Loss-Aware Efficient Energy Balancing in Mobile Opportunistic Networks

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***Abstract*—Energy management is a challenging issue addressed in networks consisting of battery-powered d With the recently emerging wireless power transfer tech many studies have utilized wireless charging to addre problem and provide energy ubiquitously to these devi making them functional continuously. Besides the well-s problems such as optimal scheduling of mobile chargers, r an interesting problem of energy balancing among a pop of mobile nodes has been considered to prolong the life the network through the opportunistic energy exchanges b the nodes. The state-of-the-art solutions target an energy l among the devices as fast as possible but they waste ener to the loss during peer-to-peer energy transfer. In this pa study the energy balancing problem that aims to minimiz the energy difference between nodes and the energy loss this process. To this end, we propose three different sharing protocols between nodes based on different heuristics. Through simulations, we show that all the proposed algorithms show better performance than the state-of-the-art. The third proposed algorithm achieves the best performance by reaching an energy balance between nodes while keeping the maximum possible energy in the network (i.e., minimum loss).**

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

I. Introduction

Energy management is an important issue to be addressed in networks consisting of battery-powered devices. Many research efforts have been made for the efficient utilization of energy at mobile devices to prolong the network life time. With the recently emerging wireless power transfer technology, wireless charging based energy replenishment of nodes is considered in several studies [1]–[3]. For example, mobile chargers, which are considered to be special devices having high energy supplies, charge themselves from energy sources, navigate to the locations of mobile nodes and transfer energy to the sensor nodes in the network periodically.

Taking this further, recently, peer-to-peer energy sharing between all kinds of nodes with bidirectional energy exchange capability[1] in the network has been utilized for different purposes. For example, for an opportunistic content delivery, energy has been considered as an incentive [6], [7] to the devices to carry the message. Similarly, energy balancing [8]–[10] among nodes has been studied to prolong the lifetime of the network (especially when there is no access to additional energy resources).

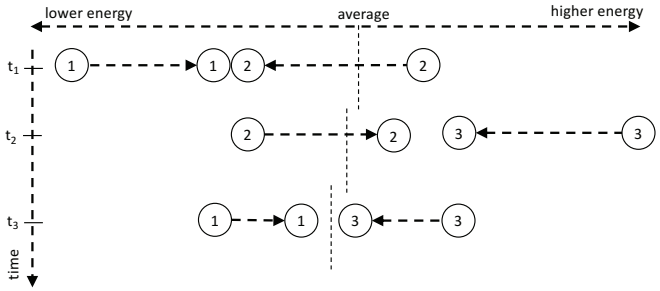

Fig. 1: Energy balancing through interactions between nodes at opposite sides of the average energy in the network. Dividing the total energy into half when nodes meet can help balancing energy among nodes but can waste energy.

Energy balancing among nodes has been targeted through the opportunistic energy exchanges between the nodes. The goal is to minimize the difference in the energy levels of all nodes. However, as nodes interact and transfer energy between each other, there occurs an energy loss. Thus, both balancing the energy among nodes and keeping the loss of total network energy as low as possible is equally important. The state-of-the-art solutions [8]–[10] suggest that the variation distance among the target energy levels of nodes and current energy levels will decrease only if the nodes in the opposite sides of the average energy in the network interact and exchange energy. While this is correct and help reach an energy balance among the devices as fast as possible, it wastes energy due to the unnecessarily frequent interactions between nodes. For example, consider the example in Fig. 1. When node 1 and node 2 meets at time t_1, node 2 gives energy to node 1 in the amount of the half of the difference of their energies. Note that due to the loss, node 1 can only receive a portion of the shared energy, hence it has a smaller energy than node 2 after this interaction. Similarly, node 3 provides energy to node 2 at time t_2 and node 3 again provides energy to node 1 at time t_3. While such an interaction protocol can help

[1]There are already several smartphones in the market with this feature such as Samsung Galaxy S10, Huawei Mate 20 Pro. There are also some prototypes [4], [5] developed by research community. While wireless charging based energy sharing provides convenience, we do not restrict the proposed solution in this paper to only wireless power transfer based energy sharing.

