Peer-to-Peer Wireless Energy Transfer in Populations of Very Weak Mobile Nodes

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***Abstract*—Wireless energy transfer provides the potential to efficiently replenish the energy and prolong the lifetime of nodes in adhoc networks. Current state-of-the-art studies utilize strong charger stations (equipped with large batteries) with the main task of transmitting their available energy to the network nodes. Different to these works, in this paper, we investigate interactive, peer-to- peer wireless energy exchange in populations of resource limited mobile agents, without the use of any special chargers.**

The agents in this model are capable of mutual energy transfer, acting both as transmitters and receivers of wireless energy. In such types of adhoc networks, we propose protocols that address two important problems: the problem of energy balance between agents, and the problem of distributively forming a certain network structure (a star) with an appropriate energy distribution among the agents. We evaluate key performance properties (and their trade-offs) of our protocols, such as their energy and time efficiency, as well as the achieved distance to the target energy distribution.

I. Introduction

In many current application domains, such as medical and environmental monitoring, industrial automation, wireless sensor networks, intelligent transportation systems, etc., the need for battery-free ultralow-power devices, possibly wearable or implantable, is increasing dramatically [1]. Recently, there has been an increasing interest to combine near-field communication capabilities and wireless energy transfer in the same portable device, allowing mobile agents carrying the devices to wirelessly exchange energy. The near-field behavior of a pair of closely coupled transmitting and receiving dual-band printed monopole antennas (suitable for mobile phone applications) can make it possible to achieve both far-field performance and near-field power transfer efficiency (from 35% to 10%) for devices located few centimeters apart [2]. Further developments on the circuit design can render a device capable of achieving bi-directional, highly efficient wireless energy transfer and be used both as a transmitter and as a receiver [3], [4]. In this context, energy harvesting and wireless energy transfer capabilities are integrated, enabling each device to act on demand either as a wireless energy provider or as an energy harvester.

Populations of such devices have to operate under severe limitations in their computational power, data storage, the quality of communication and most crucially, their available amount of energy. For this reason, the efficient distributed co-operation of the agents towards achieving large computational and communication goals is a challenging task. An important goal in the design and efficient implementation of large networked systems is to save energy and keep the network functional for as long as possible [5], [6]. This can be achieved by using wireless energy transfer as an energy exchange enabling technology and applying interaction protocols among the agents which guarantee that the available energy in the network can be eventually distributed in a balanced way.

In this paper, we present our recent line of research (presented in [7], [8], [9], [10]) on a new model for configuring the wireless energy transfer process in networked systems of mobile agents. Inspired by the Population Protocol model of [11] and [12], this is the first study (to the best of our knowledge) of bi-directional, interactive wireless charging in populations of mobile peers.

More specifically, we review two important problems under the model of interactive wireless energy transfer:

- *Energy balance in the population*: We provide an upper bound on the time that is needed to reach energy balance in the population at the loss-less case, and we investigate the complex impact of the energy levels diversity in the lossy case; also, we highlight several key elements of the charging procedure. We provide three interaction protocols which take into account different aspects of the charging procedure and achieve different performance trade-offs.
- *Energy aware star network formation in the population*: For the first time, we *introduce energy issues* in network construction protocols. More specifically, the network agents can exchange energy when they interact. In this paper, the selected network structure is *the star* and we propose *a corresponding target energy distribution*.

II. Related work

In [13], the reader can find a comprehensive overview of wireless charging techniques, the developments in technical standards, and their recent advances in network applications. In [14], the authors present an extensive literature review on the research progress in wireless networks with RF energy harvesting capability. In [15], the authors give a review of the history of wireless energy transfer and describe its recent developments. In [16], the authors present an overview of the wireless energy transfer techniques and recent developments to apply these techniques in various sensing applications. [17] is a nice a review of wireless energy standards and relevant

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communication protocols. In [18], the authors discuss themes that are related to several applications spanning from future IoT and 5G systems, to high power electrical vehicles charging. Last but not least, the book [19], is the first systematic exposition on the domain of wireless energy transfer in ad hoc communication networks. It selectively spans a coherent, large spectrum of fundamental aspects of wireless energy transfer, such as mobility management in the network, combined wireless energy and information transfer, energy flow among network devices, joint activities with wireless energy transfer (routing, data gathering and solar energy harvesting), and safety provisioning through electromagnetic radiation control, as well as fundamental and novel circuits and technologies enabling the wide application of wireless energy. In this work we do not address the communication layer. For interesting discussions of said issues the reader my refer to [20], [21].

