor E^{provide}_{C_i}/p \rfloor \cdot pJ$ energy to C_{i-1}. In this case, the energy loss is decreased from $(1-\eta_2)E^{provide}_{C_i}$ to $(1-\eta_2)(E^{provide}_{C_i} - \lfloor E^{provide}_{C_i}/p \rfloor \cdot p)J$.

(ii) If $E^{provide}_{C_i} \geq \lfloor E^{pl}_{C_{i-1}}/p \rfloor \cdot p + p$, C_i first trade $\lfloor E^{pl}_{C_{i-1}}/p \rfloor$ full batteries for $\lfloor E^{pl}_{C_{i-1}}/p \rfloor$ empty batteries of C_{i-1}. Then, if C_{i-1} is not fully charged, C_{i-1} must have one battery with $p - E^{pl}_{C_{i-1}} \bmod pJ$ energy. Then, C_{i-1} detaches this battery and exchanges one full battery with C_i. In this case, the energy loss is 0 J.

(iii) If $\lfloor E^{pl}_{C_{i-1}}/p \rfloor \cdot p + p > E^{provide}_{C_i} \geq E^{pl}_{C_{i-1}}$, C_i first detaches $\lfloor E^{pl}_{C_{i-1}}/p \rfloor$ number of full batteries and exchanges $\lfloor E^{pl}_{C_{i-1}}/p \rfloor$ number of empty batteries with C_{i-1}. Then, if C_{i-1} is not fully charged, and C_i still has at least one full battery, C_i detaches one full battery and exchanges one battery with $p - E^{pl}_{C_{i-1}} \bmod pJ$ energy with C_{i-1}. In this case, the energy loss is 0 J. If C_i doesn't have any full battery and the remaining energy of C_i is sufficient to fully charge C_{i-1}, C_i wireless transfers $(E^{pl}_{C_{i-1}} - \lfloor E^{pl}_{C_{i-1}}/p \rfloor \cdot p)/\eta_2 J$ energy to C_{i-1} and the energy loss is decreased from $(1-\eta_2)E^{pl}_{C_{i-1}}$ to $(1-\eta_2)(E^{pl}_{C_{i-1}} - \lfloor E^{pl}_{C_{i-1}}/p \rfloor \cdot p)J$. Otherwise, if the remaining energy of C_i cannot fully charge C_{i-1}, C_i transfers $E^{provide}_{C_i} - \lfloor E^{pl}_{C_{i-1}}/p \rfloor \cdot pJ$ energy to C_{i-1} and the energy loss is decreased from $(1-\eta_2)E^{provide}_{C_i}$ to $(1-\eta_2)(E^{provide}_{C_i} - \lfloor E^{pl}_{C_{i-1}}/p \rfloor \cdot p)J$.

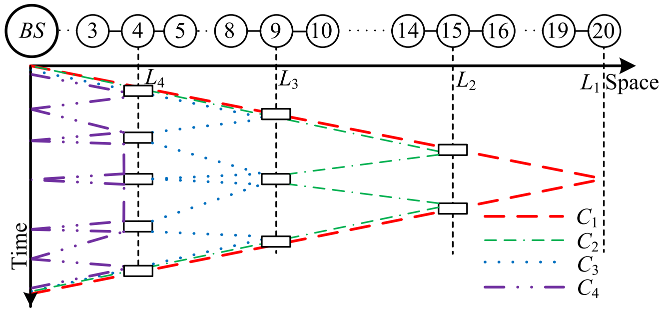


Fig. 4. Time-space view of DBP-PSB.

Fig. 4 gives the charging result of DBP-PSB. The coverage of four chargers in our DBP-PSB algorithm is increased from 16 to 20 sensors. During the "Push" phase, each charger consumes $c \cdot L_4 = 12$ J energy to travel from the BS to $L_4 = 4$. After C_4 half-charges sensors from s_1 to s_4, it has $80 - 4(b/2/\eta_1) - c \cdot L_4 = 52J$ residual energy. Then, C_4 transfers 10 J energy to C_1, C_2 and C_3, respectively. Then, C_4 has 12 J residual energy, just enough to return to the BS. C_3 half-charges sensors from s_5 to s_9, and fully charges C_2 and C_1 at $L_3 = 9$. Then C_3 returns to L_4 with 0 J residual energy. Similarly, C_2 moves to $L_2 = 15$, half-charges sensors from s_{10} to s_{15} and fully charges C_1, thus C_1 has enough energy to move to $L_1 = 20$ and charge five sensors. Furthermore, NS_3 is decreased to 3 and NS_4 to 5, thus the traveling distances of chargers is significant reduced in the "Shuttle" phase.

6 Charging in 2D Scenarios

We have investigated the MCRP problem in 1D networks. Now we generalize it to two-dimensional settings. Assume that N sensors are randomly distributed in a 2D square area and the BS is located at the bottom-left vertex of the square. We extend the DBP-PSB to 2D scenarios and propose a new scheme named C-DBP-PSB (Circle-DBP-PSB).

6.1 Overview of C-DBP-PSB Design Principles

The proposed C-DBP-PSB algorithm is devised according to two principles. The first principle is to convert the 2D network to 1D. This approach is not new. It has been adopted by various existing works [4], [9], [16], [24], [25] by constructing a shortest Hamiltonian cycle to cover all sensors. For example we can employ the Traveling Salesman Problem (TSP) algorithm to compute the shortest Hamiltonian cycle (as shown in Fig. 5), and then run the 1D algorithm to determine a sequence of L_i, $1 \leq i \leq K$, that divides the cycle into a number of segments. However, there are obvious improvements that we can make. More specifically, a charger C_i does not have to move along the cycle to L_{i+1} in order to charge the sensors between L_{i+1} and L_i. Instead, it can

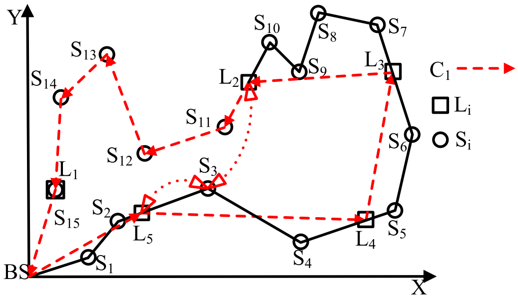


Fig. 5. Scheduling result of C_1 in HηClusterCharging(β).

take "shortcut" to reduce the traveling distance. This is in a sharp contrast to the 1D scenario where the chargers always move along the same path.

