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Mobile Energy Balancing in Heterogeneous Opportunistic Networks

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***Abstract*—Energy is a scarce resource in mobile networks consisting of devices running on batteries. Thus, many studies have looked at the energy management issue in these networks from different aspects. Thanks to the recent advances in wireless power transfer (WPT) technology, the wireless charging of the mobile devices has been considered for their continuous operation. While most of the research efforts have focused on the scheduling of mobile chargers for charging of the devices (e.g., sensor) in the field, interesting research problems such as energy balancing among a population of nodes have also emerged with the consideration of bidirectional wireless charging among nodes. Energy balancing aims to balance the energy among nodes towards prolonging the network lifetime especially when external energy sources are not available. Previous studies target an energy balance among the devices as fast as possible but they waste energy in the network during this process due to the excessive interactions between nodes. Moreover, they do not take into account the heterogeneous contact relations between the nodes in the network. In this paper, we address these issues and present efficient and loss-aware energy balancing protocols considering the contact graph heterogeneity between nodes and a time threshold for completing the energy balancing. Simulation results show that the proposed algorithms outperform the previous work by reaching a better energy balance with a lower energy loss within the restricted relations among nodes in the network.**

***Index Terms*—Energy balancing, wireless energy transfer, mobile opportunistic network.**

I. Introduction

The most critical resource for mobile networks consisting of battery-powered devices is the energy. Thus, efficient utilization and management of energy is vital for collaborative network operations. There have been many research efforts performed to provide solutions based on different methods (e.g., harvesting [1], battery replacement [2]) to this problem so that network lifetime can be prolonged.

With the recent advances in wireless power transfer (WPT) technology and increasing efforts from both the academia and industry, numerous studies have considered WPT based energy replenishment of nodes in mobile networks. Most of these studies have been performed for wireless sensor networks [3]–[5], but there are some recent studies for smartphones [6]–[8], electric vehicles [9]–[11] and Internet-of-Things (IoT) devices [12], [13]. For example, in the sensor networks domain, most of the time mobile chargers, which are special vehicles (e.g., robot, Unmanned Aerial Vehicle (UAV)) with high energy supplies are employed to periodically charge the sensors in the field.

The one-way charging of mobile devices from chargers has recently been extended to bidirectional energy sharing between the regular nodes in the network and several application specific problems have been studied benefiting from this. For example, in mobile social networks domain, thanks to the recent products (e.g., Samsung Galaxy S10, Huawei Mate 20 Pro) in the market and also some prototypes developed by research community [8], [14] bidirectional wireless charging between smartphones has been considered for crowdcharging of smartphones by other users [15]–[19]. While current form of wireless charging used in these products only happen in very close distances (i.e., almost touching), it provides a convenient process without the hassle of cables. On the other hand, peer-to-peer energy sharing has triggered a new set of research studies in different mobile network applications. For example, for an opportunistic content delivery, energy has been considered as an incentive [20]–[22] to the devices to carry the message. Similarly, an interesting problem of energy balancing [23]–[25] among nodes has been studied towards prolonging the lifetime of the network, which could be vital especially when there is no access to external energy sources. In this paper, we study the energy balancing problem utilizing the peer-to-peer energy sharing among the nodes in the network during their opportunistic encounters. Our goal is to address the deficiencies in the state-of-the-art solutions and provide loss-aware and efficient energy balancing protocols considering the heterogeneous relations between nodes.

A. Energy Balancing and Motivating Example

Energy balancing is the process of equalizing the energy at each node or minimizing the sum of the differences of their energy from the average energy (i.e., variation distance as will be detailed in the next section) in the network as much as possible. As the nodes interact and exchange energy between each other, there will be an energy loss due to the wireless charging inefficiency. Thus, the energy balancing process should consider not only the balancing of energy among nodes but also the minimization of the loss during this process.

In the very few studies [23]–[25] that look at this problem, it has been shown that the variation distance among the target energy levels of nodes and current energy levels will decrease

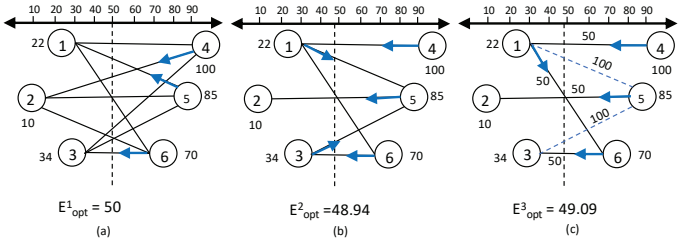

Fig. 1: (a) Energy balancing in a fully connected contact graph. (b) Energy balancing in a partially connected contact graph. (c) Energy Balancing with time limit of 50. Edges represent that the nodes meet each other opportunistically with an average intermeeting time shown as edge weight.

only if the nodes in the opposite sides of the average energy in the network interact and exchange energy. While this is true and help reach an energy balance among the devices as fast as possible, the presented results and conclusion rely on a very restrictive scenario on node interactions. It is assumed that each pair of nodes interact with equal probability, however, this is not always true in mobile opportunistic networks. In a realistic scenario, some pairs of nodes might not have any interaction opportunity with other nodes and some pairs of nodes might have large intermeeting times incurring huge waiting times for some possible interactions to occur. Another major problem with the current approaches is that they do not consider the final optimal target that can be reached after the interactions between nodes and the resulting energy loss. Instead, they rely on the initial distribution of energy and target the initial average energy in the network. Thus, a perfect energy balance (i.e., all nodes having energy equal to the average energy in the network) can not be achieved since the average energy in the network will change after some energy exchanges between nodes. In our previous work [26], we have addressed this problem for homogeneous networks, however, for heterogeneous networks a more comprehensive solution should be provided.