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reach an energy balance among nodes quickly, this can cause unnecessary wastage of energy as some nodes keep switching between the opposite sides of the average energy (which will decrease as the interactions with energy exchanges increase). In this specific example, after three interactions, node 2 has almost the same energy as in the beginning. The same level of energy distribution could have been obtained if the first two interactions were not performed and only in the third one node 3 provided energy to node 1.

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. To this end, we propose three different energy sharing protocols between nodes based on different heuristics. We evaluate the proposed algorithms and compare with the state-of-the-art solutions through simulations. The results show that the proposed algorithms show better performance than the state-of-the-art, with the third one having the best performance (i.e., balancing the energy of nodes with minimum energy loss).

The rest of the paper is structured as follows. In Section II, we discuss the related work that use peer-to-peer energy sharing in mobile networks in general and specifically for energy balancing. In Section III, we provide our assumptions on the system model and provide the problem statement. Section IV then gives the details of the proposed energy balancing algorithms. In Section V, we present the simulation settings used and provide the comparison results of the proposed solutions with the state-of-the-art solutions. Finally, we conclude the paper and outline the future work in Section VI.

II. Related Work

Wireless power transfer (WPT) has been widely employed in various applications mostly in wireless ad hoc and sensor networks. Numerous studies have looked at the energy replenishment of sensor nodes to prolong the network lifetime [1]–[3]. Recently, energy sharing has also been considered in mobile opportunistic networks in different contexts. In [11], authors focus on enhancing the energy usage of wireless networks with wireless energy sharing to minimize the chances of ending up with insufficient energy for their consumption. In [12], the benefit of peer-to-peer energy sharing through a group based charging is studied. Similarly, in [13], [14] matching of mobile users based on their ability to provide energy to each other is studied. In [15], [16], the impact of peer-to-peer energy sharing is considered to reduce the number of times mobile devices are charged through traditional ways (i.e. charging from a wall outlet). Usage of energy sharing has also been considered for content delivery in several recent works [6], [7]. The energy is shared with relay nodes as an incentive to carry the forwarded messages.

In a more related context to this paper, there are a few recent works that study the utilization of peer-to-peer energy sharing for energy balancing and network formation in mobile networks. In [8]–[10], authors exploit peer-to-peer wireless energy exchange to balance the energy within a mobile social network and propose various algorithms to be used in sharing protocol. In [17], [18], the impact of P2P energy sharing on network formation has been studied. The authors propose several interaction protocols that assume different amounts of network knowledge, achieving different trade-offs with performance, measured in terms of how close they get to the targeted energy distribution. While these works can decrease the variation distance between the energy levels of nodes and the target values (i.e., average energy) quickly, they do suffer from high energy loss in the network by design. This is because they let the nodes in the opposite sides of the target energy interact and exchange energy at every opportunity, causing the nodes change their side with respect to target several times and lose energy unnecessarily.

In order to address this problem, in this paper, we aim to both balance the energy levels among nodes and minimize the energy loss. To this end, we propose three different loss-aware energy exchange protocols between nodes. Through simulations, we show that the proposed algorithms show better performance than the state-of-the-art protocols thanks to their designs that aim an energy exchange only in useful interactions between nodes. The notations used throughout the paper are summarized in Table I.

TABLE I: Notations

Notation	Description
m	Number of nodes in the network.
$\mathcal{P}$	Interaction protocol between nodes for energy exchange.
β	Energy loss rate.
ϵ	Transferred energy.
$E_t(u)$	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}	Maximum maintainable energy with perfect balance among nodes.
$\delta(P,Q)$	Total variation distance between two distributions, P, Q.
$S_t^{+,-,=}(j)$	The set of nodes with more, less and equal energy to j.

