Data-Driven Linearization for Optimal Power Flow

Grid Incorporation for Distributed Energy System

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Agenda

- Introduction
  - Motivation: Smart Grid applications

- Background
  - Optimal Power Flow
  - End-to-end learning

- Data Driven Linearization for OPF
  - Line flow learning
  - Bus correction

- Preliminary Result

Future Energy Systems

Envision of Future Energy Systems/ Smart Grids:

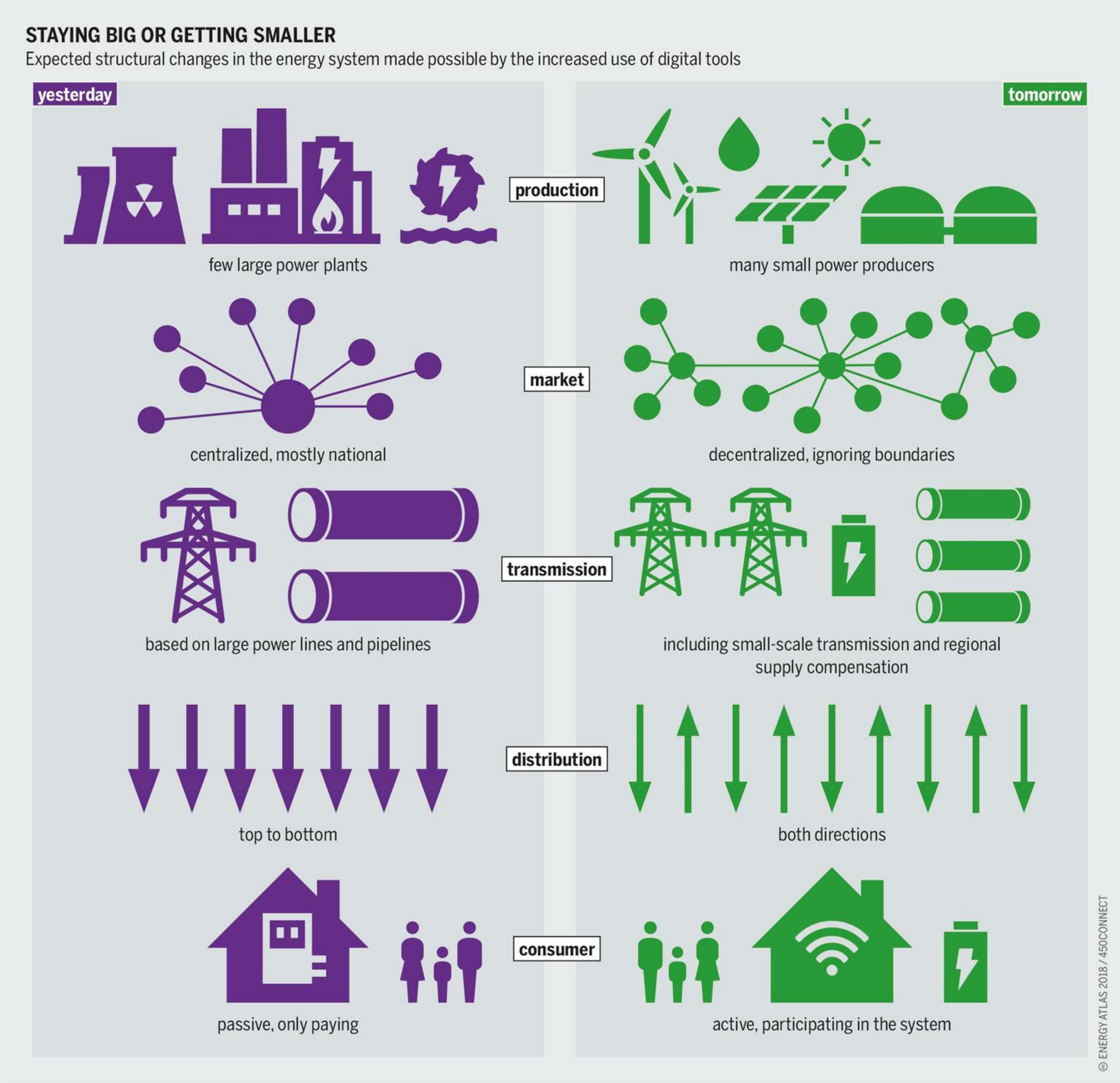
- Decentralized
- Flexible with smart devices
- Consumer can actively participate (e.g., EVs)

What smart grid means?