Consider the example in Fig. 1 with six nodes in the network and with corresponding energy levels. If each node on the negative side (i.e., having energy less than the average energy) has an opportunity to meet with each node on the positive side as in Fig. 1a, the energy sharing process will be relatively easy. The initial average energy in the network is 53.5%, however, this cannot be reached by all nodes as due to the imperfect transfer efficiency there will be a loss during energy transfers between nodes. For example, for an energy loss rate of β = 0.2 (i.e., 80% transfer efficiency), the optimal average energy reachable by all nodes will be 50%, which happens when node 5 transfers 35% to node 1 (which only gets 28% due to loss), node 4 transfers 50% to node 2 (which only gets 40%) and node 6 transfers 20% to node 3 (which only gets 16%). When there is no energy exchange opportunity (i.e., meeting) between some negative and positive side node pairs, the optimal energy achievable can be less than this. For example, for the case in Fig. 1b, the most achievable average energy is 48.94%, which happens when node 5 transfers 48.68% to node 2, making its energy $10 + 48.68 \times (1 - 0.2)$ = 48.94%. Similarly, node 6 transfers 21.05% to node 3 which gets 16.84%, node 4 transfers 51.05% to node 1 which gets 40.84%. Then, node 1 and node 3 transfer 13.89% and 1.89% to node 5 respectively, making node 5's and their own energy levels reach 48.94%. So, in this case, reaching a perfect balance was also possible but due to the incomplete contact graph between nodes, it was less than the complete contact graph case. Finally, there can be a time threshold for reaching an energy balance. In that case, we can simply ignore the edges with average intermeeting time higher than this threshold and recalculate the optimal energy balance. Fig. 1c shows the situation where the deadline for energy balance is set to 50. The dotted edges shown in the figure are ignored; hence, nodes cannot use these edges for energy exchanges. In this case, the optimal target reachable is 49.09%. However, due to the lack of meeting opportunities before the deadline, all the nodes cannot reach 49.09%. This happens when node 5 transfers 35.90% to node 2 which only gets 28.72% making node 2's energy level 38.72%. Also, node 1 transfers 13.63% to node 6, node 4 transfers 50.90% to node 1 and node 6 transfers 31.81% to node 3 which gets 25.45% and reaches an energy level of 59.45%. Overall, all nodes except 2 and 3 reach a final energy level of 49.09%, which is the average energy in the network. This example shows that with sparse contact graphs, the optimal energy balance can change and not all nodes may reach that.

B. Contributions

In this paper, we study the energy balancing problem among a population of mobile nodes that interact opportunistically. We aim to minimize both the energy difference between nodes and the energy loss during this process. However, in some cases obtaining the energy balance among all nodes in the network may not be feasible due to the limited energy exchange opportunities (i.e., meeting). Thus, we first target energy balancing as much as possible and later minimize the energy loss. The main contributions of this paper can be summarized as follows:

- We analytically find the optimal energy level in a large scale network with uniform energy distribution for a given energy transfer efficiency or loss rate.
- For a given network of any size with energy distributions at nodes, contact graph and intermeeting times between nodes, we find the optimal energy balance achievable by Mixed Integer Linear Programming (MILP).
- We propose two different energy balancing protocols based on optimal energy exchange schedules found by MILP results and based on opportunistic energy exchanges towards optimal energy balance in MILP results.
- We perform extensive simulations using meeting patterns from synthetic and real traces and show that the proposed approaches perform better than the state-of-the-art.

Notation	Description
m	Number of nodes in the network.
$\mathcal{P}$	Interaction protocol between nodes for energy exchange.
β	Energy loss rate.
τ	Time threshold to finish energy balancing.
$E_t(u)$	Energy of user u's device at time t.
$\lambda_{i,j}$	Average intermeeting time between nodes i and j.
$\overline{E_t}$	Average energy in the network at time t.
E_{opt}	Optimal average energy achievable in the network with minimum variation distance possible.
$\delta(P,Q)$	Total variation distance between two distributions, P, Q.
$\mathcal{E}_t(u)$	Ratio of node u's energy to the total energy in the network at time t.
$\mathcal{E}_t$	Energy distribution at time t on a sample space $\mathcal{M}$.
$\epsilon_{u,u'}$	The amount of energy exchanged from u to u'.
$\mathcal{L}$	The total energy loss in the network due to the energy exchanges.
$E_f(u)$	The final energy level of node u at the end of energy balancing process.

TABLE I: Notations

The rest of the paper is structured as follows. In Section II, we provide our assumptions on the system model and the problem statement. In Section III we elaborate on the analysis, MILP solution and the proposed energy balancing algorithms. In Section IV, we present the simulation settings and compare the proposed algorithms with the state-of-the-art solution. Finally, we conclude the paper and outline the future work in Section V.

II. System Model

A. Assumptions

We assume a set of m nodes denoted by $\mathcal{M} = \{u_1, u_2, ..., u_m\}$ in a mobile network. Each node is assumed to have equal battery capacity and necessary hardware for energy sending and receiving. We assume that each node knows the energy levels of other nodes, which could be simply achieved via cellular communication over a centralized server. As in previous work [23]–[25], for simplicity, we also do not consider energy loss due to mobility or other activities of the nodes. The nodes just need to send update about their energy level only after they interact and exchange energy with other nodes in the network. Thus, such updates rarely happen in mobile opportunistic networks.