III. System Model

A. Assumptions

We consider a population of m mobile nodes $\mathcal{M} = \{u_1, u_2, ..., u_m\}$, each having a limited battery, and having energy sending and receiving capabilities. Whenever two nodes interact based on a mobility pattern, 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), interacts in an exponentially distributed manner with an average mean of λ_{ij}. We also assume an energy loss rate, β, due to the nature of currently available wireless power transfer technology. We assume $\beta \in [0, 1)$ is a constant and depends on 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:

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

Since 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. As in previous work [8]–[10], for simplicity, we also do not consider energy loss due to mobility or other activities of the nodes, as this is besides the focus of the current paper.

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 [8]–[10].

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

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

Here, we do not divide the sum by two for the sake of keeping the actual differences. In our context, the total variation distance between the current energy distribution of nodes and the target energy distribution, where all nodes have the same energy, needs to be calculated. Note that the target energy level will not be equal to the current average energy in the network, as during the energy exchanges to balance energy among nodes, there will be some energy loss. This will make the average energy level decrease over time after each interaction. At any time, we define the energy distribution $\mathcal{E}_t$ on a sample space $\mathcal{M}$ by

$$\mathcal{E}_t(u) = \frac{E_t(u)}{E_t(\mathcal{M})}, \text{where, } E_t(\mathcal{M}) = \sum_{x \in \mathcal{M}} E_t(x) \tag{2}$$

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

$$\overline{E_t} = \frac{E_t(\mathcal{M})}{m} \tag{3}$$

We assume that each node knows the average energy level in the network. This could be achieved via cellular communication with a central server. The nodes only need to send updates when they interact and exchange energy, thus will happen rarely in a network with opportunistically interacting nodes. This helps nodes know the exact energy level that is targeted in real time. On the other hand, while it could be reasonable for devices like smartphones, in practice it may be costly for low power devices. Thus, in the third protocol, we do not rely on this knowledge and achieve an energy balancing with minimum loss by just using β.

IV. Loss-Aware Energy Balancing

In this section, we give the details of the three proposed energy balancing protocols. Each represents a solution attempt towards our goal to achieve an energy balance with minimal possible loss. Each solution depends on a rationale towards decreasing the loss, with the third one achieving the optimal loss.

Algorithm 1: GreedyPositive (u, u', t)

Input: (u, u'): Interacting nodes
t: Time of interaction

if *($E_{t-1}(u) > \overline{E}_{t-1}$ **and** $E_{t-1}(u') < \overline{E}_{t-1}$) **OR** ($E_{t-1}(u) < \overline{E}_{t-1}$ **and** $E_{t-1}(u') > \overline{E}_{t-1}$)* **then**
  if $E_{t-1}(u) > \overline{E}_{t-1}$ **then**
    $\mathcal{P}_{GP}(E_{t-1}(u), E_{t-1}(u'))$ = $(\overline{E}_{t-1}, E_{t-1}(u') + (1-\beta)(E_{t-1}(u) - \overline{E}_{t-1}))$
  else
    $\mathcal{P}_{GP}(E_{t-1}(u), E_{t-1}(u'))$ = $(E_{t-1}(u) + (1-\beta)(E_{t-1}(u') - \overline{E}_{t-1}), \overline{E}_{t-1})$
  end
else
  do nothing
end

A. Greedy Positive First Energy Balancing

Let $\Delta_t = \delta(\mathcal{E}_t, \mathcal{U}) - \delta(\mathcal{E}_{t-1}, \mathcal{U})$ be the decrease in variation distance from time $t-1$ to t, where at time t two nodes u and u' interact and $\mathcal{U}$ denotes the uniform distribution on $\mathcal{M}$ (i.e., $E_t(u) = \overline{E_t}\ \forall u$). Let also $z_t(x) = \mathcal{E}_t(x) - \frac{1}{m}$ denote the difference of node x's energy from the uniform distribution. It has been shown in [8]–[10] that if $z_{t-1}(u)z_{t-1}(u') < 0$, $\Delta_t < 0$. 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 split their energy equally, the energy variation distance in the network decreases. Otherwise, with $z_{t-1}(u)z_{t-1}(u') \geq 0$, $\Delta_t = 0$.

