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Mobile Energy Sharing through Power Buddies

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***Abstract*—Fueled by users' demand, mobile devices are becoming more complex, increasing their power requirements. However, the battery technology is advancing slower than demand which results in shrinking battery lives (i.e., currently around a day). Hence, users need to charge their devices frequently, mostly by tethering them to a cord. Anxiety of losing power in the middle of a critical task during which users may not have access to charging facilities have increased interest in opportunistic charging with the aim of keeping the devices with as much power as possible.**

Recently power sharing technologies and gadgets have emerged enabling harvesting power from other mobile devices in the user's vicinity. In this paper, we discuss the energy sharing in mobile social networks whose nodes are human-carried mobile devices operating on batteries. We investigate the limits of power sharing among mobile devices by analyzing their current charging patterns and the social (i.e., close-proximity) interactions between the people carrying these devices. Moreover, we propose an energy sharing model by pairing the nodes in a mobile network into power buddies. Simulation results show that a typical application scenario of energy sharing among power buddies provides a remarkable amount of saving in the utilization of power available in the entire network.

***Index Terms*—Mobile social network, energy exchange, pairwise relations.**

I. Introduction

Today, we live in a world where billions of people use mobile devices including smartphones, laptops, and tablets all over the globe [1]. The increasing adoption of wearables (e.g., smart watches and glasses) enlarges this eco-system to the new levels. The various functions (e.g., making a phone call, sending email, listening music, finding location) offered by these devices increase day by day and make our lives easier. While this ignites the proliferation of the usage among more people, it also makes us increasingly dependent on these devices. According to a recent study [2], nearly three-quarters of adults in U.S. report that they keep their smartphones within five feet most of the time and they admit that they use their phones in unusual places (e.g., while driving (55%), in shower (12%)). Another study [3] shows that 74% of all Americans have used their cell phones in an emergency situation, from small predicaments to car accidents. All these clearly show the massive appeal of mobile phones. However, these devices are battery-powered and they need to be recharged regularly, most often by being tethered to a power cord.

The improvements in battery technology could not match the growing energy demands emerging from increasingly complex capabilities of mobile devices. The average battery life of smartphones with normal usage is around a day [4]. Since battery management is critical to keep the device operational, there are many apps (e.g. [5]) that let users understand the distribution of battery usage among their applications or interfaces (e.g., networking, sensors) and help reduce the power consumption to prolong the battery life. Power packs [6], solar chargers [7] or other eco-friendly chargers like mobile hand generators [8] offer other solutions that can mitigate the risk of facing a depleted battery situation. However, they come with the expense of carrying such accessories and provide only limited solutions. Thus, as a recent survey shows, the most demanded feature of future mobile devices is still a longer battery life [9].

Due to the short battery lives in smartphones, it is inevitable that one can face a situation in which a critical task such as making an emergency phone call, sending a business related email or reaching a contact information in the device may not be performed. Moreover, a recent analysis [10] on battery charging habits of users show that there are many users who charge their devices opportunistically (i.e., with short durations and frequently) and try to keep their devices with as much power as possible. This is due to the anxiety of losing power in the middle of a critical task without access to charging facilities. However, an alternative way of powering up mobile devices is utilizing the power of other devices belonging to the user or other people. As it is very unlikely that all such devices in the vicinity will deplete their battery at the same time, such a power sharing solution could be a promising remedy especially in emergency situations in which even a small amount of charge could be sufficient to perform the urgent task. However, there are challenges of incentivizing the users and minimizing the burden of such operation on users.

Power sharing between mobile devices could be achieved by power sharing cables [11], power equalizer gadgets [12] and through wireless power transfer (WPT) technologies [13], [14]. A recent study [14] showed that current wireless power transfer technology can be utilized to easily create an on-the-go power sharing system between mobile devices. This basically transforms power from a personal resource at phone batteries to a tradable commodity. As the process of transferring power between devices can create privacy concerns, the most practical application scenario could be between friends and families. However, once such concerns are addressed and monetary incentives are provided, strangers could also benefit from this technology because even a short duration of energy sharing could extend a critical task (e.g., 12 seconds of charging will enable one minute call or two minutes of charging can support 4 minutes of video watching [14]).

