Energy Balance with Peer-to-Peer Wireless Power Transfer

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Research themes - WPT in IoT and WSNs

1. A single mobile wireless charger
2. Multiple mobile wireless chargers
3. Collaborative WPT
4. Safety issues for WPT in networks
5. Experimentation with IoT prototypes

Conferences, journals and book chapters

- IEEE ICDCS
- IEEE DCoSS
- ACM MSWiM
- IEEE WCNC
- Computer Networks, Elsevier
- Cyber Physical Systems: From Theory to Practice: CRC Press

- Studies in the WSN and IoT domains have mainly focused on applying WPT technology on networks of relatively strong computational and communicational capabilities
- Also, they assume single-directional energy transfer from special chargers to the network nodes
- **Question:** What about populations of weak devices that have to operate under severe limitations in their computational power, data storage, quality of communication and most crucially, their available amount of energy?
  - Example: Passively mobile finite state sensors

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Inspired by recent technological advances, we apply WPT concepts on Computer Science networking and computation models:

- Capability for far-field performance together with near-field power transfer efficiency for mobile devices located few centimeters apart[1]
- Devices can achieve bi-directional, efficient wireless power transfer and be used both as transmitters and as receivers[2],[3]

And by prominent Distributed Computing paradigms (Population Protocols[4]) and

- we present a **new model and three protocols** for applying and managing WPT in networked systems of mobile micro-peers

[1] A. Costanzo et al., "**Exploitation of a dual-band cell phone antenna for near-field WPT**" in IEEE WPTC, 2015

[2] A. Georgiadis et al., "**Energy-autonomous bi-directional Wireless Power Transmission (WPT) and energy harvesting circuit**" in IEEE MTT-S IMS, 2015

[3] Z. Popovic et al., "**X-band wireless power transfer with two-stage high-efficiency GaN PA/ rectifier**" in IEEE WPTC, 2015

[4] D. Angluin et al., "**Computation in networks of passively mobile finite-state sensors**" in ACM PODC, 2004

- We study interactive, peer-to-peer wireless charging in populations of much more resource-limited, mobile agents that abstract distributed portable devices.
- We assume that the agents are capable of achieving bi-directional WPT, acting both as energy transmitters and harvesters.
- We consider the cases of both loss-less and lossy WPT and provide an upper bound on the time needed to reach a balanced energy distribution in the population.
- We design and evaluate three interaction protocols that achieve different tradeoffs between energy balance, time and energy efficiency.

- Population of m mobile agents $\mathcal{M} = \{u_1, u_2, \ldots, u_m\}$
  - Each one equipped with a *battery cell*, a *wireless power transmitter* and a *wireless power receiver*
- The agents interact according to an interaction protocol $\mathcal{P}$
  - Whenever two agents meet, they can exchange energy between their respective battery cells.
- We assume that agents are identical
  - That is they do not have IDs, they have the same hardware and run the same protocol $\mathcal{P}$.
  - As a consequence, the *state* of any agent $u \in \mathcal{M}$, at any time t, can be fully described by the *energy* $E_t(u)$ available in its battery
- Any transfer of energy ε induces energy loss $L(\varepsilon) = \beta \cdot \varepsilon$, $\beta \in [0, 1)$

We study the following problem:

Definition (Population Energy Balance)

Find an interaction protocol $\mathcal{P}$ for energy balance at the minimum energy loss across agents in $\mathcal{M}$.

We measure energy balance by using the notion of *total variation distance* from probability theory and stohastic processes.

Definition (Total variation distance)

Let P, Q be two probability distributions defined on sample space $\mathcal{M}$. The total variation distance $\delta(P, Q)$ between P and Q is

$$\delta(P, Q) \overset{def}{=} \frac{1}{2} \sum_{x \in \mathcal{M}} |P(x) - Q(x)|.$$

In our case: $\delta(\mathcal{E}_t, \mathcal{U})$, where $\mathcal{E}_t$: distribution at time t, $\mathcal{U}$: uniform distribution.

Protocol 1: `Oblivious-Share` $\mathcal{P}_{\mathsf{OS}}$

Input : Agents u, u' with energy levels $\varepsilon_u, \varepsilon_{u'}$

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$$\mathcal{P}_{\mathsf{OS}}(\varepsilon_u, \varepsilon_{u'}) = \left(\frac{\varepsilon_u + \varepsilon_{u'}}{2}, \frac{\varepsilon_u + \varepsilon_{u'}}{2} \right).$$