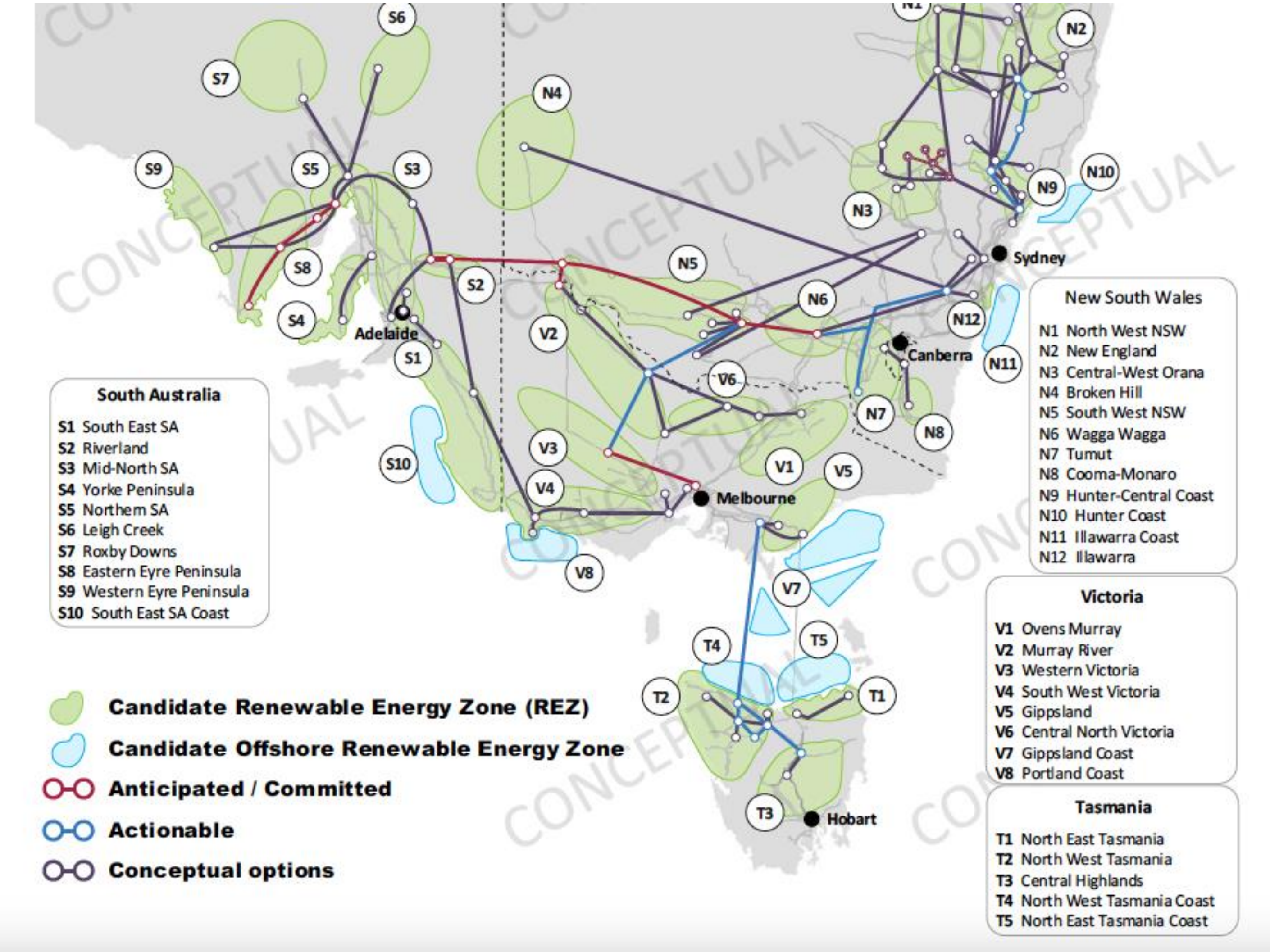
- Daily/market operations
  - Decentralized optimization
  - Lots of new devices (Storages, EVs)
  - Human interaction (Consumer response)

- Security and privacy
  - New approach to share information

- Market design & policy
  - Renewable energy zones



Australia Renewable Energy Zone



Challenge in decentralized setting

- Decentralized agent, could:
  - limited computational power
  - limited global information (e.g., might not know the line param.)
  - privacy / security

→ Currently, many smart grid applications either:
  - Discard grid side completely

  - Support a “linearized view” of grid
    - V2G model,
    - Utility portfolio optimization,
    - Large planning model with stability

  - Hesitate to use nonlinear equations

→ Huge gap between transmission/distribution grid community and the application community in smart grid

Challenge in decentralized setting

Given that the future smart grid:

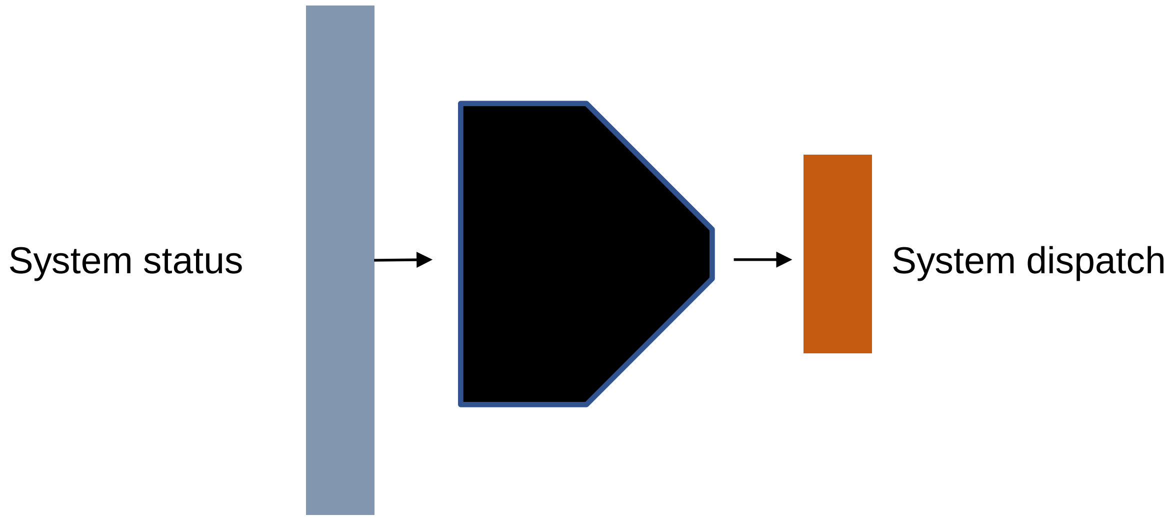
- Data-intensive (local information)
- User-oriented, and
- likely AI-based