When two nodes meet, they exchange energy according to an interaction protocol $\mathcal{P}$. The energy level of a node u at time t is denoted by $E_t(u)$. We assume each pair of nodes, (u_i, u_j), meets in an exponentially distributed manner with an average mean of $\lambda_{u_i u_j}$. We also assume an energy loss rate, $\beta \in [0, 1)$, which is assumed a constant and depends on the technology and the equipment used. When two nodes u and u' interact at time t and node u transfers ϵ energy to node u', node u' will receive $(1-\beta)\epsilon$ energy and their new energy levels will be:

$$\begin{aligned}(E_t(u), E_t(u')) &= \mathcal{P}(E_{t-1}(u), E_{t-1}(u')) \\ &= (E_{t-1}(u) - \epsilon, E_{t-1}(u') + (1-\beta)\epsilon)\end{aligned}$$

As the interaction between u, and u' doesn't affect the energy levels of any other nodes, the energy levels of all other nodes remain unchanged. The notations used throughout the paper are summarized in Table I.

B. Problem Description

The goal is to achieve an energy balance among a population of nodes with a very low variation while minimizing the energy loss due to the energy transfers among nodes. We define the energy difference among nodes using the total variation distance from probability theory as in [23]–[25].

Let P, Q be two probability distributions defined on a sample space $\mathcal{M}$. The total variation distance is calculated as:

$$\delta(P, Q) = \sum_{x \in \mathcal{M}} |P(x) - Q(x)| \tag{1}$$

Note that for the sake of keeping the actual differences, we do not divide the sum by two as in standard definition of variation distance. In our context, we consider the total variation distance between the current energy distribution of nodes and the target energy distribution, where ideally all nodes have the same energy. The target energy level will not be equal to the initial average energy in the network, as there will be some energy loss during the energy exchanges performed to balance energy among nodes. Moreover, it may not be possible to have all nodes reach the same energy level. The goal in those cases will be to minimize the variation distance between the final energy levels and the average energy in the network. We denote the energy distribution at time t on a sample space $\mathcal{M}$ by $\mathcal{E}_t$ where

$$\mathcal{E}_t(u) = \frac{E_t(u)}{E_t(\mathcal{M})}, \text{where, } E_t(\mathcal{M}) = \sum_{x \in \mathcal{M}} E_t(x)$$

for any $u \in \mathcal{M}$. We also define the average energy in the network at time t by

$$\overline{E_t} = \frac{E_t(\mathcal{M})}{m}. \tag{2}$$

III. Mobile Energy Balancing

In this section, we give the details of the proposed energy balancing protocols. We first find the optimal energy level in a large scale network with many nodes for a given loss rate. Then, we discuss a Mixed Integer Linear Programming (MILP) solution to find the optimal energy level for a given network of any size and limits on node relations. Utilizing MILP results, we then propose two different energy balancing protocols.

A. Ideal Energy Balance with Minimum Loss

Previous work [23]–[25] have shown that the energy variation distance in the network will decrease if and only if the nodes in the opposite sides of the average energy level interact and exchange energy. That is, if a node u with $E_t(u) < \overline{E_t}$ and a node u' with $E_t(u') > \overline{E_t}$ interact at time t and balance their energy, $\delta(\mathcal{E}_t, \mathcal{U}) < \delta(\mathcal{E}_{t-1}, \mathcal{U})$, where $\mathcal{U}$ denotes the uniform distribution on $\mathcal{M}$ (i.e., $E_t(u) = \overline{E_t}\ \forall u$).

In order to reduce the variation distance at every opportunity, the best algorithm in previous work (i.e., $\mathcal{P}_{OA}$ standing for *o*nline *a*verage protocol [23]–[25]) suggested that whenever a pair of nodes from opposite sides meet, they should split their total energy equally. While this will help reduce variation distance, it is assumed that the opposite sides are determined by the current average energy level in the network. However, as nodes interact and there occurs energy loss, the average energy level, $\overline{E}_t$, in the network decreases. Thus, this may cause nodes move between the negative and positive side of the current average energy level in the network, resulting in unnecessary energy loss in the network. In order to prevent this, the decision of opposite sides should be made based on the final average energy level that will reached at the end.

When each of the nodes in the network has a contact opportunity with all other nodes in the network, all nodes in the network can make their energy converge to the same average energy level in the network. To achieve this, the energy provided by the nodes with excessive energy should be sufficient to increase the energy levels of nodes in the negative side after loss. Consider a large scale network with many nodes. Also assume that the energy levels of nodes (denoted by y below) are uniformly distributed in [0,1]. The final optimal energy balance, E_{opt} (denoted by x) can be calculated as follows:

$$\begin{aligned}\int_{y=0}^{x}(x-y)dy &= \int_{x}^{1}(y-x)(1-\beta)dy \\ x^2 &= (x^2-2x+1)(1-\beta) \\ f(x) &= \beta x^2+2(1-\beta)x-(1-\beta)=0\end{aligned}$$

This function, $f(x)$ is strictly increasing function when $x \in$ [0,1] and $\beta \in$ [0,1], as $f'(x) > 0$. The solution is equal to the positive root at,

$$E_{opt} = \frac{-(1-\beta)+\sqrt{(1-\beta)}}{\beta}$$

As $(1-\beta) \leq \sqrt{(1-\beta)}$ when $\beta \in$ [0,1], E_{opt} will always be a positive number in [0,1]. For example, when the energy loss rate β is 20% (or transfer efficiency is 80%), the optimal energy balance with minimum loss and zero variation distance is 47.21%, while it is 41.42% for $\beta = 50\%$.