Therefore, the second design principle is to decouple the moving paths for charging the sensors and for recharging the chargers. "Shortcut" has been introduced in [16]. However, it does not effectively minimize the number of chargers. More specifically, denote by $d(P_1, P_2)$ the Euclidean distances between two positions P_1 and P_2. We further denote by $d_H(P_1, P_2)$ the distances between two positions P_1 and P_2 along Hamiltonian cycle H. For example, $d_H(L_5, L_4) = d(L_5, s_3) + d(s_3, s_4) + d(s_4, L_4)$ in Fig. 5. In 2D scenario, the traveling distance of two "L" points along the cycle H is equal or larger than the distance of straight line between the two points. To further reduce the traveling energy consumption, a simple shortcutting scheme is adopted in [16] to determine the shortcut of C_i. Based on this shortcutting scheme, [16] proposed an algorithm HηClusterCharging(β) for 2D scenarios.

However, the algorithm does not effectively reduce the number of chargers due to the following two limitations. First, when the algorithm calculates L_i, $1 \leq i \leq K$, it does not take the shortcuts into account. As a result, the energy saved by "shortcutting" is not further utilized for charging sensors. The chargers return to the BS with residual energy. While it reduces the total energy consumption, it does not help to decrease the number of chargers. Second, the HηClusterCharging(β) algorithm only allow shortcut to/from the already calculated positions, i.e., L_i, $1 \leq i \leq K$. Take C_1 in Fig. 5 as an example. We denote by "$\rightarrow$" a path segment along H, and "$\Rightarrow$" a straight-line movement. The trajectory for C_1 to reach L_2 is $BS \Rightarrow L_5 \Rightarrow L_4 \Rightarrow L_3 \Rightarrow L_2$, since $d(L_5, L_2) > d_H(L_2, L_3)$ and $d(L_4, L_2) > d_H(L_2, L_3)$. In other words, "shortcutting" is not possible in this example, since a shortcut can only happen at L_i. However, the length of this trajectory can be reduced if the energy transfer between chargers can occur in any position on H. For instance, as shown in Fig. 5, the trajectory of C_1 could be reduced to $BS \Rightarrow L_5 \rightarrow S_3 \Rightarrow L_2$, as $d(S_3, L_2) < d_H(L_2, L_3)$. Consequently, the energy consumption and the number of chargers can be further reduced.

Based on the above observations, we propose a new shortcutting scheme. During the "Push" phase, it (1) adopts a "circle"-based approach that allows flexible shortcutting at any position on H and (2) performs an integrated calculation to simultaneously determine L_i ($1 \leq i \leq K$) and corresponding shortcuts. During the "back" phase, it employs a "Back with Shuttle" approach to ensure all chargers to return to the BS by the end of each recharging cycle. These techniques together effectively reduce the number of chargers needed to serve the sensor network.

6.2 The "Push" Phase in 2D Networks

As discussed above, we first convert the 2D network to 1D by constructing a charging sequence to cover all sensors. To ensure the shortest length of the sequence, we use the Lin-Kernighan heuristic [26] to generate a Hamilton cycle H to cover all sensors. Without loss of generality, we label the sensors from s_1 to s_N in a counter-clockwise order along H.

Similar to the 1D solution, we aim to divide the circle into a number of segments as marked by $L_K, L_{K-1}, \ldots, L_1$. Charger C_i charges sensors from L_{i+1} to L_i along H after it gets fully charged by C_{i+1} at L_{i+1}.

As revealed by the second design principle, we intend to decouple the moving paths for charging the sensors and for recharging the chargers. Therefore, the chargers do not have to move along H. We let $\{P_{c_i}(m) | 0 \leq m \leq K-(i+1)\}$ represent the locations of C_i to be charged in its "Push" phase, where m is the index of the last mth-hop location before C_i arrives at L_{i+1}. If C_i directly moves to L_{i+1} from the BS, the number of hops is 0. while the number of hops is $K-i-1$ if the trajectory of C_i is the longest. Similarly, we use $\{P^{c_i}(n) | 0 \leq n \leq i-1\}$ to denote the set of the positions of other chargers charged by C_i between L_{i+1} and L_i. We also let $P_{C_i}^{back}$ denotes the first location in C_i's "Back" trip. If C_i has sufficient energy to return to the BS, then $P_{C_i}^{back}$ is simply the BS; otherwise, it is the point where C_i must stop since it runs out of energy.

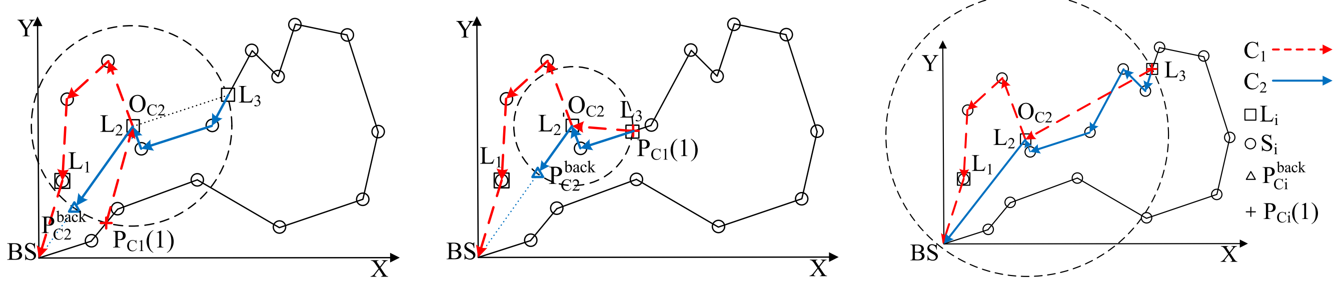
6.2.1 "Push" with "Circle"-Based Shortcut

We now focus on computing L_i ($1 \leq i \leq K$). As outlined in the previous section, we adopt a "Circle"-based approach that allows flexible shortcutting at any position on H and perform an integrated calculation to determine L_i and corresponding shortcuts at the same time.

Since the chargers work collaboratively, each charger C_i needs to charge the next charger C_{i-1} at the location L_i where C_i finishes its charging task. Thus, L_i is the starting position of charger C_{i-1}'s charging task as well as the ending position of charger C_i's. We denote by $f_S(L_{i+1}, L_i)$ the number of sensors between L_{i+1} and L_i, and denote by $f_C(L_{i+1}, L_i)$ the number of chargers that need to be replenished between L_{i+1} and L_i.

