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# Exploiting peer-to-peer wireless energy sharing for mobile charging relief[☆]

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ABSTRACT

In this paper, we investigate the utilization of peer-to-peer wireless energy sharing to relieve the users from the burden of cord-based charging. The devices of users can make use of energy available from other users' devices based on their meeting patterns so that the battery level of their devices could be maintained within an acceptable level without the need of charging it through a cable frequently. We first use dynamic programming-based optimization to find out the minimum number of cord-based charging sessions to obtain the highest possible mobile charging relief through collaborative charge sharing among pairs of nearby user devices. Then, we map our problem to roommate matching problem and find out the best matching among users that will achieve the highest network-wide relief while satisfying all users with their assigned partners. With an extensive empirical analysis based on real device charging patterns and meeting patterns between mobile users, we evaluate the charging relief offered to users in various scenarios. The results show that users can get up to 13–17% relief from their charging burden using cooperative energy exchanges without changing their existing usage habits.



## 1. Introduction

The increasing computation and communication capabilities of mobile devices have provided various advanced applications facilitating our lives. However, this made people highly dependent on these devices that run on limited batteries and need to be charged frequently. In its most common form today, users charge their mobile devices using cables. However, finding a power outlet may not be an easy task especially when the users are outside or in dense indoor areas (e.g., airport) with relatively limited number of outlets.

With the recent integration of wireless charging [1] capability into mobile devices, the users are provided with some convenience for the charging without cables. The user device is charged by placing it on a charging pad or another item such as a desk [2] or a cup holder in a car [3] with integrated wireless power transmitter capability. However, the charging pad or equipment still needs to be connected to a power source. Recently, this somewhat limited usage of wireless charging has further been extended with energy transfer between mobile devices [4–6]. Through bidirectional chargers, mobile devices could exchange energy without the need of being connected to an outlet. Such a peer-to-peer (P2P) energy sharing opportunity brings flexibility to users for finding power ubiquitously and mitigates the risks of facing an emergency situation with depleted battery [7–9].

In this paper, we investigate the potential benefit of P2P energy sharing[1] between mobile devices on reducing the burden of traditional cord-based charging process (referred to as *wall charging* in the rest of the paper). Depending on the meeting schedules with other users, a user can make use of excessive energy available from other users' devices to skip some of the wall chargings while still maintaining the device's charge within an acceptable level. Similarly, it can share its own energy with others to help them relieve from the wall charging sessions. Our goal is to maximize the charging relief of users by letting them skip as many wall charging sessions as possible through utilization of energy shared by other users in the vicinity. We aim to discover the potential benefit of P2P energy sharing on the existing charging habits of users. Hence, we assume that the charging patterns of user devices

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[1] While this can be achieved via power sharing cables, a more convenient way will be through wireless power transfer (see some prototypes [5,6] developed by research community and a recent smartphone [4] with this capability in the market). We do not restrict the proposed solution in this paper to only wireless power transfer based energy sharing, but we discuss impact of parameters (e.g., transfer efficiency) associated with wireless power transfer on the performance of the proposed solutions.

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as well as the timing and durations of their meetings with other users (from which shareable energy amounts could be derived) are known in advance.

The proposed *collaborative charging* scheme aims to benefit from the current charging habits of users. Most of the users charge their devices opportunistically with short charging sessions and more frequently than they really need [7,10] to keep their devices with as much power as possible. Thus, in order to understand to what extent collaborative charging offers relief (i.e., percentage of reduction in the number of wall chargings) thanks to the charge sharing among users, we also find out the optimum relief users could have obtained with *conservative charging* without depleting energy in their devices. In conservative charging, we find out the minimum number of wall charging sessions that could have been sufficient to maintain power for a user based on the user's own charging pattern. In collaborative charging, however, we allow both sharing and receiving of energy between users and try to minimize the total number of wall charging sessions for a pair of users. We exploit dynamic programming approach to find out the optimal charging schedules for both cases. Then, in order to find out the highest network-wide charging relief among users, we map our problem to roommate matching problem and find the best matching among users while satisfying them with their assigned partners.

The preliminary version of this study is published in [11] with initial algorithms for the skipping of user wall charging sessions. In this paper, we revise and optimize the dynamic programming approach as well as study the network-wide mobile charging relief optimization through assignment of charging partners to users. We also conduct empirical analysis using several real-world datasets with user meeting and charging patterns and quantify the potential charging relief in realistic scenarios.

The rest of the paper is organized as follows. We discuss the related work in Section 2. In Section 3, we define the problem together with an analysis towards its solution. In Section 4, we provide the details of dynamic programming based optimization algorithms for both conservative and collaborative charging schemes. Next, in Section 5, we provide a solution for the network-wide optimization through mapping it to roommate matching problem. In Section 6, we provide and discuss both numerical and empirical results for the proposed solutions. Finally, we conclude the paper and outline future work in Section 7.

## 2. Related work

With the recent development in wireless power transfer technologies, a number of studies have been conducted on how to utilize this technology to improve the energy management in mobile networks. Previous work have mainly focused on applying these technologies to prolong the lifetime of wireless ad hoc and sensor networks [12–14] having low energy requirements.

Recently, the wireless charging of smartphones have attracted a lot of interest. In [15], charging of a device while it is in the user's pocket is achieved by using magnetic field beamforming. This has been extended to the charging of multiple devices in the vicinity of a power hotspot [16]. It has been shown that with increasing number of devices, the efficiency of wireless charging at distances can increase. Besides these studies that focus on uni-directional but long distance charging, there are several recent studies that look at the P2P energy sharing among smartphones. In [5,6], some prototypes are developed to realize actual charge sharing. In [17], authors exploit P2P wireless energy exchange to balance the energy within a mobile social network and propose various algorithms to be used in the sharing protocol. In [18], the impact of P2P energy sharing on network formation and in [19] its benefit on group based charging has been studied. In [8] and [20] the pairwise assignment of users for energy exchanges has been studied. A more general work can be found in [9], in which authors focus on enhancing the energy usage of wireless networks with wireless energy sharing to minimize the chances of ending up with insufficient energy for their consumption. An energy sharing based content delivery process is also studied in [21]. While these studies provide an idea on the potential benefit of wireless energy exchange to users, the concept is studied without an integrated analysis of charging habits of individual user devices and meeting patterns between the users that can exchange energy. In this paper, different from previous work, we define the burden of charging in terms of the number of charging sessions that the devices stay plugged to the outlet (i.e., wall charging) and discuss the minimization of that number exploiting the energy shared by other users without changing the charging and movement patterns of any user. We also provide a satisfactory network-wide solution for all users by mapping our problem to roommate matching problem and assign partners to each user while satisfying all users with their assignments. The notations used throughout the paper are given in Table 1.