III. The Model

We consider a population of m mobile agents denoted as $\mathcal{M} = \{u_1, u_2, \ldots, u_m\}$, each one equipped with a *battery cell*, a *wireless energy transmitter* and a *wireless energy receiver*. Additionally, each agent u has a *state* from a set of states $\mathcal{Q}$ and a small *local memory* consisting of a small number of registers. For any time $t \geq 0$ and agent u, we denote by $C_u(t) \stackrel{def}{=} (E_u(t), q_u(t), R_u(t))$ the *configuration of u at t*, where $E_u(t)$ (resp. $q_u(t), R_u(t)$) is the *energy level* (resp. state and memory) of agent u at time t. The *relationship* between any pair of agents $\{u, v\}$ is further characterized by a *connection state* from a set of states $\mathcal{Q}'$ (different from $\mathcal{Q}$); here we set $\mathcal{Q}' = \{0, 1\}$. In particular, for any pair of agents u, v, if their connection state $q_{\{u,v\}}(t)$ at time t is equal to 1, then we say that u is connected to v at t; otherwise (i.e. if $q_{\{u,v\}}(t) = 0$) they are disconnected.

Because of the limitations of current technology, the peers have to be within a few centimeters from each other, and the size of the overall network is in the order of a few meters. The movement of the agents does not follow any specific pattern, but whenever two agents meet (e.g. whenever their trajectory paths intersect or the agents come sufficiently close), they can interact according to an *interaction protocol* $\mathcal{P}$; all agents run the *same* protocol $\mathcal{P}$. In particular, whenever agents u, v interact, they modify (a) their respective configurations (i.e. they exchange energy, modify their states and local memory) and (b) their connection state according to $\mathcal{P}$. Formally, we assume that time is discrete and that if agents u, v interact at time t, they communicate their configurations and current connection state and they jointly modify them as follows:

$$(C_u(t+1), C_v(t+1), q_{\{u,v\}}(t+1)) = \mathcal{P}(C_u(t), C_v(t), q_{\{u,v\}}(t)).$$

The configurations of all other agents, as well as every other connection state (including those involving agents u or v with other agents) remain unchanged.

Due to the nature of wireless energy technology (e.g. RF-to-DC conversion, materials and wiring used in the system, objects near the devices, etc.), any transfer of energy induces *energy loss*. Therefore, whenever an agent u transfers energy ε to agent v, the amount of energy that the latter actually receives is $(1-\beta)\cdot\varepsilon$, where β is a parameter depending on the environment and the equipment for energy transfer available to the agents. In the most general case, the value of β is *not known* by the agents and can be *different* in every interaction. In particular, we assume that in every interaction β is an *independent random variable* that follows some distribution (e.g. the normal distribution). For simplicity, we do not take into account energy loss due to movement or other activities of the agents explicitly, as this is besides the focus of our work.

In fact, we assume that most devices can be carried by individuals or other moving entities that have their own agenda, and thus devices interact when the latter happen to come in close proximity. In the most general setting, interactions between agents are planned by a *scheduler* (that satisfies certain fairness conditions ensuring that all possible interactions will eventually occur), which can be used to abstract the movement of the agents. To allow for non-trivial results in our experimental evaluation of our algorithmic solutions, here we consider a widely accepted special case of fair scheduler, namely the *probabilistic scheduler*, which was introduced in [22]. According to the probabilistic scheduler, in every time step, a single interacting pair of agents is selected independently and uniformly at random among all $\binom{m}{2}$ pairs of agents in the population.

A crucial assumption of this model (which is inspired by the population protocols model [22] and network constructors [23]) is that agents do not share memory or exchange messages unless they interact. Furthermore, agents are computationally weak machines that cannot grasp the full structure and status of the entire population. Nevertheless, through pairwise interactions agents are required to collectively eventually *converge* to a stable state.

IV. Problem definition and metrics

In [23], the authors define the *population network* at time t to be the simple, undirected graph G_t with vertex set the set of agents $\mathcal{M}$ and edge set the set of pairs of agents u, v that have $q_{\{u,v\}} = 1$. In particular, they design protocols (which they call *network constructors*) that eventually converge to certain graph structures. We significantly generalize the definition of network constructors to take into account the energy levels of the agents in the population; we call this *energy aware network formation*. To this end, we use two metrics: the *structural distance* and the *energy distance*.