Like Lemma 3 in Section 4.1, we compute L_i in 2D scenario by modelling the relationship between L_i and energy consumption. In the "Push" trip, each charger C_i gets fully charged at L_{i+1} by C_{i+1}. When C_i arrives at L_i, its energy consumption includes: (1) the energy C_i used to travel from L_{i+1} to L_i along H; (2) the energy C_i used to fully charge other chargers which are located between L_{i+1} and L_i; (3) the energy C_i used to charge sensors from L_{i+1} to L_i. In addition, C_i will retain energy just enough to return to L_{i+1}. We model the relationship between L_i and the energy consumption as below:

$$\begin{cases} B = c(d_H(L_2, L_1) + d(L_1, BS)) + b \cdot f_S(L_2, L_1), \\ B = c(d_H(L_{i+1}, L_i) + \sum_{j=1}^{f_C(L_{i+1}, L_i)} d(L_{i+1}, P^{C_i}(j)), \\ \quad + d(L_{i+1}, L_i)) + b \cdot f_S(L_{i+1}, L_i). 1 < i \leq K \end{cases} \quad (12)$$



(a) BS is located outside of O_{C_2}, and L_3 is not the first intersection point between O_{C_2} and H

(b) BS is located outside of O_{C_2}, and L_3 is the first intersection point between O_{C_2} and H

(c) BS is located inside of O_{C_2}

Fig. 6. Three different intersection cases between O_{C_2} and H.

where $c\sum_{j=1}^{f_C(L_{i+1},L_i)} d(L_{i+1}, P^{C_i}(j))$ is the amount of energy C_i transfers to other chargers between L_{i+1} and L_i.

In Equation (12), L_i is determined based on L_{i-1}. Therefore, we compute L_1 at first. Since C_1 is responsible to charge the last several sensors along H, L_1 is located at the s_N and $P^{back}_{C_1}$ is located at the BS. Once L_1 is determined, L_i could be calculated iteratively by Equation (12). During the computing process, L_i is also used to calculate $P_{C_i}(1)$ and $P^{back}_{C_i}$.

To minimize the energy that charger C_i need to be replenished before it starts the charging task at L_{i+1}, the following two conditions should be met: (1) C_i can move to the L_{i+1} from the closest location to the BS. (2) C_i can return to the closest location to the BS by using its residual energy after it finishes the charging task.

To address these requirements, a novel approach called "Circle" is proposed in this section to obtain the trajectory of each charger in the "Push" trip. The goal of "Circle" is to get the position as far as possible to the BS. The proposed approach has the following steps:

Step 1. For each charger $C_i (1 < i \leq K)$, to calculate the location of L_{i+1} by Equation (12).

Step 2. For all charging positions $\{P^{c_i}(n) | 0 \leq n \leq i-1\}$ which are located between L_{i+1} to L_i, draw a circle $O^n_{C_i}$ centered at $P^n_{C_i}$ with radius $d(P^n_{C_i}, L_{i+1})$.

Step 3. There are three different intersection cases between circle and H for calculating the previous-hop of each charger to be charged by C_i and calculating the first location $P^{back}_{C_i}$ in C_i's "Back" trip. We show the details of these cases in the later example.

Step 4. L_{i+1} should be updated, while C_i directly returns to the BS after it finishes the charging task or any charger charged by C_i moves to the charging location from the BS.

We illustrate how "Circle" approach works by taking C_2 as an example in Fig. 6.

C_2 fully charges C_1 at L_2 after C_2 finishes its charging task. To compute $P_{C_1}(1)$ and $P^{back}_{C_2}$, we draw a circle O_{C_2} centered at L_2 with radius $d(L_3, L_2)$ and a line $\overline{BS, L_2}$ from the BS to L_2. There are three different intersection cases for calculating the previous-hop of each charger to be charged by C_2 and calculating the first location in C_2's back trip.

Case 1. As shown in Fig. 6a, the BS is located outside of the circle O_{C_2}, and L_3 is not the first intersection point between O_{C_2} and H along the direction of H.

Case 2. As shown in Fig. 6b, the BS is located outside of the circle O_{C_2}, and L_3 is the first intersection point between O_{C_2} and H along the direction of H.

Case 3. As shown in Fig. 6c, the BS is located inside of the circle O_{C_2}.

When we calculate L_3 under the energy limitation of C_2 by Equation (12), the energy is reserved for C_2 charging C_1 to move from L_3 to L_2 and C_2 moving back to L_3 from L_2. Thus, C_1 has enough energy to move from any location to L_2 with the same distance with $d(L_3, L_2)$. Meanwhile, C_2 has enough energy to move to any location from L_2 with the same distance with $d(L_3, L_2)$. To ensure that C_1 can move to L_2 from the closest location to the BS, and C_2 can return to the closest location to the BS, the solutions for the three different intersection cases are introduced as below:

Solution 1. For Case 1 in Fig. 6a, $P_{C_1}(1)$ is defined as the first intersection point between O_{C_2} and H along the direction of H. $P^{back}_{C_2}$ is defined as the intersection point between $\overline{BS, L_2}$ and O_{C_2}. After C_1 gets fully charged at $P_{C_1}(1)$, it moves along a straight line to L_2. After C_2 finishes the charging task, it moves to $P^{back}_{C_2}$ from L_2.

Solution 2. For Case 2 in Fig. 6b, $P_{C_1}(1)$ is defined as L_3, and $P^{back}_{C_2}$ is defined as the intersection point between $\overline{BS, L_2}$ and O_{C_2}. C_1 moves to L_2 from L_3 and starts the charging task after it gets fully charged by C_2 at L_2. C_2 moves to $P^{back}_{C_2}$ from L_2 after it finishes the charging task.

Solution 3. For Case 3 in Fig. 6c, $P_{C_1}(1)$ and $P^{back}_{C_2}$ are defined as the BS. To guarantee the residual energy of C_2 is just 0 J when it returns to the BS, we should extend the charging coverage of C_2 by updating the location of L_3 by

$$B = c(d_H(L_3, L_2) + 2d(BS, L_2)) + b \cdot f_S(L_3, L_2). \tag{13}$$

After L_3 was updated, we draw a new circle O_{C_2} centered at L_2 with radius $d(L_3, L_2)$. Then, the $P_{C_1}(1)$ and $P^{back}_{C_2}$ can be updated by doing the above processes again.