In this paper, we study *mobile social energy networks*, in which users can share their battery powers with other mobile devices. Our contributions are (i) analysis of current battery charging habits of users and finding inefficiencies, (ii) analysis of social interactions between users in terms of power sharing opportunities, and (iii) finding out the potential saving in a mobile social energy network through assigning users to each other as power sharing buddies. We do not assume a particular power sharing method. But in our model and simulations, we consider efficiency and speed of the process of power transfer.

The rest of the paper is organized as follows. We discuss the related work in Section II. In Section III, we analyze the current charging and contact patterns of mobile users using different datasets. In Section IV, we discuss the proposed system model and provide a solution. In Section V, we describe the simulation setting and evaluation of proposed system using real mobile social network traces. Finally, we end up with conclusion in Section VI.

II. Related Work

Recently, the concept of power transfer between mobile devices has attracted a lot of attention. It has been studied in sensor networks [15], [16] where mobile charger nodes (i.e., robots, vehicles) with high volume batteries deliver energy to sensor nodes (mostly wirelessly) to prolong their lifetime. Moreover, it has been shown [17] that collaboration among mobile chargers by transferring power between each other can increase the network lifetime further.

In the context of mobile social networks (MSN), most of the studies focus on providing efficient solutions for the routing of messages [18]–[21], content distribution [22], and security [23]. However, energy sharing among nodes has not yet been much focused in MSNs. The closest works to our paper are [24] and [25]. In [24], authors study the problem of finding a subset of nodes in a mobile social network which will be in the charge of providing power to other nodes through the interaction with them such that the other nodes will not need to worry about charging their devices individually. However, these nodes are assumed to have a secondary high capacity battery units that will be used to provide power transfer to others. This will be impractical as there should be good incentives for such nodes to carry such additional storage. In [25], authors study the sharing of energy between friends in a mobile social network to improve the data delivery and content dissemination. Their focus is on content delivery performance and they do not base their model on charging patterns of nodes and the interactions between nodes, which may not be practical.

Understanding the battery consumption and charging habits of users has also been actively studied [26]–[28]. Several studies have been conducted on the real datasets [10], [29] consisting of information from various types of mobile phones.

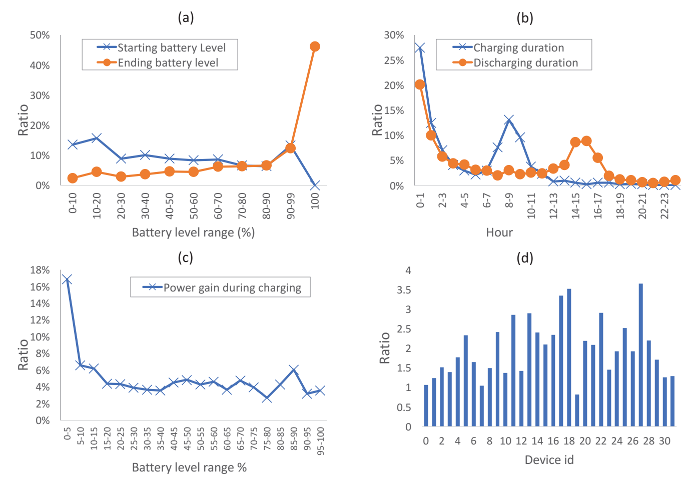

Fig. 1: Statistics showing mobile device charging behavior: a) starting and ending battery energy levels in charging and discharging, b) distribution of charging and discharging durations, c) distribution of gained energy levels during charging and d) efficiency in the usage of stored energy during charging.

Results show large variations in charging habits and interesting patterns. For example, users prefer opportunistic and frequent charging even when their charge levels are still high [10], [30]. Spatio-temporal analysis show that most users' charging behavior is mainly determined by time and location, not by remaining battery levels [31]. In this paper, we analyze the charging behaviors of users together with their interaction to exploit and understand the limits of power sharing among mobile devices.

