On the Fair Energy Sharing in Networks with Wireless Charging-capable Devices

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***Abstract*—The emerging technology of Wireless Power Transfer (WPT) has enabled mobile devices to replenish their batteries and increase their lifetime by exchanging energy with other devices in vicinity. In this paper, we study the problem of peer-to-peer WPT in a network of battery-constrained devices for which we aim to provide a fair energy allocation via mutual exchanges. In this respect, devices of lowest battery level remain functional for longer time, while respecting and satisfying a given set of wireless charging constraints. By taking into consideration the skewed energy availability in the network, as well as the loss induced by wireless energy transfer, we formulate and analyze three energy allocation schemes based on the concepts of lexicographic optimization and algorithmic graph theory, which, under different optimization criteria, aim to extend network lifetime. The performance of the proposed schemes is evaluated and compared in terms of energy efficiency and balancing quality through modeling and simulation over synthetic networks.**

***Index Terms*—Wireless Power Transfer, Reverse Wireless Charging, Fairness, Energy balancing, Resource exchange**

I. Introduction

Rechargeable battery is the current energy source for mobile devices. Due to their limited battery capacity and in order to remain operational, the devices need to be frequently charged by connecting to the power grid. Recently, a lot of attention has been given to Wireless Power Transfer (WPT) technologies [1], which allow the wireless exchange of energy. This has led to the design of mobile devices capable to recharge their battery via energy exchanges in a wireless peer-to-peer fashion. Wireless charging-capable devices can act as charging stations and may charge other wireless devices in proximity. This is known in the industry as Reverse Wireless Charging [2] and several smartphone manufacturers have already incorporated wireless charging standards, such as the Qi standard [3], in their products [4].

One of the most popular application of peer-to-peer WPT is crowd charging, where users of mobile devices form an energy resource sharing network [5]. This is based on the concept of sharing economy presented in [6], which enables the exchange of goods among similar users or users in proximity. Collaborative resource consumption assumes that a user with excessive amount of resources offers some of her resources to a fellow resource-deficient user in exchange for future resource offers, when in need. The idea behind this is to leverage on the collaboration of users in order to increase the welfare of all network participants.

An important aspect of peer-to-peer WPT, from a system design perspective, is to coordinate the exchanges so that the energy is fairly allocated to the network entities. Fairness in allocation will ensure that devices with low battery level will be recharged, hence, the network lifetime will be prolonged. However, exchanges are characterized by loss due to wireless attenuation [7] and skewed resource availability. Moreover, they are restricted by the network structure and wireless transmission conditions (e.g., distance between devices, path loss, etc.). For instance, the latest version of the Qi specification enables 5W to 15W power transfer over a distance of 5mm [1]. Such topology limitations and constraints dictate for each user the set of users it can donate and receive energy from.

A. Paper Contribution & Outline

By taking into consideration the above challenges, we examine the problem of peer-to-peer WPT in a network of battery-constrained devices and we formulate and analyze three energy allocation schemes based on lexicographic optimization and algorithmic graph theory respectively, which, under different optimization criteria, aim at extending the network lifetime. In particular, the first scheme allocates energy in a max-min (MM) fashion, attempting to increase the battery residual of the devices of minimum battery level in the network, though it does not necessarily ensure a balanced energy allocation. To treat the latter issue, we introduce a second scheme referred to as LM scheme, which applies a stronger optimization criterion, namely, lexicographic optimization. Lexicographic optimization attempts to first increase the battery residual of the devices of minimum battery level and next, if possible, it attempts to increase the second smallest battery level in the network, and so on. Contrary to MM and LM schemes, the third one, namely the Maximum Weighted Matching (MWM) scheme, does not prioritize the devices of lowest battery level but maps the problem of balanced energy sharing to a weighted matching problem in graphs. The performance of the proposed schemes is evaluated and compared in terms of energy efficiency and balancing through modeling and simulation over synthetic networks.

The remainder of this paper is organized as follows. Section II summarizes related works and distinguishes our contribution, while Section III presents the considered system model. Section IV introduces three different formulations of the problem of interest and relevant analysis. Section V presents an algorithm for lexicographic optimization, while Section VI provides the performance evaluation of the proposed schemes. Finally, Section VII concludes the paper and provides directions for future work.