Question:

- Instead of applying a standard linearization model for smart grid …
- *Would local agent be able to do linearization with data better?*
  - Can it be general?
  - E.g. Transfer from one app to another?

End-to-End Learning @ 30,000 ft

- ❑ Why not End-to-End Deep Learning?
  - ❑ Predict the most economical generation dispatch, s.t.
    All grid & operational constraints are satisfied



- ❑ Future Energy System: Line switching, utility cost changes, dynamic battery status, etc

→ Hard to incorporate

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AC Optimal Power Flow

- AC-OPF problem
  - Core subproblem within grid operations
  - Compute the most economical generation dispatch s.t.:
    - Grid/operational constraints are feasible

- ***Non-linear*** & ***non-convex***

- Computationally difficult for large systems

- Market operations: AC-OPF is “linearized”

- Many famous linearization/convexification: DC / QC / SOCP / SDP / Moment-based/ etc

Model 1 $\mathcal{O}(\boldsymbol{S^d})$: AC Optimal Power Flow

input: $S_i^d \quad \forall i \in N$

variables: $S_i^g, V_i \quad \forall i \in N, \quad S_{ij} \quad \forall (i,j) \in E \cup E^R$

minimize: $\sum_{i \in N} c_{2i}(\Re(S_i^g))^2 + c_{1i}\Re(S_i^g) + c_{0i}$ (1)

subject to: $\angle V_s = 0, \quad s \in N$ (2)

$v_i^l \leqslant |V_i| \leqslant v_i^u \quad \forall i \in N$ (3)

$\theta_{ij}^l \leqslant \angle(V_i V_j^*) \leqslant \theta_{ij}^u \quad \forall (i,j) \in E$ (4)

$S_i^{gl} \leqslant S_i^g \leqslant S_i^{gu} \quad \forall i \in N$ (5)

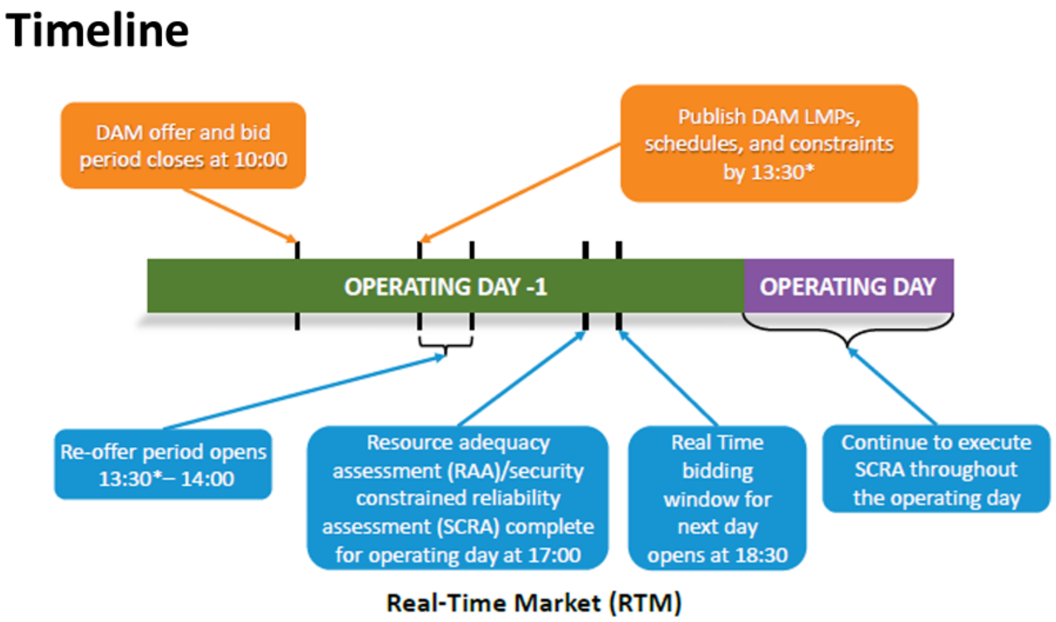
$|S_{ij}| \leqslant s_{ij}^u \quad \forall (i,j) \in E \cup E^R$ (6)

$S_i^g - S_i^d = \sum_{(i,j) \in E \cup E^R} S_{ij} \quad \forall i \in N$ (7)

$S_{ij} = Y_{ij}^* |V_i|^2 - Y_{ij}^* V_i V_j^* \quad \forall (i,j) \in E \cup E^R$ (8)

End-to-End Centralized Learning

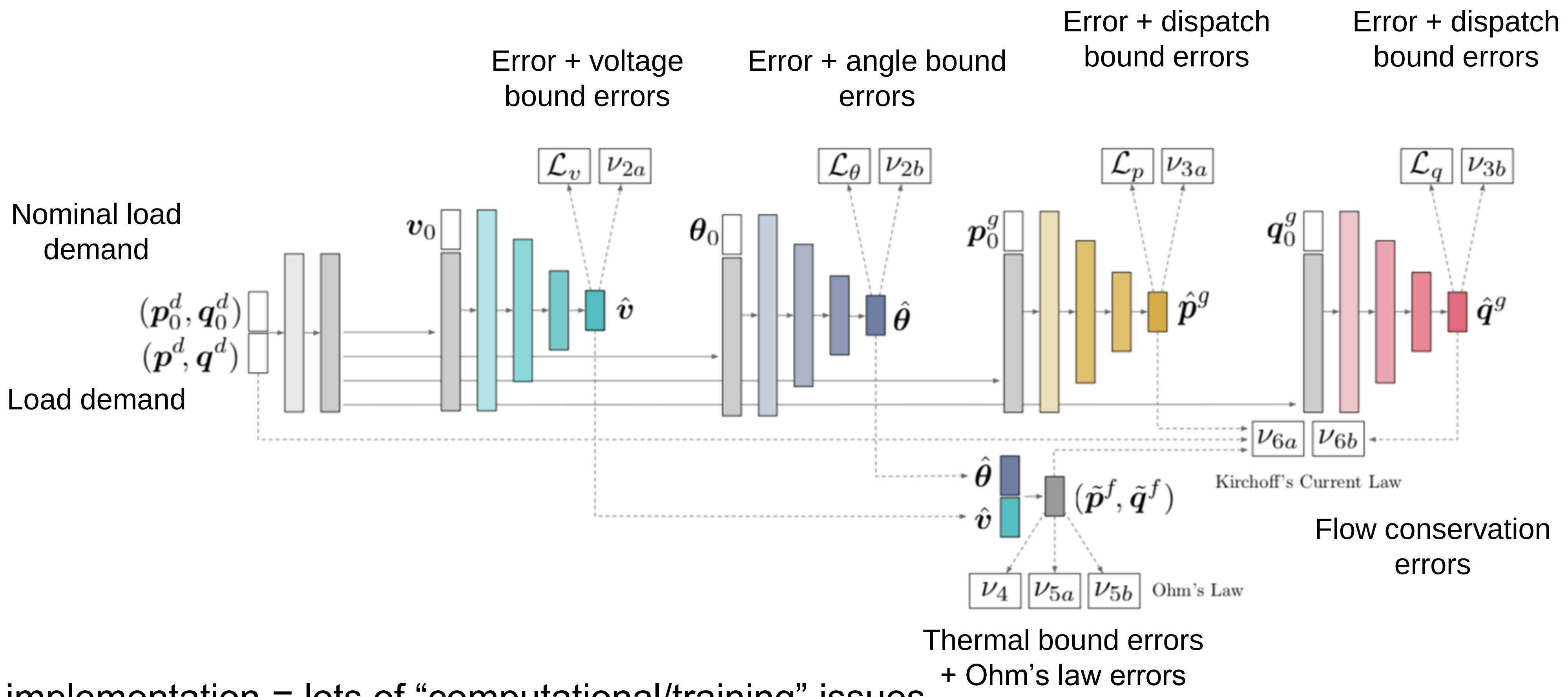
- Why Machine Learning on AC-OPF?
  - Frequency:
    - Every 5-15 min (real-time market)
    - Every couple of hours (look-ahead reliability assessment)
    - Every day (day-ahead market)
    - Every week (capacity market)
    - Every few seconds (in the future smart grid)
  - Abundant data to train
  - More accurate decisions
  - Prediction is fast => More time for operators to handle other operational/engineering issues



See WEM101: Day-Ahead Energy Markets

AC-OPF End-to-End DNN

- OPF-DNN [AAAI 2020]: Supervised learning + constraint penalty



Naïve implementation = lots of "computational/training" issues …

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Distributed/Federated Learning

Why?

- Align with Smart Grid decentralization requirement

- Agents are natural representation for energy zones

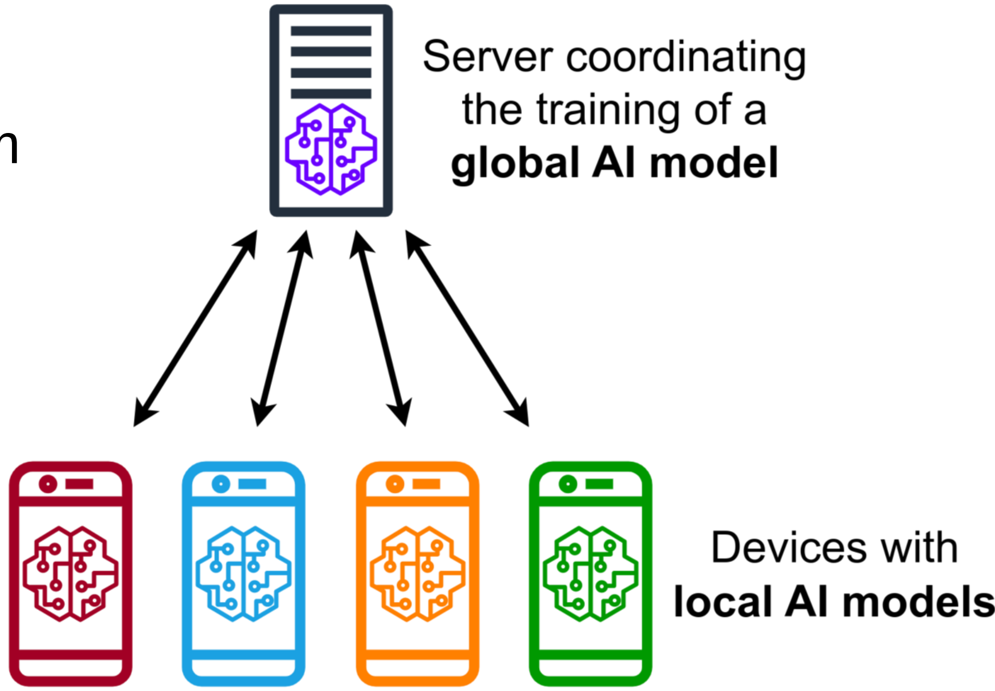
- Future vision: Machine Learning for OPTimization Problem (ML4OPT)

Why AC-OPF for the future smart grid?

- Core sub-problem of many grid operations
  - Market clearing

- Envisioning future grid problems need AC-OPF
  - V2G: EV supplying power to grid
  - Emergency backstop (Voltage congestion)

- Future HVDC grid/zone still need some time to take over

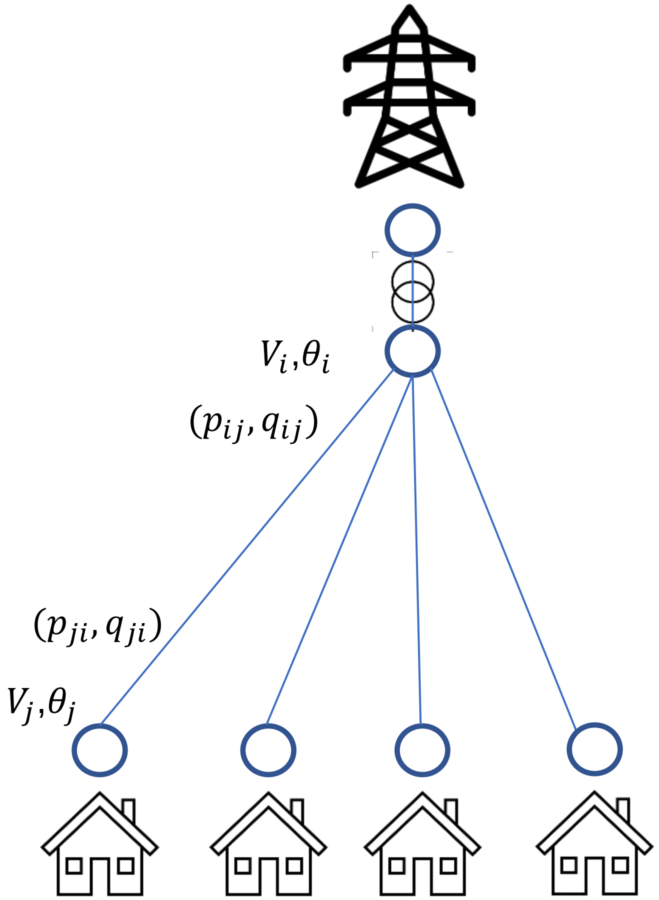


High-level Architecture

- Data-Driven Linearization Learning

1. Each line agent, in parallel, trains a linear approximation function $\hat{f}$ (one for each side) to approximate the AC power flow
   - based on observed data/state estimation

2. *Each bus agent, in parallel, aggregated all the associated line approximation function $\hat{f}$, then retrain to satisfy power balance constraints



*Still in development

Line agent

- AC Power Flow Equation
  - Ohm's Law (non-linear part of ACOPF)

$$(p_{ij}, q_{ij}) = f(V_i, V_j, \theta_i, \theta_j)$$

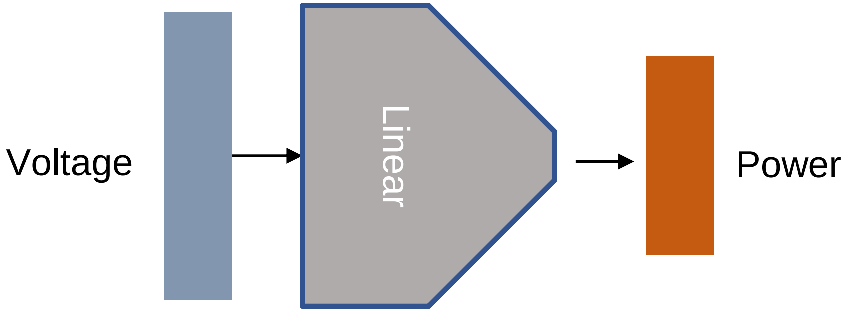
  - Describes relationship between:

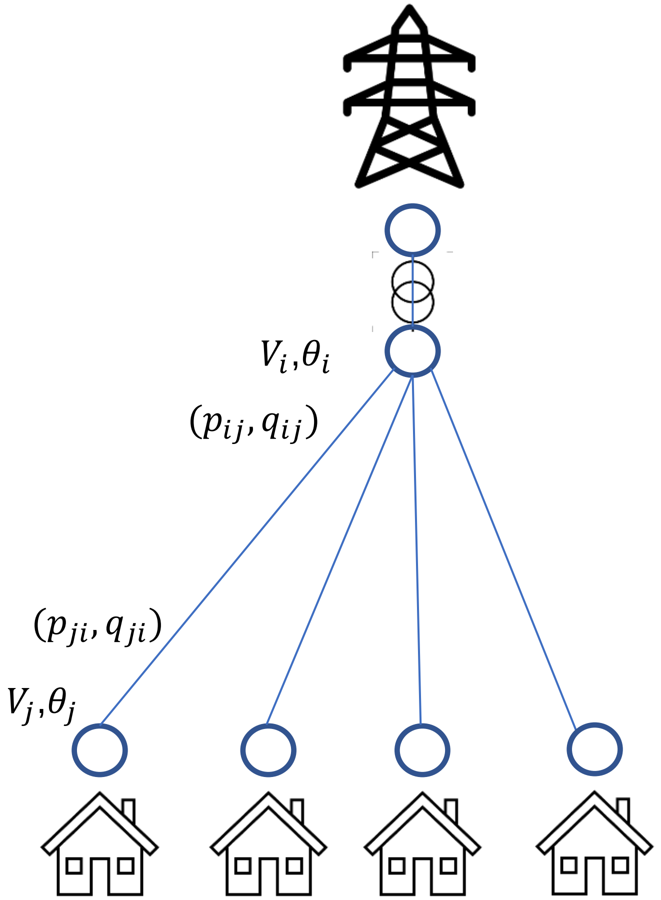
    Line (power) flow & voltage

Line agent's view:

- Given a dataset $D_{ij} = \{(p_{ijs}, q_{ijs}, V_{is}, V_{js}, \theta_{is}, \theta_{js}) | \forall\ s\}$, find a linear approximation function $\hat{f}$ s.t.

$$\min \sum_{s} L\,[(p_{ijs}, q_{ijs}), \hat{f}\,(V_{is}, V_{js}, \theta_{is}, \theta_{js})]$$





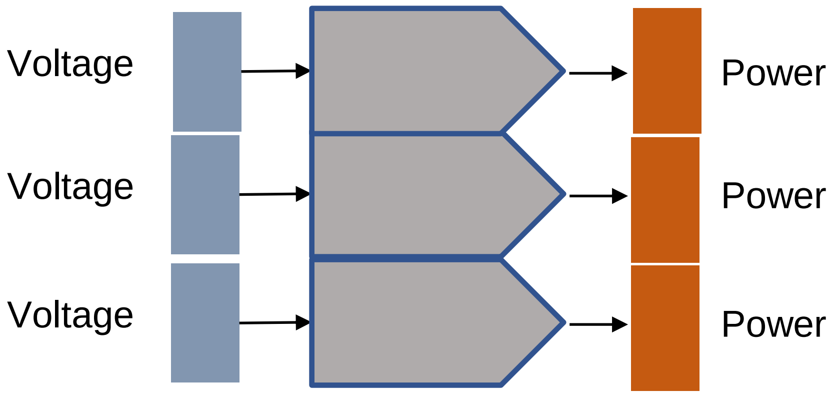
Bus agent

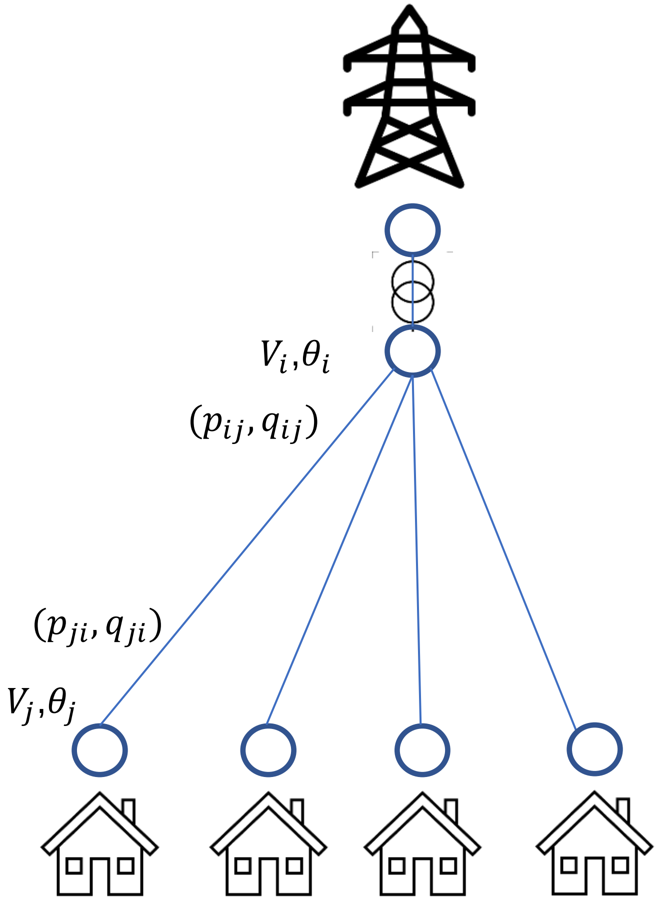
- Power Flow Balance Equation
  - Energy Conservation Law

$$\sum (p_{ij}, q_{ij}) = \sum f(V_i, V_j, \theta_i, \theta_j) = 0$$

Bus agent's view:

- Given the dataset D_{ij} from each Line agent, correct their linear approximation function $\widehat{f_{ij}}$ s.t. $\sum \widehat{f_{ij}} \quad = 0$





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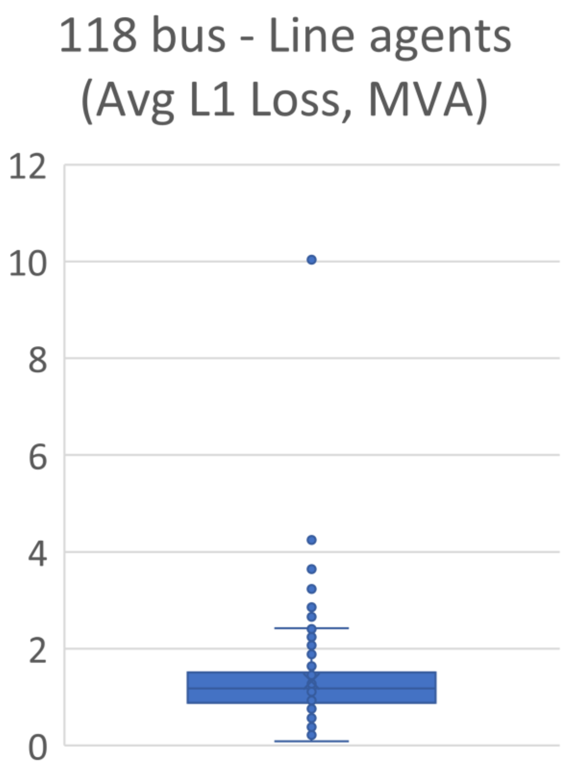
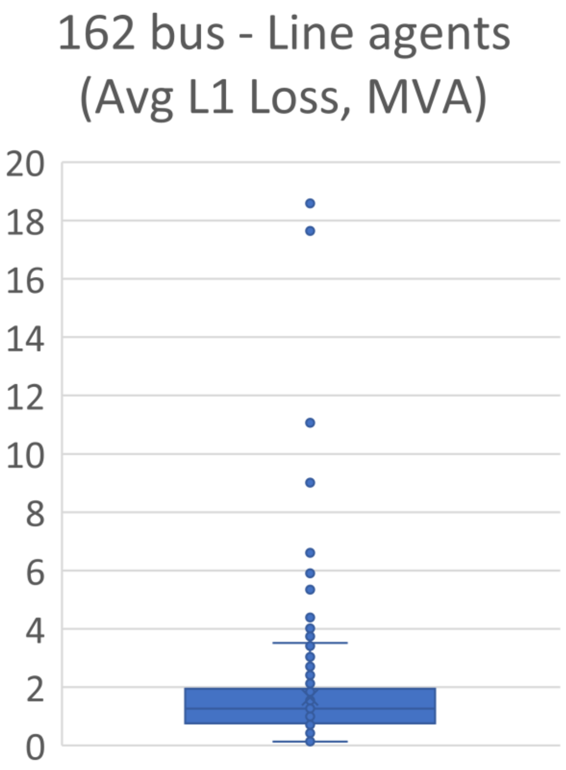
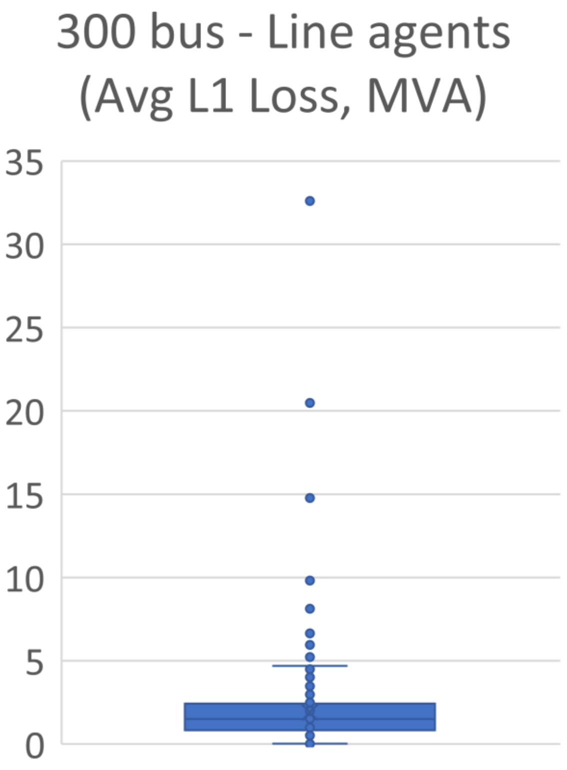
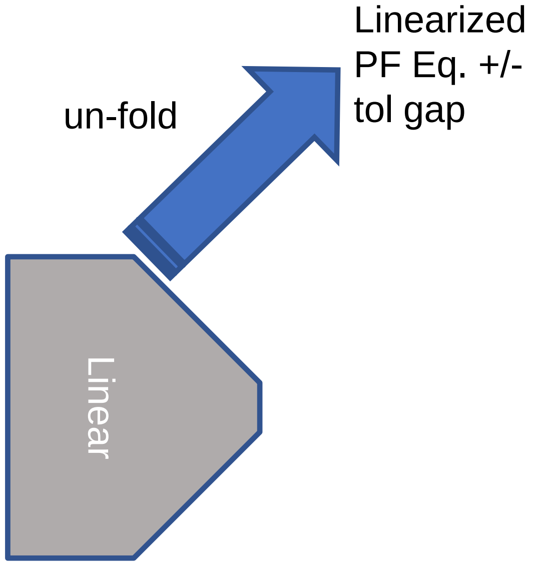
Preliminary result & analysis (2000 epoch, 3 layers)