In an ideal scenario, the energy of all nodes can reach a perfect balance at E_{opt} with a minimum of $m/2$ interactions between nodes. This happens when the energy need of a node in the negative side is perfectly provided by a node in the positive side during a single interaction and they both reach the target. This requires equal number of nodes in the opposite sides of the target energy level as well as a perfect meeting schedule between corresponding pairs that can complement each other. However, this may not be the case in practice most of the time. The energy distribution among nodes as well as the heterogeneous contact relations (i.e., meeting or not meeting, and meeting with different average intermeeting times) between nodes may result in different number of nodes in the opposite sides of the optimal average energy and affect the energy balancing process.

B. Optimal Energy Balance

In a real setting, the ideal scenario will not be the case as opportunistic interactions will be limited to only some pairs of nodes and the distribution of energy levels of nodes may not be uniform. However, in a given mobile opportunistic network contact graph[1] and the initial energy levels of nodes, we can find the optimal energy balance achievable among nodes by Mixed Integer Linear Programming (MILP).

In this paper, we target an energy balance with minimum possible energy variation distance first. Then, we target minimum loss without sacrificing the variation distance. Especially, when there are multiple ways (i.e., energy exchange schedules between nodes) of reaching a zero variation distance, utilizing the one that will result in the minimum energy loss is important. Note that depending on the application requirements, it is possible to consider other objective functions with weighted combinations of variation distance and loss in a similar way.

Let $\epsilon_{u,u'}$ denote the amount of energy exchanged from u to u' and $E_f(u)$ denote the final energy level of node u at the end of energy balancing process. Then,

$$E_f(u) = E_0(u) - \sum_{\forall u'} \epsilon_{u,u'} + \sum_{\forall u'} \epsilon_{u',u}(1-\beta)$$

Let also $\mathcal{L}$ denote the total energy loss in the network due to the energy exchanges between nodes during the balancing process. Then,

$$\mathcal{L} = \sum_{\forall u,u',\text{s.t.}u \neq u'} \epsilon_{u,u'}\beta$$

The objective is to minimize to the variation distance between the final energy distribution of nodes, $\mathcal{E}_f$, and the final uniform energy distribution, $\mathcal{U}_f$, where all nodes have energy equal to the average energy in the final network (i.e., $E_f(u) = \overline{E_f}\ \forall u$), as much as possible and then minimize the total loss in the network. More formally:

$$\min \quad \delta(\mathcal{E}_f,\mathcal{U}_f)m + \mathcal{L} \tag{3}$$

$$\text{s.t.} \quad 0 \leq \epsilon_{u,u'} \leq E_t(u)l_{u,u'} \tag{4}$$

$$k_{uu'} + k_{u'u} \leq 1 \tag{5}$$

$$\text{where} \quad \epsilon_{u,u'} \text{ is a decimal in } [0,1] \tag{6}$$

$$k_{uu'} = \begin{cases}1, & \text{if } \epsilon_{u,u'} > 0 \\ 0, & \text{otherwise}\end{cases} \tag{7}$$

$$l_{uu'} = \begin{cases}1, & \text{if } \lambda_{uu'} \leq \tau \\ 0, & \text{otherwise}\end{cases} \tag{8}$$

In objective function (3), as we give priority to the minimization of variation distance over minimization of loss, we multiply the former with a constant (i.e., m) that is larger than the maximum possible value for $\mathcal{L}$. Thus, the optimization prefers a decrease in variation distance over any decrease in

[1]This can be obtained from historical meeting patterns of nodes and thanks to the long-term regularities [27]–[29] in node relations, it can be used for predicting future meetings.

loss. (4) allows energy sharing between the nodes with average intermeeting times less than the time threshold (τ) and limits the energy sharing from each node up to its available energy. Note that energy levels of nodes are assumed to be between 0 and 1. Also, we do not allow unnecessary two way energy exchanges between nodes via (5).

Note that the optimal average energy level in this case will be equal to the average energy in the final network. That is,

$$E_{opt} = \frac{\sum_{x \in \mathcal{M}} E_f(x)}{m}. \tag{9}$$

C. Energy Balancing Protocols

Once the optimal energy balance as well as the required energy exchanges between nodes to reach that target balance is found, we propose two different energy balancing protocols to define the actual energy exchanges during the opportunistic meetings between pairs of nodes.

In the first protocol, we urge each node to follow the exact energy exchange schedule found by the MILP solution (hence named *L*inear *E*xact or $\mathcal{P}_{LE}$ in short). That is, each node waits for meeting with the nodes that it is supposed to perform an energy exchange with and exchanges energy only in the amount it is allowed to do so with them. This protocol will let the nodes reach the optimal variation distance in the network eventually but due to the non-deterministic nature of opportunistic meeting patterns, it may cause nodes wait longer than expected as well as cause them miss the advantage of any earlier meeting opportunity with some unexpected nodes.

In the second protocol, we aim to benefit from the non-deterministic meetings between nodes and let the nodes reach target energy level as soon as possible without following the suggested energy exchange schedule. Optimal target average energy level, E_{opt} is found by MILP (using (9)) as in the case of first protocol, however, the nodes do not wait specifically for the nodes that they are supposed to exchange energy with. Instead, whenever two nodes from opposite sides of E_{opt} meet, they utilize this opportunity and update their energy towards the target. Here, in order to prevent nodes from switching their sides as in the case of previous work and causing unnecessary additional energy loss, we give priority to the node whose energy is closer to the target and let it reach that target by receiving or sharing energy with the other node. We name this protocol *O*pportunistic *C*loser or $\mathcal{P}_{OC}$ in short. Note that while this protocol takes the benefit of any opportunistic meeting for energy exchange besides the scheduled ones, it can cause nodes not reach to the optimal energy levels due to the divergence from the schedule that will make them reach the optimal energy balance. This may especially adversely affect the performance when the contact graph in the network is sparse.