## 3. Problem statement

In this section, we define the problem and provide the necessary notation towards its solution. A *charging pattern* of a user device consists of alternating charging and discharging sessions. Let $\delta_c$ and $\delta_d$ denote the set of all charging and discharging sessions for a user, respectively:

$$\begin{aligned}
\delta_c &= \{\delta_c(1), \delta_c(2), \ldots, \delta_c(n)\} \\
\delta_d &= \{\delta_d(1), \delta_d(2), \ldots, \delta_d(n)\} \text{ where,} \\
&\quad \delta_d(i).l_s = \delta_c(i).l_e, \forall i \in \{1 \ldots n\} \text{ and} \\
&\quad \delta_c(i+1).l_s = \delta_d(i).l_e, \forall i \in \{1 \ldots (n-1)\}
\end{aligned}$$

We define the time from the start of one wall charging to the start of next one as a *charging cycle*. Here, each ($\delta_c(i)$, $\delta_d(i)$) represents a charging cycle with one charging and one discharging session. The attributes $l_s$ and $l_e$ represent the starting and ending charge levels (integers in [0–100]) for each of these periods.

We consider that when a mobile user meets another mobile user, they can exchange energy between each other wirelessly. Recent studies [5,6] have shown that mobile devices could easily be equipped with necessary hardware and software support to realize this. We assume that the users know each other and are interested in sharing their excessive energy with their friends non-intrusively. That is, they do not want to change their regular movement patterns and their own usage of the device. The amount of energy that could be exchanged depends on several factors including transfer speed, efficiency, duration of their meeting, maximum shareable energy by the sender without causing it have less than an acceptable energy level and the available capacity in the receiver.

The optimization problem is studied for two different cases; (i) conservative charging, and (ii) cooperative charging. While the former looks at the problem from only one user's perspective by trying to minimize the number of wall charging sessions while still keeping the device with sufficient power to operate, in the latter, we consider both receiving and sharing of energy between the users and aim to optimize the problem jointly from the perspective of both users. We formulate these problems using decision points that occur at the beginning of each cycle. Next, we discuss the details of the problem within each context.

### 3.1. Conservative charging

In this case, we study the problem from the perspective of a single user who aims to skip as many wall chargings as possible.

**Table 1**
Notation used in the paper.

| Notation | Description |
|---|---|
| $\delta_c(i)$ | $i$th charging session of user. |
| $\delta_d(i)$ | $i$th discharging session of user. |
| $\delta_c^A[t]$ | Total energy gained by user $A$ during wall charging in $t^{th}$ decision block. |
| $\delta_d^A[t]$ | Total energy lost by user $A$ during discharging in $t$th decision block. |
| $S_t^{A\rightarrow B}$ | The energy shared from $A$ to $B$ during the $t$th decision block. |
| $l_s$ | Starting charging level attribute of a charging or discharging session. |
| $l_e$ | Ending charging level attribute of a charging or discharging session. |
| $l_{\min}$ | Minimum acceptable energy level of user devices. |
| $l_{init}$ | Initial charge level of the user. |
| $X_t^A$ | Charging decision variable for user $A$ in $t$th decision block. |
| $D$ | Matrix that stores the number of wall chargings required for each charge level by every decision block. |
| $T$ | Matrix that stores the index of the $D$ matrix from which the corresponding $D$ matrix entry is derived. |
| $\mathcal{U}_t^A$ | The total unplugged time of user $A$ in $t$th decision block. |
| $\mathcal{M}_t^{A,B}$ | The meeting event between users $A$ and $B$ in $t$th decision block. |
| $\mathcal{T}_S$ | The speed of energy transfer between users. |
| $\mathcal{T}_E$ | The efficiency of energy transfer. |
| $n_A$ | Number of charging sessions of user $A$. |
| $\mathcal{R}_A(B)$ | User A's charging relief from collaborative charging with user $B$. |
| $J(\mathcal{R}_A(u_i))$ | Energy saving with charging skip pattern associated with $\mathcal{R}_A(u_i)$. |
| $\mathcal{PL}[A]$ | Preference list of user $A$ to be matched with other users for collaborative charging. |

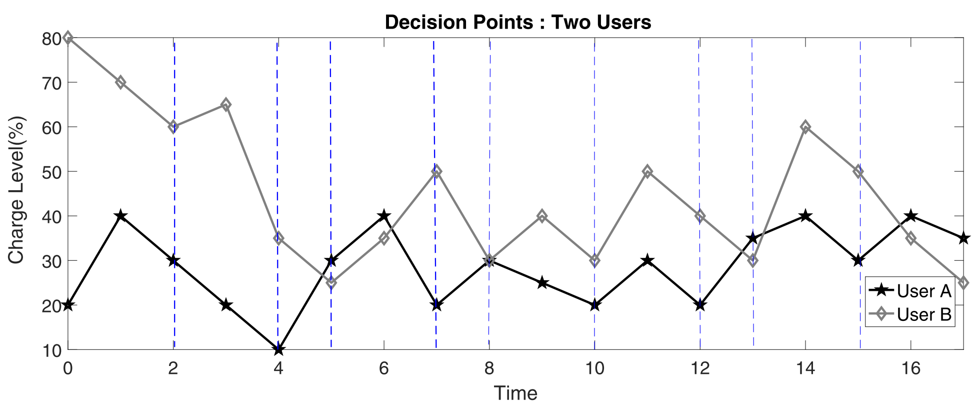


**Fig. 1.** Charging patterns and decision points of two users.

Note that in this case user is not sharing energy with others nor receiving energy from them. This case is studied in order to understand the potential charging relief users could have obtained by their own scheduling. Moreover, it also forms the base for the formulation of complicated collaborative charging case.

Fig. 1 shows example charging patterns for two different users for a certain time frame. Depending on the applications that are running on the device the discharging rate might vary at different times. Similarly, depending on the equipment used for charging or due to the active usage while charging, the charging of the device could happen at different rates. Note that in some charging sessions there could be some *idle charging* duration in which the device stays plugged after being fully charged (e.g., overnight charging). While such cases could help increase the charging relief as the charging amount in the previous skipped sessions could be compensated during those idle charging times, we do not consider them in this paper for the sake of brevity. However, all the formulations could be easily adapted to integrate such cases. Moreover, It has been shown by several studies conducted with smartphones [22,23] that the battery voltage and state of charge (SOC) or battery level has almost a linear relation after the first few battery levels, thus we assume a linear but potentially with different rate charging and discharging sessions.

The conservative charging problem here is defined as follows. Given an existing charging pattern of a user, what is the minimum number of wall charging instances that would be sufficient for the user device while keeping the same device functionality and charging habits? In such scenario, the only way a user may try to skip some of its wall chargings is purely by benefiting from the unnecessarily frequent charging in its own charging schedule.

We formulate the problem using decision points that occur at the beginning of each charging cycle. Decision points divide a given user charging pattern into blocks of time periods known as *decision blocks*. Each block starts with the start of a charging session for a user and ends with the completion of a discharging session. In this case, since there is a single user, each decision block corresponds to an individual charging cycle of the user. For user A's charging pattern shown in Fig. 1, there are six decision blocks with starting times $D = \{0, 4, 7, 10, 12, 15\}$. Similarly, for user B, there are five decision blocks with starting times $D = \{2, 5, 8, 10, 13\}$.