II. Related work

Recently, the emerging peer-to-peer Wireless Power Transfer (P2P-WPT) problems set single or multiple objectives including energy balancing and minimization of energy loss in static and mobile networks. In [8], the authors consider different energy levels and priorities in a static network of battery-limited devices and provide three protocols for energy exchange under loss-less and lossy power transfer scenarios in order to minimize energy loss, minimize the time the network reaches an energy balance state and maintain knowledge of the network energy levels in an online manner. In [9] two protocols are proposed, a local and a global one, for balancing the energy of agents in a sensor network while avoiding wasteful energy transmission. The wireless crowd charging method proposed in [7] leverages knowledge on user mobility and social relationships in order to improve the performance trade-offs between energy-efficiency, energy balance quality and convergence time. Even though our work targets the same optimization objectives of these works, our focus is mainly on the limitations imposed by the network structure and the dependency among the network topology and the obtained solutions.

The works [10], [11] have studied energy sharing in mobile social networks. In [11], the network nodes are distinguished to power source and regular nodes. At first, the authors solve the problem of wireless charger allocation, in which for a given number of wireless chargers, they select a subset of them as power source nodes based on a weighted connectivity metric. Then, they design an algorithm for power dissemination from the selected power sources to the rest of the nodes in order to reduce power losses caused by unnecessary power transfers. The proposed approach assumes high power transmission efficiency in order to achieve energy dissemination, which, to date, is in fact quite unrealistic. A peer-to-peer wireless power transfer scheme among homogeneous devices is presented by the authors in [10] who examine the limits of power sharing among mobile devices by analyzing their charging patterns and their social interactions. Analogously to our MWM approach, they treat the energy sharing problem as an assignment problem by finding a stable matching of mobile users, but they restrict their study to specific network topologies of even size and they do not take into consideration the loss induced by energy transfer.

III. System model

We consider users of reverse wireless charging-capable mobile devices who participate in an Online Power Transfer (OPT) platform. The OPT is location-aware and enables energy sharing between devices in proximity. The devices participating in the OPT are assumed to be homogeneous in terms of battery capacity, energy loss that occurs during transfer as well as wireless charging rate. Data concerning the battery level of the participating devices are periodically collected and are used to compute the devices' energy availability and demand.

A graph $G = (V, E)$ models the network of users who join the OPT platform during the time interval $[0, T]$. The edge $(i, j) \in E$ exists if i and j are in spatial proximity that allows energy sharing [3]. In the time interval of observation, we assume that the network topology does not change (e.g., the energy sharing network formed by people with smart devices on a bus).

Assume time is slotted and let $K = \{1, 2, ..., m\}$ be the set of rounds of equal length t, for which it holds $T = mt$. At round $k \in K$, a fixed amount of energy ϵ can be exchanged between the battery cells of two neighboring devices with battery capacity b_{max} in the energy network. As in [8], we assume that an energy transfer ϵ induces energy loss $L(\epsilon) = \beta \cdot \epsilon$, where $\beta \in (0, 1)$ is a constant.

At round k, let $\mathbf{Z}_k$ be a $|V| \times |V|$ matrix with elements $z_{ij}(k)$ defined as:

$$z_{ij}(k) = \begin{cases} 1, & \text{if } i \text{ donates energy to } j, \\ 0, & \text{if } i \text{ does not donate energy to } j. \end{cases} \quad (1)$$

Let $c_i(k)$ be the energy consumption of node i for communication at the end of round k which depends on its state,

$$c_i(k) = \begin{cases} c_i^a, & \text{if } i \text{ transmits/receives data}, \\ c_i^b, & \text{if } i \text{ is idle}. \end{cases} \quad (2)$$

where $c_i^b << c_i^a$.

Given the communication cost $c_i(k)$, we define the expected battery level of device i at the end of round k, if i did not participate in the energy exchanges, as

$$\hat{b}_i(k) = b_i(k-1) - c_i(k), \quad (3)$$

where $b_i(k-1)$ denotes the battery level of device i at round $k-1$. It holds that $\hat{b}_i(k) \in [0, b_{max}] \subset \mathbb{N}$.