Algorithm 1 shows the details of energy balancing process based on these two protocols. For $\mathcal{P}_{OC}$ protocol (lines 10-17), if the node in the negative side, u^-, needs less than the energy that the node in the positive side, u^+, can give after loss, u^- is given priority to reach the target. The amount of energy that u^+ has to transfer should consider the loss; thus, it should be more than what u^- will actually need (lines 13-14). Otherwise, u^+ is given priority to reach the target and the energy of u^- is increased accordingly (line 16). For $\mathcal{P}_{LE}$ protocol (lines 18-26), the energy of nodes are simply updated based on the scheduled energy exchanges between nodes. Note that by MILP formulation design either ϵ_{u^+,u^-} or ϵ_{u^-,u^+} will be more than zero at the same time, however, it is possible that both could be zero as the optimal schedule may not recommend an interaction between them even though they are in opposite sides of the average energy level.

Algorithm 1: Energy Balancing ($\mathcal{P}$, u, u', t)

Input: (u, u'): Interacting nodes
t: Time of interaction
E_{opt}: Optimal average energy from MILP

1 $(u^+, u^-) \leftarrow$ (*null*, *null*)
2 **if** *(*$E_{t-1}(u) > E_{opt}$ ***and*** $E_{t-1}(u') < E_{opt}$*)* **then**
3 $(u^+, u^-) \leftarrow (u, u')$
4 **else**
5 **if** *(*$E_{t-1}(u) < E_{opt}$ ***and*** $E_{t-1}(u') > E_{opt}$*)* **then**
6 $(u^+, u^-) \leftarrow (u', u)$
7 **end**
8 **end**
9 **if** (u^+, u^-) *is not null* **then**
10 **if** $\mathcal{P} = \mathcal{P}_{OC}$ **then**
11 $\delta_{t-1}(u^+) = E_{t-1}(u^+) - E_{opt}$
12 $\delta_{t-1}(u^-) = E_{opt} - E_{t-1}(u^-)$
13 **if** $\delta_{t-1}(u^+)(1-\beta) > \delta_{t-1}(u^-)$ **then**
14 $\mathcal{P}_{OC}(E_{t-1}(u^+), E_{t-1}(u^-)) = (E_{t-1}(u^+) - \frac{\delta_{t-1}(u^-)}{(1-\beta)}, E_{opt})$
15 **else**
16 $\mathcal{P}_{OC}(E_{t-1}(u^+), E_{t-1}(u^-)) = (E_{opt}, E_{t-1}(u^-) + (1-\beta)\delta_{t-1}(u^+))$
17 **end**
18 **else**
19 **if** $\epsilon_{u^+,u^-} > 0$ **then**
20 $\mathcal{P}_{LE}(E_{t-1}(u^+), E_{t-1}(u^-)) = (E_{t-1}(u^+) - \epsilon_{u^+,u^-}, E_{t-1}(u^-) + (1-\beta)\epsilon_{u^+,u^-})$
21 **else**
22 **if** $\epsilon_{u^-,u^+} > 0$ **then**
23 $\mathcal{P}_{LE}(E_{t-1}(u^+), E_{t-1}(u^-)) = (E_{t-1}(u^+) + (1-\beta)\epsilon_{u^-,u^+}, E_{t-1}(u^-) - \epsilon_{u^-,u^+})$
24 **end**
25 **end**
26 **end**
27 **end**

IV. Simulations

In this section, we evaluate the performance of the proposed energy balancing protocols. Next, we list the algorithms compared, performance metrics used, and describe how the simulations are set. Then, we provide the simulation results and analyze the impact of several parameters on results.

A. Algorithms in Comparison

We compare the proposed two algorithms with the best protocol claimed in [23]–[25]. Below are the key points in these protocols:

- $\mathcal{P}^*_{OA}$: This *O*nline *A*verage protocol is updated version of the state-of-the-art protocol $\mathcal{P}_{OA}$ proposed in [23]–[25]. In the original $\mathcal{P}_{OA}$, each node locally estimates the average energy level in the network using the ratio of the total energy seen in the encountered nodes to the number of encountered nodes, which may not be accurate. As we assume each node has the information about the energy levels of other nodes, for a fair comparison we assume the same for $\mathcal{P}_{OA}$ and name it as $\mathcal{P}^*_{OA}$. The protocol simply lets the nodes in opposite sides of the current average energy in the network interact and equally split their energies. For fair comparison, we also use E_{opt} here to decide the boundary between opposite sides.
- $\mathcal{P}_{LE}$: In the *L*inear *E*xact protocol, when the nodes meet, they only share the exact amount of energy that MILP solution (obtained by IBM CPLEX solver [30]) finds to reach the E_{opt} with minimum possible variation and loss after that.
- $\mathcal{P}_{OC}$: In the *O*pportunistic *C*loser protocol, E_{opt} is obtained via MILP similar to $\mathcal{P}_{LE}$, but the nodes opportunistically try to reach that target. That is, they do not wait for the other nodes that they are supposed to exchange energy found by MILP, but utilize every meeting opportunity with the nodes in the opposite side. The one with the closer energy level to the target is given priority to reach the target first.