6.2.2 A Concrete Example

We provide an example in Fig. 7 as to show the trajectory of each charger during the "Push" trip in 2D scenario. Suppose

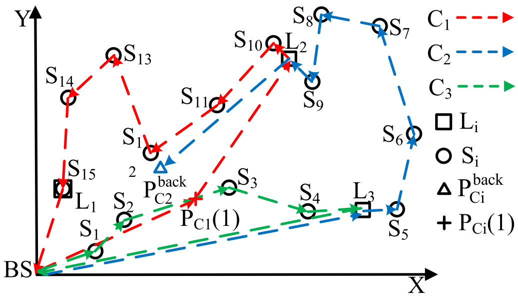


Fig. 7. Scheduling result of DC-PSB in 2D scenario.

there are 15 sensors in the 2D network and the Hamiltonian cycle H has been constructed. By applying "Circle" to cycle H, three chargers are required to cover all sensors. In the following, we show how each charger works and the trajectory of each charger's "Push" trip:

C_1: C_1 is responsible for charging sensors between L_1 and L_2. When C_1 starts from the BS, it straight moves to $P_{C_1}(1)$. For $d(P_{C_1}(1), L_2) = d(L_3, L_2)$, C_1 straight moves to L_2 from $P_{C_1}(1)$. Thus, its trajectory is $BS \Rightarrow P_{C_1}(1) \Rightarrow L_2 \rightarrow S_{10} \rightarrow S_{11} \rightarrow S_{12} \rightarrow S_{13} \rightarrow S_{14} \rightarrow L_1 \rightarrow BS$.

C_2: C_2 straight moves to L_3 from the BS to start its charging task. It charges sensors from L_3 to L_2. After C_2 fully charges C_1 at L_2, it moves to the first location $P^{back}_{C_2}$ in its "Back" trip. $P^{back}_{C_2}$ is located at the line $\overline{BS, L_2}$ and $d(P^{back}_{C_2}, L_2) = d(L_2, L_3)$. Thus, the trajectory of C_2 is $BS \Rightarrow L_3 \rightarrow S_5 \rightarrow S_6 \rightarrow S_7 \rightarrow S_8 \rightarrow S_9 \rightarrow L_2 \Rightarrow P^{back}_{C_2}$.

C_3: C_3 is responsible for charging sensors between the BS and L_3. In addition, C_3 fully charges C_1 at $P_{C_1}(1)$, and fully charges C_2 at L_3. After C_3 finishes its charging task, it directly return to the BS from L_3. The trajectory of C_3 is $BS \rightarrow S_1 \rightarrow S_2 \rightarrow S_3 \rightarrow S_4 \rightarrow L_3 \Rightarrow BS$.

6.3 "Back" with "Shuttle"

Before continuing, we first give the notations used in this section. Assume that there are total number of K chargers in the network. In addition, K_1 out of K chargers stay at the network with 0 J energy, and K_2 out of K chargers have already returned to the BS.

In Section 6.2, "Circle" is proposed to construct the trajectory of each charger in the "Push" trip, and it also computes the first locations $\{P^{back}_{C_i} | 0 \leq i \leq K_1\}$ in the K_1 chargers' "Back" trip. It is notable that charger C_1 and C_K can return to the BS after they finish the charging task, so $K_1 \in [0, K-2]$ and $K_2 \in [2, K]$. In this section we show how to replenish enough energy to carry the K_1 chargers to return to the BS by using the K_2 chargers.

First, we use Lin-Kernighan heuristic [26] to generate a shortest charging path CP to cover all K_1 chargers. Assume $C^{pl}_i (1 \leq i \leq K_1)$ is each charger which needs to be charged and $P^{pl}_{C_i}$ is the current position of charger C^{pl}_i. For returning to the BS, the energy that C^{pl}_i needs to be replenished is

$$E^{pl}_{C_i} = c \cdot d(P^{pl}_{C_i}, BS). \tag{14}$$

To take all K_1 chargers move back to the BS, the total energy required is

$$E^{pl}_{K_1} = \sum_{i=1}^{K_1} E^{pl}_{C_i}. \tag{15}$$

We apply DBP-PSB algorithm to the path CP. The K_2 chargers start from the BS with full energy and replenish energy to the K_1 chargers along the path CP. To calculate the farthest distance L_i that the ith charger among the K_2 chargers travels away from the BS, we have the following equation based on Lemma 3

$$\begin{cases} B = c(d_P(L_2, L_1) + d(L_2, L_1)) + \sum_{j=1}^{N_1} E^{pl}_{C_j}, \\ B = c(d_P(L_{i+1}, L_i) + id(L_{i+1}, L_i)) + \sum_{j=1}^{N_i} E^{pl}_{C_j}, 1 < i < K_2, \\ B = c(d_P(BS, L_{K_2}) + K_2 d(BS, L_{K_2}) + \sum_{j=1}^{N_{K_2}} E^{pl}_{C_j}. \end{cases} \tag{16}$$

where the N_i is the number of chargers to be charged by the ith charger among the K_2 chargers, and the $d_P(L_{i+1}, L_i)$ is sum of euclidean distances of line segments between two positions L_{i+1} and L_i on the charging path CP.

Thus, the total energy that the K_2 chargers can provide to the K_1 chargers along CP is

$$E^{provide}_{K_2} = \sum_{i=1}^{K_2} (B - d_P(L_{i+1}, L_i) - icd(L_{i+1}, L_i)). \tag{17}$$

We compare E^{pl}_{back} and $E^{provide}_{K_2}$ to determine whether the K_2 chargers can provide enough energy to carry the K_1 chargers to return to the BS.

(i) IF $E^{provide}_{K_2} > E^{pl}_{K_1}$, it indicates that the K_2 chargers can provide exessive energy to carry the K_1 chargers back to the BS. To reduce the total traveling distance, we calculate K'_2, the number of chargers which can provide just enough energy to carry the K_1 chargers, by Equations (16) and (17). Then, we select any K'_2 chargers from the K_2 chargers and starts from the BS.

(ii) IF $E^{provide}_{K_2} = E^{pl}_{K_1}$, it implies that the K_2 chargers can provide just enough energy to carry the K_1 chargers move back to the BS.

(iii) IF $E^{provide}_{K_2} < E^{pl}_{K_1}$, it indicates that the K_2 chargers can not carry the K_1 chargers move back to the BS. To enable the K_1 chargers return to the BS, we design a "Back with Shuttle" phase.

For "Back with Shuttle" phase, the main idea is how to use the chargers which have been carried to the BS to charge the K_2 chargers. Thus, the K_2 chargers can get more energy to carry the remaining chargers on CP to return to the BS. K_2 chargers start from the BS in the "Back with Shuttle" phase. $P^{pl}_{C_j} (1 \leq j \leq K_1)$ is the position of the nearest charger to the current position of K_2 chargers, and denote j chargers have been carried back to the BS. Assume the K_2 chargers can provide $E(P^{pl}_{C_j})^{provide}_{K_2}$ energy when they start from $P^{pl}_{C_j}$ with full energy, and the remaining $K_1 - j$ chargers need $E^{pl}_{K_1 - j}$ energy to return to the BS. "Back with Shuttle" works as follows:

(i) After the K_2 chargers charge C^{pl}_j, C^{pl}_j returns to the BS. We determine whether the K_2 chargers start from $P^{pl}_{C_j}$ can provide enough energy to the $K_1 - j$ chargers.