Then, for node i in G, taking into account its potential participation in the energy exchange process, the battery level at the end of round k, $b_i(k) \in [0, b_{max}] \subset \mathbb{N}$ is given by the expression:

$$b_i(k) = \hat{b}_i(k) - \sum_{j \in N_i} z_{ij}(k)\epsilon + \sum_{j \in N_i} z_{ji}(k)(\epsilon - L(\epsilon)), \quad (4)$$

where $N_i = \{j \in V : (i, j) \in E\}$ is the one-hop neighborhood of node i in G.

IV. Problem Statement

As stated before, fairness in energy allocation is defined in terms of prolonging network lifetime. At the time period of observation, it is possible that a device with high battery level may donate energy without receiving any. We consider this to be fair as long as the energy exchange at the end of the round under examination does not result in the donating device having battery level lower than: (a) the current network minimum battery level (simple optimization criterion), and (b) the battery level of the device receiving the donation (stronger optimization criterion).

Starting with the simple optimization criterion of maximizing the minimum battery level of the network, in Subsection IV-A, we formulate the problem of fair energy sharing as a max-min optimization. Since the latter focuses only on the transfer of energy to devices of minimal battery level, which does not necessarily result in a balanced energy allocation throughout the considered network, in Subsection IV-B, we apply the stronger optimization criterion of lexicographic optimization. In particular, we consider that the energy allocation is fair, in terms of balancing, if the sorted vector of battery levels is lexicographically optimal. Finally, in Subsection IV-C, we relax the optimization priority of the minimal battery level devices by mapping the problem of fair energy allocation to a maximum weighted matching problem.

A. Energy allocation in a max-min fashion (MM)

In a given round, we aim to allocate energy to devices via energy exchanges between neighboring nodes in G so that the battery residual of the devices of minimum battery level is increased by $\epsilon - L(\epsilon)$. It should be noted that such an optimization does not provide a means of allocating energy to devices that do not have minimal battery level. The Maximin problem at round k takes the form:

$$\mathbf{P1} : \max \min_{i \in V} b_i(k) \tag{5}$$

subject to

$$\sum_{j \in N_i} z_{ij}(k) + z_{ji}(k) \leq 1, \quad \forall i \in V, \tag{6}$$

$$b_i(k) \geq 0 \quad \forall i \in V, \tag{7}$$

$$b_i(k) \leq b_{max} \quad \forall i \in V, \tag{8}$$

$$z_{ij}(k) = 0, \quad \forall j \notin N_i, \tag{9}$$

$$z_{ij}(k) \in \{0, 1\} \quad \forall i, j \in V. \tag{10}$$

Constraint (6) means that, at a given round, device i may either donate energy to only one of its neighbors or receive an energy donation from only one of its neighbors. Constraints (7) and (8) ensure that the battery level of devices is within $[0, b_{max}]$, while constraint (9) indicates that energy exchange cannot occur between two non-neighboring devices in the energy graph. Finally, constraint (10) captures the binary nature of the decision variables $z_{ij}(k)$.

The Maximin problem $\mathbf{P1}$ is equivalent to the following simple Integer Linear Programming problem:

$$\mathbf{P2} : \max y \tag{11}$$

subject to

$$y - b_i(k) \leq 0, \quad \forall i \in V, \tag{12}$$

and the constraints (6), (7), (8), (9) and (10) of $\mathbf{P1}$.

The additional constraint (12) sets the auxiliary decision variable y as a lower bound for each of the individual variables $b_i(k)$.

To determine a feasible solution for the ILP problem $\mathbf{P2}$, we adapt a Branch-and-Cut technique [12].

B. Energy allocation in a max-min fair fashion (LM)

After solving IV-A, it may be possible to further increase some of the devices' battery level. Lexicographic optimization [13] attempts to first increase, if possible, the battery residual of the devices of minimum battery level in the network and next, if there are choices available, it attempts to increase the second smallest battery level in the network, and so on.

