Hawaiian Electric
Maui Electric
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Grid Optimization with Solar (GO-Solar) Experiences with:

Data-driven and Machine Learning Approaches for High-pen PV Grids

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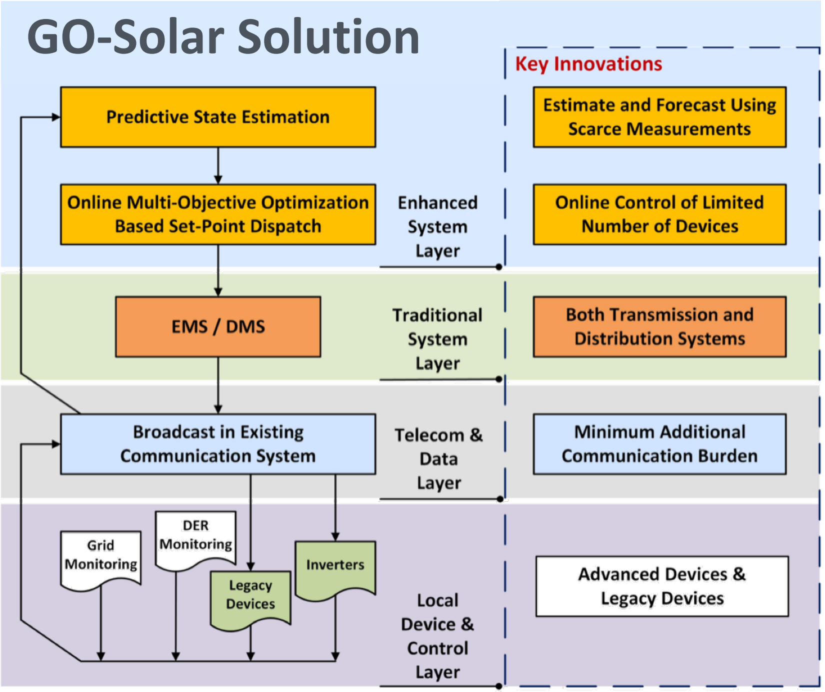
SOLAR ENERGY TECHNOLOGIES OFFICE
U.S. Department Of Energy

Project Objectives

Challenge #1:
Operations with Extreme penetrations of distributed PV

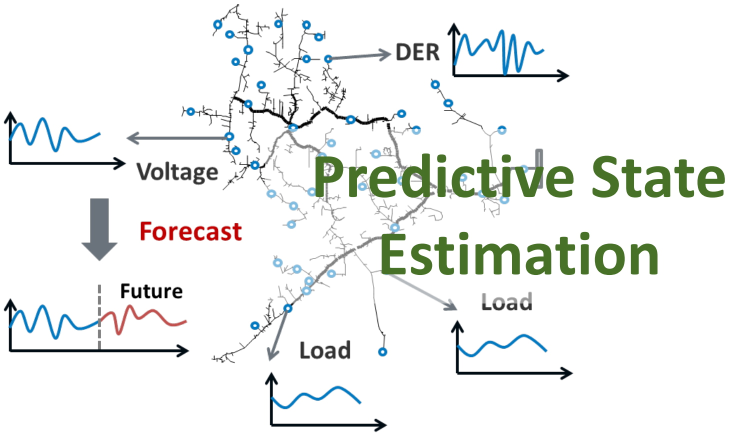
Challenge #2:
Communicate and control with millions of DERs

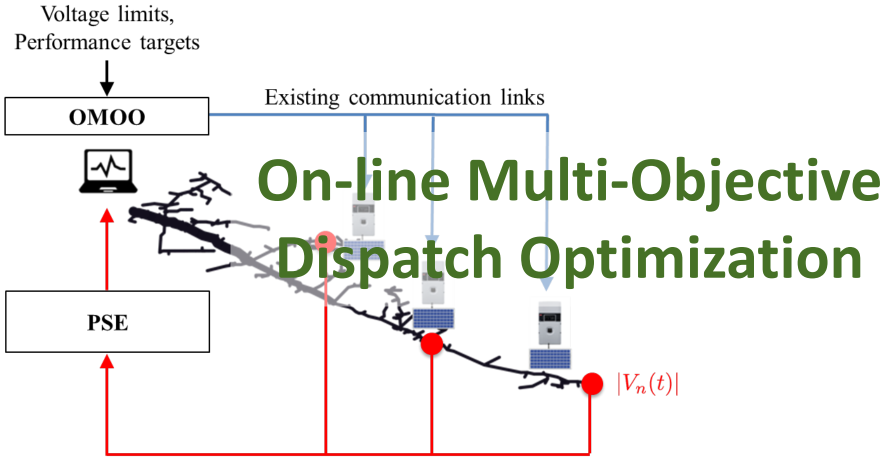


Manage **extreme penetrations of solar** and other DERs **using only a few measurement points** through matrix completion and multi-kernel learning-based **predictive state estimation (PSE)** **and only a few control nodes** dispatched through dual timescale **online multi-objective optimization (OMOO)** using voltage-load sensitivities to guide fast feedback response