B. Performance Metrics

We use the following metrics in the performance comparison of the aforementioned algorithms:

- *Total variation distance:* This is calculated by $\delta(\mathcal{E}_t,\mathcal{U}_t)$. That is, we find the ratio of the energy levels of nodes to the total energy in the network at each time, take the absolute difference from uniform distribution at that time and sum it for all nodes.
- *Total energy in the network:* This is the sum of energies at all nodes. Note that as the nodes interact and lose energy, the total available energy in the network decreases.
- *Number of interactions:* This shows the number of interactions between nodes during which an energy exchange happened towards reaching a balance.
- *Total variation distance at a given total energy:* As the performance of the protocols may vary based on total variation distance and total energy in the network, we use this combined metric as an indicator of true performance.
- *Total variation distance at a given number of interactions:* Similarly, we use this metric to understand the impact of necessary interactions towards reaching the minimum possible total variation distance.

C. Datasets

We use both real and synthetic traces to define the meeting relations between the nodes in the network. Real traces are obtained from one of the commonly used datasets in DTN literature [31] for performance analysis of routing algorithms. With synthetic traces, we aim to generate different contact graphs with various sparsity levels.

- **Cambridge dataset:** These are the Bluetooth recordings between the iMotes carried by 36 students from Cambridge University for a duration of almost two months.
- **Synthetic dataset:** This is a dataset generated randomly among 30 nodes with a mean intermeeting time ($\lambda_{i,j}$) of a random value between [1000, 15000] minutes. We use different time thresholds to generate graphs with different average neighbor counts in the contact graph as well.

Note that depending on the energy sharing technology used between nodes, the proximity requirements and corresponding energy transfer efficiency might be different. For example, for wireless energy sharing between smartphones, they need to be very close to each other as if they are touching. On the other hand, for example in the real traces we used above, the interactions between nodes happen through Bluetooth communication which has a range in the order of several meters. However, we assume that such interactions can still be considered as an indication of nodes in close proximity of each other so that they can communicate and come closer to perform energy exchange operation if needed. We also assume that when nodes meet, they stay close enough to each other until they can achieve the required energy transfer under the energy balancing protocol in use. We look at the impact of transfer efficiency in our results, which can be considered as the relaxation of this assumption to some extent. Enhancing the proposed protocols considering the partial energy transfers between nodes during meetings with limited duration will also be the subject of our future work.

D. Performance Results

In this section, we present the results of our evaluation through simulations. First of all, we assign an initial energy level to each node between 0 and 100. From the beginning of the simulation, we let the devices interact following their exponentially distributed intermeeting times and exchange energy based on the characteristics of each energy balancing protocol compared. Each simulation is repeated 100 times for statistical smoothness. For main simulations we use an energy loss rate, β, of 0.2. But we also show the impact of β on results.

In Fig. 2, we first show the optimal energy balance in graphs with different sparsity. To this end, we use the synthetic dataset and contact graph and for different time thresholds (τ) and loss rates (β) we calculate the optimal average energy reachable (E_{opt}) and corresponding variation distance and total loss at E_{opt}. Note that τ simply causes removal of edges between pairs with intermeeting time higher than τ, yielding a sparser contact graph. As the results show, optimal

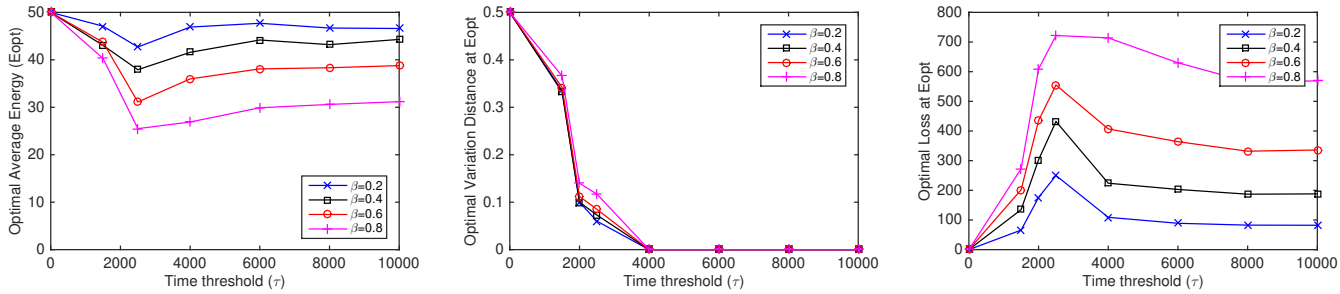

Fig. 2: Impact of time threshold (τ) and loss rate (β) on optimal average energy achievable (E_{opt}) and corresponding variation distance and total loss at E_{opt}.