Definition IV.1. Vector $\mathbf{x} \in \mathbb{R}^m$ is called *lexicographically greater* than vector $\mathbf{y} \in \mathbb{R}^m$ and it is denoted by $\mathbf{x} \succ \mathbf{y}$, if there exists $j \in \{1, ..., m\}$ such that $x_i = y_i$ for all $i \in \{1, ..., j-1\}$ and $x_j > y_j$. If $\mathbf{x} \succ \mathbf{y}$ or $\mathbf{x} = \mathbf{y}$, then we write $\mathbf{x} \succcurlyeq \mathbf{y}$.

At the end of round k, the battery level of device i is given by:

$$b_i(k) = \begin{cases} \hat{b}_i(k), & \text{if } i \text{ does not share/donate energy,} \\ \hat{b}_i(k) + \epsilon - L(\epsilon), & \text{if } i \text{ receives energy,} \\ \hat{b}_i(k) - \epsilon, & \text{if } i \text{ donates energy.} \end{cases} \tag{13}$$

The vector of the devices' battery level is then given by $\mathbf{b} = (b_1, b_2, ..., b_{|V|})$. We define $\mathbf{f}(\mathbf{b})$ to be the $|V|$-dimensional vector whose coordinates are those of $\mathbf{b}$ arranged in non-decreasing order, i.e.,

$$\mathbf{f}(\mathbf{b}) = (f_1(\mathbf{b}), f_2(\mathbf{b}), ..., f_{|V|}(\mathbf{b})), \tag{14}$$

where $f_1(\mathbf{b}) \leq f_2(\mathbf{b}) \leq ... \leq f_{|V|}(\mathbf{b})$.

As in problem **P1**, at a given round, we aim to determine the matrix of energy exchanges $\mathbf{Z}$ in order to find a vector $\mathbf{b_o}$ for which $\mathbf{f}(\mathbf{b_o})$ is lexicographically maximal over the set X of all possible vectors of devices' battery level given by Eq.(13), arranged in non-decreasing order and dictated by the wireless charging constraints (i.e., the network structure) presented in problem **P1**, which means that $\mathbf{f}(\mathbf{b_o})$ is lexicographically greater than or equal to $\mathbf{f}(\mathbf{x})$, $\forall \mathbf{x} \in X$. Any optimal solution vector $\mathbf{b_o}$ is called *max-min fair* on set X with respect to $\mathbf{f}$.

The max-min fairness optimization problem is formulated as follows:

$$\mathbf{P3} : \operatorname{lex} \max_{X} \mathbf{f}(\mathbf{b}) \tag{15}$$

subject to the constraints (6), (7), (8), (9) and (10) of $\mathbf{P1}$.

In Section V we provide a max-min fairness algorithm that obtains the lexicographical maximal energy allocation.

C. Energy allocation as a problem of Maximum Weighted Matching in the energy graph (MWM)

For a given round, the problem of fair energy allocation via exchanges without prioritizing the devices of low battery level, as in Section IV-B, may be formulated as a matching problem on a subgraph of the energy graph G. A matching of a graph is a set of edges no two of which share a vertex [14]. Given a weight function $w : E \to \mathbb{R}$, the weight $w(G)$ of graph G is defined to be the sum of the weights of all its edges. A maximum weighted matching M^* of G is a matching whose weight is the maximum among all matchings of G.

At round k, we define the weight function $w_k : E \to \mathbb{N}$. For edge $(u, v) \in E$ it holds that

$$w_k(u,v) = \hat{b}_u(k) - \hat{b}_v(k). \tag{16}$$

We aim to find a Maximum Weighted Matching (MWM) of the directed subgraph $G_k = (V, E_k, w_k)$ with $E_k = \{(u,v) \in E : w_k(u,v) > \epsilon\}$. Finding a MWM of G_k ensures that all the selected edges, i.e., energy exchanges, will increase the battery level of devices without decreasing the battery level of the ones with equal or smaller battery level.