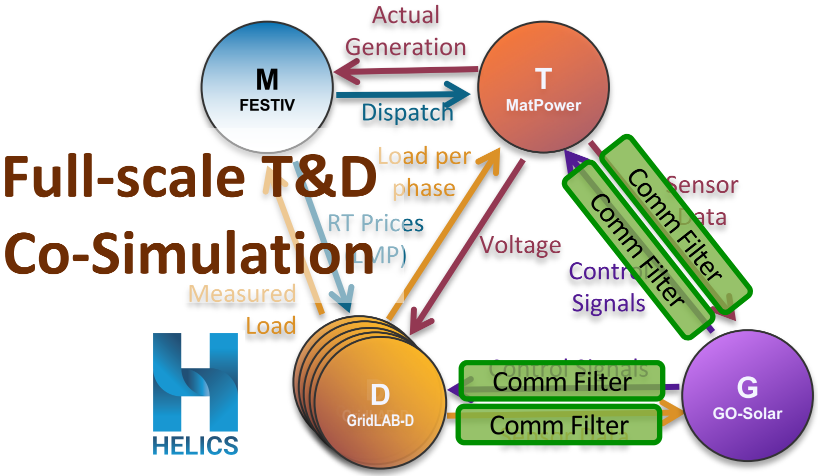
GO-Solar Key Activities

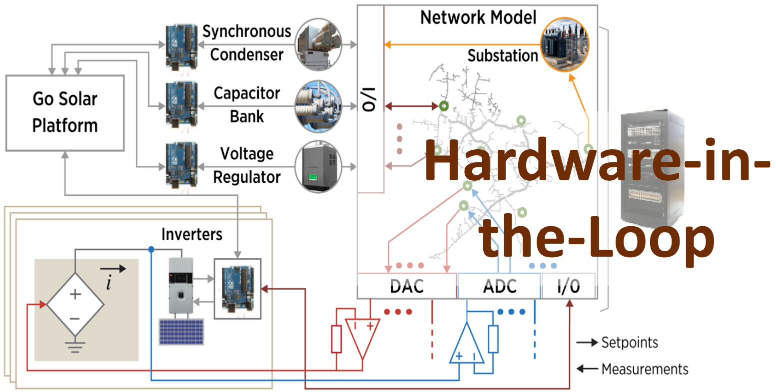
Algorithms





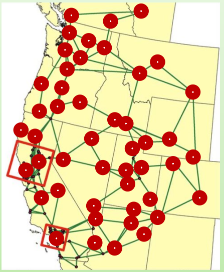
Validation





Innovation: Matrix Completion for State Estimation

vs. Conventional state estimation

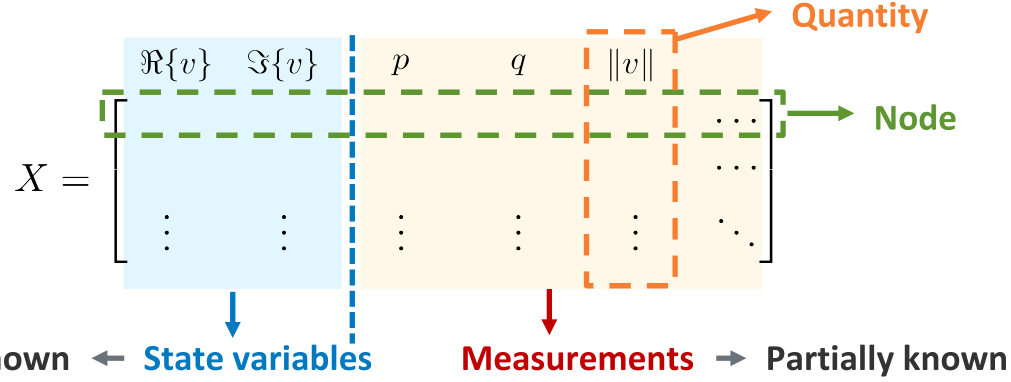


– Weighted least squares
– Objective: Minimize the weighted residuals

Requires redundant measurements

Key idea: Estimate unknown elements using correlation

Concept:
Netflix Recommendation System
+ Power Systems Constraints (linearized)