Formally, let H be a *target graph* on m vertices. For two graphs H, G on the same vertex set $\mathcal{M}$, we denote by $H \triangle G$ the hamming distance between those graphs, i.e. $H \triangle G \stackrel{def}{=} \sum_e |\mathbf{1}_e(H) - \mathbf{1}_e(G)|$, where the summation is over all $\binom{m}{2}$ possible edges and $\mathbf{1}_e(H)$ (resp. $\mathbf{1}_e(G)$) is the indicator variable for the existence of e in H (resp. G). We

define the *structural distance* of the population from the target graph H at time t as follows:

$$\delta_t^s(H, G_t) \stackrel{def}{=} \min_{G \sim G_t} H \triangle G,$$

where G_t is the population network at time t and the minimum is taken over all graphs G that are isomorphic to G_t.

The energy distance is defined in analogy to the *total variation distance* in probability theory and stochastic processes [24], [25]. Let $\mathcal{E}^*$ be a *target distribution*, defined on $[m] = \{1, 2, \ldots, m\}$ and, for any $t \geq 0$, let $\mathcal{E}(t)$ be the relative energy distribution at time t given by $\mathcal{E}_u(t) = \frac{E_u(t)}{\sum_u E_u}, u \in \mathcal{M}$. Let also $\Sigma(m)$ be the set of permutations of $[m]$. We define the *energy distance* of the population from the target energy distribution $\mathcal{E}^*$ at time t as follows:

$$\delta_t^e(\mathcal{E}^*, \mathcal{E}(t)) \stackrel{def}{=} \min_{\sigma \in \Sigma(m)} \frac{1}{2} \sum_{i=1}^{m} |\mathcal{E}_i^* - \mathcal{E}_{\sigma(u_i)}(t)|,$$

where the minimum is among all permutations of $[m]$, $\mathcal{E}_{\sigma(u_i)}(t)$ is the relative energy level of agent $\sigma(u_i)$ at time t and $\mathcal{E}_i^*$ is the target distribution at point i of its domain.

The general formulation of the problem that we consider in this paper is as follows:

Definition 1 (Energy aware network formation)**.** *Consider a population $\mathcal{M}$ of agents. Let H be a target graph on $\mathcal{M}$ and $\mathcal{E}^*$ a target distribution. Let also ϵ be a small positive constant. Assuming the probabilistic scheduler, find a protocol that, when run by the agents in the population, there is $t \geq 0$ such that (a) $\delta_t^s(H, G_t) = 0$, (b) $\delta_t^e(\mathcal{E}^*, \mathcal{E}(t)) \leq \epsilon$ and (c) the total energy loss is minimized, i.e. $E_{total}(0) - E_{total}(t) = \sum_u E_u(0) - \sum_u E_u(t)$ is as small as possible.*

In this work, we consider two special cases of the Energy Aware Network Formation Problem: (a) the *Population Energy Balance* problem and (b) the *Energy Aware Star Formation* problem. In the Population Energy Balance Problem, the structure is irrelevant (alternatively, this version of the problem may be thought as the energy aware construction of the complete graph), and the ultimate goal is to achieve approximate energy balance at the minimum energy loss across agents in $\mathcal{M}$. For this special case, we also make the additional assumption that the energy loss factor is constant for each interaction (rather than a random variable). In the second problem, we consider the construction of one of the most basic graph structures, namely the star. Furthermore, we assume that the target distribution is such that *the relative energy level of each node is proportional to its degree*. Our motivation for this problem comes from the fact that star formations usually arise in wireless networks when nodes are organized in a cluster, in which case a cluster-head is selected to which all communication is forwarded. In view of this, the energy level of the cluster-head should be proportional to the number of nodes in its cluster. Therefore, the target energy level of the central node of the star at time t should be $a = \frac{E_{total}(t)}{2}$, while the target energy level of a peripheral node should be $b = \frac{E_{total}(t)}{2(m-1)}$. Setting without loss of generality $\mathcal{E}^* = \{a, b, b, \ldots, b\}$, the minimum of $\frac{1}{2}\sum_{i=1}^{m} |\mathcal{E}_i^* - \mathcal{E}_{\sigma(u_i)}(t)|$ (which is equal to the energy distance $\delta_t^e(\mathcal{E}^*, \mathcal{E}(t))$) is attained by choosing any permutation σ that assigns the agent with the largest energy level to u_1.