In order to formulate the MWM as an ILP problem, we define the weight matrix $W_k = (w_{ij}(k))$ and the adjacency matrix of graph G_k, $A_k = (a_{ij}(k))$, as well as the matrix of binary decision variables $Z_k = (z_{ij}(k))$. Then, the corresponding ILP problem can be expressed as follows:

$$\mathbf{P4} : \max_{Z_k} \sum_{i=0}^{|V|} \sum_{j=0}^{|V|} w_{ij}(k) \cdot a_{ij}(k) \cdot z_{ij}(k) \tag{17}$$

subject to

$$\sum_{j=1}^{|V|} a_{ij}(k) \cdot z_{ij}(k) + a_{ji}(k) \cdot z_{ji}(k) \leq 1 \quad \forall i \in V, \tag{18}$$

$$z_{ij}(k) \in \{0,1\} \quad \forall i,j \in V. \tag{19}$$

Constraint (18) indicates that, at a given round, device i may either donate energy to only one of its neighbors or receive an energy donation from only one of its neighbors and constraint (19) captures the binary nature of the decision variables $z_{ij}(k)$.

The Maximum Weighted Matchings of graphs G_k, $k = 1, ...m$ can be computed with the exact algorithm presented in [15].

V. Algorithm for max-min fairness

The proposed algorithm aims to solve the problem presented in IV-B, that is, to maximize fairness in energy allocation in a lexicographically optimal fashion at a given round of energy exchange. At the beginning of round k, it sorts the nodes in non-decreasing order of expected battery level $\hat{b}_i(k)$. For each node $i \in V_{min}$, where V_{min} is the set of nodes with minimum expected battery level at the current iteration, it computes the set of its one-hop neighbors, N_i, whose expected battery level after donating energy at round k, will remain above the expected battery level of i. Therefore, it increases the battery level of any device only at the expense of devices whose expected battery level at the end of round k is greater than the battery level of the device receiving the donation. In line 11, all devices with minimum expected battery level, $i \in V_{min}$, are sorted in non-decreasing order of neighborhood size $|N_i|$. For each node j in the sorted list with $|N_i| > 1$, the algorithm assigns i to its neighbor $j \in N_i$ with the highest battery level. Once a neighbor is assigned to i, both i and its selected neighbor are removed from the set of candidate nodes for energy sharing V' and from all the neighborhood sets $\{N_i\}_{i \in V_{min}}$. The procedure terminates when the set of candidate nodes V' is empty.

Algorithm 1: Algorithm for fair energy allocation via exchanges at round k.

Input : Energy network $G = (V, E)$, vector of devices' battery level $\mathbf{b}(k-1)$, vector of devices' communication cost $\mathbf{c}(k)$.

Output: Binary matrix $\mathbf{Z}(k) = (z_{ij}(k))$ of max-min fair energy exchanges **at round** k .

1 Sort nodes in non-decreasing order of expected battery level $\hat{b}_i(k) = b_i(k-1) - c_i(k)$, $u \in V$ and store the different values of battery level, in increasing order, in list B.
2 $V' \leftarrow V$
3 **while** $V' \neq \emptyset$ **do**
4   **for** $b \in B$ **do**
5     $V_{min} = \{i \in V' : \hat{b}_i(k) = b\}$
6   **for** $i \in V_{min}$ **do**
7       $C_i = \{j \in V' \setminus V_{min} : (i,j) \in E\}$
8       $N_i = \{j \in C_i : b_j(k-1) - c_j(k) - \epsilon > b_i(k-1) - c_i(k)\}$
9       $f(i) = |N_i|$
10   **end**
11     $S = argsort\{f\}$
12   **for** $s \in S$ **do**
13   **if** $N_s \neq \emptyset$ **then**
14   Assign to s its neighbor $w \in N_s$ with the highest battery level, $z_{ws}(k) = 1$
15         $V' \leftarrow V' \setminus \{w, s\}$
16         $N_u \leftarrow N_u \setminus \{w\}, \forall u \in S$
17   **end**
18   **end**
19   **end**
20 **end**

VI. Performance Evaluation & Numerical Results

A. Simulation Setup & Experimentation Methodology

In this section, we evaluate via modeling and simulation the performance of the proposed approaches for the problem of fair energy allocation via exchanges, in terms of various metrics and we compare the obtained results. For the MM problem presented in Section IV-A, we apply a Branch-and-Cut method [12], which solves the corresponding Integer Linear Programming problem **P2**, while for the MWM presented in IV-C, we employ the exact algorithm presented in [15].