III. Mobile Data Analysis

A. Energy Utilization

In this part, we analyze the charging behavior of mobile devices to understand how efficiently the power of their batteries is utilized. To this end, we analyze the battery usage and charging patterns of 100 same brand (i.e., Nexus) smartphones in a dataset presented in [32]. Figure 1 shows some of the collected statistics. The first graph shows that users are slightly more likely to start their charging devices with low battery level (i.e., 0-20%), but with uniform likelihood at other battery levels. Around 50% of charging events end with full charge (i.e., 100%). The second graph shows that charging durations are most often limited to 0-2 hours, but it can take up to 8-9 hours when the devices are left plugged over-night (even though there is no benefit of keeping them plugged after fully charged). The discharging takes mostly around 14-15 hours but due to the opportunistic charging behavior, short discharging durations also happen which make their likelihood even higher. The third graph also shows the opportunistic charging behavior as the amount of 0-10% battery level gain is highest and the rest of the battery levels has similar ratios. We discuss the fourth graph as we explain what is calculated there at the end of the section.

We define a charging event $C = (l_s, l_e, t_s, t_e, t_f)$ as a 5-tuple with l_s and l_e as the starting and ending charge levels (i.e. percentage of current battery capacity charged), and t_s and t_e as the start and end times of charging activity. Note that some users may leave their devices plugged (e.g., overnight) even it is fully charged (see the bump in 8-9 hours in Figure 1-b). Thus, in order to accurately model charging behavior in such cases, we use another parameter t_f to denote the time when the battery is fully charged. When the charging event does not end with full charge (i.e., $l_e < 100\%$), t_f is set to ∞. Similarly, we denote a discharging event with $D = (l_s, l_e, t_s, t_e)$. Here, we do not need an additional parameter analogous to t_f to denote the first time the battery depleted (i.e., battery level became 0%), because the device cannot record battery level after its battery is depleted and the last time of record will show last battery level and the time before the device lost its power (in other words, we will be ignoring the times when the devices are out of power).

The historical changes on a mobile device's power could be defined as the set of alternating charging and discharging events, where the previous event's end charge level becomes the current event's starting level.

$$\begin{aligned} U &= \{C_1, D_1, C_2, D_2, \ldots, C_n, D_n\} \text{ where} \\ & \quad C_i.l_e = D_i.l_s \text{ and } D_i.l_e = C_{(i+1)}.l_s, \forall i \in \{1..n\} \\ & \quad C_i.t_e = D_i.t_s \text{ and } D_i.t_e = C_{(i+1)}.t_s, \forall i \in \{1..n\} \end{aligned}$$

The charging rate of a device depends on various factors including the model of the device, type of battery, and the gadget (e.g., cord or wireless) and connection type used (e.g., usb, ac, inductive). Similarly, the discharging rate of a device will depend on how actively it is used, which is influenced by several factors including the number of apps, addiction of its user to its phone etc. We calculate each device's average charging rate (λ_c) and discharging rate (λ_d) as follows:

$$\begin{aligned} \lambda_c &= \left(\sum_{i=1}^{n} \frac{C_i.l_e - C_i.l_s}{\min\{C_i.t_e, C_i.t_f\} - C_i.t_s} \right) / n \\ \lambda_d &= \left(\sum_{i=1}^{n} \frac{D_i.l_e - D_i.l_s}{D_i.t_e - D_i.t_s} \right) / n \end{aligned}$$

In order to understand the efficiency in charging habits of users, we first need to describe what an optimum charging would be within the constraints of a user and device. To this end, we define a perfect charging cycle, $P = \{C_{avg}, D_{avg}\}$, consisting of a charging event from 0% to 100% with average charging rate and a discharging event from 100% to 0% with average discharging rate. More formally:

$$\begin{aligned} C_{avg} &= (0, 100, t_s, t_s + 100/\lambda_c, t_s + 100/\lambda_c) \\ D_{avg} &= (100, 0, t_s + 100/\lambda_c, t_s + 100/\lambda_c + 100/\lambda_d) \end{aligned}$$

Then, the wastage in charging behavior (i.e. how inefficiently the energy stored in the device's battery is used) of a user in a time frame $[T_1, T_2]$ could be defined as the ratio of total power received during all charging events to the total power needed if a perfect cycle of charging and discharging events would happened during $[T_1, T_2]$.

$$\mathcal{W}_{T_1}^{T_2} = \frac{(\lambda_c + \lambda_d)}{(T_2 - T_1)\lambda_c \lambda_d} \left(\sum_{\forall C_i \in [T_1, T_2]} C_i.l_e - C_i.l_s \right)$$

We calculated this wastage value ($\mathcal{W}$) for 31 of the users in the dataset who had at least 50 charging events and plotted the results in Figure 1-d. As the figure shows, the wastage varies for different users, but on average energy gained during current user behaviors is about two times higher compared to what they would really need with perfect charging and discharging cycles. Even though it will be very impractical for a user to follow a perfect charging behavior, we consider it to understand to what extent the users could get close to these limits while sharing their power with other users within the constraints of their devices (e.g. charging/discharging rates).