Objective function $\boxed{min(\text{Rank of matrix } X)}$ **New**

Constraints **Known elements in X = Measurements**

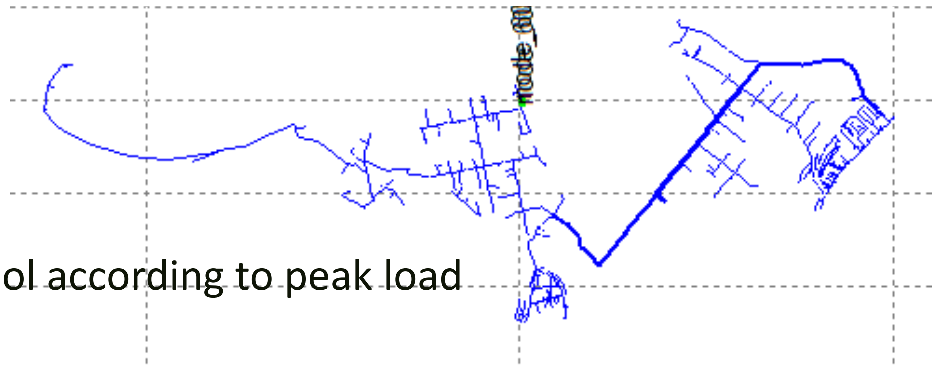
(2-point Linearized) power flow equations[3]

[1] Y. Zhang, A. Bernstein, A. Schmitt, and R. Yang, "State Estimation in Low-Observable Distribution Systems Using Matrix Completion," HICSS-52 conference, 2019.
[2] P. Donti, Y. Liu, A. Schmitt, A. Bernstein, R. Yang, and Y. Zhang, "Matrix Completion for Low-Observability Voltage Estimation," submitted to IEEE Transactions on Smart Grid, 2019.
[3] Andrey Bernstein and Emiliano Dall'Anese, "Linear Power-Flow Models in Multiphase Distribution Networks", presented at the 7th IEEE International Conference on Innovative Smart Grid Technologies (ISGT Europe 2017), Torino, Italy September 26–29, 2017

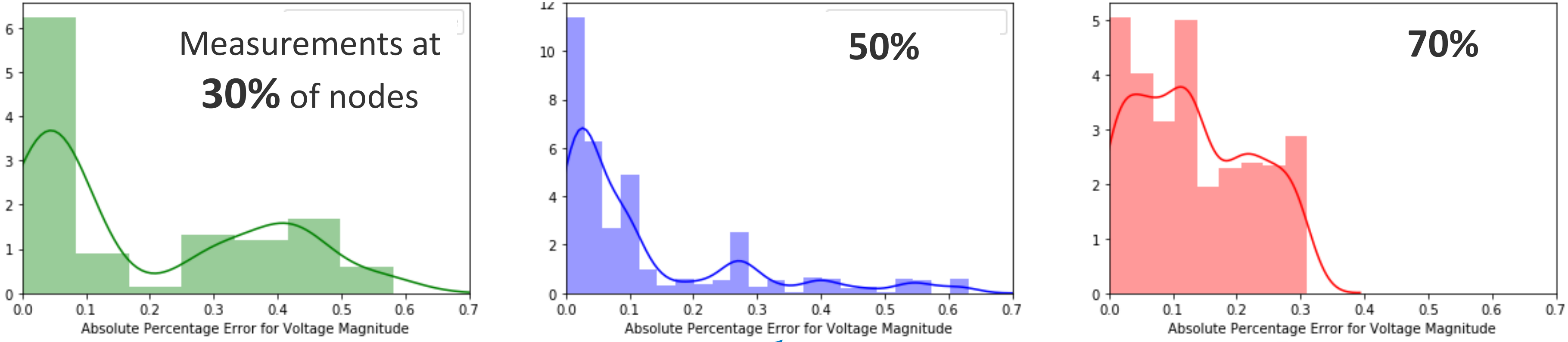
Example Results

Actual HECO Feeder

- 2576 nodes, 536 loads
- Load profiles are aggregated from load pool according to peak load
- 1-minute power flow simulations



Distribution of Absolute Percentage Error for Voltage Magnitude



Usually < 0.1% error
(0.1V on 120V base)

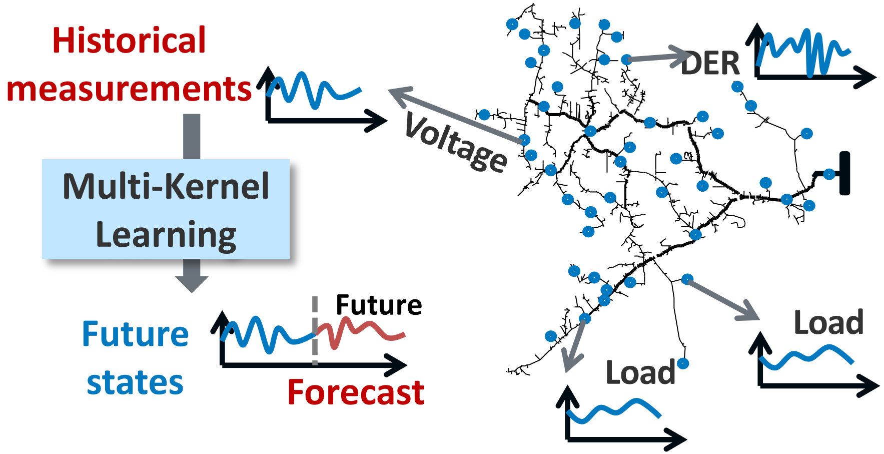
Always < 0.7% error
(0.85V on 120V base)