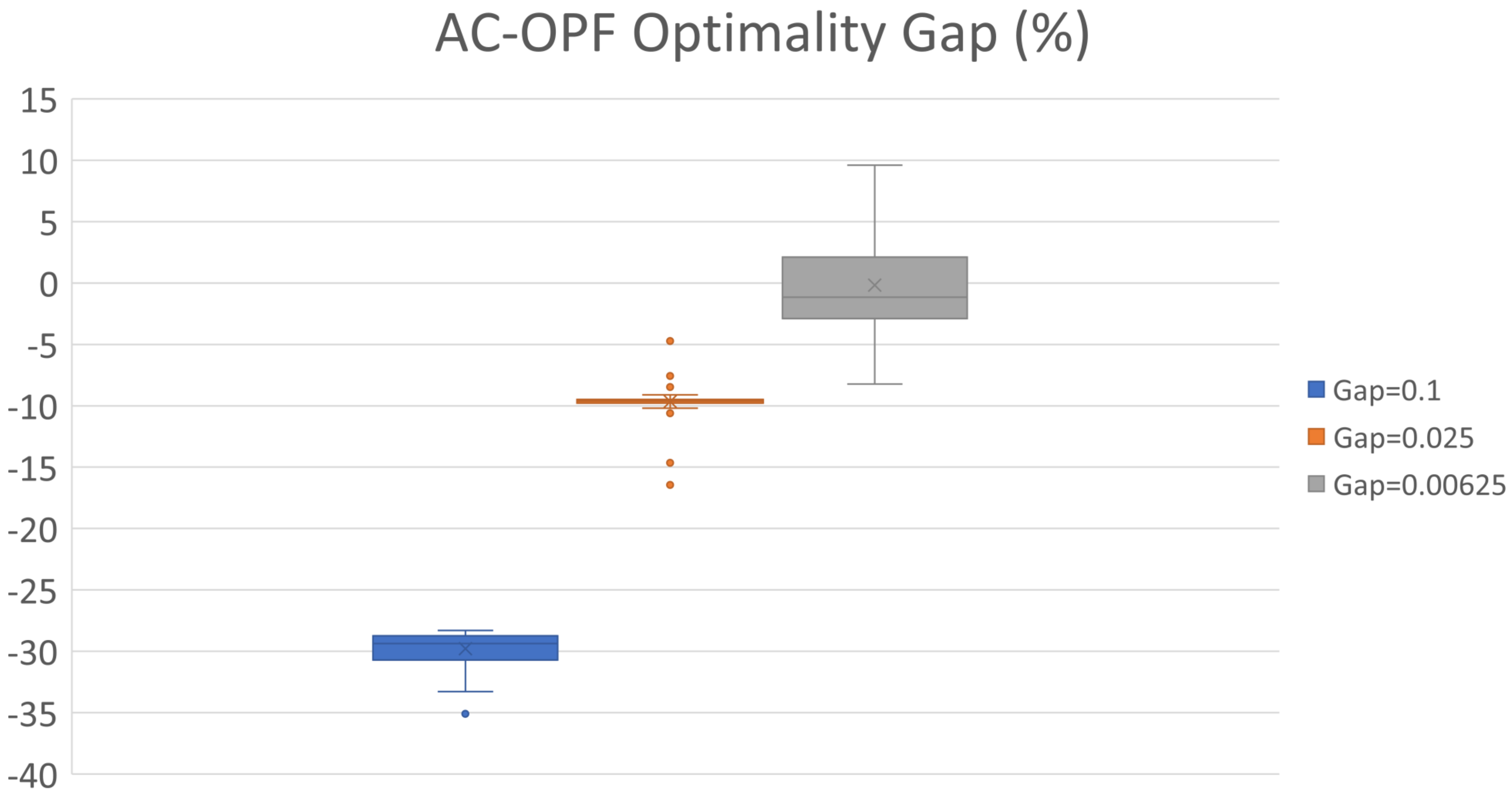






Preliminary result & analysis (2000 epoch, 2 layers)





Conclusion & Future Work

- Introduce issues on grid incorporation in the smart grid / future energy systems

- Distributed Linearization Model for (AC) Power Flow
  - Data-driven approach
  - Distributed
  - Line: trains power flow equation
  - Bus: enforces power balance constraints

- Preliminary Results
  - Power flow training
  - AC OPF validation