B. Energy Exchange Opportunities

For mobile devices to be able to exchange power, they should be in close proximity. In other words, the people carrying these mobile devices should be interacting. In order to quantify such a social interaction between people, in this part, we analyze the meeting patterns of mobile devices from several mobile social network datasets. These datasets mainly contain the logs of device-to-device (D2D) interactions of different type of wireless devices carried by people. Bluetooth, WiFi or similar short range protocols are used to detect the mobile devices that are in close enough proximity to be able to communicate with each other. Such a close relationship can also be indicative[1] of an opportunity of transferring power between the devices of these users. Thus, in this part, using the traces of mobile devices, we analyze the social relations of the people carrying mobile devices to understand potential of energy exchange opportunities.

We assume that if there are no other restrictions, each of the nodes with larger battery energy level is willing to share its power with a neighbor until their battery energy levels will be equalized. Thus, to calculate the expected value of the potential power exchanges between two devices, we can calculate the expected value of differences of battery percentages when two mobile devices encounter each other. Let X denote the discrete distribution function (with $p(x)$ showing pdf at x) of battery energy level at a specific time period (i.e. hour) and let Z denote the distribution function of absolute difference $Z = |X_1 - X_2|$ where X_1 and X_2 are two different statistically independent instances of X. Then:

$$E[Z] = \sum_{k=0}^{100} \left(\sum_{x=k}^{100} p(x)p(x-k) + \sum_{x=0}^{100-k} p(x)p(x+k) \right)$$

[1] As the communication range can be in the order of several meters, the ability of devices to communicate does not mean they can do power transfer at the same distances. However, with an additional small effort (i.e., getting closer) the users can make their devices exchange power through cables or wireless power transfer.

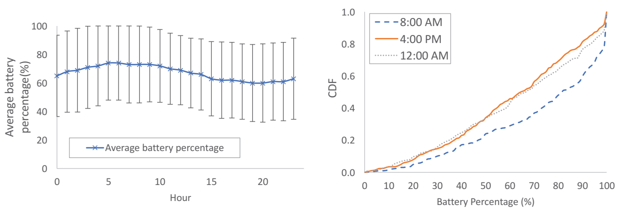

Fig. 2: Average battery level at every hour and its distribution.

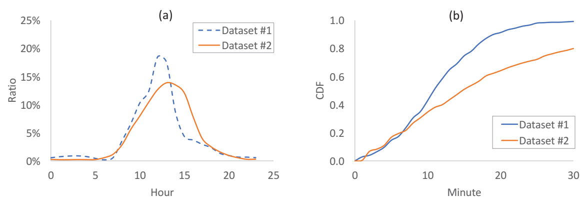

Fig. 3: Empirical results from real mobile social network traces: a) distribution of contact times between nodes during a day b) total daily contact duration distribution for all pairs of nodes.