Even better with more measurements

Similar for Voltage angle (Nearly always <0.25deg at 30%)

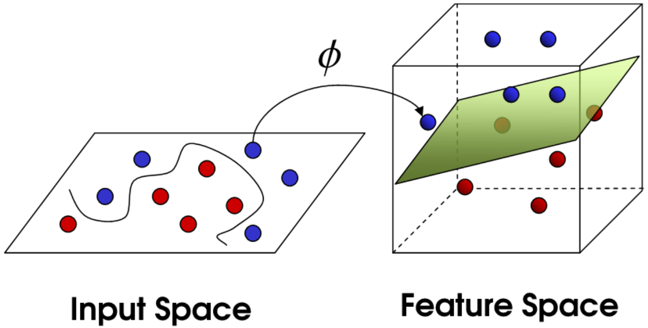
Innovation: Multi-Kernel Learning for State Forecasting

Goal: Learn the spatiotemporal correlation between measurements and system states



Kernel Learning Concept

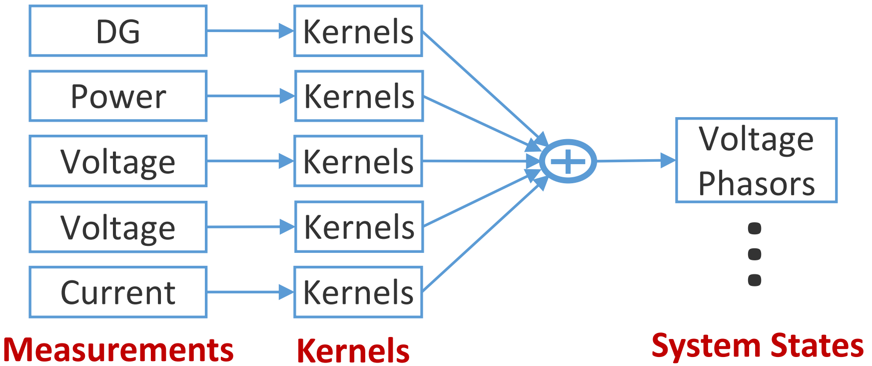
- Use kernel functions to map the input space to a higher-dimension feature space
- Learn the relationship in the feature space



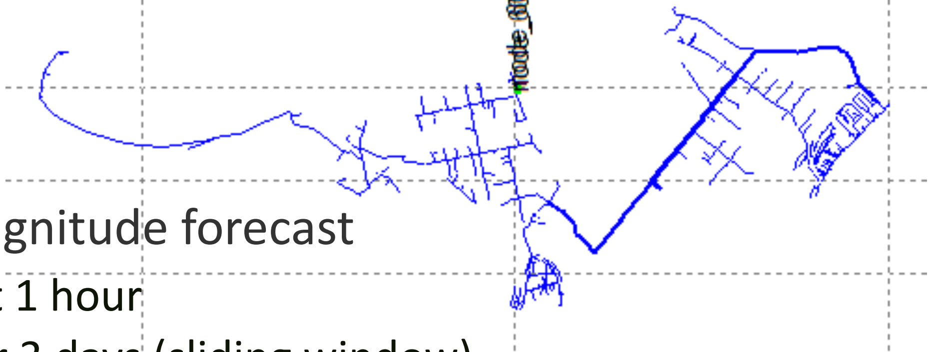
Source: R. G. Esfahani and A. A. Mohammad, "Towards an anomaly detection technique for web services based on kernel methods," IEEE Innovations in Information Technology, 2009.

Expanding to Multi-Kernel

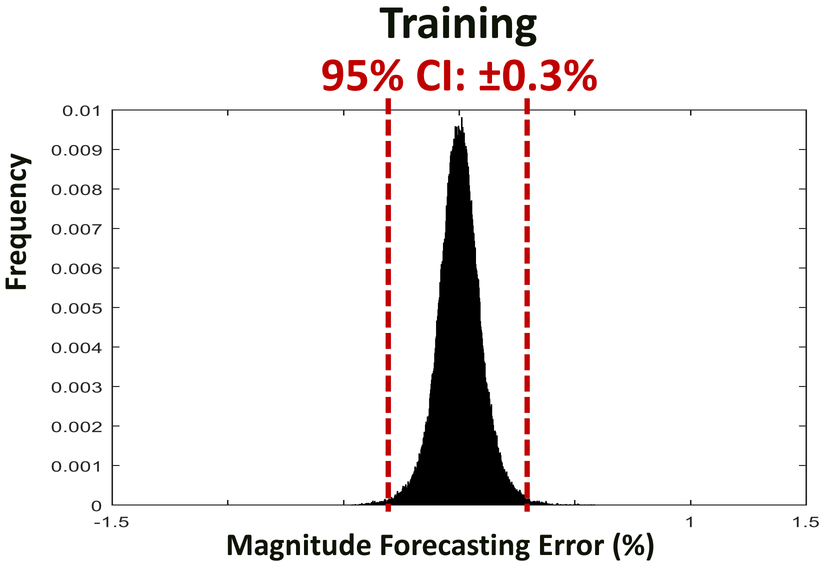
- Kernels for different measurements
- Optimize the combination