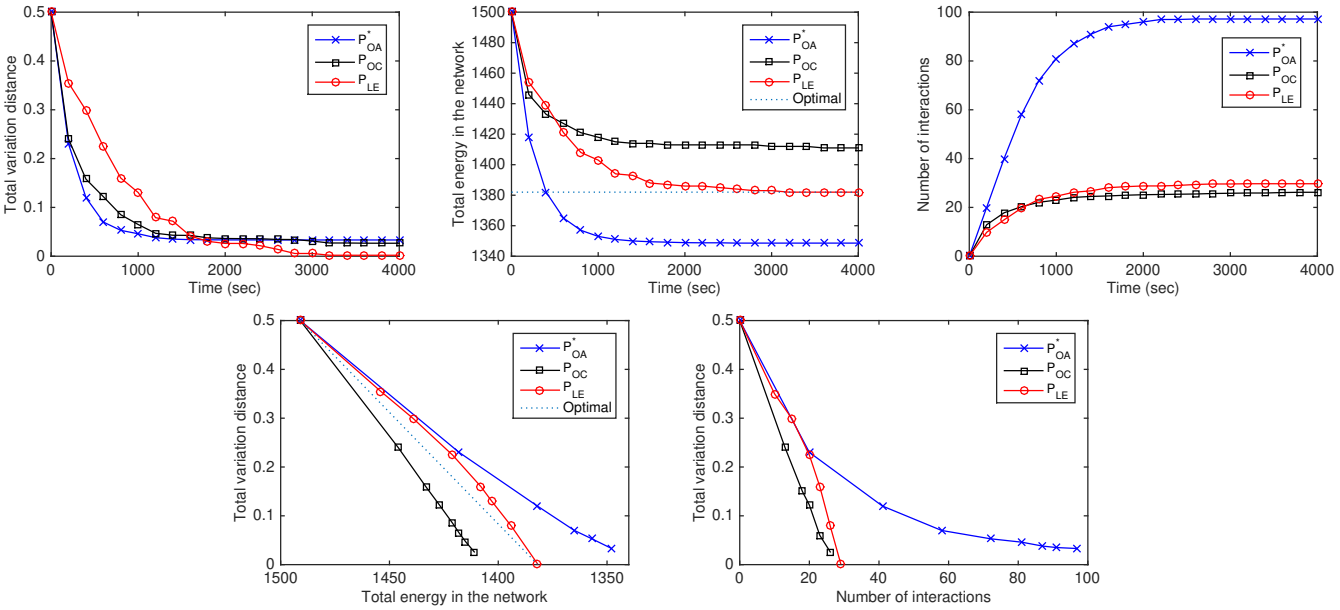

Fig. 3: Comparison of all algorithms in terms of (a) variation distance, (b) total energy remaining in the network, (c) total number of interactions, (d) variation distance at each total energy level and (e) variation distance at each total number of interactions (when β=0.2, τ=4000) using synthetic dataset.

variation distance gets lower as τ increases and hits zero around $\tau = 4000$ min. The loss associated with this optimal variation distance on the other hand increases initially and gets smaller later. This is because with smaller τ values, the existing pairwise relations is trimmed further and some nodes either have very small contacts or are totally isolated from others. Thus, perfect energy balancing giving zero variation distance was not possible. However, once this threshold is exceeded, the loss could be lowered by finding better energy exchange schedules. Note that E_{opt} results also are inline with this reasoning. Moreover, we see that as β increases, the optimal average energy achievable with different time thresholds decreases but it follows a similar pattern at different loss rates.

In Fig. 3, we show the performance comparison of all algorithms using the aforementioned performance metrics in synthetic traces. In Fig. 3a, we see that P_{LE} can achieve the lowest variation distance among others. P^*_{OA} and P_{OC} have a similar variation distance which is slightly higher than the variation distance of P_{LE}. However, when we look at the total energy levels in the network shown in Fig. 3b, we observe that P^*_{OA} sacrifices a lot of energy during the energy balancing process. On the other hand, P_{OC} keeps more energy in the network even more than P_{LE}. This is because as it also uses some unscheduled energy exchange opportunities towards the optimal average energy level, it diverges from optimal variation distance but this does not cause losing energy in the network unnecessarily. Moreover, the number of interactions between nodes in P^*_{OA} is the highest among all compared algorithms, as shown in Fig. 3c, while proposed algorithms limit the interactions. When we compare the variation distance at the same total energy in the network in Fig. 3d, we observe that P^*_{OA} indeed has the worst performance. On the other hand, P_{LE} reaches the optimal energy level and decreases

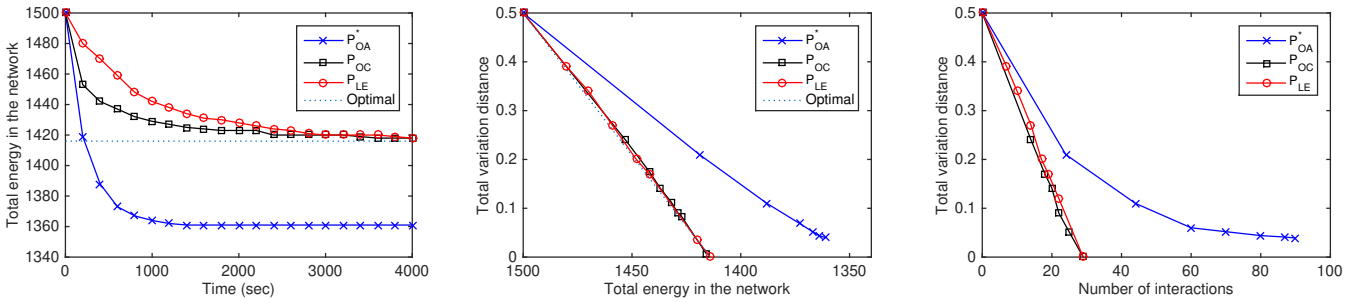

Fig. 4: Comparison of all algorithms in terms of (a) total energy remaining in the network, (b) variation distance at each total energy level and (c) variation distance at each total number of interactions (when β=0.2, τ=10000) using synthetic dataset.