Assume that there are $n$ decision blocks and let $\delta_c[t]$ and $\delta_d[t]$ denote the total energy gained (i.e., $\delta_c(t).l_e - \delta_c(t).l_s$) during wall charging and total energy lost (i.e., $\delta_d(t).l_e - \delta_d(t).l_s$) during discharging throughout the $t$th decision block. The objective function in conservative charging is then formally described as:

$$\min \sum_{t=1}^{n} X_t \tag{1}$$

$$\text{subject to } D_t.l_e = (D_t.l_s + \delta_c[t]X_t - \delta_d[t])\}, \ \forall t \in [1, n] \tag{2}$$

$$D_t.l_e \geq l_{min}, \ \forall t \in [1, n] \tag{3}$$

$$D_1.l_s = \delta_c(1).l_s \tag{4}$$

$$D_{t+1}.l_s = D_t.l_e \ \forall t \in [1, (n-1)] \tag{5}$$

where, $l_{\min}$ is the minimum acceptable level (e.g., 1%) and $X_t$ is the charging decision variable $\in$ {0,1}, with 0 meaning the current charging session is skipped.

### 3.2. Cooperative charging

In this case, users are allowed to both send and receive energy between each other. Therefore, the optimal skipping pattern has to be determined considering the amount of energy that will be exchanged between users. The decision points (i.e., start of charging cycles) coming from both users will form decision blocks with partitioned charging cycles of users. Moreover, some decision points might divide a charging session of a user into two or more parts.

The set of decision points that come from both users in Fig. 1 is $D$ = {0, 2, 4, 5, 7, 8, 10, 12, 13, 15}, which is $D_A \cup D_B$. When a decision point causes a split in the charging session of a user, since we assume skipping of wall chargings completely (i.e., no partial skipping allowed), the skip decision made for a portion of a wall charging inside a decision block should match with the decision made for the remaining portion of the same wall charging in the next decision points. In order to reach the optimal skipping solution that maintains this, for every such decision point, both results (skipping or not) have to be stored until the split of a charging period with decision points is over and only the optimal one should be picked. The splitting of a charging session can create different types of decision blocks based on which the solution is modeled:

- **Full($u$)**: The decision block contains the entire charging session of the user $u$.
- **First_Split($u$)**: The decision block contains only the beginning portion of the split charging session of the user $u$.
- **Mid_Split($u$)**: The decision block contains neither the start nor the end of the user $u$'s charging session but has a middle part.
- **Last_Split($u$)**: The decision block contains only the ending portion of the split charging session of the user $u$.

For example, in Fig. 1, the third decision block (i.e., from time 4 to 5) is First_Split($A$) and the next one (i.e., from time 5 to 7) is Last_Split($A$) and Full($B$). It is possible that a decision block can only include discharging session for a user (e.g., user $B$ in third decision block). Such blocks could be considered for users like a Full split with no charging. Moreover, some of the combinations of these block types for a pair of users is not possible. For example, while there is a First_Split($A$), there cannot be a Mid_Split($B$). The valid combinations have to be carefully analyzed towards the solution.

Let $\delta_c^A[t]$ and $\delta_d^A[t]$ denote the total energy gained by user $A$ during wall charging and total energy lost by user $A$ during discharging throughout the $t^{th}$ decision block. Moreover, let $S_t^{A\to B}$ denote the energy shared from $A$ to $B$ during the $t^{th}$ decision block and $\mathcal{T}_E$ denote the efficiency of transfer. The objective function in cooperative charging is then formally described as:

$$\min \ \sum_{t=1}^{n} \left(X_t^A + X_t^B\right) \tag{6}$$

$$\text{subject to} \ \ D_{t+1}^A.l_e = D_t^A.l_s + \delta_c^A[t]X_t^A - \delta_d^A[t] + \mathcal{T}_E S_t^{B\to A} - S_t^{A\to B} \tag{7}$$

$$D_{t+1}^B.l_e = D_t^B.l_s + \delta_c^B[t]X_t^B - \delta_d^B[t] + \mathcal{T}_E S_t^{A\to B} - S_t^{B\to A} \tag{8}$$

$$D_t^k.l_e \geq l_{min}, \ \ \forall t \in [1, n], \forall k \in \{A, B\} \tag{9}$$

$$D_1^k.l_s = \delta_c^k(1).l_s \ \forall k \in \{A, B\} \tag{10}$$

$$D_{t+1}^k.l_s = D_t^k.l_e \ \forall t \in [1, (n-1)], \ \ \forall k \in \{A, B\} \tag{11}$$

where, $l_{\min}$ is the minimum acceptable level (e.g., 1%) and $X_t^A$, and $X_t^B$ $\in$ {0,1} are the charging decision variables for $A$ and $B$, respectively, with 0 meaning the current charging session is skipped.

## 4. Dynamic programming based optimization

We use a dynamic programming based approach to find out the optimal charging pattern in both problems. At each decision point, the algorithm tries to recursively find the best charging levels that will result in the minimum number of wall chargings for each user. The solution includes two matrices: $D$ and $T$. $D$ matrix stores the integer value that represents the number of wall chargings required for each charge level by every decision block and $T$ matrix stores the index of the $D$ matrix from which that value is derived. In the subsequent sections, we provide the details of the solution for each of these cases.

### 4.1. Optimization for conservative charging

In this case, a two dimensional D matrix is considered where the first dimension represents the decision points and the second dimension represents the charge level for the user of interest. The algorithm takes the list of wall charging amounts ($\delta_c$[]), and the list of discharging amounts ($\delta_d$[]) for the user as a parameter. $l_{init}$ is the initial charging level for the given charging pattern. For example, for A's pattern in Fig. 1, $l_{init}$ is 20%. Values from $D[0][l_{\min}]$ to $D[0][0]$ is initialized to 0 because it is ensured that each of these charging levels could be achieved at the beginning without any wall charging. All other values in $D$ matrix are initialized to some very high integer value.

