Mobile charging relief using wireless energy sharing

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By the utilization of wireless energy we shall 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 that could be maintained within an acceptable level. At first we use dynamic programming-based optimization to find out the minimum number of cord-based charging sessions to obtain the highest possible mobile charging relief by collaborative charge sharing among pairs of nearby user devices. Next, 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.

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.

By the integration of wireless charging 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 with integrated wireless power transmitter capability.

However, the charging pad still needs to be connected to a power source.

we investigate the potential benefit of P2P energy sharing between mobile devices on reducing the burden of traditional cord-based charging process (referred to as *wall charging* from now onwards).

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 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.

Related work

Most of the users charge their devices opportunistically with short charging sessions and more frequently than they really need to keep their devices with as much power as possible.

- The proposed *collaborative charging* scheme aims to benefit from the current charging habits of users.
- Thus, in order to understand to what extent collaborative charging offers relief(i.e., percentage of reduction in the number of wall chargings) ,
- We 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.
- We use the following notations:

Notation	*Description*
$\delta_c(i)$	*i th charging session of user.*
$\delta_d(i)$	*i th discharging session of user.*
$\delta_A c[t]$	Total energy gained by user *A during wall charging in t th decision block.*
$\delta_A d[t]$	Total energy lost by user *A during discharging in t th decision block.*
$S_{A\rightarrow B}$	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.
$X_A(t)$	**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.*
U_A	The total unplugged time of user *A in t th decision block.*
$M_{A,B}$	The meeting event between users *A and B in t th decision block.*
$\mathbf{T}_s$	**The speed of energy transfer between users.**
T_E	The efficiency of energy transfer.
n_A	Number of charging sessions of user *A* .
$R_A(B)$	User A's charging relief from collaborative charging with user *B* .
$J(R_A(u\ i))$	Energy saving with charging skip pattern associated with R *A (u i)* .
$P_L[A]$	Preference list of user *A to be matched with other users for collaborative charging.*

Problem Statement

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 δ_c and δ_d denote the set of all charging and discharging sessions for a user, respectively:

$\delta_c = \{\delta_c(1), \delta_c(2), \ldots, \delta_c(n)\}$

$\delta_d = \{\delta_d(1), \delta_d(2), \ldots, \delta_d(n)\}$ where,

$\delta_d(i).l_s = \delta_c(i).l_e, \forall i \in \{1 \ldots n\}$ and

$\delta_c(i+1).l_s = \delta_d(i).l_e, \forall\ i \in \{1 \ldots (n-1)\}$

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 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.

That is, they do not want to change their regular movement patterns and their own usage of the device.

The optimization problem is studied for two different cases :

(i) conservative charging

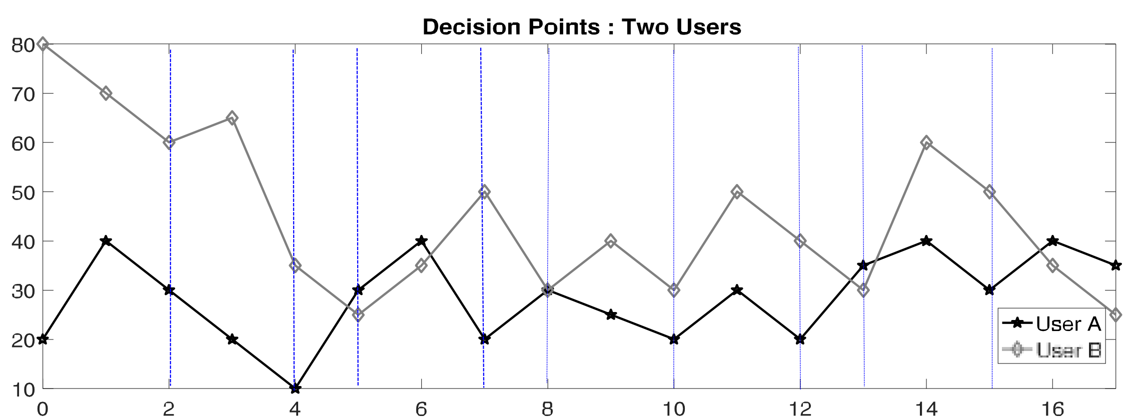
(ii) cooperative charging

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. 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).

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.

Fig1:Charging patterns and decision points of two users



Conservative charging

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 δ_c [t] and δ_d [t] denote the total energy gained (i.e., δ_c (t). l e − δ_c (t). l s) during wall charging and total energy lost (i.e., δ_d (t). l e − δ_d (t). l s) during dis- charging throughout the t th decision block.

The objective function in conservative charging is then formally described as: min n t=1 X t (1) subject to D t . l_e = (D t . l_s + δ_c [t] X t − δ_d [t]) } , ∀ t ∈ [1 , n] (2) D t . l_e ≥l min , ∀ t ∈ [1 , n] (3) D 1 . l_s = δ_c (1) . l_s (4)D t+1 .l s = D t . l_e ∀ t ∈ [1 , (n −1)] (5) where, l_{min} is the minimum acceptable level (e.g., 1%) and X t is the charging decision variable ∈ {0,1}, with 0 meaning the current charging session is skipped.