For the experimental evaluation, we use synthetic networks modeled by Small-World (SW) graphs which are considered as the most appropriate ones for the representation of the structure and evolution of social networks [16]. The results are averaged over 200 distinct topologies, for each configuration presented in Table I. For each topology, we observe $k = 10$ rounds of energy exchange. The amount of energy exchanged in one round is set to $\epsilon = 10$ units. The initial battery level of devices follows a uniform distribution in $[0, 100] \subset \mathbb{N}$ and the corresponding communication cost is selected uniformly at random in $[1, 5] \subset \mathbb{N}$.

TABLE I
SUMMARY OF EXPERIMENTAL OPTIONS

Parameters	Available Options		
# of devices $\|V\|$	100	200	300
SW initial degree d	5	10	
Loss parameter β	0.3	0.5	

We evaluate the performance of the presented approaches by measuring the final minimum network energy $\min_i b_i(k)$, as well as the final total network energy $E = \sum_{i=1}^{|V|} b_i(k)$, where $b_i(k)$ is the battery level of device i at the end of round k, which is the final round of observation. The total number of energy exchanges is employed as a measure of energy transfer efficiency. A high number of energy exchanges implies significant energy loss and therefore, reduced network lifetime. Finally, the fairness index F proposed in [17] is used as a measure of energy allocation fairness in terms of balancing and it is given by the expression

$$F = 1 - \frac{2\sigma}{b_{max} - b_{min}}, \tag{20}$$

where σ is the standard deviation of the devices' battery level, b_{min} and b_{max} is the lower and upper bound of the devices' battery level respectively. The maximum fairness $F_{max} = 1$ is achieved when $\sigma = 0$.

B. Numerical Results

In order to highlight the differences and tradeoffs of the proposed energy sharing approaches, we provide, for various network setups and two different scenarios of energy loss, the achieved scores of the final total network energy (Fig. 1), the total number of exchanges (Fig. 2), the fairness index (Fig. 3) and the final minimum network energy (Fig 4). For demonstration purposes, the figures display the results that correspond to 30% and 50% loss of the transferred energy during an exchange, as the most indicative ones. It should also be noted that in all the stacked bar plots, both primary bars and sub-bars start from $y = 0$, in the vertical axis y.

1) Impact of network size and density: From Figs.1,2 we can derive that, when the MM approach is applied, the network density, defined as the ratio of the number of network edges to the maximum possible number of network edges, affects notably the number of exchanges and consequently, the final

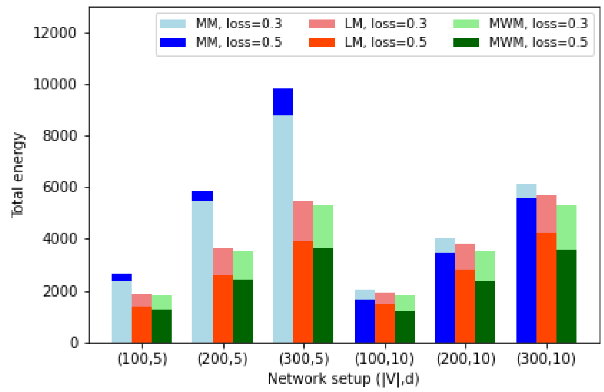

Fig. 1. Total network energy after 10 rounds of energy exchange with MM, LM and MWM.

