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Grid Optimization with Solar (GO-Solar)

National Renewable Energy Laboratory (NREL)

Award # DE-EE00032960

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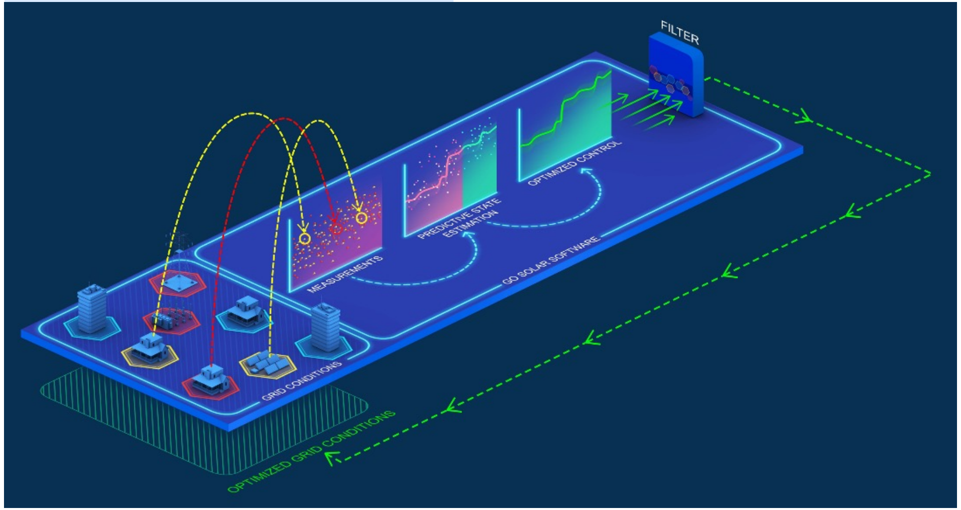
Project Objectives

GO-Solar Solution

Challenge #1:
Operations with extreme penetrations of distributed PV

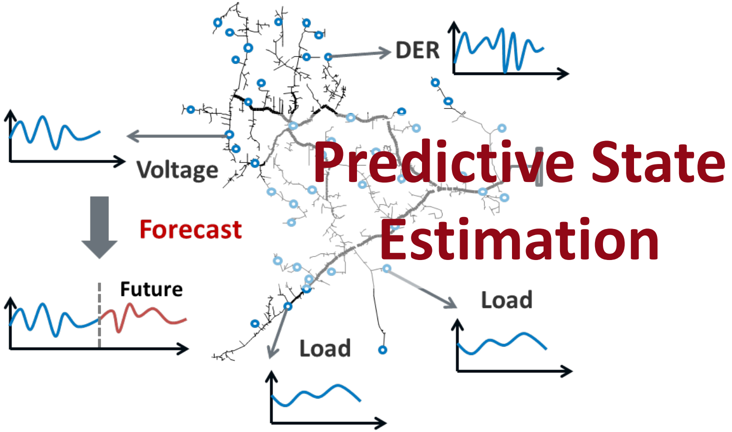
Challenge #2:
Communicate and control with millions of DERs

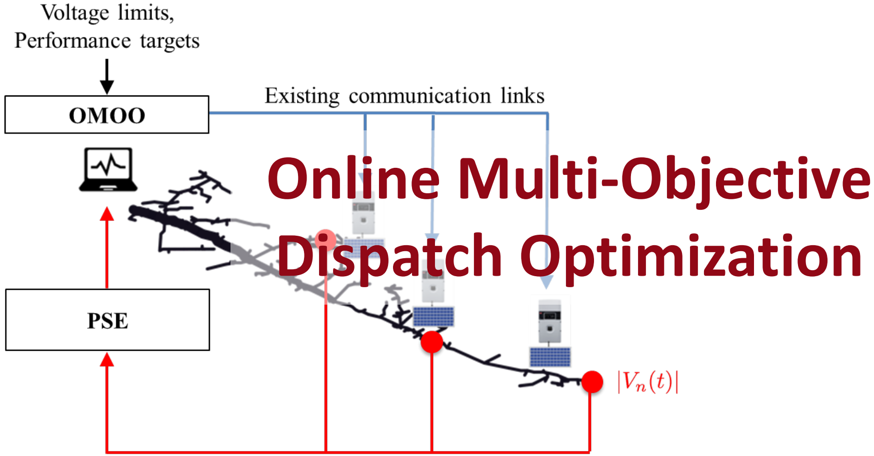


Manage **extreme penetrations of solar** and other DERs **using only a few measurement points** through matrix completion and multi-kernel learning-based **predictive state estimation (PSE)** **and only a few control nodes** dispatched through dual timescale **online multi-objective optimization (OMOO)**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