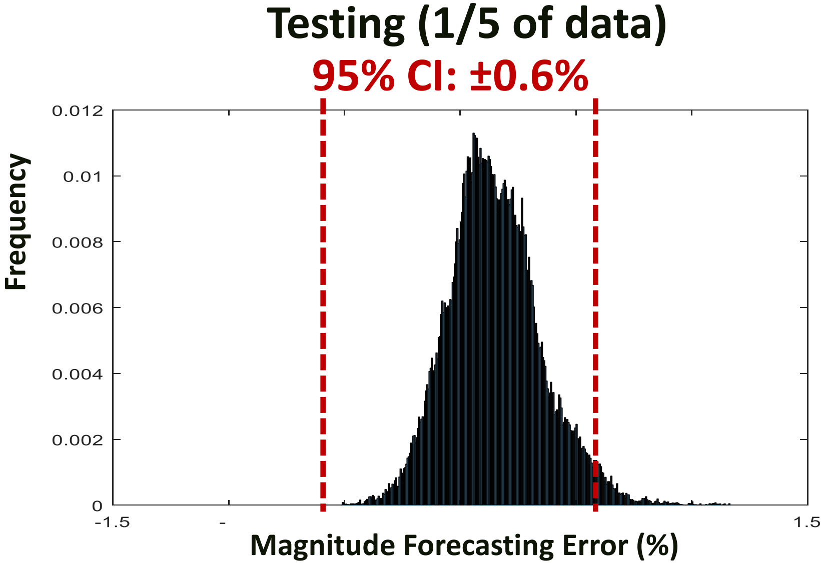


Example Results



- 15-minute ahead @1min voltage magnitude forecast
- Input: P and Q at load nodes for the past 1 hour
- Training: 1-minute power flow results for 3 days (sliding window)





Similar for Angle estimates: Training <0.2deg, Test <0.4deg

OMOO: Two-Time-Scale Optimization

Slow (every X minutes)

- Solve OPF to produce setpoints
- Provides nominal setpoints for DERs and legacy devices

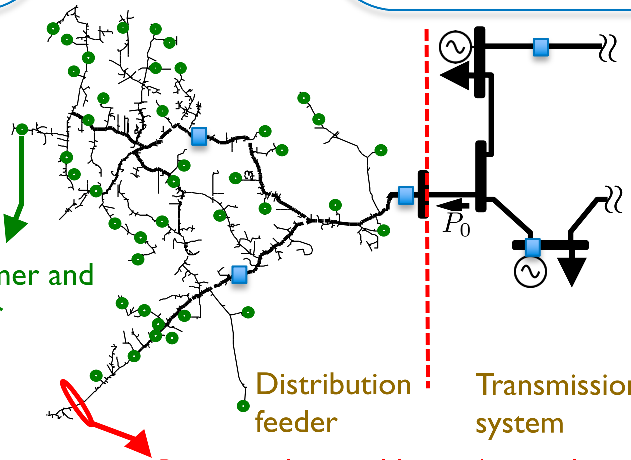
Planned path for X minutes

Fast (every Y seconds)

- Use online optimization to “follow the plan” produced by slow-scale optimizer
- Adjusting the setpoints of DERs in real time.

Control in real time:

- DERs
- Legacy devices



Slow Scale OMOO – VLSM-based OPF

- **Voltage-Load Sensitivity Matrix (VLSM)** based mixed-integer linear OPF [4]
  - Can handle integer constraints for taps/caps

Step 1: Build VLSM (periodically)

$$|\delta V| = |VLSM_P||\delta P| + |VLSM_Q||\delta Q|$$

$$\begin{vmatrix} \delta V_1 \\ \delta V_2 \\ \vdots \\ \delta V_n \end{vmatrix} = \begin{vmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & \ddots & & p_{2n} \\ \vdots & & \ddots & \\ p_{n1} & p_{n2} & & p_{nn} \end{vmatrix} \begin{vmatrix} \delta P_1 \\ \delta P_2 \\ \vdots \\ \delta P_n \end{vmatrix} + \begin{vmatrix} q_{11} & q_{12} & \cdots & q_{1n} \\ q_{21} & \ddots & & q_{2n} \\ \vdots & & \ddots & \\ q_{n1} & q_{n2} & & q_{nn} \end{vmatrix} \begin{vmatrix} \delta Q_1 \\ \delta Q_2 \\ \vdots \\ \delta Q_n \end{vmatrix}$$