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

 Issn No : 1006-7930

	Full/None	First-Split	Mid-Split	Last-Split
Full/None	(0,0)	(0, $X B t$)	($X B t$, $X B t$)	($X B t$, 0)
First-Split	(0, $X A t$)	N/A	N/A	($X B t$, $X A t$)
Mid-Split	($X A t$, $X A t$)	N/A	N/A	N/A
Last-Split	($X A t$, 0)	($X A t$, $X B t$)	N/A	N/A

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).

In Table 1 , we provide (source, destination) index assignments at the fourth dimension of D matrix with different decision block type combinations.

Table1:(Source, destination) index assignments for D matrix's fourth dimension based on charging decisions of users with different types of decision blocks.

The valid combinations have to be carefully analyzed towards the solution.

Let $\delta_A c[t]$ and $\delta_A d[t]$ denote the total energy gained by user A during wall harging and total energy lost by user A during discharging throughout the t th decision block.

Moreover, let $S_{A \to B}\, t$ denote the energy shared from A to B during the t th decision block and T_E denote the efficiency of transfer.

The objective unction in cooperative charging is then formally described as:

$$\min \sum_{t=1}^{n} X_A t + X_B t \qquad \textbf{(6)}$$

subject to $D\,A\,t{+}1\,.l_e = D\,A\,t\,.l_s + \delta A\,c[t]\,X_A t - \delta A\,d[t] + T_E\, S_{B \to A}\, t - S_{A \to B}\, t$ **(7)**

$D_B\, t{+}1\,.l_e = D_B\, t\,.l_s + \delta B\,c[t]\,X_B t - \delta B\,d[t] + T_E\, S_{A \to B}\, t - S_{B \to A}\, t$ **(8)**

$D\,k\,t\,.l_e \geq l\,\min \ \forall\, t \in [1, n], \forall\, k \in \{A, B\}$ **(9)**

$D\,k\,1\,.l_s = \delta k\,c(1)\,.l_s \ \forall\, k \in \{A, B\}$ **(10)**

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

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

Dynamic programming

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.

Optimization for cooperative 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 (δ_c []), and the list of discharging amounts (δ_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.

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 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 mini- mum 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.
Once the algorithm finishes, we apply a general solution read- out approach to find the actual wall charging sessions used.

Algorithm 1:

Input: δ_c[]: Charging amounts; δ_d []: discharging amounts
Output: Number of minimum wall charging sessions for the user
for each decision block Dt do
    for each charging level $0 \le l \le 100$ do
        current = D[t][l]
            for each $X_t \in \{0, 1\}$ do
                $l_{new} = \min(100, l + \delta c[t]X_t) - \delta d[t]$
                if $l_{new} \ge l\min$ then
                    if current+X_t < D[t+1][l_{new}] then
                        D[t+1][l_{new}] = current+X_t
                        T[t+1][l_{new}] = 1
                    end
                end
            end
    end
end
return min { D [n][l] $\forall$ l $\ge$l min }

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 skipped.

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.
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 U_A t denote the total unplugged time of user A in decision block t ∈ {1, 2, . . . , n}. The charging session in a decision block will always be earlier than the discharging session within the block by definition of blocks. U_A t 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.

Let U_A t denote the total unplugged time of user A in decision block t ∈ {1, 2, . . . , n}. The charging session in a decision block will always be earlier than the discharging session within the block by definition of blocks.

U_A t 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.

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 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. 2 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.

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.

Table 2 shows the optimal charging decision results for both cases.

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 2: optimal charging decisions for each scenario

In conservative case, decision blocks consist of charging cycles. In collaborative charging the number of decision blocks is more than the actual charging cycles. Table 3 shows the actual decisions made for each decision block in collaborative charging. In conservative scenario, the results show that node A could have skipped 4 th and 6 th charging blocks, while node B could have skipped its 1 st and 4 th blocks (skipping 1 st and 3 rd 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

To achieve that both node A and B share energy between each other and receive energy from each other.

Fig. 2 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. We have used the following methodology to merge the charging and meeting patterns of users from different datasets.

Algorithm 2: Cooperative charging decision pattern algorithm.