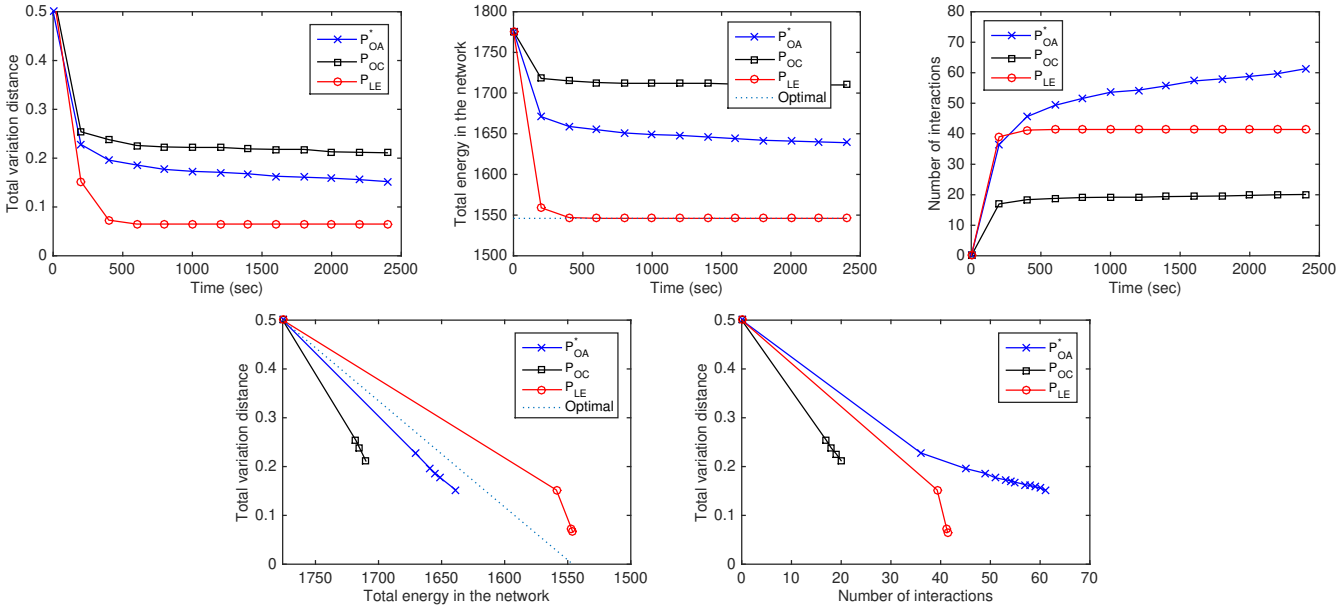

Fig. 5: Comparison of all algorithms in terms of (a) variation distance, (b) total energy remaining in the network, (c) total number of interactions, (d) variation distance at each total energy level and (e) variation distance at each total number of interactions (when β=0.2, τ=4000) using Cambridge dataset.

the total variation distance gradually. Here, P_{OC} shows an interesting behavior as it achieves a better variation distance at a given total energy in the network but it cannot reach the smallest possible variation distance as P_{LE} does. Thus, if some variation distance is tolerable, P_{OC} can be considered performing better than P_{LE}. Moreover, P_{OC} achieves this with smaller variation distance at a given interaction count than other algorithms, as it is shown in Fig. 3e. P^*_{OA} again performs the worst due to its design.

In the results shown in Fig. 4, we relaxed the time threshold and set it to 10000 min in order to increase the contact graph density and the energy exchange opportunities. Here, results for only three metrics are shown for the sake of brevity. We observe that with this increased time threshold, the total energy that could be kept in the network has increased (i.e., loss decreased). P_{OC} has also caused more loss initially which was not the case in earlier results. Another significant change is that the performances of P_{OC} and P_{LE} get closer in terms of total variation distance at a given total energy and number of interactions. These can be explained by the increased energy exchange opportunities.

In Fig. 5, we show the performance comparison of all algorithms in Cambridge traces. In Fig. 5a, we see that even P_{LE} cannot reach a variation distance of zero, but it is still the best compared to others. Interestingly, P^*_{OA} achieves better variation distance than P_{OC}, which was not the case in synthetic data. However, as it is shown in Fig. 5b, P^*_{OA} causes more loss in the network compared to P_{OC}. P_{LE} reaches the optimal energy in the network with the smallest possible variation distance. In terms of total variation distance at a given total energy level, P_{OC} performs better than others for earlier energy levels, but it cannot reach the variation distance others can do, as shown in Fig. 5d. The interactions for P^*_{OA} is the highest again among all algorithms while P_{OC} has

the smallest interactions that is also considerably less than the interactions of P_{LE} which was not the case in synthetic data. This is because in Cambridge dataset, the contact graph density is smaller than it is in synthetic traces and P_{OC} stops interacting further when nodes greedily reaches the target.

V. Conclusion

In this paper, we study the energy balancing problem among the nodes in a mobile opportunistic network. We aim to both balance the energy levels of nodes and minimize the energy loss during this process considering the heterogeneous relations among nodes as well as a time threshold to finish the balancing. We first find the optimal average energy achievable using a MILP based formulation then propose two different energy balancing protocols utilizing its results. In the former, we use the exact energy exchanges suggested by the MILP solution to reach the optimal target while we opportunistically try to reach that target in the latter. Simulation results in both synthetic and real traces show that the proposed algorithms perform better than the previous work and they have advantages to one another in different performance metrics and contact graph densities. In our future work, we will relax the availability of energy level information at nodes and consider the impact of limited meeting duration during energy sharing. We will also integrate the energy consumption of nodes due to other activities and the social network relations between users [32] to the proposed energy balancing protocols.

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