**Algorithm 1:** Conservative charging decision algorithm.

```
Input: δc[]: Charging amounts; δd[]: discharging amounts
Output: Number of minimum wall charging sessions for the user
for each decision block D_t do
    for each charging level 0 ≤ l ≤ 100 do
        current = D[t][l]
        for each X_t ∈ {0, 1} do
            l_new = min(100, l + δc[t]X_t) - δd[t]
            if l_new ≥ l_min then
                if current+X_t < D[t+1][l_new] then
                    D[t+1][l_new] = current+X_t
                    T[t+1][l_new] = l
                end
            end
        end
    end
end
return min{D[n][l] ∀l ≥ l_min}
```

The details of the dynamic programming based solution for the conservative charging is shown in Algorithm 1. The main principle on which the algorithm works is, for each charge level (i.e., from 0 to 100) at each decision block ($D_t$), it finds out what charge

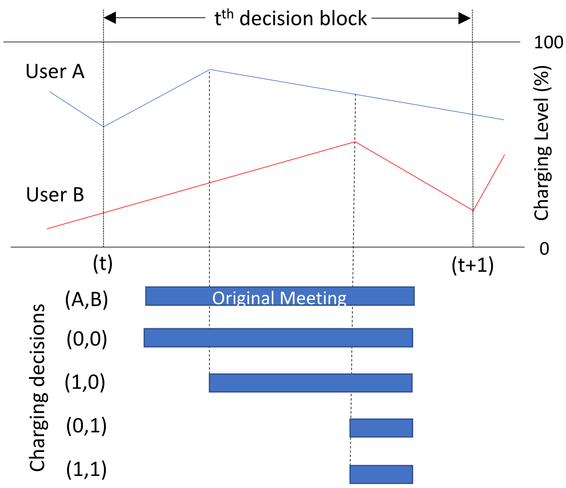


**Fig. 2.** Total duration with energy exchange opportunity determined by the intersection of user meetings, charging patterns and charging decisions of users.

level could be reached by either decision (skipping ($X_t$=0) or not ($X_t$=1)) and updates the number of wall chargings at that level with the smallest ever seen as long as it is more than the minimum acceptable level and less than 100%. Note that if the smallest wall charging count is achieved with a skip from previous decision point, the number of wall chargings from previous decision point is transferred. On the other hand, if the wall charging in that decision block is used, the number of wall chargings from previous decision point is incremented by 1 and used in the update. The same logic is applied recursively for all charging cycles to find the optimal skip sequence at the end. The running time of the algorithm is $O(100|D|)$, while brute force solution has $O(2^{|D|})$ complexity.

Once the algorithm finishes, we apply a general solution readout approach to find the actual wall charging sessions used. We start at the last decision block and get the index with the minimum number of charging sessions from *D* matrix. Each position in *D* matrix is associated with its previous cell using *T* matrix. If the value in current index of *D* matrix has increased compared to its previous value, then the wall charging session at that decision block is used, otherwise it is skipped.

### 4.2. Optimization for cooperative charging

In cooperative charging, in order to increase the overall charging relief for users, they consider exchanging energy between each other. However, for each energy exchange opportunity within the decision blocks, the amount of actual energy exchange amounts should be decided to obtain the optimal charging pattern at the end. The energy exchange between users can potentially happen when they actually meet and are not charging. Hence, the amount of energy that could be shared between these devices will be determined by their meeting and charging patterns as well as their charging decisions. In Fig. 2, an example decision block with a single meeting between two users is illustrated. If both users decide to skip their charging session in the decision block, the energy exchange opportunity duration will be equal to the total meeting duration. However, if one of the users decides to use its wall charging in that decision block, that portion of their meeting has to be excluded as we assume it is not practical to exchange energy for users while being charged.

Let $\mathcal{U}_t^A$ denote the total unplugged time of user A in decision block $t \in \{1, 2, \ldots, n\}$. The charging session in a decision block will always be earlier than the discharging session within the block by definition of blocks. $\mathcal{U}_t^A$ should be either from the start of charging till the end of discharging or from the start of discharging till its end depending on the charging decision. More formally:

$$\mathcal{U}_t^A = \begin{cases} \left(\delta_d^A[t].t_s, \delta_d^A[t].t_e\right) & \text{if } X_t^A = 1 \\ \left(\delta_c^A[t].t_s, \delta_d^A[t].t_e\right) & \text{otherwise} \end{cases} \quad (12)$$

Here, $t_s$ and $t_e$ denote the start and end times, respectively.

Let $\mathcal{M}_t^{A,B}$ denote the meeting event between users *A* and *B*, $\mathcal{T}_S$ denote the speed of wireless energy transfer and $\mathcal{T}_E$ denote the efficiency of transfer. The total amount of energy that can be exchanged between *A* and *B* in decision block *t*, $\mathcal{E}_t^{A,B}$, can be computed by:

$$\mathcal{E}_t^{A,B} = \mathcal{I}_t^{A,B} * \mathcal{T}_S * \mathcal{T}_E \text{ where,} \quad (13)$$

$$\mathcal{I}_t^{A,B} = \mathcal{M}_t^{A,B} \bigcap \mathcal{U}_t^A \bigcap \mathcal{U}_t^B \quad (14)$$

Here, $\mathcal{I}_t^{A,B}$ is the intersection of total meeting duration between *A* and *B* and total unplugged times of A and B.

It is also important to remark that $\mathcal{E}_t^{A,B}$ should be considered as the maximum energy that could be exchanged but the actual energy exchange between users depends on the current charge level of each user device. A user device's charge level cannot exceed 100% and cannot be less than $l_{\min}$ by definition. Moreover, note that in order to reach an optimal solution at the end, the optimal energy exchange values at each individual decision block could be less than $\mathcal{E}_t^{A,B}$ even though device capacity restrictions allow it.

In this case, D matrix is defined as a four dimensional matrix. The first dimension represents the decision points and the second and third dimensions represent the charge level for each user. The last dimension is used to keep track of decisions made for charging sessions split into multiple decision blocks. Due to the binary decision used for skipping a charging session as a whole, the charging decision made for all portions of a charging session at different decision blocks has to match. Consider the example in Fig. 3. In the first decision block (from $t$ to $t+1$), there is a First_Split(A) and a Full(B). Thus, updates based on different charging decisions made for user *A* on *D* matrix are written into different indexes at the fourth dimension. In the second decision block, as there is a Mid_Split(A), only the updates with consistent decisions are allowed to be made on D matrix's corresponding index at fourth dimension (e.g., there can not be skip (i.e., 0) after not skipping in previous block). In the next decision block, there is a Last_Split(A) and a First_Split(B). In this case, optimal decision for A should be selected and written on the first index (0) at fourth dimension. However, due to the split of B, the corresponding fourth dimension index for the updates is found using the B's charging decision. In the fourth decision block, as there is a Last_Split(B) with a Full(A), the final decision for user B's charging session is made and written into the first index at fourth dimension. The fifth block has a Full(A) and a Full(B), thus, only the first index at fourth dimension is used for the updates.