Input: $\delta_{\mathbf{c}}[]/\delta_{\mathbf{d}}[]$: Charging/discharging amounts; M[]: meeting patterns

Output: Number of minimum total charging sessions for both users.

for *each decision block* D_t **do**

  for *each charging level* $0 \leq \mathbf{l_A} \leq 100$ **do**

    $(c_A, c_B) \leftarrow$ Decide the charging types for both users

    for *each charging level* $0 \leq \mathbf{l}_{\mathbf{B}} \leq 100$ **do**

      for *each* (X_{At}, X_{Bt}) *case* **do**

        $I_{A,Bt} \leftarrow$ Max duration for energy exchange with (c_A, c_B)

        $(sc, dt) \leftarrow$ Fourth dimension indexes based on current case

        for *each* $0 \leq k \leq I_{A,Bt}$ **do**

          $\overrightarrow{A} = \min(100, l_A + \delta_{Ac}[t]\, X_t) - k^* T_S - \delta_{Ad}[t]$

          $\overleftarrow{B} = \min(100, l_B + \delta_{Bc}[t]\, X_t) + (k^* T_S{}^* T_E) - \delta_{Bd}[t]$

          $\overleftarrow{A} = \min(100, l_A + \delta_{Ac}[t]\, X_t) + (k^* T_S{}^* T_E) - \delta_{Ad}[t]$

          $B = \min(100, l_B + \delta_{Bc}[t]\, X_t) - k^* T_S - \delta_{Bd}[t]$

          for *each* $(l_A, l_B) \in \{(\overrightarrow{A}, \overleftarrow{B}), (\overleftarrow{A}, \overrightarrow{B})\}$ **do**

            if $l_A \geq l_{\min}$ *and* $l_B \geq l_{\min}$ **then**

              new = $D[t][l_A][l_B][sc] + X_{At} + X_B$

              if *new* $< D[t+1][l_A][l_B][dt]$ **then**

                $D[t+1][l_A][l_B][dt]$ = new

                $T[t+1][l_A][l_B] = (l_A, l_B, sc, k)$

              end

            end

          end

        end

      end

    End

  End

End

return $\min\{D[n][l_A][l_B][0]\ \forall\ l_A, l_B \geq l_{\min}\}$

Decision blocks	1	2	3	4	5	6	7	8	9	10
Energy (B → 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 → B)	0	0	0	0	0	5	0	0	0	4
B's decisions	0	0	0	1	0	0	1	0	1	0

Table 3: Charging decisions for each decision block in cooperative case.

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
Optimal charging decisions in each charging scenario.

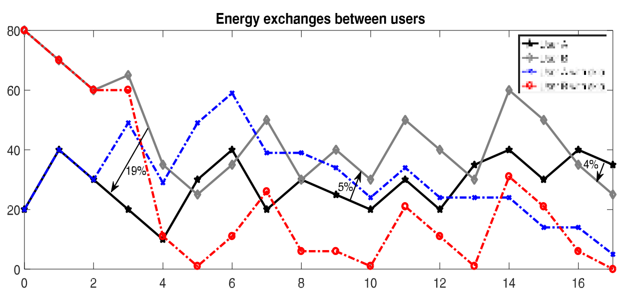


Fig.2. Charging patterns and skips after cooperative charging. Arrows show the direction and the amount of energy shared between the users.

Fig.3 shows the impact of transfer efficiency and speed on average mobile charging relief in dataset. As expected, the results clearly show that the relief will increase if the wire- less energy sharing between devices is more efficient (when T S = 1%/min). The figure also shows that when the transfer speed is 0, it is equal to the conservative case results but when the transfer speed increases, there is a significant gain in charging.

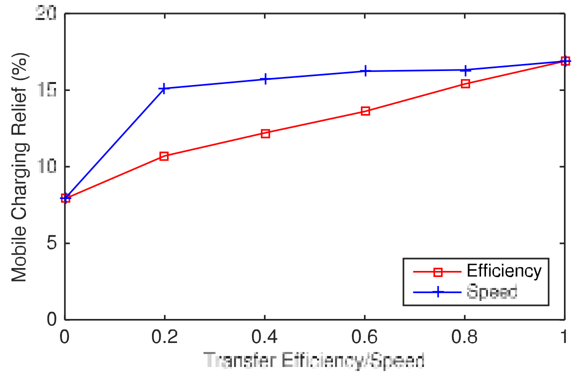


Fig.3. Impact of wireless power transfer efficiency and speed on the average mo- bile charging relief.

Conclusion

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.

References

[1]T. Zou , W. Xu , W. Liang , J. Peng , Y. Cai , T. Wang , Improving charging capacity for wireless sensor networks by deploying one mobile vehicle with multiple removable chargers, Ad Hoc Netw. 63 (2017) 79–90 .

[2] L. Xie , Y. Shi , Y.T. Hou , W. Lou , H.D. Sherali , S.F. Midkiff, On renewable sensor networks with wireless energy transfer: the multi-node case, in: Proc. SECON, IEEE, 2012, pp. 10–18 .

[3] E. Bulut , B.K. Szymanski , Mobile energy sharing through power buddies, in: Wireless Communications and Networking Conference (WCNC), 2017, IEEE, 2017, pp. 1–6 .

[4] A. Dhungana , E. Bulut , Energy sharing based content delivery in mobile social networks, in: 2019 IEEE 20th International Symposium on"A World of Wire- less, Mobile and Multimedia Networks"(WoWMoM), IEEE, 2019, pp. 1–9

[5] M.A. Hoque , S. Tarkoma , Characterizing smartphone power management in the wild, in: Proceedings of the 2016 ACM International Joint Conference on Per- vasive and Ubiquitous Computing: