Grid Optimization with Solar (GO-Solar) Experiences with:
Data-driven and Machine Learning Approaches for High-pen PV Grids

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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

Predictive State Estimation

Full-scale T&D Co-Simulation

Hardware-in-the-Loop

On-line Multi-Objective Dispatch Optimization

Voltage limits, Performance targets

Existing communication links

| $V_n(t)$ |
Innovation: Matrix Completion for State Estimation

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

Key idea: Estimate unknown elements using correlation

<table>
<thead>
<tr>
<th>Node</th>
<th>Quantity</th>
</tr>
</thead>
<tbody>
<tr>
<td>$X_{\mathbb{R}{v}}$</td>
<td>$X_{\mathbb{I}{v}}$</td>
</tr>
<tr>
<td>$p$</td>
<td>$q$</td>
</tr>
<tr>
<td>$|v|$</td>
<td></td>
</tr>
</tbody>
</table>

Objective function

\[ \text{min}(\text{Rank of matrix } X) \]

Constraints: Known elements in $X = \text{Measurements}$

(2-point Linearized) power flow equations

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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

[Graphs showing 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

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)

**Training**

95% CI: ±0.3%

**Testing (1/5 of data)**

95% CI: ±0.6%

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

**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

Maximize customer and utility/aggregator objectives

Respect electrical limits (e.g., voltage regulation)
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)**

\[
\begin{align*}
\delta V &= \begin{bmatrix} VLSM_P \end{bmatrix} \delta P + \begin{bmatrix} VLSM_Q \end{bmatrix} \delta Q \\
\delta V_1 &= \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \end{bmatrix} \delta P_1 + \begin{bmatrix} q_{11} & q_{12} & \cdots & q_{1n} \end{bmatrix} \delta Q_1 \\
\delta V_2 &= \begin{bmatrix} p_{21} & \cdots & p_{2n} \end{bmatrix} \delta P_2 + \begin{bmatrix} q_{21} & \cdots & q_{2n} \end{bmatrix} \delta Q_2 \\
& \vdots \\
\delta V_n &= \begin{bmatrix} p_{n1} & p_{n2} & \cdots & p_{nn} \end{bmatrix} \delta P_n + \begin{bmatrix} q_{n1} & q_{n2} & \cdots & q_{nn} \end{bmatrix} \delta Q_n
\end{align*}
\]

**Step 2: Solve OPF MILP (minutes)**

\[
\begin{align*}
\text{Min } Z &= \omega_1 \xi_C + \omega_2 \Delta V + \omega_3 M_{\text{reg}} \\
C &= \lambda_{\text{Load}} \sum_{i=1}^{n} \left( p_{\text{control}(i)}^{\text{Load}} \right)^2 + \lambda_{\text{PV}} \sum_{i=1}^{n} \left( p_{\text{PV}(i)}^{\text{PV}} \right)^2 + \lambda_{\text{PV}} \sum_{i=1}^{n} \left( Q_{\text{PV}(i)}^{\text{PV}} \right)^2 \\
&+ \lambda_{\text{ES}} \sum_{i=1}^{n} \left( p_{\text{ES}(i)}^{\text{ES}} \right)^2 + \lambda_{\text{cap}} \sum_{i=1}^{n} \left( s(i) Q_{\text{cap}(i)} \right)^2 \\
&+ \lambda_{\text{reg}} \sum_{t=1}^{n_{\text{reg}}} \left( M_{\text{Tap}(t)} - M_{\text{Tap}(t)}^{\text{opt}} \right)^2
\end{align*}
\]

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

- 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

OMOO Example Results

Tracking setpoint while maximizing DER objectives

Substation kW

Transmission, too

PV systems

EVs
Challenge: Data

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

Symbolic aggregation approximation + K-means clustering

AMI data

Typical profiles

Synthetic SFO
4.3M Consumers
10M electrical nodes

- Rural 12.47kV
- Rural 25kV
- Urban 12.47kV
- Urban 4kV
- Urban delta
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?
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
Thank You!

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