

Differentially Private Optimal Power Flow

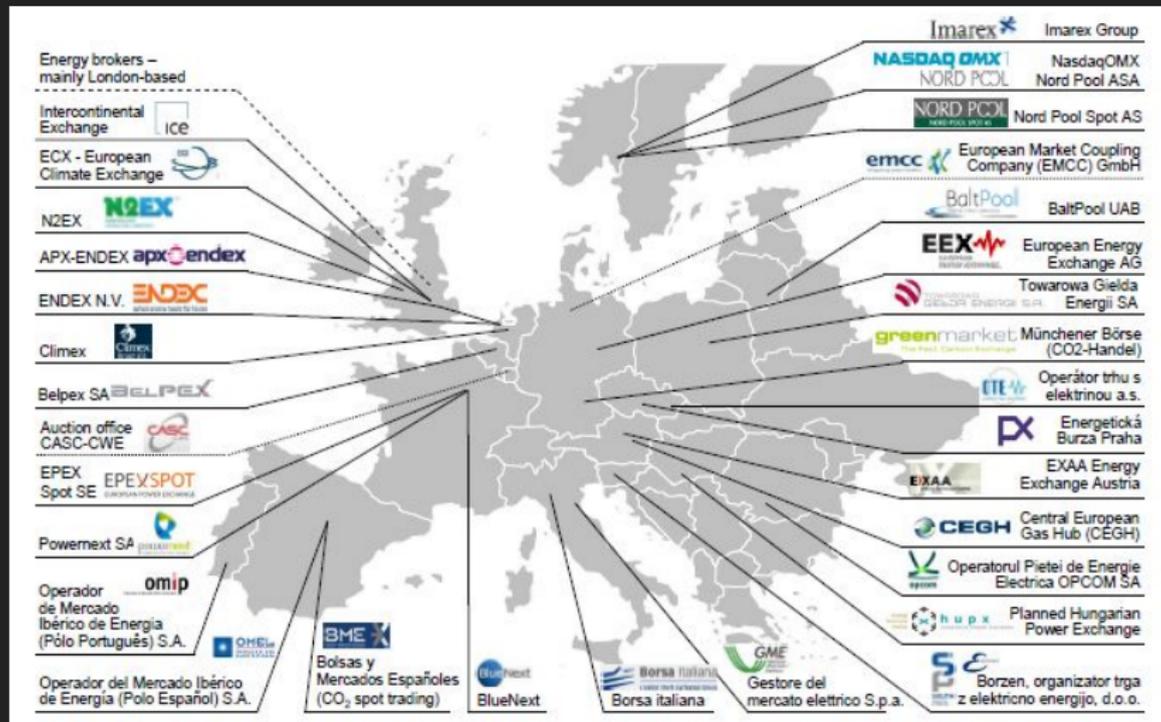
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Power generation is decentralized



Continental scale



Complex markets, complex constraints

Physical

- ▶ Laws: Ohm's law, Kirchoff circuit laws
- ▶ Limits: Line capacity, flow rates, generation

Spatial

- ▶ Power sources in different regions
- ▶ Network structure of transmission lines

Temporal

- ▶ Time needed to ramp up/ramp down
- ▶ Respond to changing loads and demands

Optimal Power Flow: Background and Motivation

Coordination via optimization

Minimize the cost

- ▶ No two power plants are exactly alike (efficiency, cost, ...)

Optimize power delivery

- ▶ Set parameters: system voltages, “bus angles”, ...

Full problem: AC OPF

Faithful model of physics behind power network

- ▶ Objective: minimize total generation cost
- ▶ Constraints: voltage, current, and generation limits

A very thorny problem

- ▶ Non-convex, discrete and continuous
- ▶ Complex valued: formulations involve sine, cosine, etc.

Linearized version: DC OPF

LP version of AC OPF

- ▶ Simplify problem (remove current limits, voltages)
- ▶ Make **small-angle** approximations ($\sin(\theta) \approx \theta$)

Network model

- ▶ Generators located at nodes (“**buses**”)
- ▶ Power can flow between neighboring nodes

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Generated power + net flow
equals demand at each node

More formally

Constants

- ▶ Generation costs c_i , limits m_i , demands d_i (“loads”)
- ▶ Network matrix B (“bus susceptances”)

Variables

- ▶ Generation amount g_i and flow control θ_i (“bus angle”)

More formally: DC OPF linear program

$$\text{minimize: } \sum_i c_i g_i$$

$$\text{subject to: } g + B\theta = d$$

$$-m \leq g \leq m$$

$$-1/3 \leq \theta \leq 1/3$$

What about privacy?

Nodes have data

- ▶ Loads: how much power is being demanded at each node?
- ▶ Costs: how much does power generation cost?

Solution naturally split between nodes

- ▶ Tell each power plant how much to generate
- ▶ Protect agent's data from joint view of **other** agents

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More formally, this calls for...

Joint Differential Privacy

Solving the DC OPF Problem under Joint Differential Privacy

Idea: net flow at each node is low sensitivity

Net flow: Flow out minus flow in

- ▶ Vector $B\theta$ gives the (signed) net flow at each node
- ▶ Potential: flow $\approx \theta_i - \theta_j$ for neighboring (i, j)

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What happens if one node's load changes by Δ ?

- ▶ Generate more power at cheapest nodes with capacity
- ▶ **Total** absolute change in net flows at most 2Δ

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DC OPF constraints:
conservation of flow

Compute generation P_g from noisy net flows

Three step process:

1. Solve original DC OPF problem exactly, get θ^*
2. Compute noisy flows:

$$\hat{f} = B\theta^* + \text{Lap}_{\epsilon/2\Delta}$$

3. Compute generation:

$$g_i + \hat{f} = d_i$$

What about the bus angles θ ?

OK to publish noisy flows, but not bus angles

- ▶ Need this info to induce noisy flow:

$$\hat{\theta} \text{ such that } \hat{f} = B\hat{\theta}$$

Possible problems

- ▶ Out of range: $\hat{\theta}$ too big/too small?
- ▶ **No** consistent solution for $\hat{\theta}$?

More refined: Projected Laplace mechanism

Add noise and project

- ▶ Polytope of noisy flows realizable by valid bus angles
- ▶ Add Laplace noise to get noisy net flows \hat{f}
- ▶ Project to polytope, solve for $\hat{\theta}$ and publish

Wrapping Up: Three Takeaways

JDP is a good fit for graph problems

Data associated with each node

- ▶ Local pieces of solution can be distributed to nodes
- ▶ Handy link parts of inputs and parts of solutions

Relaxations of JDP possible

- ▶ Graph structure gives relation between agents
- ▶ Protect data against just the joint view of **neighbors?**

More to do for private optimization

Plenty of past work on private optimization

- ▶ Linear programs
- ▶ (Separable) convex programs

“Minor” assumptions are not always minor

- ▶ Know optimal value
- ▶ Only inequality (one-sided) constraints
- ▶ Can violate constraints “a little bit”

Many other uses for privacy in power flow problems

Further directions

- ▶ Protect more data (network structure?)
- ▶ Improve accuracy for specific network topologies
- ▶ Handle richer problems, towards AC OPF

Possible game theory and mechanism design angles

- ▶ Achieve approximate truthfulness
- ▶ Make it harder for agents to signal through costs
- ▶ Compute market clearing prices

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