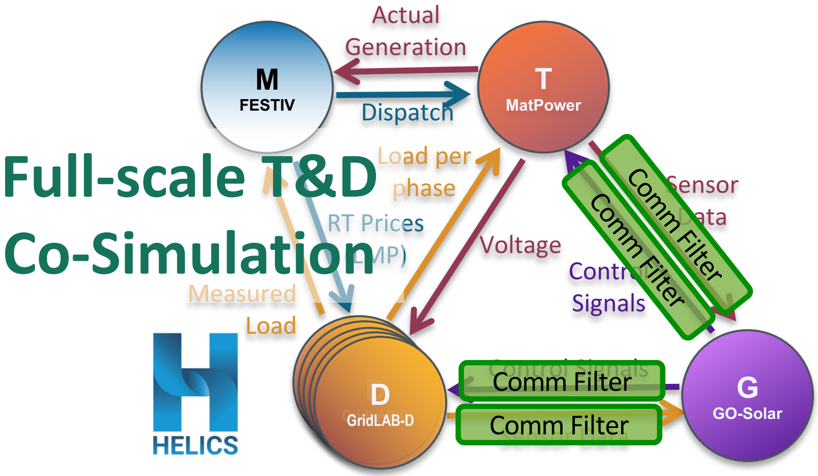
GO-Solar Key Activities

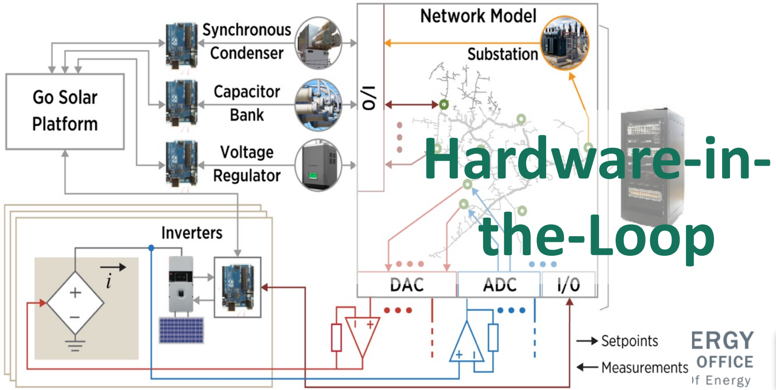
Algorithms





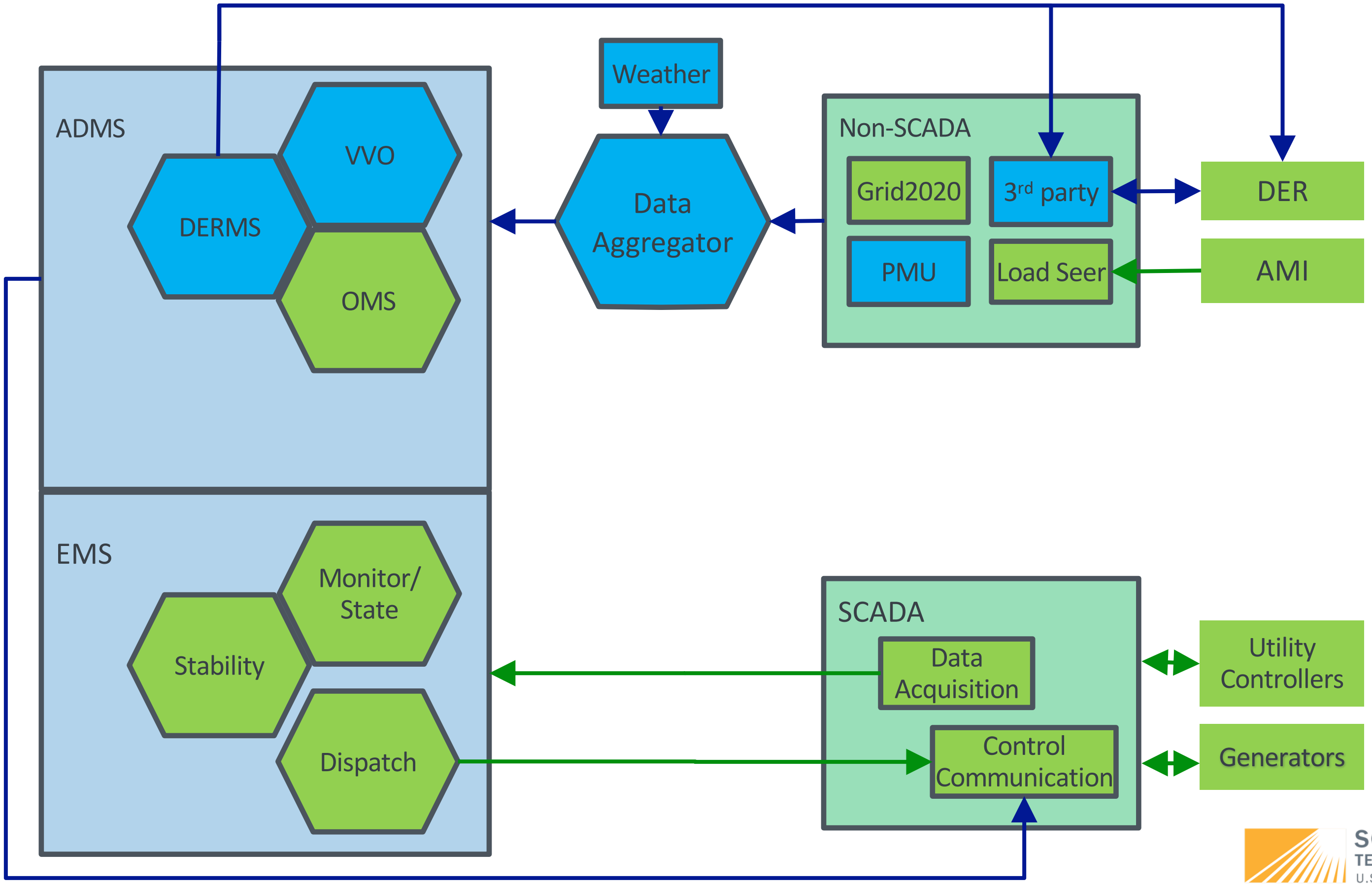
Validation





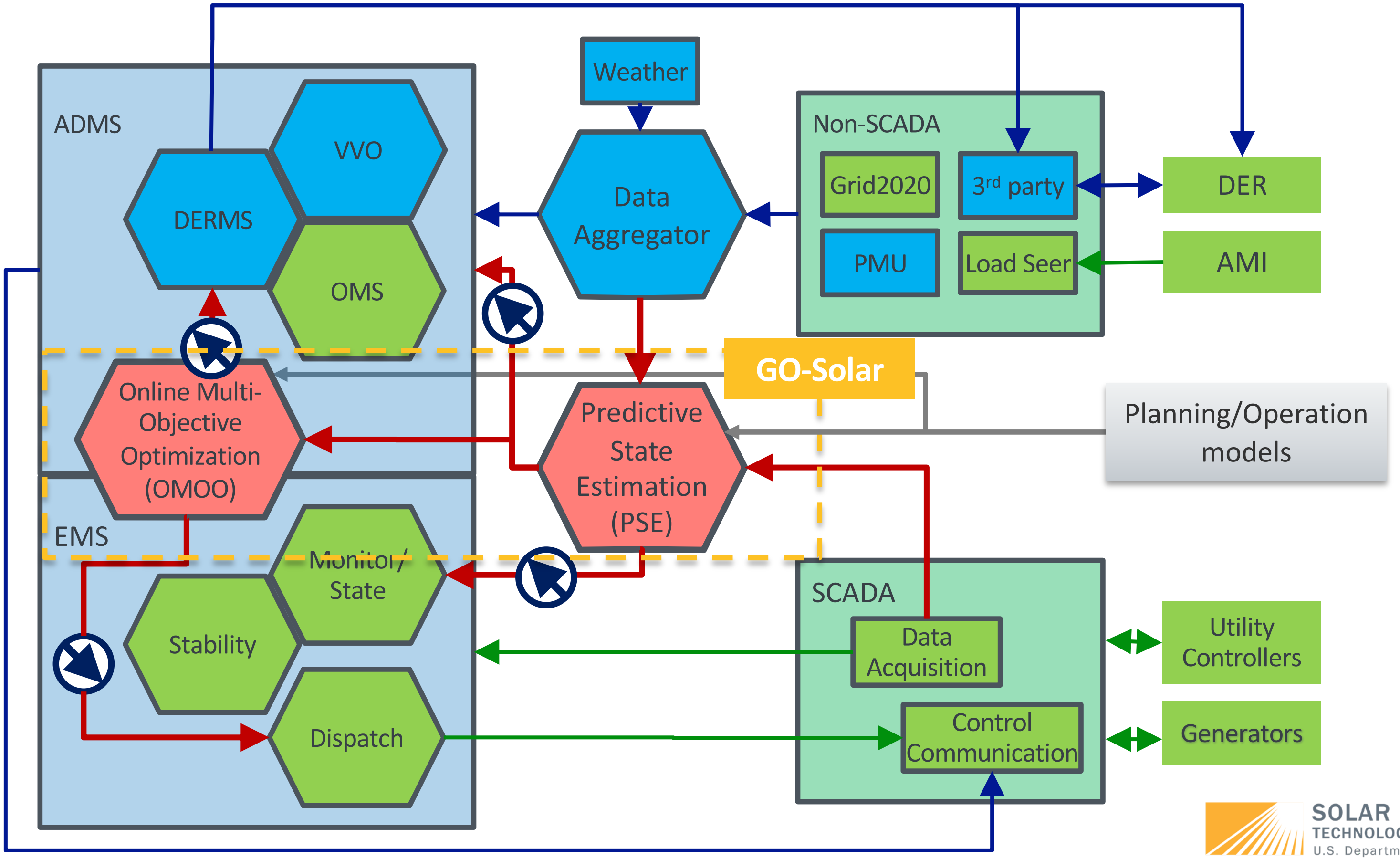
GO-Solar Interface with Enterprise Systems