In Table 2, we provide (source, destination) index assignments at the fourth dimension of D matrix with different decision block

**Table 2**
(Source, destination) index assignments for D matrix's fourth dimension based on charging decisions of users with different types of decision blocks.

| User A | User B | | | |
|---|---|---|---|---|
| | Full/None | First Split | Mid-Split | Last Split |
| Full/None | (0,0) | (0, $X_t^B$) | ($X_t^B$, $X_t^B$) | ($X_t^B$,0) |
| First Split | (0, $X_t^A$) | N/A | N/A | ($X_t^B$, $X_t^A$) |
| Mid-Split | ($X_t^A$, $X_t^A$) | N/A | N/A | N/A |
| Last Split | ($X_t^A$,0) | ($X_t^A$, $X_t^B$) | N/A | N/A |

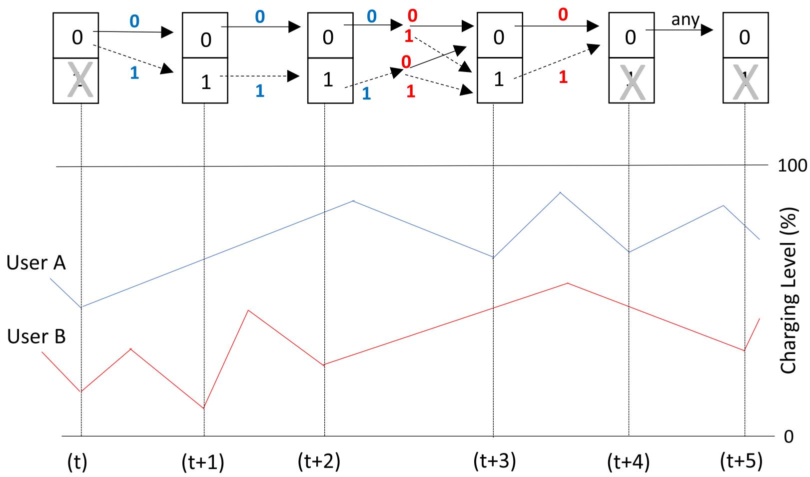


**Fig. 3.** Dynamic programming table cell updates in the fourth dimension on a sample charging pattern of two users with different charging types included in decision blocks.

type combinations. For example, for the second decision block in Fig. 3, which has a Mid_Split(A) and a Full(B), if A's decision is to skip, source index will be 0 and written to 0 to keep the consistent decision. Note that some of the combinations are not possible due to the definition of decision blocks that start with the start of charging sessions.

The details of the dynamic programming based solution for cooperative charging is presented in Algorithm 2 . The algorithm takes the list of all wall charging and discharging events with amounts, start and end times and finds out the minimum wall charging sessions needed to keep the both devices always more than $l_{\min}$. The algorithm covers all four possible charging decision cases for a pair of nodes and finds out the maximum duration that could be used for energy exchanges. Then, for each possible duration less than this maximum, it finds the corresponding charge levels that will be reached by each user (lines 10–14). Considering either direction of energy exchange (i.e., when $A$ sends and $B$ receives ($\overrightarrow{A}$, $\overleftarrow{B}$) or when $A$ receives and $B$ sends ($\overleftarrow{A}$, $\overrightarrow{B}$)), it then updates the D matrix values based on previous iteration (lines 15–23). Note that the corresponding (source, destination) index values at the fourth dimension is determined using the aforementioned principle (line 9). The running time of this algorithm is $O((100)^2|D|(E))$, where $E$ is the average shareable energy range. Brute force solution has $O(4^{|D|})$ complexity.

**Algorithm 2:** Cooperative charging decision pattern algorithm.

1 **Input:** $\delta_{\mathbf{c}}[]/\delta_{\mathbf{d}}[]$: Charging/discharging amounts; $\mathcal{M}[]$: meeting patterns
2 **Output:** Number of minimum total charging sessions for both users.
3 **for** *each decision block* $D_t$ **do**
4 $\quad(c_A, c_B) \leftarrow$ Decide the charging types for both users
5 $\quad$**for** *each charging level* $0 \le \mathbf{l_A} \le 100$ **do**
6 $\quad\quad$**for** *each charging level* $0 \le \mathbf{l_B} \le 100$ **do**
7 $\quad\quad\quad$**for** *each* $(X_t^A, X_t^B)$ *case* **do**
8 $\quad\quad\quad\quad\mathcal{I}_t^{A,B} \leftarrow$ Max duration for energy exchange with $(c_A, c_B)$
9 $\quad\quad\quad\quad(sc, dt) \leftarrow$ Fourth dimension indexes based on current case
10 $\quad\quad\quad\quad$**for** $0 \le k \le \mathcal{I}_t^{A,B}$ **do**
11 $\quad\quad\quad\quad\quad\overrightarrow{A}$ = min(100, $l_A$ + $\delta_c^A$[t]$X_t$) - k*$\mathcal{T}_S$ - $\delta_d^A$[t]
12 $\quad\quad\quad\quad\quad\overleftarrow{B}$ = min(100, $l_B$ + $\delta_c^B$[t]$X_t$) + (k*$\mathcal{T}_S$ *$\mathcal{T}_E$) - $\delta_d^B$[t]
13 $\quad\quad\quad\quad\quad\overleftarrow{A}$ = min(100, $l_A$ + $\delta_c^A$[t]$X_t$) + (k*$\mathcal{T}_S$* $\mathcal{T}_E$) - $\delta_d^A$[t]
14 $\quad\quad\quad\quad\quad\overrightarrow{B}$ = min(100, $l_B$ + $\delta_c^B$[t]$X_t$) - k*$\mathcal{T}_S$ - $\delta_d^B$[t]
15 $\quad\quad\quad\quad\quad$**for** *each* $(l_A, l_B) \in \{(\overrightarrow{A}, \overleftarrow{B}), (\overleftarrow{A}, \overrightarrow{B})\}$ **do**
16 $\quad\quad\quad\quad\quad\quad$**if** $l_A \ge l_{\min}$ *and* $l_B \ge l_{\min}$ **then**
17 $\quad\quad\quad\quad\quad\quad\quad$new = D[t][$l_A$][$l_B$][$sc$]+$X_t^A + X_t^B$
18 $\quad\quad\quad\quad\quad\quad\quad$**if** *new* $<$ *D[t+1][$l_A$][$l_B$][$dt$]* **then**
19 $\quad\quad\quad\quad\quad\quad\quad\quad$D[t+1][$l_A$][$l_B$][$dt$] = new
20 $\quad\quad\quad\quad\quad\quad\quad\quad$T[t+1][$l_A$][$l_B$] = ($l_A$, $l_B$, $sc$, $k$)
21 $\quad\quad\quad\quad\quad\quad\quad$**end**
22 $\quad\quad\quad\quad\quad\quad$**end**
23 $\quad\quad\quad\quad\quad$**end**
24 $\quad\quad\quad\quad$**end**
25 $\quad\quad\quad$**end**
26 $\quad\quad$**end**
27 $\quad$**end**
28 **end**
29 return $\min\{D[n][l_A][l_B][0]\,\forall l_A, l_B \ge l_{\min}\}$

## 5. Network-wise optimization

The previous section finds out the optimal collaborative charging decision patterns for a pair of nodes. In a network of smartphone users, each user can potentially consider exchanging energy with all other users. The Algorithm 2 could be extended with additional dimensions to find out an optimal solution for every size of group of users at the expense of increased complexity. On the other hand, sharing energy with multiple other users may not be practical and users may have concerns about their privacy. To this end, in this section, we focus on grouping of users into pairs and let them exchange energy with only one other user. A centralized graph based matching solution could provide the highest network-wide mobile charging relief among users. However, in reality, this may not address the individual preferences of users and may result in users not satisfied with their assignments. To address this issue, we map our problem to *stable roommate matching problem* (SRP). The goal is to find a stable matching among a group of users such that there will not exist a pair of nodes which are not assigned to each other and both prefer each other to their assigned partners under the current matching. Note that this problem is distinct from the stable-marriage problem as the stable-roommates problem allows matches between any pair of nodes, not just between two disjoint classes such as men and women [24].