(ii) If $E(P^{pl}_{C_j})^{provide}_{K_2} \geq E^{pl}_{K_1-j}$, it shows that the K_2 chargers starts from $P^{pl}_{C_j}$ with full energy, and they can provide enough energy to carry all remaining chargers on path CP return to the BS. In this case, the j chargers which have returned to the BS shuttle between the BS and $P^{pl}_{C_j}$ to fully charge the K_2 chargers at $P^{pl}_{C_j}$. Subsequently, the K_2 chargers starts from $P^{pl}_{C_j}$ to charge the remaining $K_1 - j$ chargers. The total shuttle times of of the j chargers is

$$NS^{pl}_j = \left\lceil \frac{K_2 cd(P^{pl}_{C_{j-1}}, P^{pl}_{C_j}) + cd(BS, P^{pl}_{C_j})}{B - 2cd(BS, P^{pl}_{C_j})} \right\rceil. \tag{18}$$

(iii) If $E(P^{pl}_{C_j})^{provide}_{K_2} < E^{pl}_{K_1-j}$, j chargers total shuttle NS^{pl}_j times between the BS and $P^{pl}_{C_j}$ to fully charge the K_2 chargers. The K_2 chargers start from $P^{pl}_{C_j}$ and replenish enough energy to the next charger C^{pl}_{j+1}. After C^{pl}_{j+1} returns to the BS, the $j+1$ chargers which have returned to the BS shuttle NS^{pl}_{j+1} times between the BS and $P^{pl}_{C_{j+1}}$ to full charge the K_2 chargers.

(iv) We continue to compare $E(P_{C^{pl}_{j+1}})^{provide}_{K_2}$ and $E^{pl}_{K_1-(j+1)}$. If $E(P^{pl}_{C_{j+1}})^{provide}_{K_2} < E^{pl}_{K_1-(j+1)}$, let $j = j+1$ and repeat the above process. Until $E(P^{pl}_{C_{j+1}})^{provide}_{K_2} \geq E^{pl}_{K_1-(j+1)}$, the "Back with Shuttle" phase finishes. Then, the K_2 chargers start from $P^{pl}_{C_{j+1}}$ to replenish energy to the remaining $K_1 - (j+1)$ chargers on CP.

7 Performance Evaluation

In this section, we have carried out extensive simulations to evaluate the performance of the proposed algorithms.

7.1 Simulation Setup

We evaluate the proposed algorithms in both 1D and 2D networks. Following similar settings in [4], [16], sensors are powered by a 1.5 V 2,000 mAh Alkaline rechargeable battery, the capacity is b = 1.5 V × 2 A × 3,600 sec = 10.8 KJ. Chargers are powered by 18,650 Li-ion batteries, whose cell voltage and quantity of electricity is 3.7 V/ 3,000 mAh. Each detachable battery consists of five 18,650 Li-ion batteries, then the capacity of each detachable battery is p = 3.7 V × 3 A × 3,600 sec = 200 KJ. The battery set of a charger consists of 10 detachable battery packs, so the battery capacity of a charger is B = $2{,}000$ KJ. The moving cost of a charger is $c = 50$ J/m. Further, we assume the network design lifetime is 100 recharging cycles and the price of each charger is 100 dollars. By considering the cost of the components for building the automatic battery swap system in [22], the default price of chargers equipped with DBP to be 150 dollars. In terms of the electricity price in the United States, the electricity cost is 0.1 dollars per KWh (3,600 KJ).

7.2 Performance Measure

We compare PSB with PushWait in the 1D scenario with no energy loss, compare DBP-PSB with PSB and ηPushWait in the 1D scenario with energy loss, and compare C-DBP-PSB with HηClusterCharging(β) in 2D scenario. Three performance metrics are used to evaluate the algorithms:

(i) Number of chargers. NC is the number of chargers that can ensure all sensors are always alive. It is directly related to the cost of network building.

(ii) Energy usage effectiveness. It relates to the cost of network operation. EUE is defined as [16]

$$EUE = \frac{E^{pl}}{E^{pl} + E^{oh}}, \tag{19}$$

where E^{pl} is the energy obtained by sensors and E^{oh} is the sum of E^{tr} and E^{lo}. E^{tr} is the energy consumed by chargers' traveling and E^{lo} is the energy loss.

(iii) Unit cost (UC). We denote by UC the cost for each sensor to get fully charged in each cycle of the network design lifetime. UC is defined as

$$UC = \frac{(E^{pl} + E^{oh}) \cdot DL \cdot PE + NC \cdot PC}{DL \cdot N}, \tag{20}$$

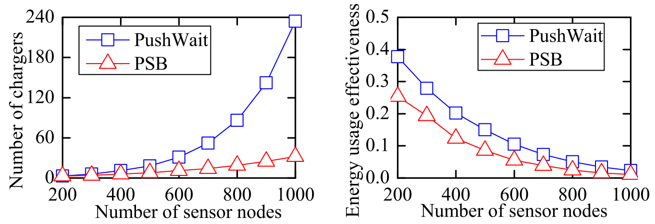
where PC is the price of a charger, PE is the price of one unit energy, and DL is the designed lifetime of the sensor networks in terms of the number of recharging cycles.

7.3 Results in 1D without Energy Loss

In 1D scenario, we assume that sensor nodes are randomly uniformly deployed in a 1D line, and the distance between two adjacent sensors is 100 m. The wireless charging efficiency between a charger and a sensor is by default $\eta_1 = 1.5\%$, and the charging efficiency between chargers is $\eta_2 = 30\%$.

Fig. 8 shows the two performance metrics NC and EUE comparisons in the 1D scenario with no energy loss. Fig. 8a shows that that NC increases with the number of sensor nodes. Obviously, with the increase of the number of sensors, PSB performs better than PushWait. Fig. 8b compares the EUE when the number of sensor nodes is changed. It can be seen that PushWait has the optimal EUE.

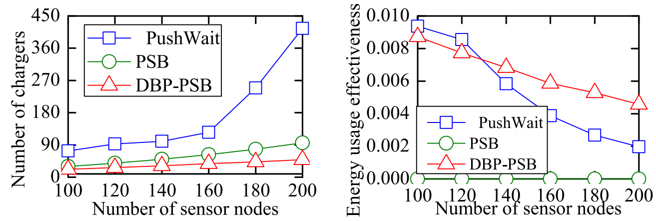
Fig. 9 compares another performance metric, UC. From Fig. 9a we can see PSB has lower UC, and this advantage is even more evident when there is greater number of sensors. Then we fix the number of sensors at 400. Figs. 9b and 9c compare the UC when changing the battery capacity of a charger and a sensor, and PSB has the best performance. In Fig. 9d, the UC of the two algorithms get larger when the moving cost of a charger increases. This is because the increase in the chargers moving cost always has negative effect: increasing the amount of energy consumed by chargers traveling. Fig. 9e shows PSB always has the best UC when varying the network design lifetime. Fig. 9f shows the more costly the charger is, the more advantageous PSB is.