We calculated the battery level distributions and the averages at every hour during a day using the same smartphone dataset [32]. Figure 2 shows both the average values with error bars showing the standard deviation and distribution of battery percentages at three different hours (i.e., 8 am, 4 pm and 12 am). Note that the average battery percentages are very close to each other during the day. However, the standard deviation is very high (i.e. 24-29%). During the night, people charge their devices, thus highest average battery values are achieved between 5-8 am. On the other hand, usage during the day causes average value to go down. The smallest average values are achieved between 4-8 pm. Therefore, the distribution in 8:00 am has incline towards larger battery level percentages. When we calculate $E[Z]$ in these three hours, we observe a range of [29-33]%. This value will be one of the factors that will determine the amount of energy exchanges. Contact durations and frequencies between nodes as well as possible limitations on the amount of energy the nodes want to share, the efficiency and speed of transfer will all affect the final transfer amount. As the smartphone dataset we analyzed do not include information about node interactions (and we are not aware of any dataset including both at the same time), we analyzed two mobile social network traces (#1: Cambridge [33], #2: MIT Reality mining [34]). Assuming that the battery energy levels of the devices are independent from the contact patterns of their users, we use time domain to establish a relation between them from different datasets. Figure 3-a shows the distribution of all contact times (i.e., hour) of nodes with each other. As expected, most of the meetings in both datasets happen during day time (8 a.m. to 5 p.m.) and especially during lunch. During these time frames the average battery values of nodes could differ around 10-11% (Figure 2-a). Moreover, from the distribution shown in Figure 3-b, we observe that most of the pairs have around 10-30 minutes of total daily contact time. Thus, the total contact duration could be limiting factor in some cases.

IV. Proposed System and Solution

In order to use the power in a mobile network efficiently, we propose the sharing of power between users' mobile devices. In previous section, we showed that there is a room for this kind of power exchanges without affecting the current charging behavior of users but there might be also limiting factors (such as the short contact durations).

Let's assume that there are N nodes of same type in a network and each node interacts with some of the other nodes. Depending on the encounter frequencies and duration and the power differences at the batteries of nodes during meetings, each node estimates the expected power gain opportunities from other nodes. Assume that two nodes i and j have a meeting starting at t_s and ending at t_e, and the battery percentages of the nodes at the start of the meeting are β_i and β_j. Without loss of generality, assume that $\beta_i < \beta_j$. Thus, the power transfer will occur from j to i. Also, assume that node j performs its next individual charging when its battery reaches $\beta_{j_{min}}$. We assume that node j will be willing to share power with node i until the time it feels uncomfortable about its battery energy level. In other words, it will share until either the battery levels of nodes become equal or it hits minimum comfortable battery level. Then, the power gain of node i (G_i) in this meeting will be:

$$G_i = \min\left\{\alpha \min\left(\frac{\beta_j - \beta_i}{2}, \beta_{j_{min}}\right), (t_e - t_s)S\right\}$$

Here, α is the efficiency of power transfer between nodes, and S is the speed of transfer (e.g., energy level percentage per minute). If the contact duration is not long enough to achieve the maximum desired power exchange, then the gain is determined by contact duration and transfer speed.

Once each node calculates total G_i during a day from the contact history with every other nodes; it creates a preference list of its friends (i.e., being power exchange buddies) in terms of their total expected benefit to itself. Given the preference list of each node, we want to get the maximum benefit from the entire system when all nodes are assigned to each other. To this end, we formulate the problem as a stable matching problem such that in the resulting matching there will be no pair of nodes that will prefer to be matched differently than their currently assigned buddies. As we look for pairs of nodes, we assume N is even[2]. To guarantee a stable matching, we adapt Gale-Shapley algorithm [35] to our problem.

Algorithm 1 shows the steps of finding a guaranteed stable matching. First we make every node free (i.e., not assigned a buddy) and set the index of the node that is not being asked for

[2]If N is odd, last pair could be considered as a group of three nodes and algorithm could be adjusted accordingly.

Algorithm 1 FindPowerBuddies (N, preferenceList [ ][ ] pL)

```
1: totalAssigned = 0
2: for each node i in N do
3:     buddies[i] ← nil
4:     notAskedIndex[i] = 1
5: end for
6: while totalAssigned < N do
7:     Choose a node i not assigned yet
8:     c = pL[i][notAskedIndex[i]]
9:     if buddies[c] == nil then
10:        buddies[i] = c
11:        buddies[c] = i
12:        totalAssigned += 2
13:    else if order(pL[c], i) < order(pL[c],buddies[c]) then
14:        buddies[i] = c
15:        buddies[buddies[c]] ← nil
16:        buddies[c] = i
17:    else
18:        notAskedIndex[i]++
19:    end if
20: end while
```

being a buddy to the first node in the preference list of each node (Lines 1-5). Then, until we assign every node to another node, we process each not assigned node. We first find the first friend node in that node's preference list not being asked before (Line 8). If this candidate (c) node is not assigned to any other node yet, we assign it to this node (Lines 9-12). If it is assigned to another node already, we check if the order of preference of this assigned node in the candidate node's preference list is later than this new node who asked for being buddy. If that is the case, we assign the candidate node and this new node as new buddies and release the previous buddy of candidate node (Line 13-16). If neither the candidate node is free nor it prefers to update its current buddy, we check the next node in the preference list of the not assigned nodes (Line 17-18). The algorithm guarantees a stable matching and its complexity is $O(N^2)$. Moreover, it finds the optimal solution as each node is assigned to its best valid friend.