To this end, we first run the collaborative charging algorithm for every pair of nodes in the network. Then, for a given node, say A, we calculate the relieves obtained from each other user. Let $n_A$ denote the total number of charging sessions of user A. The charging relief that user A obtains from a collaborative charging, $\mathcal{R}_{\mathcal{A}}$, is defined as the ratio of skipped charging sessions to the total number of charging sessions. That is:

$$\mathcal{R}_A = \frac{n_A - \sum_{t=1}^{n_A} X_t^A}{n_A} \tag{15}$$

Denoting $\mathcal{R}_A(B)$ as the user A's relief from collaborative charging with the user B, we then form a preference list for user A, $\mathcal{PL}[A]$, in the descending order of obtained relief. In some cases, however, there may be more than one user that provide the same relief to the user. To break such tie situations, we use reduction in the energy amount obtained due to the skipped charging sessions.

$$\begin{aligned} \mathcal{PL}[A] = \{&u_1, u_2, \dots, u_n \mid \\ &\mathcal{R}_A(u_i) > \mathcal{R}_A(u_{i+1}) \text{ or} \\ &\mathcal{R}_A(u_i) = \mathcal{R}_A(u_{i+1}) \text{ and } J(\mathcal{R}_A(u_i)) > J(\mathcal{R}_A(u_{i+1}))\} \end{aligned} \tag{16}$$

Here, $J(\mathcal{R}_A(u_i))$ represents the energy saving with skipped pattern associated with $\mathcal{R}_A(u_i)$. Once each user forms its preference list as described, we then adapt Irving's algorithm [25] to find out a stable matching among users, if it exists. Note that since the matchings will be mutual, we assume that there are even number of users in the network.

Algorithm 3 shows the details of the proposed matching process. For each free user not assigned a partner, the first user in the preference list is proposed. If the proposed user has not been matched with any other user yet, it immediately accepts the proposal and a pending matching is assigned. On the other hand, if the proposed user has already been matched with some other user, it checks if the new proposer has better rank in its preference list than the current matched user. If that is the case, previous proposer is set free and it is matched with this new proposer. Otherwise, both users remove each other from their preference lists mutually. Once a user is assigned a partner, it also deletes all other users in its preference list with ranking more than the assigned user. In some rare cases, this process may end up with some users having still more than 1 users in their preference lists. In that case, a further elimination is conducted with some special cycles of users described in lines 25–29. At the end, if each user has only one other user in their preference lists, the stable matching is obtained.

## 6. Evaluation

In this section, we first provide results of running conservative and cooperative charging on an example pattern of two users. Then, we conduct an empirical analysis using various mobile datasets with user meeting and charging patterns and find out the potential charging relief in realistic scenarios.[2]

### 6.1. Numerical example

We have used the charging patterns for two users shown in Fig. 1 and run the optimization algorithms for both cases. Table 3 shows the optimal charging decision results for both cases. In conservative case, decision blocks consist of charging cycles but in collaborative charging the number of decision blocks is more than the actual charging cycles. Thus, in Table 4, we show the actual decisions made for each decision block in collaborative charging.

[2] The Java codes developed to generate the results in this section are available at https://github.com/aashish33128/Mobile-Charging-Relief/tree/master/EnergySharing.

**Algorithm 3:** Collaborative charging partner matching algorithm.

1 **Input:** a set of users $\mathcal{N}$, and their preference lists $\mathcal{PL}$
2 **Output:** Matched collaborative charging partner for all, if exists.
3 //step 1
4 **for** *each free user $i \in [1, \mathcal{N}]$ as proposer* **do**
5  **if** *$\mathcal{PL}$[proposer] is not empty* **then**
6   $u \leftarrow \mathcal{PL}[proposer]$.first()
7   **if** *$u$ is not proposed earlier* **then**
8    Match ($u$, proposer)
9   **else**
10    current $\leftarrow u$.hasProposalsFrom()
11    **if** *$u$ prefers current over proposer* **then**
12     Remove $u$ from$\mathcal{PL}$[proposer] and*proposer* from $\mathcal{PL}[u]$
13    **else**
14     current.setFree()
15     Remove $u$ from$\mathcal{PL}$[current] and*current* from $\mathcal{PL}[u]$
16     Match ($u$, proposer)
17    **end**
18   **end**
19  **end**
20 **end**
21 **for** *each user $i$ matched to a user $m$* **do**
22  Remove $i$ from$\mathcal{PL}$[r] and$r$ from $\mathcal{PL}[i]$, $\forall r$ with rank($r$) > rank($m$)
23 **end**
24 //step 2
25 **for** *each user $p_i$ with $|\mathcal{PL}[p_i]| > 1$* **do**
26  Find a cycle $(p_i, q_i, p_{i+1}, q_{i+1}, \dots q_{s-1}, p_s = p_i)$, where
27  $q_i$ = second preference in $\mathcal{PL}[p_i]$ and$p_{i+1}$ = last preference in $\mathcal{PL}[q_i]$
28  Remove $q_i$ from$\mathcal{PL}[p_{i+1}]$ and$p_{i+1}$ from $\mathcal{PL}[q_i] \forall i$
29 **end**
30 return matching if $\nexists$ a user $i$ with $|\mathcal{PL}[i]| > 1$

**Table 3**
Optimal charging decisions in each charging scenario.

| Scenario | Charging sessions | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|---|
| Conservative | **A's decisions** | 1 | 1 | 1 | 0 | 1 | 0 |
| | **B's decisions** | 0 | 1 | 1 | 0 | 1 | N/A |
| Cooperative | **A's decisions** | 1 | 1 | 0 | 1 | 0 | 0 |
| | **B's decisions** | 0 | 1 | 0 | 1 | 1 | N/A |

**Table 4**
Charging decisions for each decision block in cooperative case.

| Decision blocks | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| **Energy (B $\rightarrow$ A)** | 0 | 19 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **A's decisions** | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 0 |
| **Energy (A $\rightarrow$ B)** | 0 | 0 | 0 | 0 | 0 | 5 | 0 | 0 | 0 | 4 |
| **B's decisions** | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 0 |

In conservative scenario, the results show that node A could have skipped 4th and 6th charging blocks, while node B could have skipped its 1st and 4th blocks (skipping 1st and 3rd would also be optimal). This results in a total of 4 skips for both nodes.

In cooperative charging scenario, out of 10 decision blocks, user A is able to skip 6 of them. However, not all of these are independent decisions as well as some of these decision blocks with skip decisions have only discharging. Thus, there is no skipping of actual charging. Similarly, for user B, 7 of them can be skipped.