(a) The value of the NC when varying the number of sensors

(b) The value of the EUE when varying the number of sensors

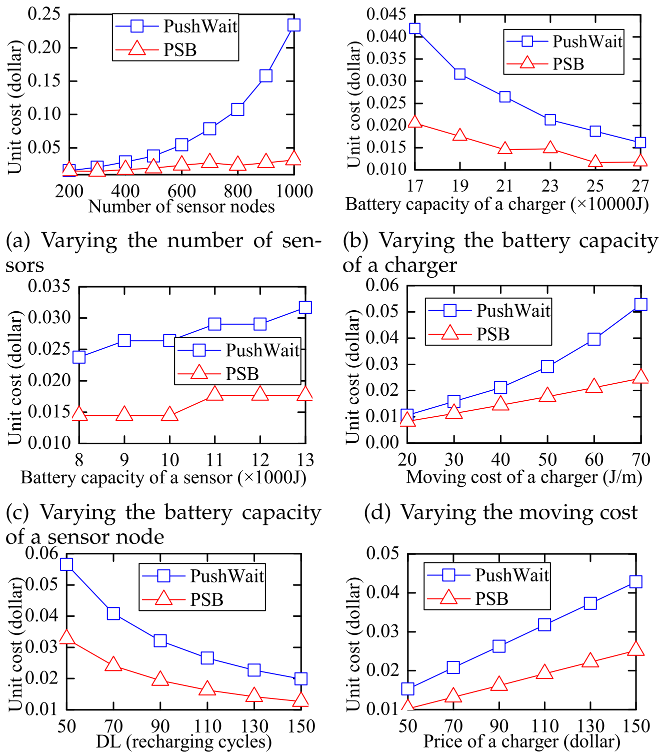
Fig. 8. NC and EUE comparisons in 1D scenario with no energy loss.



(a) The value of the NC when varying the number of sensors

(b) The value of the EUE when varying the number of sensors

Fig. 10. NC and EUE comparisons in 1D scenario with energy loss.



(a) Varying the number of sensors

(b) Varying the battery capacity of a charger

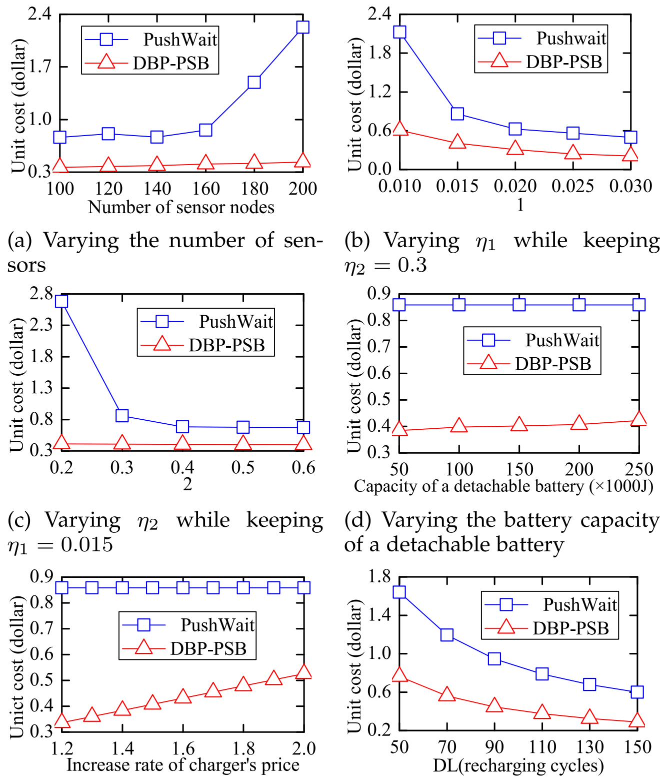
(c) Varying the battery capacity of a sensor node

(d) Varying the moving cost

(e) Varying the network design lifetime

(f) Varying the price of a charger

Fig. 9. Performance comparisons in 1D scenario with no energy loss.



(a) Varying the number of sensors

(b) Varying η_1 while keeping $\eta_2 = 0.3$

(c) Varying η_2 while keeping $\eta_1 = 0.015$

(d) Varying the battery capacity of a detachable battery

(e) Varying the increase rate of the charger's price equipped with DBP

(f) Varying the network design lifetime

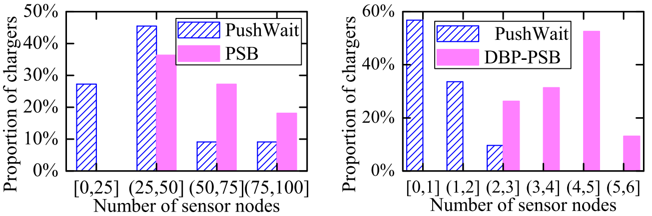
Fig. 11. Performance comparisons in 1D scenario with energy loss.

7.4 Results in 1D with Energy Loss

In this section, we verify the performance of proposed DBP-PSB algorithm in the 1D scenario with energy loss.

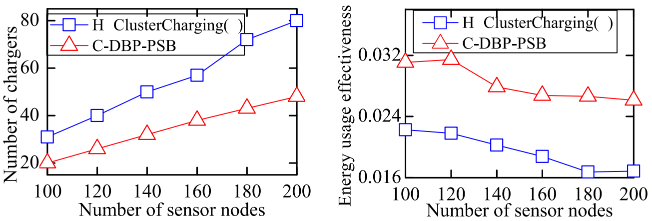
Fig. 10 shows the comparison of NC and EUE. As shown in Fig. 10a, all the three algorithms need more chargers than in the scenario with no energy loss. Especially for ηPushWait, when the number of sensors exceeds 160, NC increases rapidly. DBP-PSB has the smallest NC. Fig. 10b shows the comparison of EUE. DBP-PSB has higher EUE than ηPushWait when the number of sensors is more than 120, and with the increase of the number of sensors, this advantage becomes more outstanding. PSB is not an algorithm for energy loss scenario, so there is enormous energy loss during energy transfer between chargers in the "Shuttle" phase. Therefore, PSB has the lowest EUE.

Since the value of the PSB's EUE approximates to 0, we compare ηPushWait and DBP-PSB in Fig. 11. Fig. 11a shows the UC of ηPushWait increases with the number of sensors, especially when the number is more than 160. The number of sensors has little effect on the UC of DBP-PSB. When there are a large number of sensors, its advantage is even more outstanding. Then, we fix the number of sensors at 160. Figs. 11b and 11c respectively compare the UC of the two algorithms when $\eta 1$ and $\eta 2$ are changed. First, set $\eta 2 = 30\%$ and change $\eta 1$, we can see the UC of ηPushWait is always twice more than that of DBP-PSB. Further, set $\eta 1 = 1.5\%$ and change $\eta 2$, because DBP-PSB uses DBP, the change of $\eta 2$ has little effect on the UC of DBP-PSB. Fig. 11d shows the effect of the capacity of each detachable battery on the algorithm performance. As shown in Fig. 11d, the UC of DBP-PSB increases slightly with the capacity of each detachable battery. To equip DBP to the charger will cause higher charger price, so as shown in Fig. 11e, the UC of DBP-PSB also increases with the price of chargers when DBP is equipped. However, even when the price of chargers is doubled after they are equipped with DBP, the UC of DBP-PSB is only 61 percent of that of ηPushWait. Fig. 11f



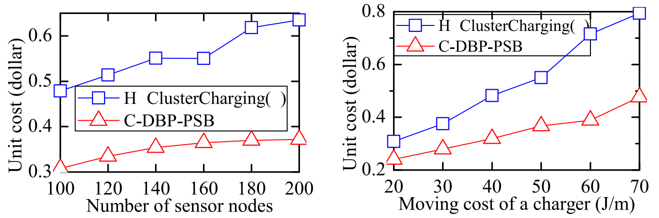
(a) The value of CCE in 1D without energy loss (b) The value of CCE in 1D with energy loss

Fig. 12. CCE comparisons.

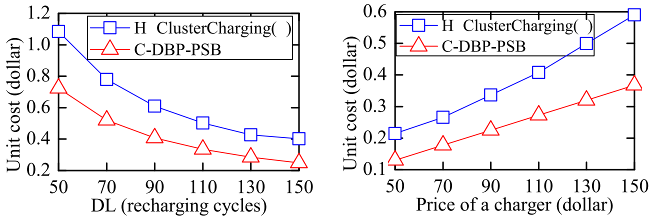


(a) The value of the NC when varying the number of sensors (b) The value of the EUE when varying the number of sensors

Fig. 13. NC and EUE comparisons in 2D scenario.

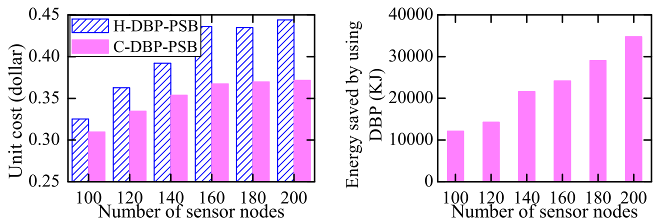


(a) Varying the number of sensors (b) Varying the moving cost



(c) Varying the network design lifetime (d) Varying the price of a charger

Fig. 14. Performance comparisons in 2D scenario.



(a) The value of the UC when varying the number of sensors (b) The energy saved by using DBP

Fig. 15. The benefit of "circle"-based shortcut and using DBP.

shows the UC of DBP-PSB is always less than half that of ηPushWait when the network design lifetime varies.

We are also interested in investigating how many sensors can be charged by each charger. Thus, another metic charger coverage effectiveness (CCE) is proposed and Fig. 12 shows the results. In a loss-free network, as shown in Fig. 12a, the CCE of PSB is better than that of PushWait. In PushWait, more than 80 percent of the chargers can only cover less than 50 sensors. On the contrary, in PSB, there are more than 60 percent of the chargers can cover 50 or more sensors. In energy loss scenario, Fig. 12b shows that the coverage of 90 percent of the chargers is less than 2 sensors in ηPushWait, while DBP-PSB leads to significantly improved results, with all chargers covering more than 2 sensors.

7.5 Results in 2D Scenario

Next we evaluate the effectiveness of the proposed C-DBP-PSB algorithm in general 2D scenario. We assume that sensors are randomly uniformly deployed over a 10 km $\times$ 10 km square area. The wireless charging efficiency between a charger and a sensor is by default $\eta_1 = 5\%$, and the charging efficiency between chargers is $\eta_2 = 30\%$.

Two metrics NC and EUE have been compared in Fig. 13. Fig. 13a shows that C-DBP-PSB can cover all sensors with less NC. Fig. 13b shows the EUE of C-DBP-PSB is better than HηClusterCharging(β). The reasons are: first, "circle"-based shuttle is critical to reduce the energy consumption and the number of chargers; second, in C-DBP-PSB, exchanging detachable battery reduces energy loss.

Fig. 14 compares UC in 2D scenario. In Fig. 14a, the UC of C-DBP-PSB is about 60 percent of that of HηClusterCharging(β) when changing the number of sensor. Then we fix the number of sensors at 160, Fig. 14b compares UC when changing the moving cost of each charger. It can be seen that C-DBP-PSB has the best performance. Fig. 14c shows C-DBP-PSB always has the best UC when the network design lifetime varies. Fig. 14d shows with the rise of charger price, C-DBP-PSB has greater advantage than HηClusterCharging(β).

To investigate how much benefit "circle"-based shuttle brings about, we compare C-DBP-PSB with H-DBP-PSB in Fig. 15a. The difference between C-DBP-PSB and H-DBP-PSB is that H-DBP-PSB uses the similar shortcut scheme with [16]. From Fig. 15a we can see the UC of C-DBP-PSB is always less than that of H-DBP-PSB when the number of sensors varies. Fig. 15b shows how much energy saved by using DBP. Since the number of chargers increases with the number of sensors, the amount of energy transferred between chargers is increased, andmore energy is saved by using DBP.

8 Conclusion

In this paper, we have studied the problem of low-cost collaborative mobile charging in WSNs. In contrast to existing solutions, we have considered the cost of both network building and operation. We introduce a novel concept called "Shuttling" and introduce an optimal charging algorithm, which is proven to achieve the minimum number of chargers in theory. We also point out the limitations of the optimal algorithm. In the scenario with no energy loss during charging, we proposed the Push-Shuttle-Back algorithm. We have formally proved PSB achieves the optimal number of chargers and the optimal shuttle times. To address the problem of energy loss in real application scenario, we have proposed to exploit detachable battery packs and developed a scheduling algorithm named DBP-PSB. We have further extended it to 2D scenarios and introduced the C-DBP-PSB algorithm. We have carried out extensive simulations to demonstrate the performance of our proposed algorithms in terms of wireless charging cost and efficiency.