Step 2: Solve OPF MILP (minutes)

$$Min\ Z = \omega_1 \xi C + \omega_2 \Delta V + \omega_3 M_{reg}$$

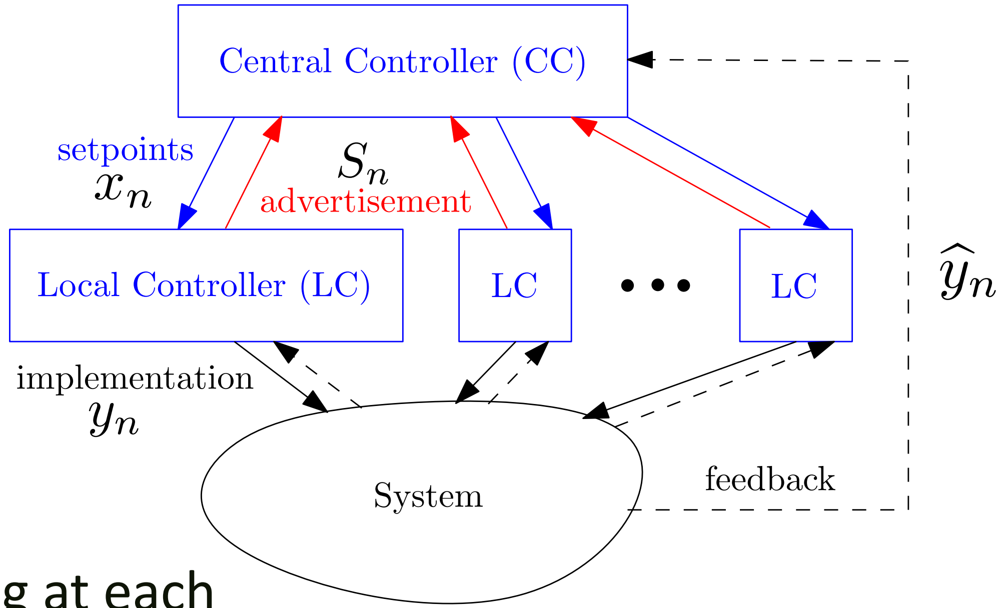
$$\begin{aligned} C &= \lambda_{Load} \sum_{i=1}^{n} \left(P_{control}^{Load}(i)\right)^2 + \lambda_{PV}^{P} \sum_{i=1}^{n} \left(P_{control}^{PV}(i)\right)^2 + \lambda_{PV}^{Q} \sum_{i=1}^{n} \left(Q_{control}^{PV}(i)\right)^2 \\ &+ \lambda_{ES}^{Q} \sum_{i=1}^{n} \left(P_{control}^{ES}(i)\right)^2 + \lambda_{cap} \sum_{i=1}^{n} \left(s(i) Q_{cap}(i)\right)^2 \\ &+ \lambda_{reg} \sum_{t=1}^{n_{reg}} \left(M_{Tap}(t) - M_{Tap}^{0}(t)\right)^2 \end{aligned}$$

Output: Dispatch/set points path for DERs and Legacy Utility Devices

[4] X. Zhu and Y. Zhang, “Coordinative Voltage Control Strategy with Multiple-Resource for Distribution Systems of High PV Penetration,” *World Conference on Photovoltaic Energy Conversion (WCPEC-7)*, Waikoloa, Hawaii, June 10-15, 2018.

Fast Scale – OMOO

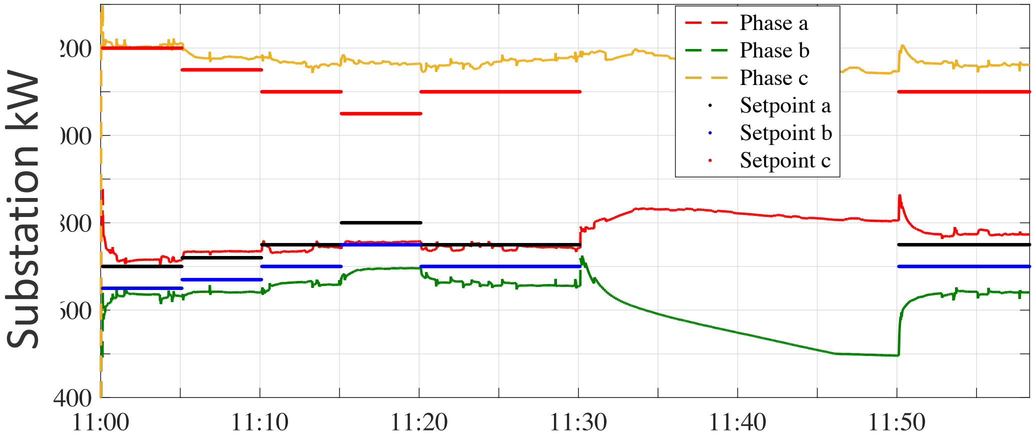
- Goal: follow OPF plan
- Key ideas:
  - Hierarchical control
  - Lots of math with provable bounds
  - Single-step gradient
    - Rather than converging at each timestep, loosely converge across fast time steps

