

Efficient and Scalable Geographical Peer Matching for P2P Energy Sharing Communities

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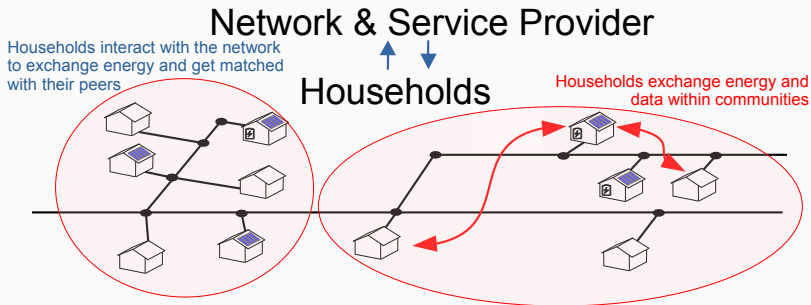


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Introduction 1/2: Context & Motivation

Peer-To-Peer Energy Sharing



Motivations

- Current state-of-the-art: **small datasets** and **groups of 2-3**.
- Can we scale up and use larger groups? Yes!

Introduction 2/2: Challenges & Contributions

Challenges for Peer Matching

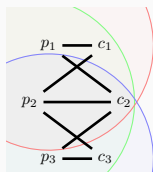
1. peers have a **limited knowledge** of the future;
2. computing peer's preferences requires **communication + computation**;
3. **geographically closer** is better;
4. **NP-hard** problem for groups of size 3+.

Contributions

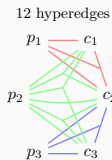
1. **mathematical modelling** of the *Geographical Peer Matching* (GPM) problem;
2. introduce (different variants of) **3 matching algorithms**;
3. study trade-off **cost-efficiency** vs. **computational-overhead** using real data;
4. both **efficient** and **scalable** is possible!

Geographical Peer Matching (GPM)

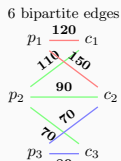
Goal: match a set of prosumers P with a set of consumers C .



(a) Search Radius



(b) Hypergraph



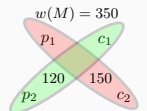
(c) Pairwise weights

(k, Δ) -GPM Problem

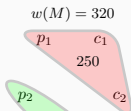
- Bipartite hypergraph matching M with *maximum weight* such that:

- k -bounded
- max diameter $\leq \Delta$
- weights are dynamically computed

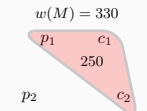
- **NP-hard!**



(d) Round Robin



(e) Single Pass



(f) Classic Greedy

3 matching algorithms computing $\mathcal{O}(kn^2)$ weights instead of $\mathcal{O}(n^k)$.

But how cost-efficient are they?

Comparison of Peer Matching Algorithms

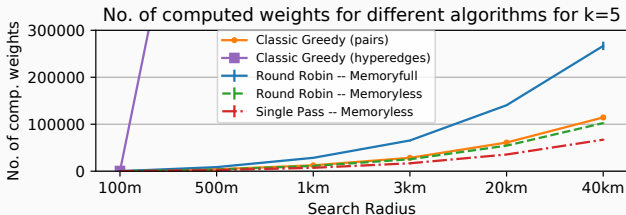
Evaluation using real energy consumption from 2221 households.

Algo.	Order	WF	100m	500m	1km	3km	20km	40km
Round Robin	Incr.	WA	9.5%	60.9%	74.2%	78.8%	81.6%	83.8%
		WB	9.3%	61.7%	73.7%	78.5%	80.3%	82.4%
		WC	9.5%	60.9%	74.3%	78.9%	81.6%	83.9%
		WD	9.3%	61.7%	74.1%	79.0%	81.0%	83.2%
	Decr.	WA	9.5%	61.7%	74.8%	79.0%	82.2%	85.0%
		WB	9.6%	64.4%	77.9%	82.9%	85.0%	87.4%
		WC	9.5%	74.7%	61.7%	79.0%	82.1%	84.8%
		WD	9.6%	64.4%	78.1%	83.4%	85.6%	88.3%
Rsc.	WB	9.6%	58.7%	77.9%	82.8%	84.8%	87.3%	
	WB	9.5%	61.1%	75.0%	79.7%	83.6%	86.9%	
Single Pass	Decr.	WA	9.5%	58.7%	68.8%	71.1%	74.7%	77.6%
		WB	9.5%	61.1%	73.6%	78.7%	82.5%	86.0%
Classic Greedy	WB	9.6%	64.3%	77.5%	83.2%	86.7%	90.5%	

* the percentages are the fraction of the single 2221-households obtained by the matchings; best results for each radius is in bold and green background.

13 variants

- 3 matching algorithms
- 4 weight functions:
 - cost-based (A/C) or saving-based (B/D)
 - memoryless (A/B) vs. memoryfull (C/D)
- Increasing / Decreasing / Resource prosumers order



Summary of results

- We introduce the **Geographical Peer Matching** problem,
- 3 **computationally-efficient** matching algorithms,
- all are also **cost-efficient** based on our extensive study:
 - up to 90% of the benefit of an unrealistic unbounded matching,
 - up to 84% with small communities (5) and small diameter (3km).

Future Work

- make the matching procedures more **edge-friendly**,
- how to update the matching **dynamically**.