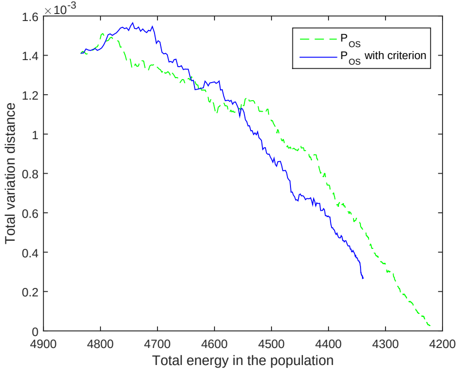
- $\delta(\mathcal{E}_0, \mathcal{U})$: the total variation distance between the initial energy distribution and the uniform energy distribution
- Interactions planning: probabilistic scheduler

Theorem

Let $\mathcal{M}$ be a population of chargers using protocol $\mathcal{P}_{OS}$. Let also $\tau_0(c)$ be the time after which $\mathbb{E}[\delta(\mathcal{E}_{\tau_0(c)}, \mathcal{U}_{\tau_0(c)})] \leq c$. Then $\tau_0(c)$ can be bounded.

- Bound: $\tau_0(c) \leq \frac{1}{2}\binom{m}{2} \ln\left(\frac{\delta(\mathcal{E}_0, \mathcal{U})}{c}\right)$

- Problem!: $L(\varepsilon) = \beta\varepsilon$. $\mathcal{P}_{OS}$ proved not to be suitable for energy balance in the case of lossy energy transfer.
- Any transfer between two agents affects also the relative distance of energy levels of non-interacting agents from the total average.
- The energy lost at every step does not contribute sufficiently to the reduction of total variation distance between the distribution of energies and the uniform distribution.