V. The Population Energy Balance Problem

Let $\mathcal{U}$ to be the uniform distribution on $\mathcal{M}$. We will say that the population has energy balance ϵ at time t if and only if $\delta_t^e(\mathcal{U}, \mathcal{E}(t)) \leq \epsilon$. It is evident from the definition of our model that $\delta_t^e(\mathcal{U}, \mathcal{E}(t))$ is a random variable, depending on the specific distribution of energies in the population and the choice is made by the probabilistic scheduler at time t. Therefore, we are rather interested in *protocols that reduce the total variation distance on expectation with the smallest energy loss*. Furthermore, we measure the efficiency of a protocol $\mathcal{P}$ by the expected energy loss and the expected time needed for the protocol to reach energy balance.

A. The protocol Oblivious-Share $\mathcal{P}_{OS}$

A simple protocol for energy balance in the case of loss-less energy transfer (i.e., for $\beta = 0$), is Oblivious-Share $\mathcal{P}_{\text{OS}}$. $\mathcal{P}_{\text{OS}}$ states that, whenever two agents u, u' interact, they split their cumulative energy in half. In the following Lemma, it is shown that, when all agents in the population use protocol $\mathcal{P}_{\text{OS}}$, the total variation distance decreases in expectation. The proof not only leads to an upper bound on the time needed to reach energy balance (see Theorem 1), but more importantly, highlights several key elements of the energy transfer process, which we exploit when designing interaction protocols for the case $\beta > 0$.

Lemma 1 ([7])**.** *Let $\mathcal{M}$ be a population of chargers using protocol $\mathcal{P}_{OS}$. Assuming interactions are planned by the probabilistic scheduler and there is no loss from energy exchanges, we have that*

$$\mathbb{E}[\delta_t^e(\mathcal{U}, \mathcal{E}(t)) | \mathcal{E}(t-1)] \leq \left(1 - \frac{2}{\binom{m}{2}}\right) \delta_t^e(\mathcal{U}, \mathcal{E}(t-1)).$$

It is worth noting that the upper bound of Lemma 1 is tight when the distribution of energies is such that there is only one agent with energy above or below the average. Lemma 1 is used to prove that $\mathcal{P}_{\text{OS}}$ is quite fast in achieving energy balance in the loss-less case.

Theorem 1 ([7])**.** *Let $\mathcal{M}$ be a population of agents using protocol $\mathcal{P}_{OS}$. Let also $\tau_0(c)$ be the time after which $\mathbb{E}[\delta_t^e(\mathcal{U}(\tau_0(c)), \mathcal{E}(\tau_0(c)))] \leq c$, assuming interactions are planned by the probabilistic scheduler and there is no loss from energy exchanges. Then $\tau_0(c) \leq \frac{1}{2}\binom{m}{2} \ln\left(\frac{\delta_t^e(\mathcal{U}, \mathcal{E}(0))}{c}\right)$, where $\delta_t^e(\mathcal{U}, \mathcal{E}(0))$ is the total variation distance between the initial energy distribution and the uniform energy distribution.*

B. The protocol Small-Transfer $\mathcal{P}_{ST}$

The protocol Small-Transfer $\mathcal{P}_{\text{ST}}$ suggests having only small energy transfers between interacting agents. Ideally, we only allow exchanges of infinitesimal energy $d\varepsilon$ which simplifies our analysis (in the experiments, we just choose a very small fixed value ε). Even though this idea is wasteful on time,

we provide both analytic and experimental evidence that it achieves energy balance without wasting too much energy. For this very protocol, we realize the fact that under current technology, repetitive transfers of small energy amounts may be inefficient in view of the overhead incurred in any transfer.

We prove the following lemma concerning the total variation distance change in a population of agents that use protocol $\mathcal{P}_{\text{ST}}$.