2030 Expected



GO-Solar Interface with Enterprise Systems

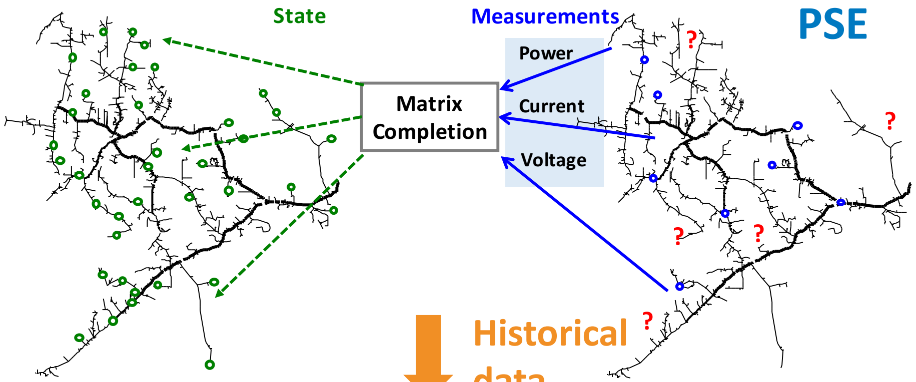
With GO-Solar

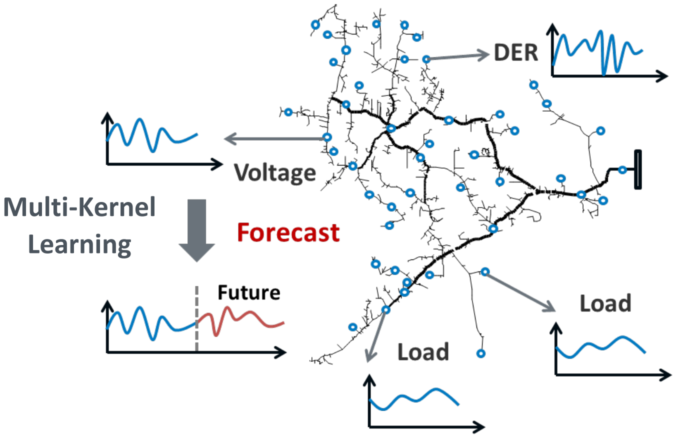


GO-Solar Technology

Integrated GO-Solar Platform

PSE





Forecasted voltages

Optimal set points

OMOO

Fast (every Y seconds)

- Uses online optimization to follow the optimal trajectory
- Adjusts the set points of DERs in real time

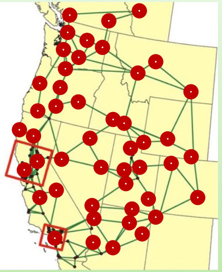
Planned set points

Slow (every X minutes)

- Solves OPF to mitigate potential voltage violations
- Provides nominal setpoints for DERs and legacy devices

Matrix Completion for State Estimation

vs. Conventional state estimation



- Weighted least squares
- Objective: Minimize the weighted residuals

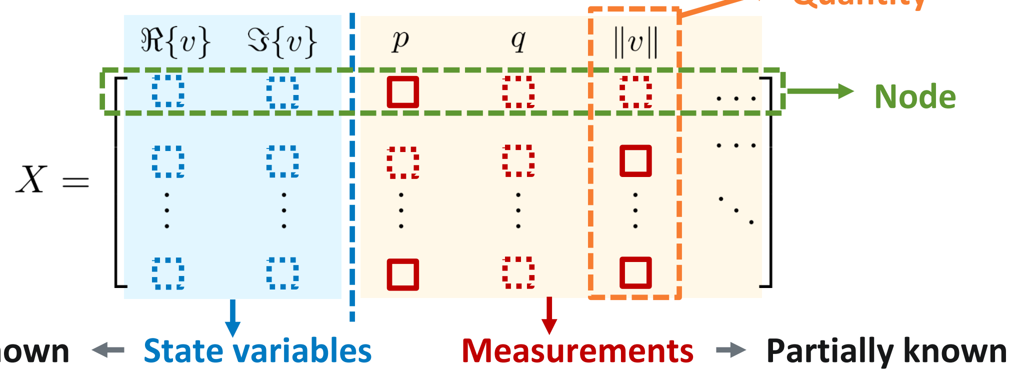
Requires redundant measurements

Key idea: Estimate unknown elements using correlation

Concept:

Netflix Recommendation System

+ Power Systems Constraints (linearized) [1]-[3]



Objective function $\min$ **(Rank of matrix X)** **New**

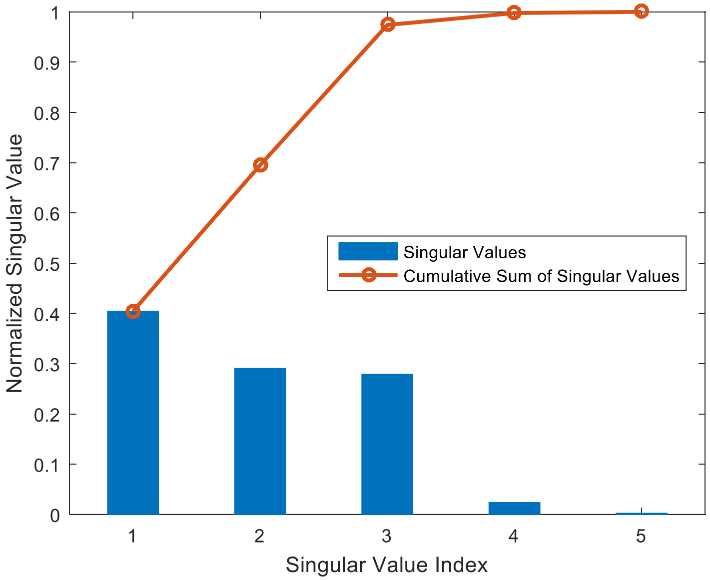
Constraints **Known elements in X = Measurements**

(2-point Linearized) power flow equations

[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," in *IEEE Transactions on Smart Grid*, vol. 11, no. 3, pp. 2520-2530, May 2020.
[3] Y. Liu, A. Sagan, A. Bernstein, R. Yang, X. Zhou, and Y. Zhang, "Matrix Completion Using Alternating Minimization for Distribution System State Estimation," *IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids*, Tempe AZ, October 6-9, 2020.

Why It Works?

- Low rank assumption



Data matrix of HECO system

- Theoretical guarantee

$$\begin{aligned} \min_{X} \quad & \|X\|_* \\ \text{s.t.} \quad & X_{ij} = M_{ij} \end{aligned}$$

There exists a minimum number of entries required to uniquely recover the unknown low-rank matrix X [4]

- Power flow equations
  - Physical constraints satisfied

[4] Benjamin Recht, "A simple approach to matrix completion," *Journal of Machine Learning Research,* 12, 2001.