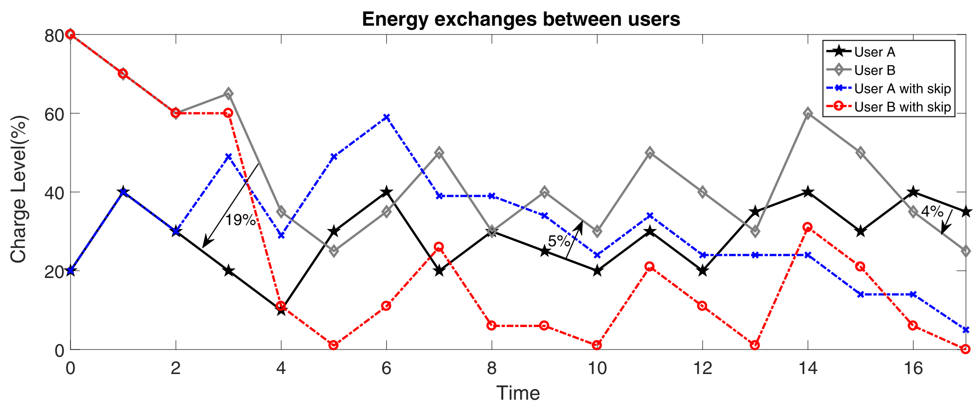


**Fig. 4.** Charging patterns and skips after cooperative charging. Arrows show the direction and the amount of energy shared between the users.

Note that there are multiple energy exchanges between users in order to get to the optimal point. As the decision blocks do not correspond to the actual individual charging cycles of users, the skipping decisions for each decision block have to be converted to the skipping pattern for charging cycles. From Fig. 4 and Table 4, we can deduce the original charging decision sequence for user A and user B shown in Table 3. This results in a total of 5 skips for both nodes, showing the advantage of cooperative P2P sharing over conservative case. To achieve that both node A and B share energy between each other and receive energy from each other. Fig. 4 shows the charging patterns after the optimal skips are done. Here, we assume that when a user skips a wall charging, a minimal/zero discharge happens during that duration in this example, however, a discharge could have been applied with an average discharging rate during a skipped charging sessions and algorithms could be updated accordingly.

### 6.2. Empirical results

#### 6.2.1. Datasets

Mobile devices should be in close proximity to be able to transfer power. In order to see the potential benefit of the proposed P2P energy sharing for charging relief of users in real settings, we have used several mobile network datasets with meeting patterns of user devices. These datasets mainly contain the logs of device-to-device (D2D) interactions of different types of wireless devices carried by people. While the D2D communication range is in the order of several meters, such interactions could be considered as an indication of users seeing each other and potentially asking for energy exchange from each other. Each of these datasets represents a different environment with a different number of users and durations [26]:

- **Haggle dataset:** [27] These are the Bluetooth sightings recorded between the iMotes carried by 41 attendants of Infocom Conference held in Miami in 2005. It spans a four day period.
- **Cambridge dataset:** [28] These are the Bluetooth recordings among 36 students with iMotes from Cambridge University for a duration of almost two months.
- **MIT Reality dataset:** [29] It consists of the mobility traces of 97 Nokia 6600 smart phones carried by MIT students and staff during an academic year. We used data from the three month period of Spring semester.

While the above datasets provide information about the meeting patterns of users, they do not include battery charge level information of the devices. Assuming that the battery energy levels of the devices are independent from the contact patterns of their users, we use another dataset to extract that information and combine charging and meetings patterns of user devices using the time domain of these datasets.

- **DeviceAnalyzer dataset** [30]: It includes all kinds of logs of Android users who downloaded the app worldwide. For the experiment, we have extracted 9 days of battery charging status information from 40 users.

Having these datasets, we have used the following methodology to merge the charging and meeting patterns of users from different datasets. We first extract the meeting count distribution among pairs (Fig. 5a), the hourly meeting time distribution in a day (Fig. 5b) and the meeting duration distribution among all meetings (Fig. 5c). Then using the 40 users data from DeviceAnalyzer [30] with charging patterns, we assign them meetings from the aforementioned meeting count, time and duration distributions. Note that the user meeting patterns from different datasets are different from each other. In general, users in Haggle dataset have the highest number of daily meetings with the shortest durations. However, as expected naturally, the meeting time distributions are similar (e.g., with the highest frequency around lunch time).

#### 6.2.2. Simulation results

We first run the conservative charging algorithm for each of the 40 users and collaborative charging algorithm for each of the 780 pairs of nodes to obtain the mobile charging relief in each case (with $\mathcal{T}_S = 1\%/\text{min}$ and $\mathcal{T}_E = 1$). Each of the results here is the average of 10 different runs. Fig. 6 shows the CDF of the relief among all users and pairs for conservative and collaborative charging, respectively. Note that each cooperative charging result with different dataset used for meeting pattern generation is shown with a legend of the corresponding dataset. The results show that almost half of the users can not have any charging relief with conservative charging, while there are some users who can obtain up to 50% relief. In collaborative case, only in a few of the pairs, users cannot experience any relief. Moreover, the number of users that can experience high relief increases remarkably thanks to the power of sharing. Comparing the collaborative charging results obtained with different datasets, we observe that users obtain the highest relief with Haggle dataset while the lowest relief is obtained with MIT dataset. This is because in Haggle dataset users have more meeting than in others, which then provides more energy exchange opportunity to users yielding higher charging relief. MIT data has the smallest number of meetings. Even though the durations are longer than in other datasets, due to the fewer number of meetings, the lowest relief is obtained. However, it is still more than the relief users can achieve by conservative charging. Cambridge dataset has characteristics in between the other

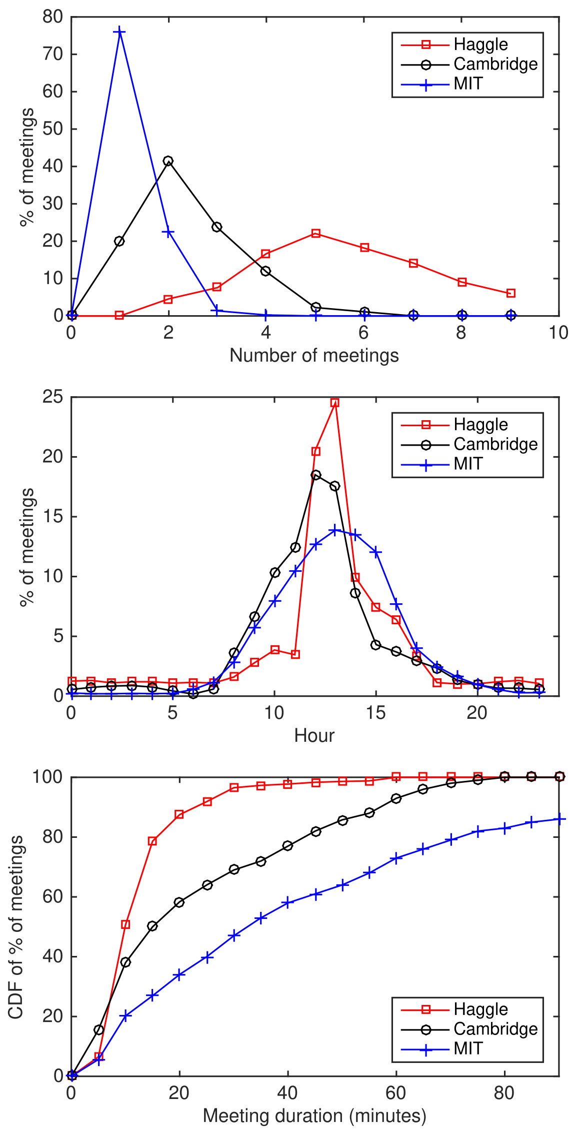


**Fig. 5.** Statistics from real mobile network traces: (a) distribution of number of meetings between pairs of nodes, (b) hourly distribution of meeting times between nodes during a day, and (c) distribution of meeting durations.