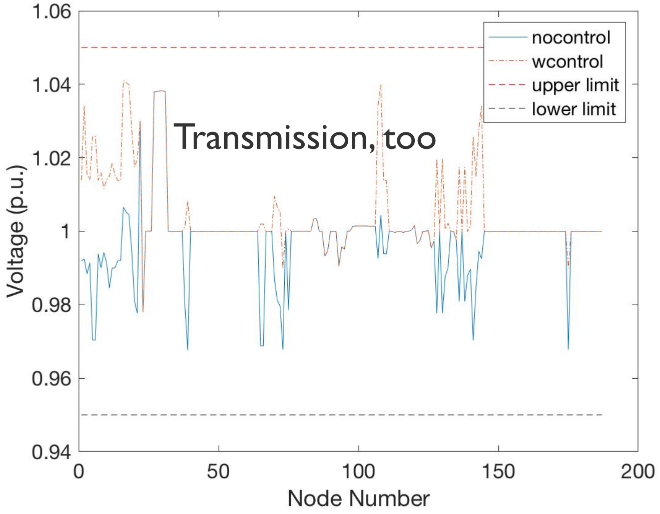


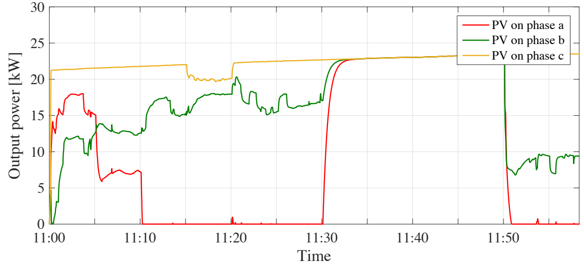
[5] A. Bernstein and E. Dall'Anese, "Bi-Level Dynamic Optimization with Feedback," *the 5th IEEE Global Conference on Signal and Information Processing (GlobalSIP)*, Montreal, Quebec, Canada, Nov. 2017.

OMOO Example Results

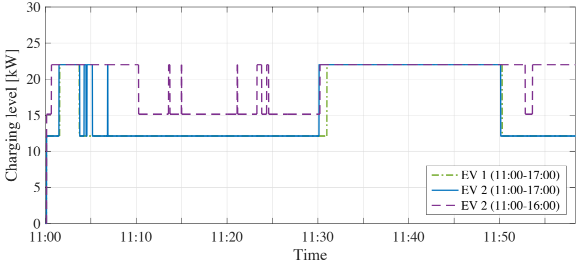
Tracking setpoint while maximizing DER objectives