Lemma 2 ([7])**.** *Let $\mathcal{M}$ be a population of chargers using protocol $\mathcal{P}_{ST}$. Given any distribution of energy $\mathcal{E}(t-1)$, let $|A^+(t-1)|$ (respectively $|A^-(t-1)|$) be the number of agents with available energy above (respectively below) the current average. Assuming interactions are planned by the probabilistic scheduler, we have that*

$$\mathbb{E}[\Delta_t|\mathcal{E}(t-1)] \leq \frac{4}{E_{total}(t)}\left(\beta - \frac{|A^+(t-1)|\cdot|A^-(t-1)|}{m(m-1)}\right).$$

It is worth noting that the upper bound on the total variation distance change from the above Lemma is quite crude (and can be positive if β is not small enough). However, this is mainly a consequence of our analysis; in typical situations, the upper bound can be much smaller. For example, in the cases where the energy distribution $\mathcal{E}(t-1)$ at time $t-1$ is such that $|A^+(t-1)| \approx |A^-(t-1)| \approx \frac{m}{2}$ gives the bound $\mathbb{E}[\Delta_t|\mathcal{E}(t-1)] \leq -\frac{1-\beta}{E_{total}(t)}d\varepsilon$, which is negative for any $\beta \in (0,1)$. This is also verified by our experimental evaluation of $\mathcal{P}_{\text{ST}}$. Nevertheless, the upper bound that we get from Lemma 2 highlights key characteristics of the interactive energy transfer process as we pass from loss-less (i.e., $\beta = 0$) to lossy energy transfer (i.e., $\beta > 0$).

C. The protocol Online-Average $\mathcal{P}_{OA}$

By the analysis of the expected total variation distance change in Lemma 1 for energy transfer without losses, we can see that the total variation distance decreases when the interacting agents have energy levels that are on different sides of the average energy in the population. Using the notation form the proof of Lemma 1, if agents u, u' interact at time t, then we must either have $u \in A^+(t-1)$ and $u' \in A^-(t-1)$, or $u \in A^-(t-1)$ and $u' \in A^+(t-1)$, in order for the total variation distance $\delta^e_t(\mathcal{U}, \mathcal{E}(t))$ to drop below $\delta^e_t(\mathcal{U}, \mathcal{E}(t-1))$. The situation becomes more complicated when there are losses in energy transfers, but the analysis in Subsection V-B suggests that, under certain constraints on the energy distribution and the energy loss factor β, the total variation distance decreases whenever there is an interaction between a high relative energy agent and a low relative energy agent.

In view of the above, an ideal interaction protocol would only allow energy transfers between agents with energy levels that are on opposite sides of the average energy in the population. In particular, this would imply that, at any time t, each agent x would need to know the sign of $z_x(t) = \frac{E_x(t)}{E_{total}(t)} - \frac{1}{m}$, which is possible if x knows (in addition to its own energy level $E_x(t)$) the average energy $\frac{E_{total}(t)}{m}$ in the population. However, this kind of global knowledge is too powerful in our distributed model, since we assume that agents are independent and identical with each other. In particular, this implies that not only are agents not aware of other agents they have not yet interacted with, but also, that they have no way of knowing whether they have met with another agent at some point in the past.

The main idea behind our interaction protocol Online-Average $\mathcal{P}_{\text{OA}}$ is that, even in our weak model of local interactions, agents are still able to compute local estimates of the average energy based on the energy levels of agents they interact with. To do this, every agent needs to keep track of the total number of interactions she has done, as well as her current estimation for the average energy. This is accomplished by having each agent $x \in \mathcal{M}$ maintaining two local registers, namely (a) $\text{num}(x)$, which is used to count the number of interactions that x has been involved in, and (b) $\text{avg}(x)$, which stores the current estimation of x for the average energy. Furthermore, $\text{num}(x)$ is initialized to 1, and $\text{avg}(x)$ is initialized to $E_0(x)$. We give the formal description of our protocol below.

It is worth noting that $\mathcal{P}_{\text{OA}}$ may not perform up to par in the general case where interactions are planned by a potentially adversarial scheduler, because the local estimates kept by agents for the average can be highly biased. On the other hand, in our experimental evaluation, we show that $\mathcal{P}_{\text{OA}}$ outperforms both $\mathcal{P}_{\text{OS}}$ and $\mathcal{P}_{\text{ST}}$ when agent interactions are planned by the probabilistic scheduler. Furthermore, it is much faster than $\mathcal{P}_{\text{ST}}$ in terms of the expected number of useful interactions (i.e., interactions that change the energy distribution in the population) needed to reach energy balance.