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REFERENCES

[1] A. Kurs, A. Karalis, R. Moffatt, J. D. Joannopoulos, P. Fisher, and M. Soljačić, “Wireless power transfer via strongly coupled magnetic resonances,” *Science*, vol. 317, no. 5834, pp. 83–86, 2007.

[2] K. Kang, Y. S. Meng, J. Bréger, C. P. Grey, and G. Ceder, “Electrodes with high power and high capacity for rechargeable lithium batteries,” *Science*, vol. 311, no. 5763, pp. 977–980, 2006.

[3] X. Lu, D. Niyato, P. Wang, and D. I. Kim, “Wireless charger networking for mobile devices: Fundamentals, standards, and applications,” *IEEE Wireless Commun.*, vol. 22, no. 2, pp. 126–135, Apr. 2015.

[4] Y. Peng, Z. Li, W. Zhang, and D. Qiao, “Prolonging sensor network lifetime through wireless charging,” in *Proc. IEEE 31st Real-Time Syst. Symp.*, 2010, pp. 129–139.

[5] S. Zhang, Z. Qian, F. Kong, J. Wu, and S. Lu, “P3: Joint optimization of charger placement and power allocation for wireless power transfer,” in *Proc. IEEE Conf. Comput. Commun.*, 2015, pp. 2344–2352.

[6] W. Xu, W. Liang, X. Lin, and G. Mao, “Efficient scheduling of multiple mobile chargers for wireless sensor networks,” *IEEE Trans. Veh. Technol.*, vol. 65, no. 9, pp. 7670–7683, Sep. 2016.

[7] J. Johnson, E. Basha, and C. Detweiler, “Charge selection algorithms for maximizing sensor network life with UAV-based limited wireless recharging,” in *Proc. IEEE 8th Int. Conf. Intell. Sensors Sensor Netw. Inf. Process.*, 2013, pp. 159–164.

[8] L. Fu, P. Cheng, Y. Gu, J. Chen, and T. He, “Minimizing charging delay in wireless rechargeable sensor networks,” in *Proc. IEEE INFOCOM*, 2013, pp. 2922–2930.

[9] L. He, et al., “ESync: An energy synchronized charging protocol for rechargeable wireless sensor networks,” in *Proc. 15th ACM Int. Symp. Mobile Ad Hoc Netw. Comput.*, 2014, pp. 247–256.

[10] S. Guo, C. Wang, and Y. Yang, “Joint mobile data gathering and energy provisioning in wireless rechargeable sensor networks,” *IEEE Trans. Mobile Comput.*, vol. 13, no. 12, pp. 2836–2852, Dec. 2014.

[11] C. Wang, J. Li, and Y. Yang, “Low-latency mobile data collection for wireless rechargeable sensor networks,” in *Proc. IEEE Int. Conf. Commun.*, 2015, pp. 6524–6529.

[12] L. He, P. Cheng, Y. Gu, J. Pan, T. Zhu, and C. Liu, “Mobile-to-mobile energy replenishment in mission-critical robotic sensor networks,” in *Proc. IEEE Conf. Comput. Commun.*, 2014, pp. 1195–1203.

[13] C. Wang, L. Ji, F. Ye, and Y. Yang, “Recharging schedules for wireless sensor networks with vehicle movement costs and capacity constraints,” in *Proc. 11th Annu. IEEE Int. Conf. Sensing Commun. Netw.*, 2014, pp. 468–476.

[14] L. He, L. Kong, Y. Gu, J.-S. Pan, and T. Zhu, “Evaluating the on-demand mobile charging in wireless sensor networks,” *IEEE Trans. Mobile Comput.*, vol. 14, no. 9, pp. 1861–1875, Sep. 2015.

[15] W. Xu, W. Liang, X. Ren, and X. Lin, “On-demand energy replenishment for sensor networks via wireless energy transfer,” in *Proc. IEEE 25th Annu. Int. Symp. Pers. Indoor Mobile Radio Commun.*, 2014, pp. 1269–1273.

[16] S. Zhang, J. Wu, and S. Lu, “Collaborative mobile charging,” *IEEE Trans. Comput.*, vol. 64, no. 3, pp. 654–667, Mar. 2015.

[17] A. Madhja, S. Nikoletseas, and T. P. Raptis, “Hierarchical, collaborative wireless energy transfer in sensor networks with multiple mobile chargers,” *Comput. Netw.*, vol. 97, pp. 98–112, 2016.

[18] J. Zhao, X. Dai, and X. Wang, “Scheduling with collaborative mobile chargers Inter-WSNs,” *Int. J. Distrib. Sensor Netw.*, vol. 2015, 2015, Art. no. 15.

[19] W. Xu, W. Liang, X. Lin, G. Mao, and X. Ren, “Towards perpetual sensor networks via deploying multiple mobile wireless chargers,” in *Proc. 43rd Int. Conf. Parallel Process.*, 2014, pp. 80–89.

[20] C. Wang, J. Li, F. Ye, and Y. Yang, “Multi-vehicle coordination for wireless energy replenishment in sensor networks,” in *Proc. IEEE 27th Int. Symp. Parallel Distrib. Process.*, 2013, pp. 1101–1111.

[21] W. Jung, J. Park, S. Lee, K. Kim, and S. Kim, “Optimal control of passive locking mechanism for battery exchange using pontryagin’s minium principle,” in *Proc. 8th Asian Control Conf.*, 2011, pp. 1227–1232.

[22] J. Wu, G. Qiao, J. Ge, H. Sun, and G. Song, “Automatic battery swap system for home robots,” *Int. J. Adv. Robot. Syst.*, vol. 9, pp. 1–9, 2012.

[23] Y. Wu, M. Teng, and Y. Tsai, “Robot docking station for automatic battery exchanging and charging,” in *Proc. IEEE Int. Conf. Robot. Biomimetics*, 2009, pp. 1043–1046.

[24] L. Shi, J. Han, D. Han, X. Ding, and Z. Wei, “The dynamic routing algorithm for renewable wireless sensor networks with wireless power transfer,” *Comput. Netw.*, vol. 74, pp. 34–52, 2014.

[25] C. Wang, J. Li, F. Ye, and Y. Yang, “Improve charging capability for wireless rechargeable sensor networks using resonant repeaters,” in *Proc. IEEE 35th Int. Conf. Distrib. Comput. Syst.*, 2015, pp. 133–142.

[26] S. Lin and B. W. Kernighan, “An effective heuristic algorithm for the traveling-salesman problem,” *Operations Res.*, vol. 21, no. 2, pp. 498–516, 1973.

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