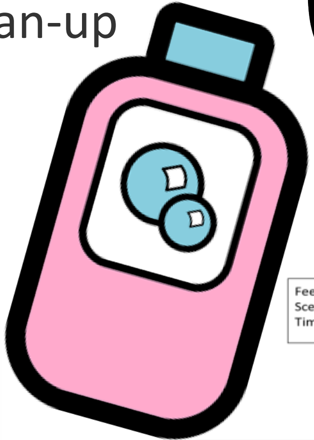
PV systems

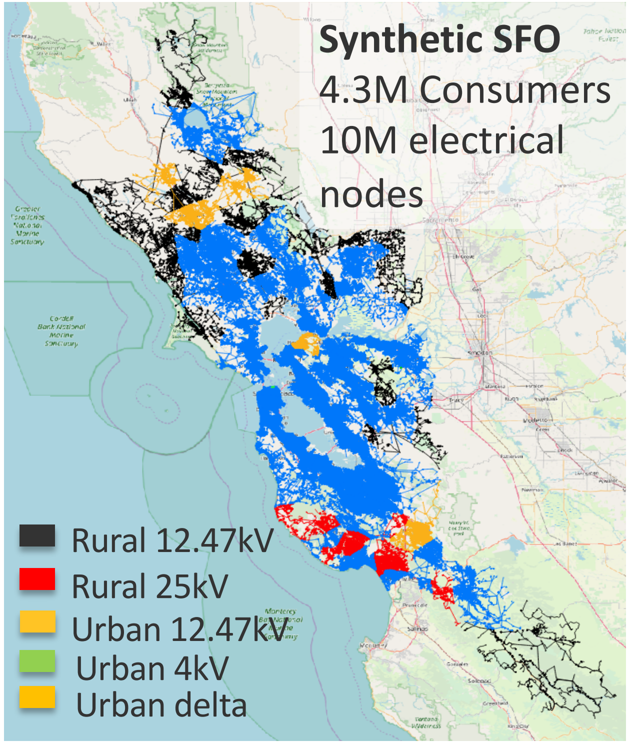


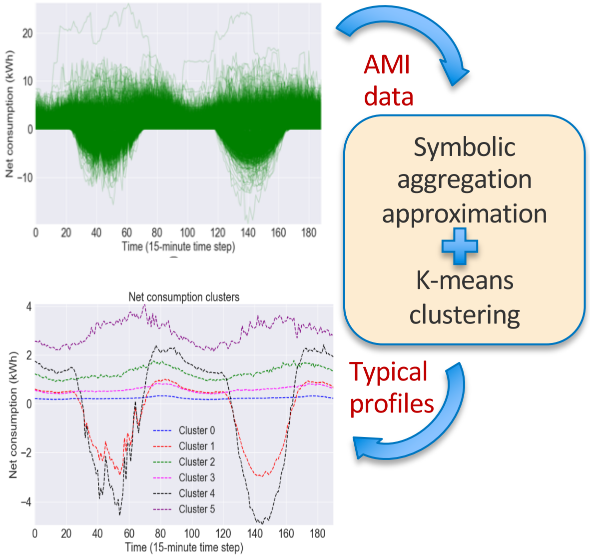
EVs

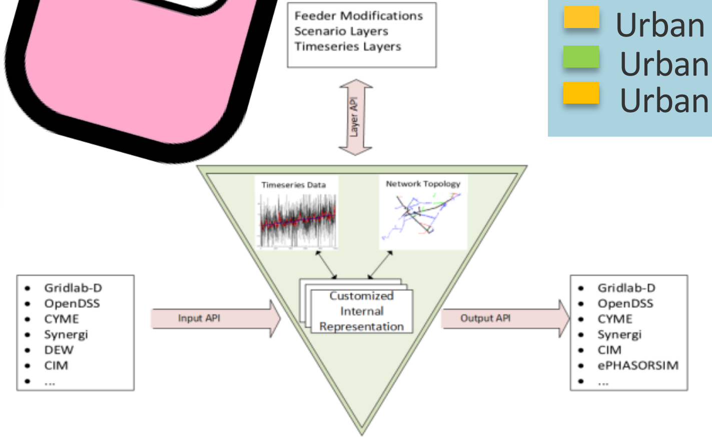
Challenge: Data

- Step 1: Get enough Data
- Step 2: Massage It
- Step 3: Visualize and Clean-up
- Step 4: Repeat





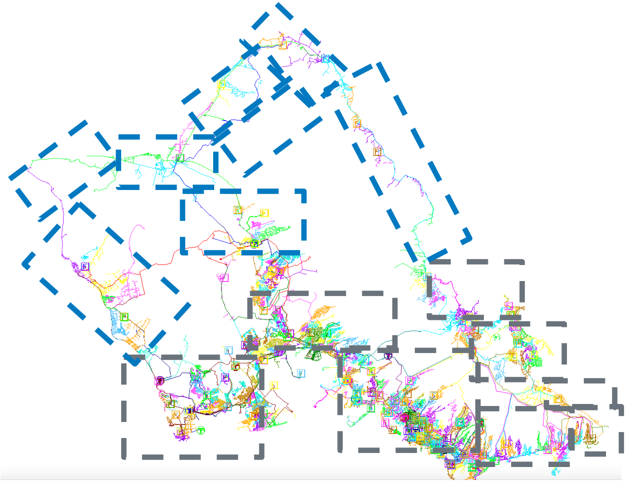


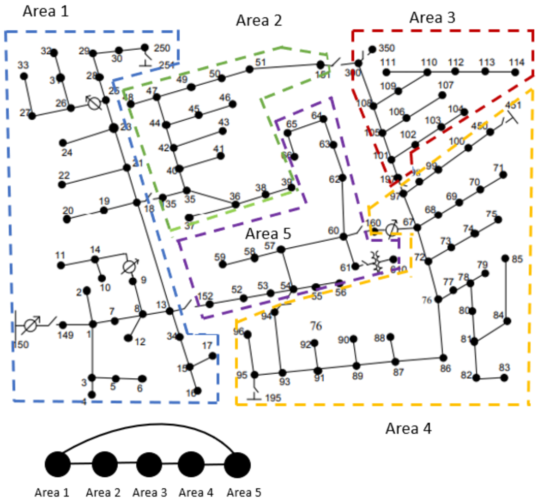


Challenges: Scalability

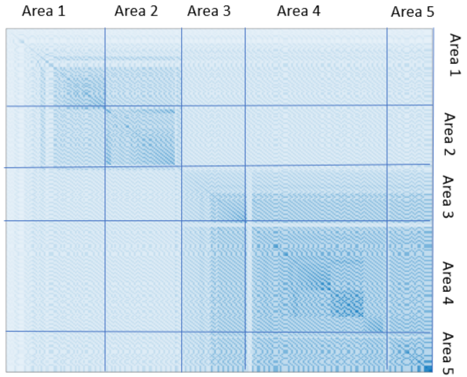
Issue: Many orders of magnitude larger systems

Ideas:
- Near optimality (close can be good enough)
- Decentralized/Distributed approaches
- Decomposition





Issue: How to split?



Sensitivity Heatmap

Challenge: System Changes

- Issue: The grid keeps changing
- Things we're trying on GO-Solar (distribution reconfiguration)
  - Known change
    - Update PF model, still get accurate estimates
    - Working on algorithms to detect change
  - Unknown change
    - Measure Error
      - If high error: Revert to traditional methods
    - Retrain

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Thank You!

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