While energy sharing in the opposite sides of the average energy will decrease the variation distance, it may cause nodes move between the negative and positive side of the average energy level in the network (as shown in Fig. 1), and causes unnecessary energy loss in the network. In order to solve this problem and minimize the energy loss in the network as much as possible while achieving low variation distance among peers, we propose to make one of the nodes greedily reach the current average energy level in the network (i.e., target) immediately. Moreover, we give priority to the positive node. That is, if two nodes u and u' at different sides of the average energy level in the network interacts, the one in the positive side gives its excessive energy above the target to the one in the negative side. Note that, as the interactions in the network continue, the target energy level will decrease thus, this node may need to interact and decrease its energy again. However, this will not waste energy as the node will still stay in the positive side. If the node in the negative side was given the priority to reach the target first, then this would make the node switch to the positive side as the new interactions happen and the average energy in the network decreases. Algorithm 1 shows the interaction process of this *G*reedy *P*ositive first protocol, or $\mathcal{P}_{GP}$ in short.

B. Greedy Closer First Energy Balancing

In the greedy positive first protocol, it is still possible that some of the nodes in the negative side can switch to the

Algorithm 2: GreedyCloser (u, u', t)

Input: (u, u'): Interacting nodes
t: Time of interaction

1 $(u^+, u^-) \leftarrow$ (*null*, *null*)
2 **if** *(*$E_{t-1}(u) > \overline{E}_{t-1}$ ***and*** $E_{t-1}(u') < \overline{E}_{t-1}$*)* **then**
3 $(u^+, u^-) \leftarrow (u, u')$
4 **else**
5 **if** *(*$E_{t-1}(u) < \overline{E}_{t-1}$ ***and*** $E_{t-1}(u') > \overline{E}_{t-1}$*)* **then**
6 $(u^+, u^-) \leftarrow (u', u)$
7 **end**
8 **end**
9 **if** (u^+, u^-) *is not null* **then**
10 $\delta_{t-1}(u^+) = E_{t-1}(u^+) - \overline{E}_{t-1}$
11 $\delta_{t-1}(u^-) = \overline{E}_{t-1} - E_{t-1}(u^-)$
12 **if** $\delta_{t-1}(u^+)(1-\beta) > \delta_{t-1}(u^-)$ **then**
13 $\mathcal{P}_{GC}(E_{t-1}(u^+), E_{t-1}(u^-)) = (E_{t-1}(u^+) - \frac{\delta_{t-1}(u^-)}{(1-\beta)}, \overline{E}_{t-1})$
14 **else**
15 $\mathcal{P}_{GC}(E_{t-1}(u^+), E_{t-1}(u^-)) = (\overline{E}_{t-1}, E_{t-1}(u^-) + (1-\beta)\delta_{t-1}(u^+))$
16 **end**
17 **end**

positive side. For example, if the positive node has a very high excessive energy and can provide the node in the negative side with more energy than it actually needs to reach the target, this will make the node in the negative side switch to the positive side. To address this, we propose a new protocol which gives priority to the node that is closest to the target energy level and let it reach the target. Note that this has to be handled separately depending on different cases.

Algorithm 2 shows the details of the *G*reedy *C*loser first protocol, or $\mathcal{P}_{GC}$ in short. 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 should be more than what u^- will actually need (lines 12-13). Otherwise, u^+ is given priority to reach the target and the energy of u^- is increased accordingly (line 14-15).

C. Greedy Optimal Energy Balancing

The proposed protocols in previous sections aim to minimize the energy loss while achieving a small variation distance of energy level distribution of nodes with respect to the uniform distribution at the current time. However, as nodes interact, the average energy in the network, $\overline{E}_t$ will decrease and it will require the nodes that already reached the current average in the network interact again to reach this new target. For example, in $\mathcal{P}_{GC}$ protocol, there is still a possibility for negative side nodes that reach the target find themselves later in the positive side. Similarly, if priority is given to the nodes in the positive side as it is closer to the current target, even though it reaches the current average energy in the network, it can find itself again in the positive side.