VI. The Energy Aware Star Formation Problem

In this section we present our proposed interaction protocols that form a star network structure and aim to minimize the energy distance metric as defined above. At any time t, the probabilistic scheduler selects two agents u,v to interact and the protocols run in order to change the configuration of each agent. The protocols differ on the way that two agents interact, on the amount of energy that two agents exchange and on the size of the agents' memory. The set of states is defined as $\mathcal{Q} = \{c, p, h_1, \ldots, h_d\}$. If the state of an agent is c (resp. p), the agent is characterized as central (resp. peripheral). The states $h_i,\ i \in \{1, \ldots, d\}$ are not network structure states but are used to allow the algorithms to improve their decisions. However, these states are not used by all proposed algorithms. More specifically, in $\mathcal{P}_{FT}$ and $\mathcal{P}_{HT}$ the agent may be either central or peripheral. Initially, in all protocols, the agents are considered to be central.

A. The protocol Full Transfer $\mathcal{P}_{FT}$

In this section we present a straightforward protocol that can be seen as a lower bound to the performance of the other proposed protocols discussed in sections below.

In this protocol there are three main interaction cases. The first case is when both agents are central. In this case one of them will randomly be selected to remain central and the other

one will become peripheral and it will transmit all its available energy (except a small amount of it, denoted as E_{min}, which is needed in order for the agent to remain operational) to the central agent. In addition, a connection between them will be established. In the second case, both agents are peripherals. If a connection between them exists, the algorithm removes it and no energy is transferred between them. In the final case, one agent is considered to be central, and the other one is peripheral. In this case, if there is no connection between them, the algorithm establishes it and like in the previous case, no energy is transferred between them.

After evaluating the proposed protocols, which focus on the star network formation problem, through simulations we found that this protocol under-performs in most metrics. While it converges to its final energy distribution with few interactions, it produces a high energy loss and energy distance from the target distribution. This is due to the protocol's random nature.

B. The protocol Half Transfer $\mathcal{P}_{HT}$

In this section we describe the protocol Half Transfer $\mathcal{P}_{HT}$, which allows the agents to store their own initial energy level in their memory. Notice that this does not constitute global knowledge by the agents.

The decisions made by this protocol differ from the $\mathcal{P}_{FT}$ in two ways. When two central agents interact, the agent with highest energy level at that time will remain central, while the other one will become peripheral. The second difference lies in the amount of energy that is transferred when there is an energy exchange. The peripheral agent will keep half of its initial energy and will transmit the rest. This decision is based on the observation that in order to achieve the desired energy distribution, the central agent will have to acquire half of the total energy of the network. Aside from these two differences, $\mathcal{P}_{HT}$ operates exactly like $\mathcal{P}_{FT}$.

This protocol improves on the results of the $\mathcal{P}_{FT}$. It achieves lower energy distance from the target distribution with less energy loss. It's convergence time is similar to that of $\mathcal{P}_{FT}$.

C. The protocol Degree Aware $\mathcal{P}_{DA}$

The Degree Aware protocol $\mathcal{P}_{DA}$ *aims to estimate the total number of agents* that are present in the network. This information is useful since each agent can adapt its energy exchanges in order to reduce the energy distance. Each central agent's estimation is the number of their connected neighbors. The non central agents store the maximum estimation among the agents that they have interacted with. The maximum estimation is exchanged in each interaction, thus ensuring its propagation to every agent.

In order to improve the estimation, each agent goes through d *halted states* $(h_1, h_2, \ldots, h_d)$; d is a parameter whose choice was fine-tuned through simulations. The simulation results showed that, for this protocol, the optimal value is $d = 1$. The transition from a halted state to the next one is performed whenever the agent interacts with a central agent, that has a higher estimation. Each agent, will only transmit energy to agents with a higher estimation than its own, after they have passed through every halted state and have become peripherals. There are four main interaction cases in this protocol.

In the case where both agents are centrals, the agent with the lowest estimation becomes a 1^{st} level halted agent. A connection between them is established, the estimation of the central agent is increased by one and the estimation of the halted agent is updated to this maximum value as well.

In the case where each agent is either peripheral or halted, the agents exchange the maximum estimation and delete their connection if it exists.