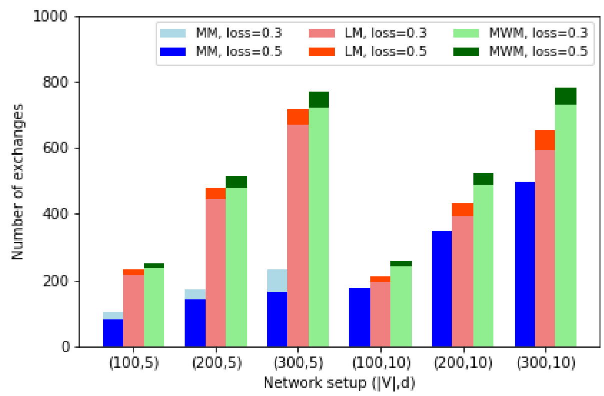

Fig. 2. Number of exchanges after 10 rounds of energy exchange with MM, LM and MWM.

total network energy. In Fig. 1 we observe that the MM approach yields the highest final total energy in all network settings, since, contrary to the LM and MWM approaches, which aim to allocate evenly the energy among devices, it optimizes the energy allocation only to devices of minimum battery level. This requires less energy exchanges, as depicted in Fig. 2, which results in smaller energy loss induced by energy transfer. As shown in Fig. 2, in the MM approach, the number of exchanges increases as the neighborhood size grows, while the LM approach exhibits the opposite behavior. More precisely, greater neighborhood implies higher probability of energy donation from a high-battery to a low-battery device and since these exchanges are prioritized in LM, the remaining devices will exhibit small battery level difference, therefore, they will not exchange energy. In the MWM approach, where devices of low battery level are not prioritized, the neighborhood size does not impact the number of exchanges. It is also noticed in Fig.3 that the MM approach distributes more fairly the energy among the devices in dense networks, contrary to LM and MWM which exhibit a slight decrease in the fairness index when the network density increases. On the other hand, LM and MWM achieve higher

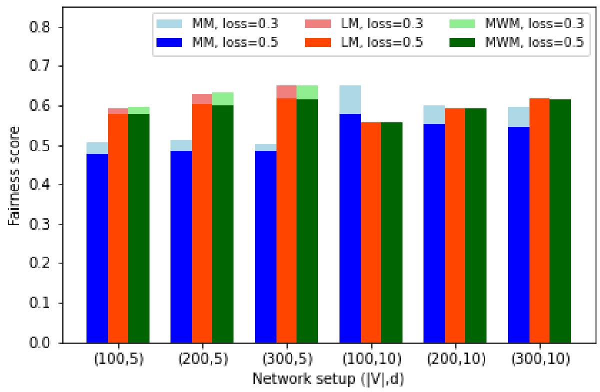

Fig. 3. Fairness score after 10 rounds of energy exchange with MM, LM and MWM.

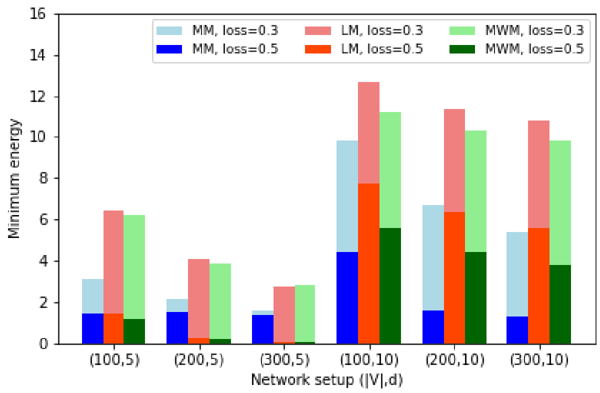

Fig. 4. Minimum energy after 10 rounds of energy exchange with MM, LM and MWM.

minimum network energy as depicted in Fig. 4. Therefore, LM and MWM balance better the trade-off between fairness in energy exchange and final minimum network energy.

2) Impact of energy loss: In most of the examined cases, smaller values of loss bring higher values of final total network energy, since less energy is lost in aggregate via exchanges. This does not hold for the MM approach in sparse networks as shown in Fig. 2. In particular, we observe that, compared to the scenario of 30% loss of the transferred energy, energy loss equal to 50% results in a smaller number of energy exchanges that aim to maximize the minimum network battery level, eventuating in higher final total network energy (Fig.1). This is due to the fact that high energy loss implies slow charging of low-battery devices (i.e., the set of minimum battery level devices at a given round of energy exchanges is likely to remain the same at the next round) leading to battery drain of their few (due to network sparsity) neighboring devices, which in turn, become unavailable for future energy exchanges. Finally, it is clear from Figs. 3,4 that, for low values of loss, the network lifetime is prolonged by all approaches, achieving higher minimum battery level and more balanced energy allocation to devices.