To this end, we propose a third protocol called *G*reedy closer to *O*ptimal first protocol, or $\mathcal{P}_{GO}$ in short. We aim to maximize the benefit from each interaction, hence we make one of the nodes in the interacting pair reach the final optimal target immediately and stop interacting with others. This achieves a larger variation distance decrease per interaction and keeps the possible maximum energy in the network. However, the key point here is to find this optimal target energy level in the final network when all interactions finish and every node's energy is balanced.

For a given population of nodes and their energies, this can be calculated in a discrete manner through iterations. Let us divide the nodes in the network into three sets based on a reference energy level j as follows:

$$S_t^+(j) = \{x \in \mathcal{M} \mid E_t(x) > j\} \tag{4}$$

$$S_t^-(j) = \{x \in \mathcal{M} \mid E_t(x) < j\} \tag{5}$$

$$S_t^=(j) = \{x \in \mathcal{M} \mid E_t(x) = 0\} \tag{6}$$

Assume that E_{opt} is the optimal average target energy in the network that can be reached by all nodes with the minimum energy loss. It is clear that in the optimal way each node should reach this target directly. That is, the nodes having more energy than this target should give their excessive energy to others and the nodes having less energy than this target should receive energy from others in the amount of the difference. However, due to the loss, the nodes that will give energy to receiving nodes should transfer more than what they actually need. E_{opt} will then be obtained when the sum of receiving nodes energy can be supplied by giver nodes with minimal loss. More formally,

$$\begin{aligned} E_{opt} &= \arg\min_j \{\mathcal{B}_j^+ - \mathcal{B}_j^-\} \text{ where,} \\ \mathcal{B}_j^+ &= \sum_{\forall x \in S_0^+(j)} (E_0(x) - j) \\ \mathcal{B}_j^- &= \sum_{\forall x \in S_0^-(j)} \left(\frac{j - E_0(x)}{1-\beta}\right) \end{aligned}$$

In a large scale network with many nodes having uniformly distributed energy levels in [0,1], the expected value of E_{opt} can also be calculated as follows:

$$\begin{aligned} \int_{y=0}^{x} (x-y)dy &= \int_{x}^{1} (y-x)(1-\beta)dy \\ x^2 &= (x^2 - 2x + 1)(1-\beta) \\ f(x) = \beta x^2 + 2(1-\beta)x - (1-\beta) &= 0 \end{aligned} \tag{7}$$

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,

$$\begin{aligned} E_{opt} &= \frac{-2(1-\beta) + \sqrt{4(1-\beta)}}{2\beta} \\ &= \frac{-(1-\beta) + \sqrt{(1-\beta)}}{\beta} \end{aligned} \tag{8}$$

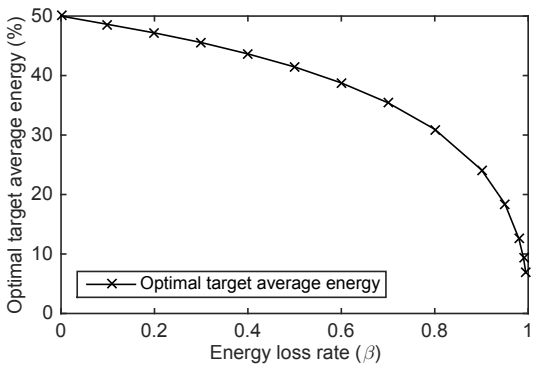

Fig. 2: Optimal target average energy for different energy loss rates for a large-scale network with uniform energy distributions.

Algorithm 3: GreedyOptimal(u, u', t)

Input: (u, u'): Interacting nodes
t: Time of interaction

1 *Replace* all $\overline{E}_{t-1}$ in GreedyCloser(u, u', t) with E_{opt}
2 Run the same algorithm

As $(1-\beta) \leq \sqrt{(1-\beta)}$ when $\beta \in$ [0,1], the value of E_{opt} is positive and lies in [0,1].