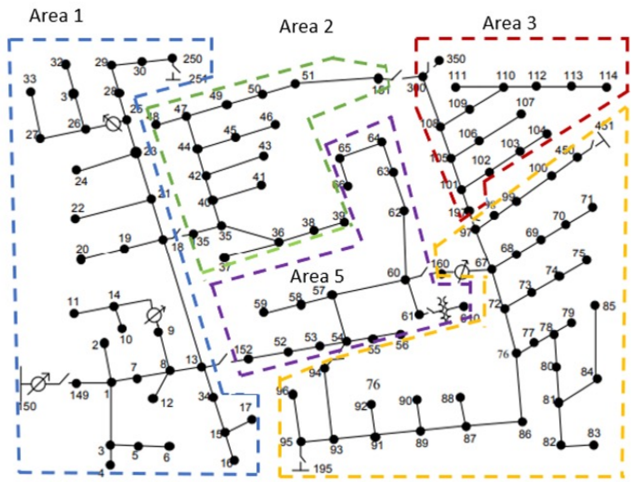
Theoretical Bound on Sample Complexity

Theorem[1]: Let M be an $n_1 \times n_2$ $(n_1 \geq n_2)$ matrix of rank r such that the following h linear equality constraints are satisfied: $\langle A^{(l)}, M \rangle = b^{(l)}$ for all $l = 1 \cdots h$. Suppose that m entries of M are sampled uniformly at random. Then there exists a function $F\left(n_1, n_2, r, A^{(l)}, \mathrm{M}, \beta\right) < \infty$ such that if $m \geq \max\{F, 2\beta n_1 \log n_1\}$ for some $\beta \geq 1$, then the solution to the constrained matrix completion problem is unique and equal to M with probability at least $1 - 6{n_1}^{-\beta}$.

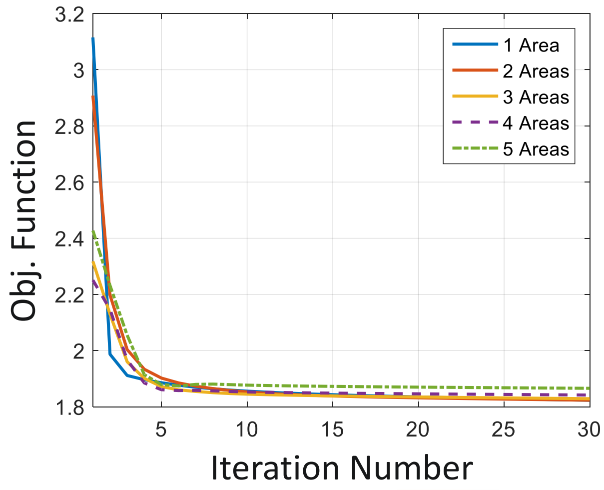
- For specific form of F, please refer to [1]: J. Comden et al., "Sample Complexity of Power System State Estimation using Matrix Completion", 2019 IEEE SmartGridComm.

Distributed Matrix Completion

- Challenges
  - Formulated as a semidefinite program
  - Computationally intensive



- Solution [5]
  - Distributed algorithm
  - Communication
  - Guaranteed convergence



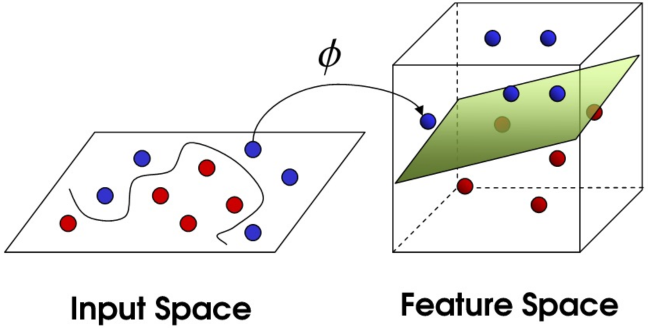
[5] A. Sagan, Y. Liu, and A. Bernstein, "Decentralized low-rank state estimation for power distribution systems," *IEEE Transactions on Smart Grid*, 2021.

Multi-Kernel Learning for State Forecasting

Goal: Learn the spatiotemporal correlation between measurements and system states

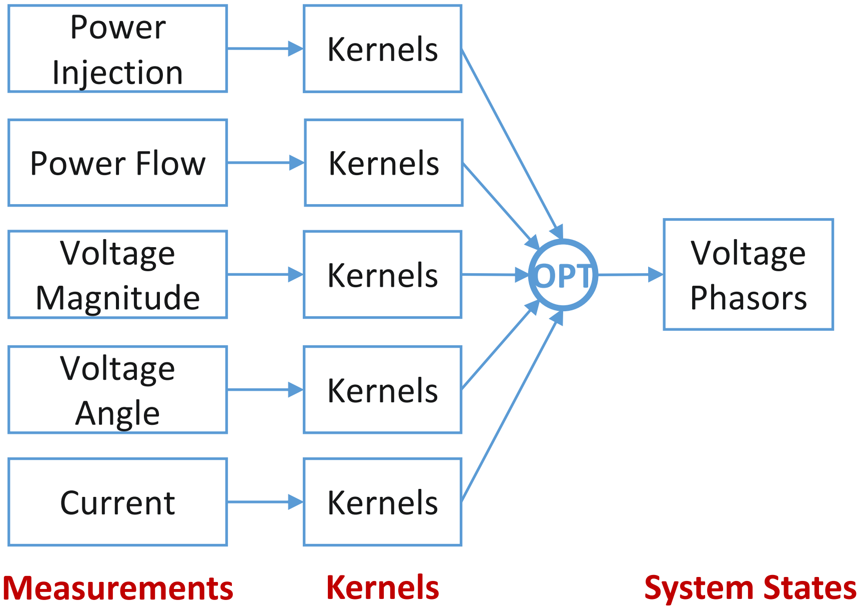
Kernel Learning Concept

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



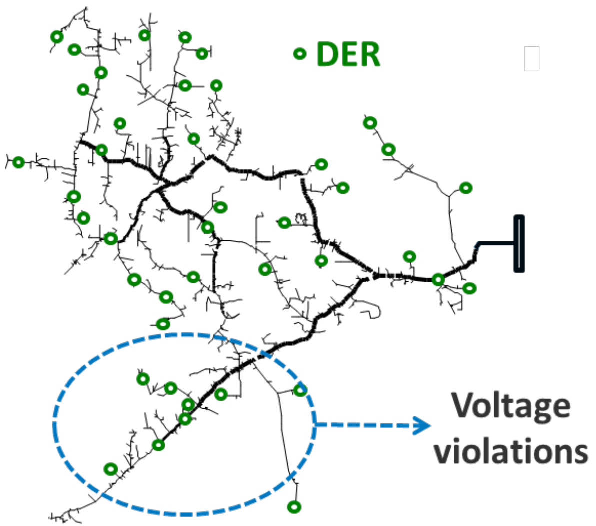
Source: *R. G. Esfahani and A. A. Mohammad, "Towards an anomaly detection technique for web services based on kernel methods," IEEE Innovations in Information Technology, 2009.*

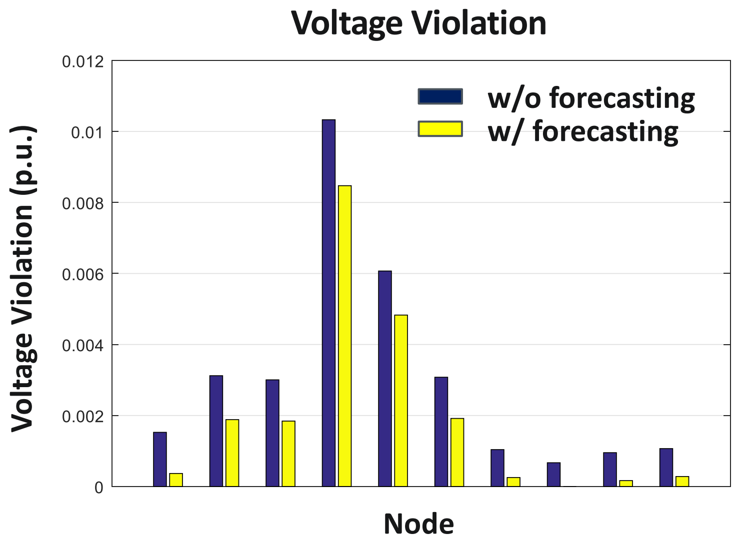
Expanding to Multi-Kernel Learning



Importance of PSE

- Proactively dispatch controllable resources
- Better coordinate control efforts
- Prioritize the control needs