VII. Conclusion

In this paper we studied the problem of peer-to-peer Wireless Power Transfer in a network of battery-constrained devices to which we attempted to allocate the energy fairly, so that devices of lowest battery level remain functional for a long time, while satisfying a given set of wireless charging constraints. By taking into consideration the skewed resource availability in the network as well as the loss induced by energy transfer, we formulated and analyzed three energy allocation approaches based on lexicographic optimization and algorithmic graph theory, which, under different optimization criteria, aimed to extend network lifetime. The performance of the proposed approaches was evaluated in terms of energy efficiency and balancing quality through simulation over synthetic networks.

It should be noted that in this work, we assumed the use of homogeneous devices in terms of battery capacity, energy loss as well as wireless charging rate. It is of high research and practical importance, and apart of our current and future research, to consider the formulation and solution of the fair energy sharing problem under the assumption of heterogeneous devices in terms of the aforementioned characteristics.

References

[1] J. Huang, Y. Zhou, Z. Ning and H. Gharavi,“Wireless Power Transfer and Energy Harvesting: Current Status and Future Prospects,” *IEEE Wireless Communications*, Vol. 26, No. 4, pp. 163-169, August 2019.
[2] https://www.samsung.com/global/galaxy/what-is/wireless-powershare/
[3] https://www.wirelesspowerconsortium.com/qi/
[4] https://qi-wireless-charging.net/qi-enabled-phones/
[5] A. Dhungana and E. Bulut, “Peer-to-peer energy sharing in mobile networks: Applications, challenges, and open problems”, *Ad Hoc Networks*, Vol. 97, 102029, 2020.
[6] M. Felson and L. Spaeth. Joe, “Community structure and collaborative consumption: A routine activity approach”, *American behavioral scientist*, Vol. 21, Issue 4, pp. 614-624, 1978.
[7] T. Ojha, T. P. Raptis, M. Conti, and A. Passarella, “Balanced wireless crowd charging with mobility prediction and social awareness”, *Computer Networks*, Vol. 211, 108989, 2022.
[8] S. Nikoletseas, T. P. Raptis, C. Raptopoulos, “Wireless charging for weighted energy balance in populations of mobile peers”, *Ad Hoc Networks*, Vol. 60, pp. 1-10, 2017.
[9] H. Michizu, Y. Sudo, H. Kakugawa and T. Masuzawa, “Energy Balancing by Wireless Energy Transfer in Sensor Networks”, *Sixth International Symposium on Computing and Networking Workshops*, pp. 337-343, 2018.
[10] E. Bulut and B. K. Szymanski,“Mobile Energy Sharing through Power Buddies,” *IEEE Wireless Communications and Networking Conference (WCNC)*, pp. 1-6, 2017.
[11] K. Sakai, M. -T. Sun, W. -S. Ku and J. Wu, “Towards Wireless Power Transfer in Mobile Social Networks,” *in IEEE Transactions on Network Science and Engineering*, Vol. 9, No. 3, pp. 1091-1103, 1 May-June 2022.
[12] John E. Mitchell, “Branch-and-Cut Algorithms for Combinatorial Optimization Problems”, 1988.
[13] D. Nace, M. Pioro, “A tutorial on max-min fairness and its applications to routing, load-balancing and network design”, 2006.
[14] A. Gibbons, “Algorithmic graph theory”, Cambridge University Press, 1985.
[15] J. Edmonds, “Paths, trees and flowers”, *Canadian Journal of Mathematics*, Vol. 17, pp. 449 - 467, 1965.
[16] V. Karyotis, E. Stai, and S. Papavassiliou, “Evolutionary Dynamics of Complex Communications Networks,” *CRC Press*, USA, 2013.
[17] T. Hoßfeld, L. Skorin-Kapov, P. E. Heegaard and M. Varela, ”Definition of QoE Fairness in Shared Systems,” *in IEEE Communications Letters*, vol. 21, no. 1, pp. 184-187, Jan. 2017.