In Fig. 2, we show the values of E_{opt} for different energy loss rates. The results are average of 1000 runs among 100 nodes where each node's energy is determined randomly between 0 and 100%. For example, when there is a 20% energy loss during transfers, the optimal energy balance with minimum loss and zero variation is 47.213%.

As shown in Algorithm 3, the interaction protocol between nodes will be similar to the $\mathcal{P}_{GC}$ protocol except that E_{opt} will be used instead of $\overline{E}_{t-1}$. If the nodes in the opposite sides of E_{opt} interact, the one that can reach the target first based on energy exchanges between them is given priority.

Note that in an ideal scenario, with $n/2$ interactions, a perfect energy balance among all nodes can be achieved at E_{opt}. 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 and perfect meeting schedule between corresponding pairs that can complement each other. In practice, usually this is not the case as due to uniform distribution, there will not be equal number of nodes in both sides of the final optimal average and the meeting patterns of nodes may be very different.

V. Simulations

In this section, we present the results of our evaluation through simulations. We create a network of $m = 100$ nodes and assign each of them an energy level between 0 and 100 units randomly. We also generate a meeting pattern between each pair of nodes using an exponential distribution with a mean, $\lambda_{i,j}$, randomly selected from 1000 sec to 7000 sec. From the beginning of the simulation, we let the devices interact and exchange energy based on the characteristics of each protocol proposed. We then compare our algorithms with the state-of-the-art algorithm, $\mathcal{P}_{OA}$ [8]–[10], in terms of several metrics. Note that 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. For a fair comparison[2], we assume each node has the global information and knows the exact average in the network in that protocol too, thus name this version as $\mathcal{P}^*_{OA}$. Note that $\mathcal{P}^*_{OA}$ performs better than $\mathcal{P}_{OA}$.

Each simulation is repeated 1000 times for statistical smoothness. Error bars are not shown as the results were highly concentrated around the mean. For main simulations we use an energy loss rate, β, of 0.2. But we also show the performance of the best algorithm proposed, $\mathcal{P}_{GO}$, with different β values.

In Fig. 3-a, we show the total variation distance comparison for all algorithms. P^*_{OA} can provide smaller variation distance than the proposed algorithms. However, this is achieved with a very high energy loss, as shown in Fig. 3-b. Moreover, the number of interactions between nodes is also the highest among all compared algorithms, as shown in Fig. 3-c. Thus, when we compare the variation distance at the same total energy in the network in Fig. 3-d, we see that it achieves the worst performance. On the other hand, P_{GO} achieves the best performance and decreases the variation distance towards the optimal energy, E_{opt}, gradually. It also achieves this with minimum number of interactions. Thus, as it is shown in Fig. 3-e, it gives the best performance in terms of the total variation distance at a given interaction time.

The other proposed algorithms, P_{GP} and P_{GC}, perform better than P^*_{OA}, and worse than the P_{GO}. P_{GC} can achieve similar total variation distance (Fig. 3-b) at a given total energy in the network as P_{GO} and very close total energy in the network around the same simulation time (Fig. 3-d). However, as the nodes aim to reach the current average energy in the network their interaction does not stop as in P_{GO}, thus total variation distance at a given total interaction (with energy exchanges) count is worse than the case in P_{GO} (Fig. 3-e).

The impact of energy loss rate on the performance of P_{GO} is also shown in Fig. 3-f. P_{GO} always reaches the target if it is run sufficiently long. However, we notice that with higher β, the linear decrease converts to non-linear decrease. This is because, with higher β, E_{opt} gets lower, hence the difference in the number of nodes in the opposite sides of E_{opt} increases. This then results in less meeting likelihood between opposite side nodes in earlier times. Moreover, due to the high energy loss, the nodes in negative side receive small energy and cannot reach the target quickly. Thus, the variation distance decreases slowly. However, P_{GO} eventually reaches the optimal target with minimal loss.