Slow-Scale OMOO: VLSM-based Optimization

- **Voltage-Load Sensitivity Matrix (VLSM)** based mixed-integer linear problem [6]
  - 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 MILP (minutes)

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

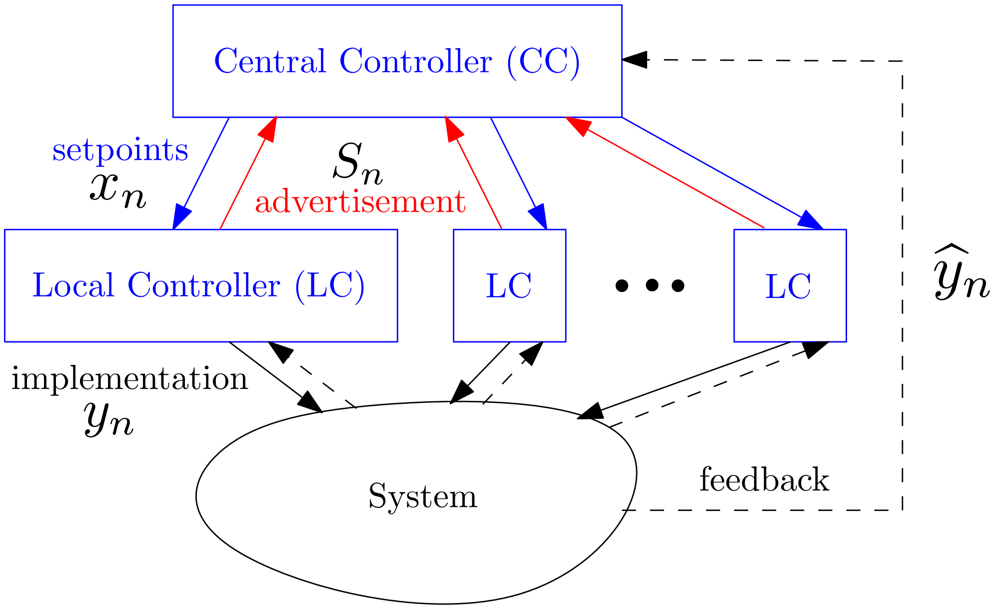
$$\begin{aligned} C &= \lambda_{Load} \sum_{i=1}^{n} \left(P_{control}^{Load}(i)\right)^2 + \lambda_{PV}^{P} \sum_{i=1}^{n} \left(P_{control}^{PV}(i)\right)^2 + \lambda_{PV}^{Q} \sum_{i=1}^{n} \left(Q_{control}^{PV}(i)\right)^2 \\ &+ \lambda_{ES}^{Q} \sum_{i=1}^{n} \left(P_{control}^{ES}(i)\right)^2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

Output: Dispatch/set points for DERs and utility legacy devices

[6] 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: Online Optimization

- Goal: Follow OPF trajectory
- Key ideas [7]:
  - Hierarchical control
  - Lots of math with provable bounds
  - Single-step gradient
    - Rather than converging at each timestep, loosely converge across fast time steps



Output: Adjusted DER setpoints in real time

[7] 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.

Voltage Estimation

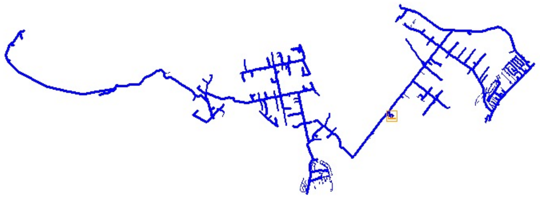
- Different sensors
  - Substation SCADA: P, Q, |V|, θ
  - Grid 2020: P, Q, |V|
  - AMI: P, |V|

HECO Feeders

2576 nodes

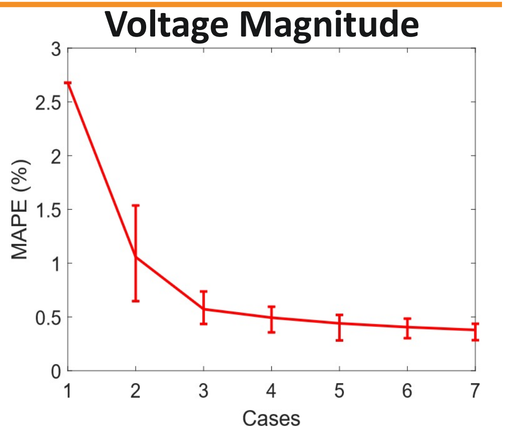
535 nodes w/ loads

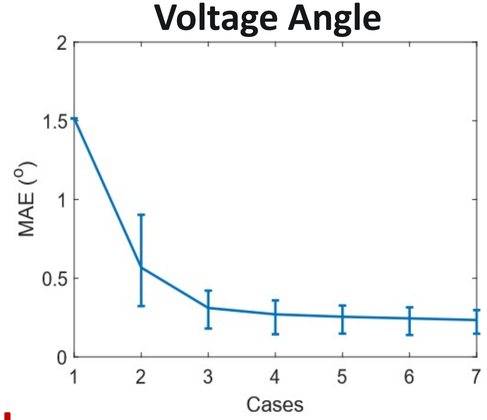
100% PV penetration



- Realistic scenarios

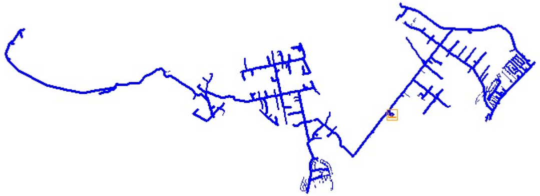
Case	1	2	3	4	5	6	7
0 Inj.	√	√	√	√	√	√	√
Sub.	√	√	√	√	√	√	√
Grid 2020	X	1%	1%	1%	1%	1%	1%
AMI	X	X	1%	2%	3%	4%	5%