Protocol 2: `Small-Transfer` $\mathcal{P}_{\mathsf{ST}}$

Input : Agents u, u' with energy levels $\varepsilon_u, \varepsilon_{u'}$

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if ε_u ≥ ε_u' − dε then
    P_ST(ε_u, ε_u') = (ε_u − dε, ε_u' + (1 − β)dε)
else if ε_u' ≥ ε_u − dε then
    P_ST(ε_u, ε_u') = (ε_u + (1 − β)dε, ε_u' − dε)
else if |ε_u − ε_u'| < dε then
    do nothing.
```

$$\mathcal{P}_{\mathsf{ST}}(\varepsilon_u, \varepsilon_{u'}) = (\varepsilon_u - d\varepsilon, \varepsilon_{u'} + (1-\beta)d\varepsilon)$$

$$\mathcal{P}_{\mathsf{ST}}(\varepsilon_u, \varepsilon_{u'}) = (\varepsilon_u + (1-\beta)d\varepsilon, \varepsilon_{u'} - d\varepsilon)$$

- $d\varepsilon$: infinitesimal amount of energy exchanged

- $|A_{t-1}^{+}|$ (respectively $|A_{t-1}^{-}|$): the number of agents with available energy above (respectively below) the current average
- $\Delta(t) = \delta(\mathcal{E}_t, \mathcal{U}) - \delta(\mathcal{E}_{t-1}, \mathcal{U})$: total variation distance change

Lemma

Let $\mathcal{M}$ be a population of chargers using protocol $\mathcal{P}_{ST}$. Given any distribution of energy $\mathcal{E}_{t-1}$, the total variation distance change can be bounded.

- Bound: $\mathbb{E}[\Delta_t | \mathcal{E}_{t-1}] \leq \frac{4}{E_t(\mathcal{M})} \left(\beta - \frac{|A_{t-1}^{+}| \cdot |A_{t-1}^{-}|}{m(m-1)} \right)$.

- The total variation distance decreases when the interacting agents have energy levels that are on different sides of the average energy in the population
- An ideal interaction protocol would only allow transfers between agents with energy levels that are on opposite sides of the average energy in the population
- However, this kind of global knowledge is too powerful in our distributed model.
- Solution!: Agents are still able to compute local estimates of the average energy based on the energy levels of agents they interact with.

Protocol 3: `Online-Average` $\mathcal{P}_{\mathsf{OA}}$

Input : Agents u, u' with energy levels $\varepsilon_u, \varepsilon_{u'}$

Set $\text{avg}(u) = \frac{\text{avg}(u)\cdot\text{num}(u)+\varepsilon_{u'}}{\text{num}(u)+1}$ and $\text{avg}(u') = \frac{\text{avg}(u')\cdot\text{num}(u')+\varepsilon_{u}}{\text{num}(u')+1}$.

Set $\text{num}(u) = \text{num}(u) + 1$ and $\text{num}(u') = \text{num}(u') + 1$.

if $(\varepsilon_u > \text{avg}(u)$ *and* $\varepsilon'_u \leq \text{avg}(u'))$ *OR* $(\varepsilon_u \leq \text{avg}(u)$ *and* $\varepsilon'_u > \text{avg}(u'))$ **then**

  if $\varepsilon_u > \varepsilon_{u'}$ **then**

$$\mathcal{P}_{\mathsf{OA}}(\varepsilon_u, \varepsilon_{u'}) = \left(\frac{\varepsilon_u + \varepsilon_{u'}}{2}, \frac{\varepsilon_u + \varepsilon_{u'}}{2} - \beta\frac{\varepsilon_u - \varepsilon_{u'}}{2}\right)$$

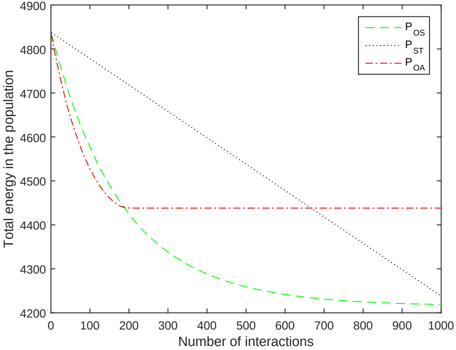
  else if $\varepsilon_u \leq \varepsilon_{u'}$ **then**

$$\mathcal{P}_{\mathsf{OA}}(\varepsilon_u, \varepsilon_{u'}) = \left(\frac{\varepsilon_u + \varepsilon_{u'}}{2} - \beta\frac{\varepsilon_{u'} - \varepsilon_u}{2}, \frac{\varepsilon_u + \varepsilon_{u'}}{2}\right)$$

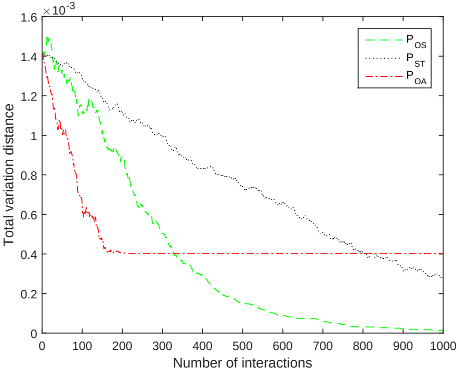
else

  do nothing.

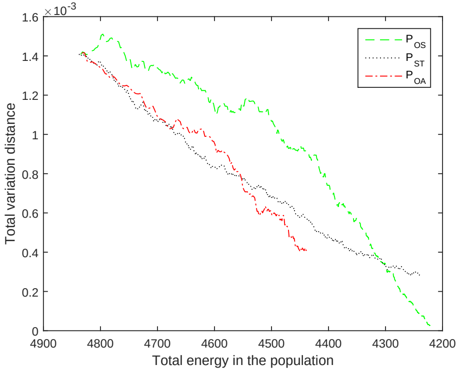
- Simulations with Matlab R2014b
- 1000 useful interactions, where the nodes to interact are selected by a probabilistic scheduler
- Initial energy level value to every agent of a population consisting of $|m| = 100$ agents uniformly at random, with maximum battery cell capacity 100 units of energy
- The constant β of the loss function is set to three different values
- For statistical smoothness, we apply the deployment of repeat each experiment 100 times



- The energy loss rate for $\mathcal{P}_{\text{OS}}$ and $\mathcal{P}_{\text{OA}}$ is high in the beginning, until a point of time when energy stops leaking outside the population
- $\mathcal{P}_{\text{ST}}$ has a smoother, linear energy loss rate, since ε is a very small fixed value



- Best absolute balance is provided by $\mathcal{P}_{\text{OS}}$
- However, note that this is a conclusion regarding only the energy balance, not taking into account the losses from the charging procedure



- Although $\mathcal{P}_{\mathrm{OS}}$ achieves very good balance quickly, the impact of energy loss affect very negatively its performance.
- For the same amount of total energy in the population, $\mathcal{P}_{\mathrm{ST}}$ and $\mathcal{P}_{\mathrm{OA}}$ achieve better total variation distance than $\mathcal{P}_{\mathrm{OS}}$.
- $\mathcal{P}_{\mathrm{OA}}$ outperforms both $\mathcal{P}_{\mathrm{OS}}$ and $\mathcal{P}_{\mathrm{ST}}$. Furthermore, it is much faster than $\mathcal{P}_{\mathrm{ST}}$ in terms of the number of useful interactions.

Our relevant research is being published:

1. Interactive Wireless Charging for Energy Balance. 36th IEEE International Conference on Distributed Computing Systems (ICDCS), Nara, Japan 2016.
2. Interactive Wireless Charging for Weighted Energy Balance. 12th IEEE International Conference on Distributed Computing in Sensor Systems (DCOSS), Washington D.C., USA, 2016.
3. Energy Balance with Peer-to-Peer Wireless Charging. Conference paper, under review, 2016.
4. Energy Balance with Peer-to-Peer Wireless Power Transfer. Journal article, to be submitted.

Thank you!

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