[2]Note that this is for fair comparison with only $\mathcal{P}_{GP}$ and $\mathcal{P}_{GC}$ as $\mathcal{P}_{GO}$ does not use the global information of average network energy. In $\mathcal{P}_{GO}$, each node just calculates E_{opt} using β and decides accordingly.

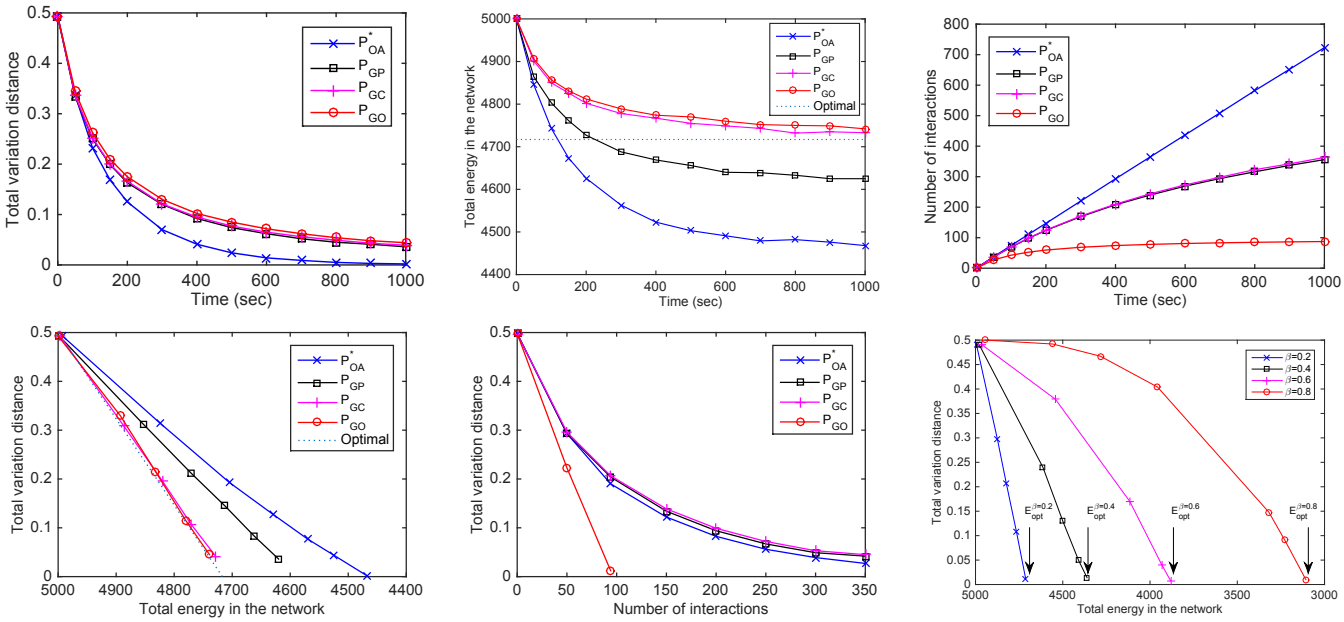

Fig. 3: Comparison of proposed algorithms with the state-of-the-art algorithm in terms of (a) variation distance, (b) total energy remaining in the network, (c) total number of interactions, (d) variation distance at each total energy level and (e) variation distance at each total number of interactions (when β=0.2). (f) shows the impact of different loss rates on $\mathcal{P}_{GO}$ performance.

VI. Conclusion

In this paper, we look at the energy balancing problem among a population of mobile nodes that interact opportunistically. We aim to both balance the energy levels of nodes and minimize the energy loss during this process. We propose three different energy sharing protocols and through simulations we show that they show better performance than the state-of-the-art, with the third one achieving the best performance. In our future work, we will consider the impact of intermeeting times between nodes and integrate social network metrics to speed up this process of balancing.

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