Accurate state estimation with Sub. + 1% Grid 2020 + 1% AMI

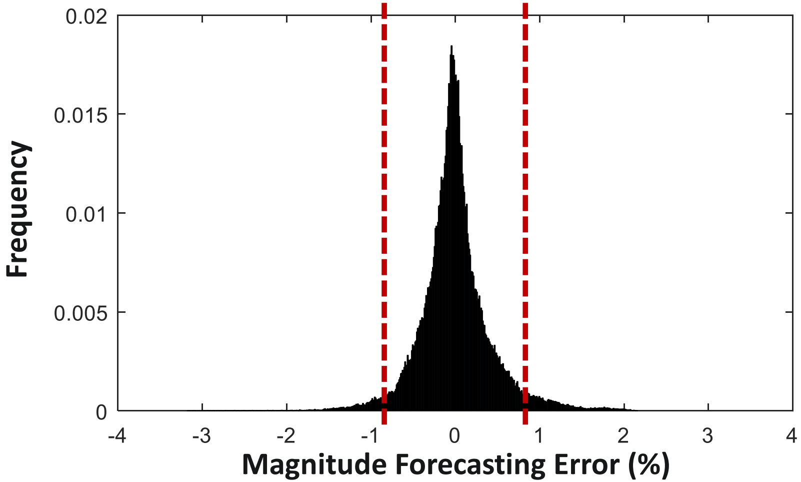
Voltage Forecasting



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

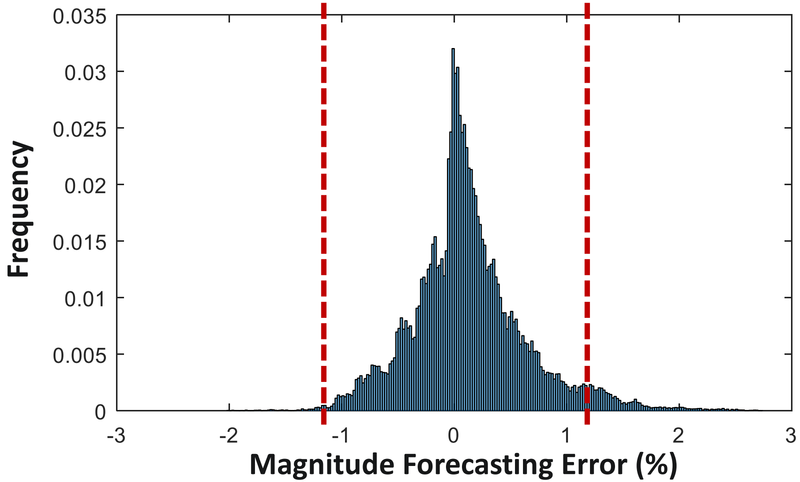
Training

95% CI: ±0.91%



Testing (1/5 of data)

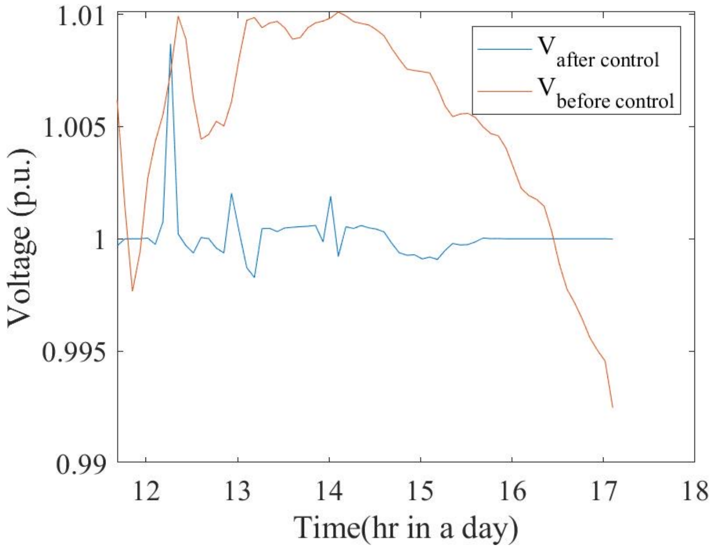
95% CI: ±1.13%



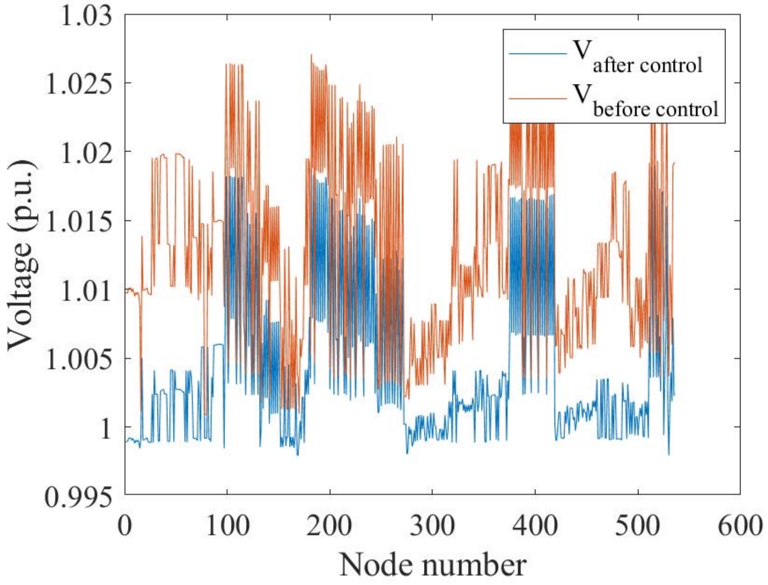
93.26% of the absolute errors smaller than 1%

Slow-Scale OMOO

Time series voltage control results



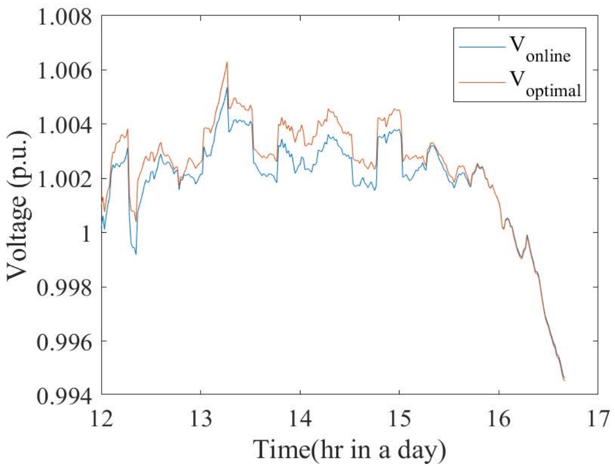
Snap-shot voltage control results



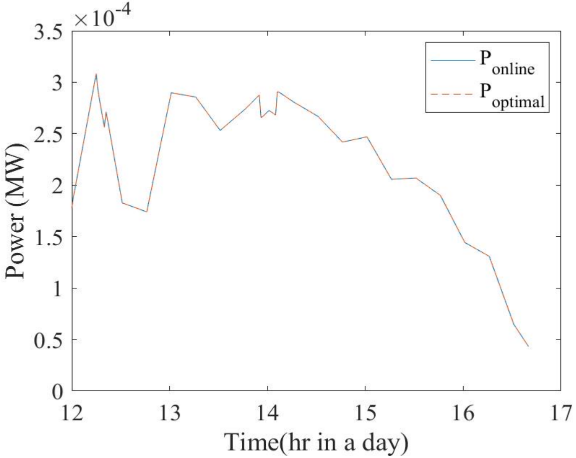
The voltage is closer to the voltage objective which is 1 p.u. after the slow-scale control is performed

Fast-Scale OMOO

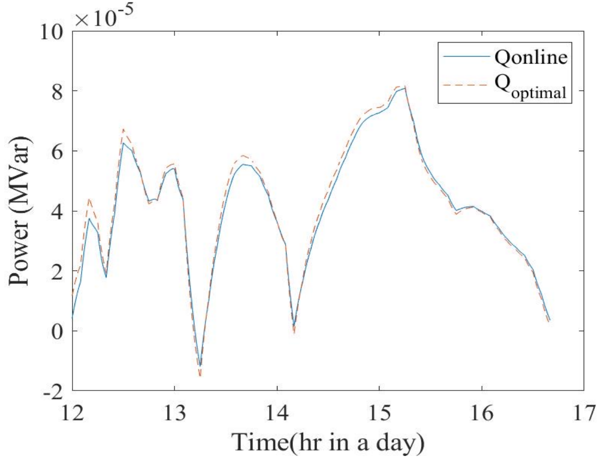
Time series voltage control results



PV P set point tracking profile



PV Q set point tracking profile



Tracking Error

	Voltage	PV P set point	PV Q set point
Tracking Error (%)	0.06	0.02	2

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Pathway to Real-World Application