In the case where one agent is central and the other one is peripheral, if the central agent has lower estimation than the peripheral, it becomes a 1^{st} level halted agent and updates its estimation. Otherwise, their states remain the same, but if the agents are not connected, they establish a connection and update their estimations to the new maximum one. If the energy level of an agent times the maximum estimation (between these two agents) is larger than the energy level of the other agent, it will transmit to it an amount of energy that is equal to $(1/k) \times (E_u \times E_v)/(E_u + E_v)$ where parameter k *is used to limit the energy exchanged between the agents and thus the energy loss*, when the estimation is not equal to the actual network size. Through simulations we observed that the optimal value of the parameter k for this protocol is $k = 7$.

In the fourth case where one agent is central and the other one is halted, if the halted agent has larger estimation than the central, the latter becomes halted as well. Else, if the central agent has the larger estimation but the level of the halted agents is not d, i.e. its state is not the h_d, it moves to the next level halted state. Otherwise, if the central agent has the highest estimation and the halted agent's state is the last one, then the halted agent becomes peripheral. If the agents are not connected, they establish a connection between them, and increase the estimation of the central agent by one. If the energy level of an agent times the maximum estimation (between these two agents) is larger than the energy level of the other agent, it will transmit to it an amount of energy that is equal to $(1/k) \times (E_u \times E_v)/(E_u + E_v)$. Also, both agents will update their estimation to the maximum one between them.

This protocol achieves near-zero energy distance with low energy loss. It requires more interactions than the previous two protocols in order to converge to the desired energy distribution, since the agents need to go through d additional states until they become peripherals. The higher the parameter d, the higher the number of required interactions is. In other words, the protocol achieves *a tunable trade-off* between energy efficiency and convergence time.

D. The protocol Fully Adaptive $\mathcal{P}_{FA}$

The protocol Fully Adaptive $\mathcal{P}_{FA}$ aims to improve on the ideas of $\mathcal{P}_{DA}$, which assumes slightly stronger agents with the ability to store more information on their memory. In addition to storing the estimation of the network size, each agent also stores the energy level (at the time of their interaction) of the last central agent (e_c) it has interacted with. This protocol works in the same way as $\mathcal{P}_{DA}$. The main difference lies in

the way the agents exchange energy. There are two different types of energy exchanges.

(a) When a central agent (u) interacts with either a peripheral or a d-level halted agent (v), the energy to be exchanged between them is calculated with this formula $e_{sent} = (1/k) \times (E_u(R_u-1)-E_v)/(R_u+1)$. When this value is negative (resp. positive), it means that u has less (resp. more) energy than it is required in order to achieve the desired energy distribution and thus it receives (resp. transmits) that (absolute) amount of energy from (resp. to) v.

(b) When two peripheral agents (u, v) interact, before they exchange energy, they attempt to find the optimal energy level a peripheral agent should have according to the desired energy distribution. This is done by using the stored value for the energy of the last central agent they have interacted with and is defined as $e_p^{u/v} = E_c/(R_{u/v} - 1)$. Both agents calculate this value and they exchange energy if and only if they are on opposite sides of both these calculated values (i.e. $E_u > e_p^u$ & $E_v < e_p^u$ & $E_u > e_p^v$ & $E_v < e_p^v$). If all these conditions are true, then the agent with the highest energy level (e.g. agent u) transmits energy according to the following formula: $e_{sent} = (1/k) \times (E_v - E_u)/2$. As in the previous protocol, k is used to limit the energy exchanged between the agents and thus the energy loss, when the estimation is not equal to the actual network size.

The values $d = k = 1$ are selected for this protocol, since the simulation results indicated that increasing the value of these parameters negatively affected the protocol's performance. This protocol achieves near-zero energy distance and minimal energy loss. It converges to the desired energy distribution in a relatively small number of interactions when compared to the $\mathcal{P}_{DA}$.

VII. Conclusion

In this paper we studied two main problems on the new topic of interactive wireless charging in populations of resource-limited, mobile agents, namely the energy balance and the energy aware network formation (particularly for the creating a star structure). We consider both the lossless and lossy cases of energy transfer. Three protocols for the problem of energy balance between the network agents and an upper bound on the time needed to reach energy balance are provided. In addition, four interaction protocols have been proposed for the problem of energy aware star network formation. These protocols assume different amounts of knowledge of the network and achieve different trade-offs between energy balance, time and energy efficiency.

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