V. Simulation Results

We have built a real data driven simulator to evaluate the proposed system. We used the node contact information from the mobile social network traces analyzed in Section III. Since we did not have the battery usage information of nodes in those datasets, we have used the charging and discharging patterns (presented in Figure 1 and Figure 2) obtained from DeviceAnalyzer dataset [32]. Then, we found the preference lists of nodes, and the power buddy of each node node using the Algorithm 1.

Table I shows the comparison of finding power buddies procedure in the two datasets. There are 36 and 82 nodes in these datasets who meet with other nodes at least once. This results in 18 and 41 pairs of power buddies. We define the goodness of a power buddy assignment as the ratio

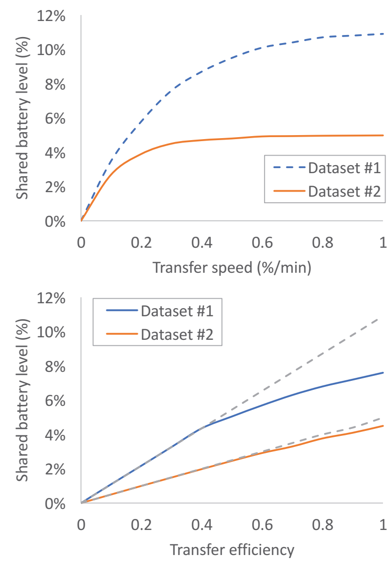

Fig. 4: Shared batter energy levels in a day based on transfer speed and transfer efficiency.

of obtained power exchange opportunity (i.e. total contact duration) with that assignment to the maximum possible power exchange opportunity that would be achieved if the nodes could choose first nodes in their preference lists. The matchings in the datasets show 87% and 71% of goodness, respectively. Moreover, the resulting buddy assignment can provide 26% and 16% of energy needs (with no loss in transfer and 1% battery energy level of transfer speed in a minute) of users on average in these datasets, respectively. This can let users delay their charging decisions and increase average (charging, discharging) cycle duration, yielding a smaller $\mathcal{W}$. In current simulation setting and paper, we assume no charging behavior change and focus on quantifying potential energy exchange opportunities. Modeling the users' willingness to update their charging patterns in reaction to energy sharings with others (which will decrease $\mathcal{W}$ further) is the subject of our future work.

	Dataset #1	Dataset #2
Power buddy pair count	18	41
Matching Goodness	87%	71%
Energy supply	26%	16%

TABLE I: The performance comparison of running Algorithm 1 on two datasets.

In Figure 4, we show the average battery energy levels shared per node. First graph shows that as the transfer speed increases, the shared amount increases up to some point. This is because the other factors become limiting factor at that point. Similarly, in second graph, we observe that as transfer efficiency increases (when transfer speed is 0.3%/min), the shared amount increases linearly with efficiency to some point.

Similarly, this happens due to other factors. The interesting observation here is the different reactions in different datasets to these efficiency differences. In our future work, we will analyze the datasets to find a relation between their features and this reaction behavior.

VI. Conclusion

In this paper, we study the energy sharing problem in mobile social energy networks with its challenges and potentials. We first analyze the current energy utilization in the batteries of mobile devices and explore the potential benefits of energy sharing between mobile devices to decrease the inefficient utilization. We then formulate the problem as the assignment of users to other users to achieve the optimal benefit of proposed energy sharing system. Simulation results on real mobile device traces demonstrate that the proposed energy sharing model often reduces the inefficiency in a mobile social network without requiring the users to change their default behavior. In future work, we will consider power exchanges between multiple people and find optimal grouping of such people within a mobile social network to improve the performance of sharing. We will also develop incentive mechanisms to affect people's default behavior and encourage them to create more power sharing opportunities.

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