Objectives

- Manage extreme penetrations of solar and other DERs
- Achieve system-wide control targets

Real-world system: Oahu system

- ~1-million electric nodes

Challenges

- **Real-time**

  Needs to be fast enough to operate in real time

- **Data Aware**

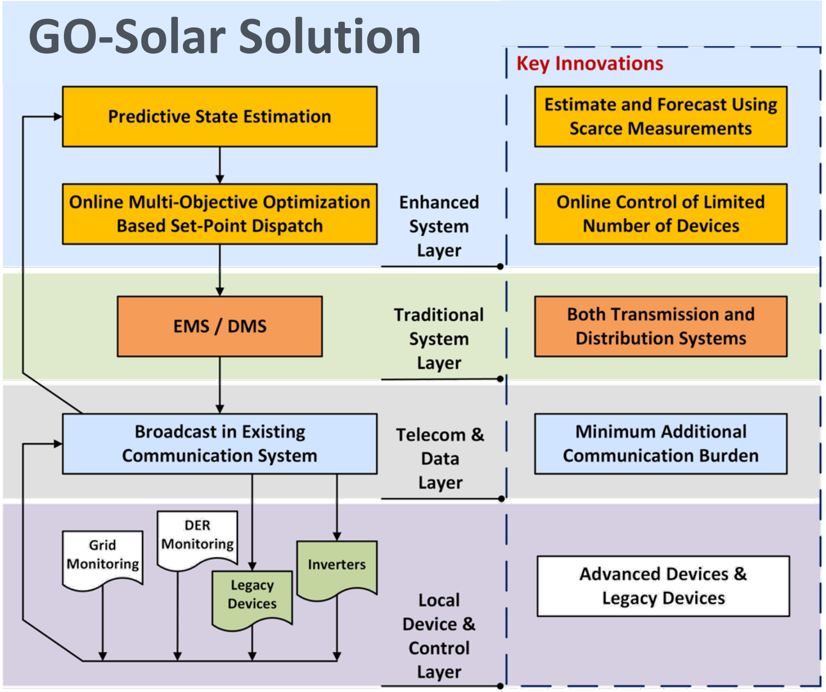
  Makes best use of time-varying asynchronous measurements

- **Scalable**

  Needs to be able to control millions of devices

  Hierarchical control

Summary



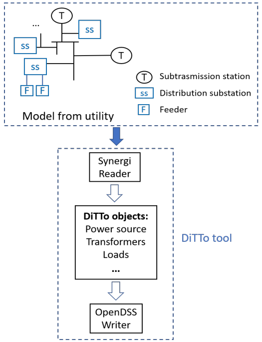
- Key innovations
  - Real-time and predictive situational awareness from PSE
  - Coordinated control of legacy devices and DERs

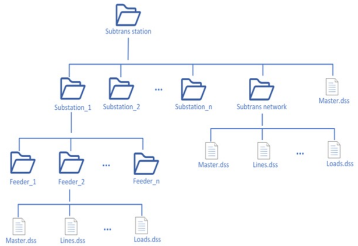
- Future work
  - Incomplete and inaccurate system models
  - Machine learning with partial physical information

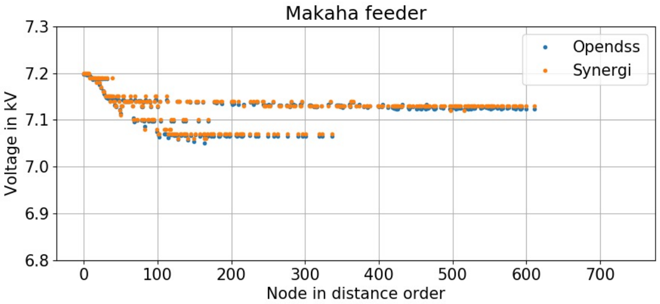
Large-Scale Co-Simulation

Electrical Model Development and Setup

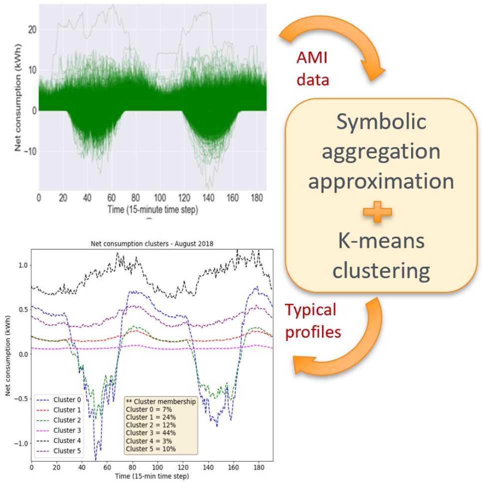
- Model conversion from Synergi
  - Improved DiTTo