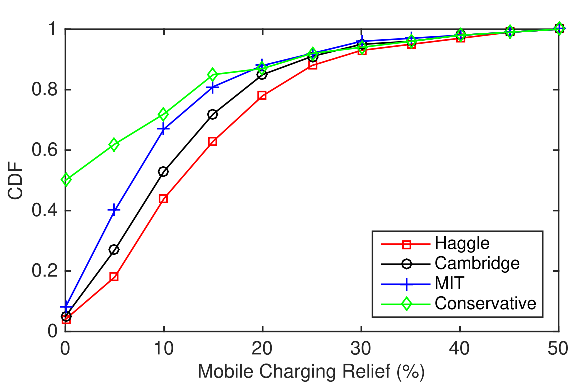


**Fig. 6.** CDF of mobile charging relief obtained among all users and pairs with conservative and collaborative charging, respectively.

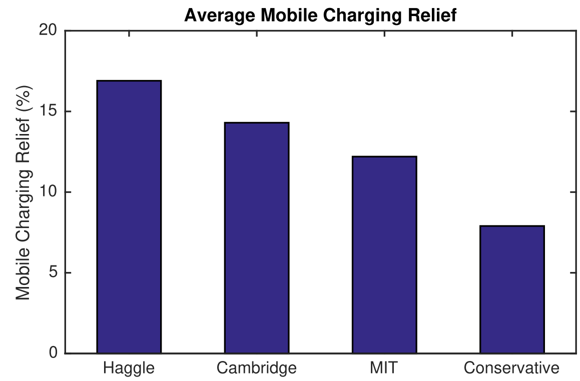


**Fig. 7.** Average mobile charging relief with conservative and different collaborative charging cases.

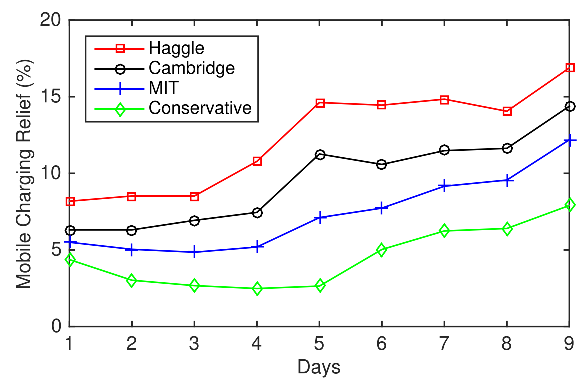


**Fig. 8.** Average mobile charging relief with different number of days of data used.

two datasets. Thus, a performance in between their performance is obtained.

In Fig. 7, we show the average mobile charging relief obtained for users in the network with conservative and collaborative charging. For collaborative charging, the results show the average relief obtained by users assigned after running optimal charging partner assignments in Algorithm 3. Results with Haggle dataset shows the highest average relief due to the aforementioned reasons. This is also the double of the relief users could experience with conservative charging only.

Next, to understand the impact of data size on the results, we obtain average charging relief with fewer than 9 days of Device-Analyzer dataset. Fig. 8 shows these results. Here, each data point indicates the cumulative usage of dataset. For example, results at point 5 shows the results obtained with 5 days of data from the beginning. The results show that the average user charging relief remains somewhat constant after a few days, given the same meeting patterns. The jump on the last day and the small savings in the first 3 days are due to the impact of partial charging/discharging sessions included in these end cases. We also observe that most of the users have discharging only sessions during the first day, which reduces the average charging relief for all users in the network. Similarly, for the last charging cycle, most of these cycles have only the portion of their charging session without any discharging. Thus, most of these last charging sessions are skipped easily increasing the average relief for the 9 day result.

Fig. 9 shows the impact of transfer efficiency and speed on average mobile charging relief in Haggle dataset. As expected, the results clearly show that the relief will increase if the wireless energy sharing between devices is more efficient (when $\mathcal{T}_S = 1\%/\text{min}$). The figure also shows that when the transfer speed is 0, it is equal to the conservative case results but when the trans-

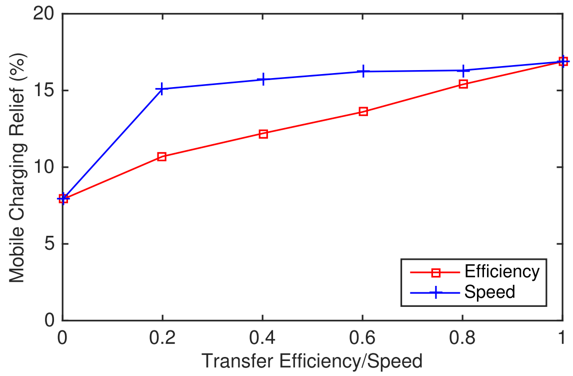


**Fig. 9.** Impact of wireless power transfer efficiency and speed on the average mobile charging relief.

fer speed increases, there is a significant gain in charging relief (when $\mathcal{T}_E = 1$). However, the result is not increasing linearly because contact duration becomes dominant and optimal energy that is exchanged within the decision block does not change much. A slower but efficient transfer also performs well.

## 7. Conclusion

In this paper, motivated by the recent technologies enabling wireless energy sharing between mobile devices, we investigate to what extent the burden of charging process on users could be released. We develop a dynamic programming based optimization model and find out the minimum number of charging sessions that would be sufficient for users to keep their devices with the power they need through utilization of excessive energy from other users in the vicinity. We first study both conservative and collaborative charging. Then, in order to achieve a network-wide charging relief among a group of users, we map our problem to roommate matching problem and find out the best matching among users that will achieve the highest network-wide relief while satisfying all users with their assigned partners. With the empirical results based on different datasets of user meetings and charging patterns, we observe that users can achieve up to 13–17% relief without affecting their existing usage habits of mobile devices. In our future work, we will embed an online charge sharing algorithm among peers using the predictions of charging and meeting patterns in mobile social networks [31,32]. Moreover, we will study a market mechanism and pricing for energy exchanges for the environments with users that do not know each other.

## Conflict of interest

None.

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