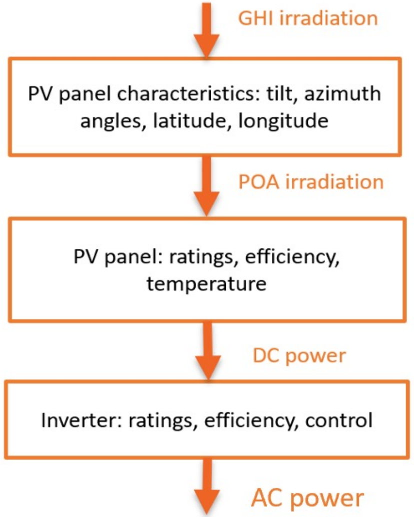




- Load profile



- PV profile



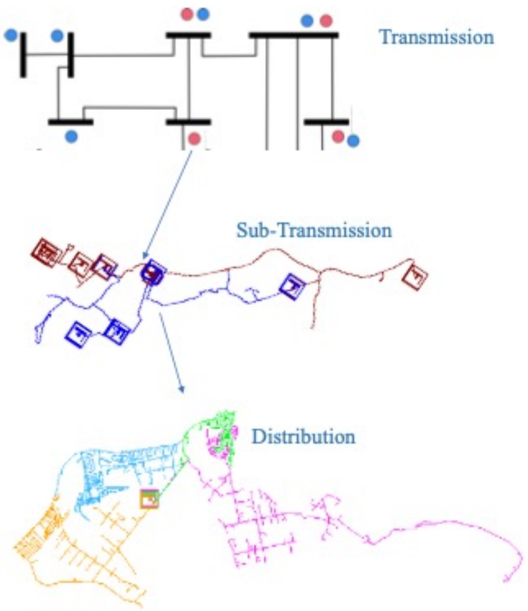
Scenario Summary

- Focus
  - 2030 unity PF
  - 2030 with GO-Solar

	2020 (not simulated)	2030 Baseline	2030 with GO-Solar
Bulk generation		Closest year Plexos Planning Model (2028)	
Transmission Network		Closest year Plexos Planning Model (2028)	
Sub-transmission & Distribution Network		Unchanged, in nominal configuration	
138kV connected PV	None	None	
46kV PV	based on Synergi model actual locations and size.	Projected capacity and locations based on documents from HECO forecasting group. Assumed single-axis tracking at average tilt angle of existing systems	
12kV PV	based on Synergi model	Projected capacity based on documents from HECO forecasting group. New devices **Randomly** sited with sampled orientation and tilt diversity	
Loads		Estimated diversity based on clustering and representative AMI data (2018). Assumed unchanged.	
Irradiance Profile		Based on nearest substation SCADA data for 2018. Same time period as loads	
Storage	Not included	Storage is a stretch goal that will be considered only after PV-only simulation is done. A key challenge is the need to specify realistic dispatch patterns, which might vary widely	
Control Scheme		T dispatch from FESTIV. DPV per Rule 14H. SubT PV controlling to voltage output with no curtailment. Local control for Caps (always on at substation, local control at SubT) and Taps (SubT Caps on/off manually morning/evening)	T dispatch from FESTIV. SubT/D: GO-Solar stack (PSE + OOMO) 1 per 46kV system and 1 per 12kV feeder or feeder bank. Controlling PV and Caps/Taps. Non-controlled PV operated using volt/var, volt/watt, etc.
Simulation Setup		1 week covering peak demand period. 1 week including highest PV to load ratio	

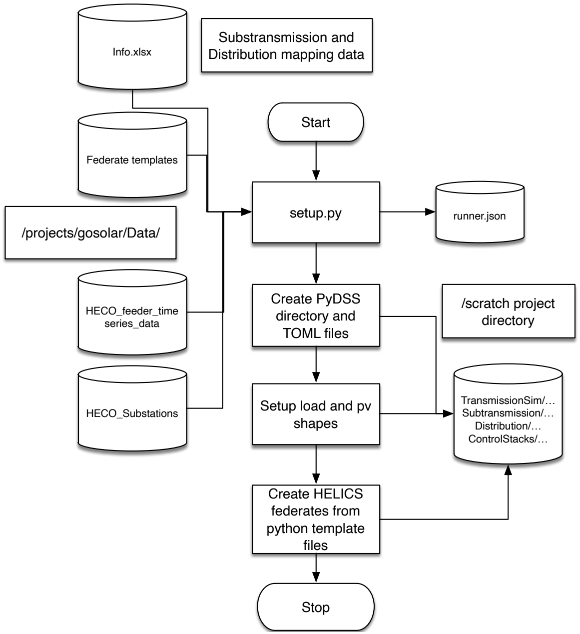
Simulation Overview

- 3 layered co-simulation
  - Transmission (MATLAB)
  - Subtransmission (OpenDSS)
    - 41 Networks
  - Distribution (OpenDSS)
    - 411 Feeders
  - For each OpenDSS network, a GO Solar Control Stack is assigned and included in the workflow
  - Electrical nodes counts:
    - 200 (T) + 373,539 (MV) + 51,259 devices = 425,000.
- HELICS Platform

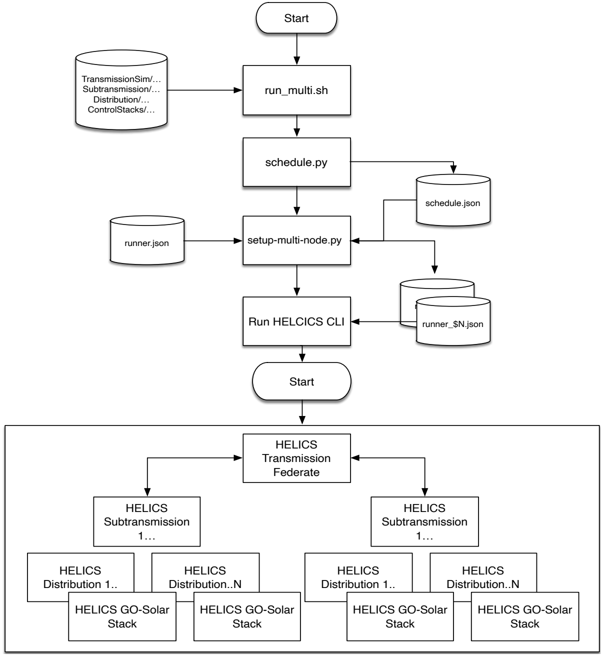


HPC Setup

Configuration data and PV and Load profile.

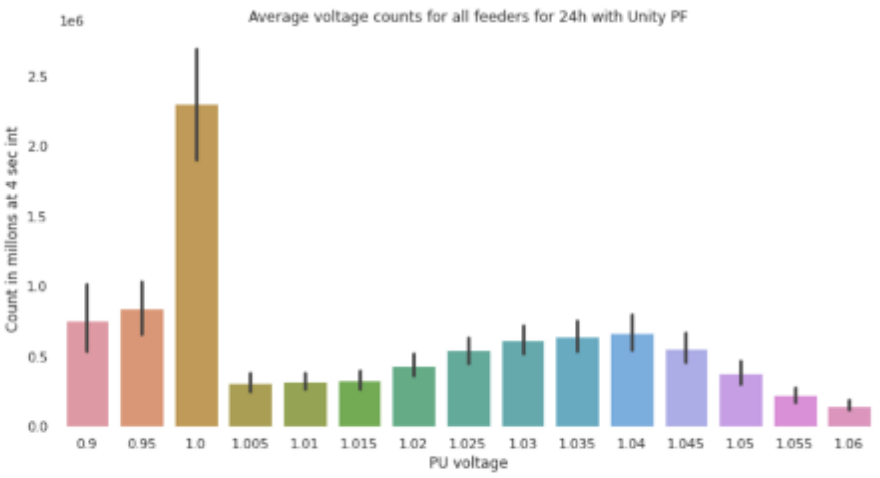


Run federates on multiple nodes and HELICS cosim

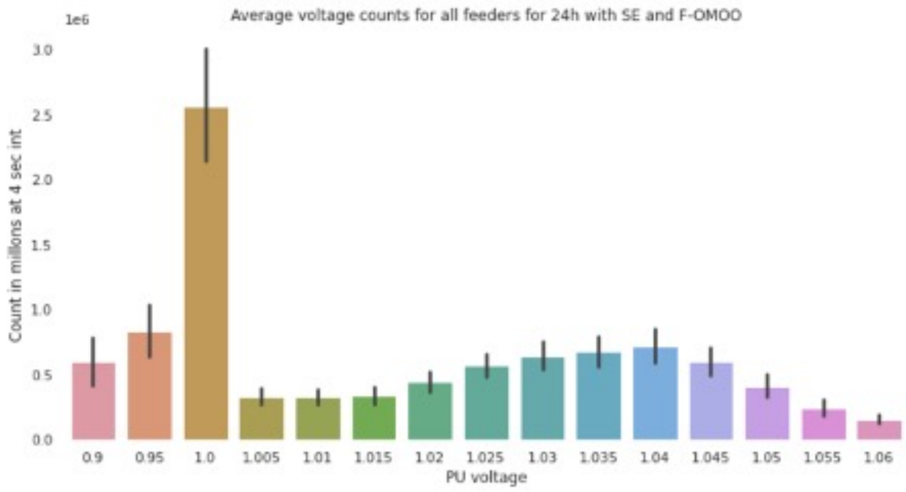


Results

- Voltage distribution



Run time = 7 hours



Run time = 12 hours

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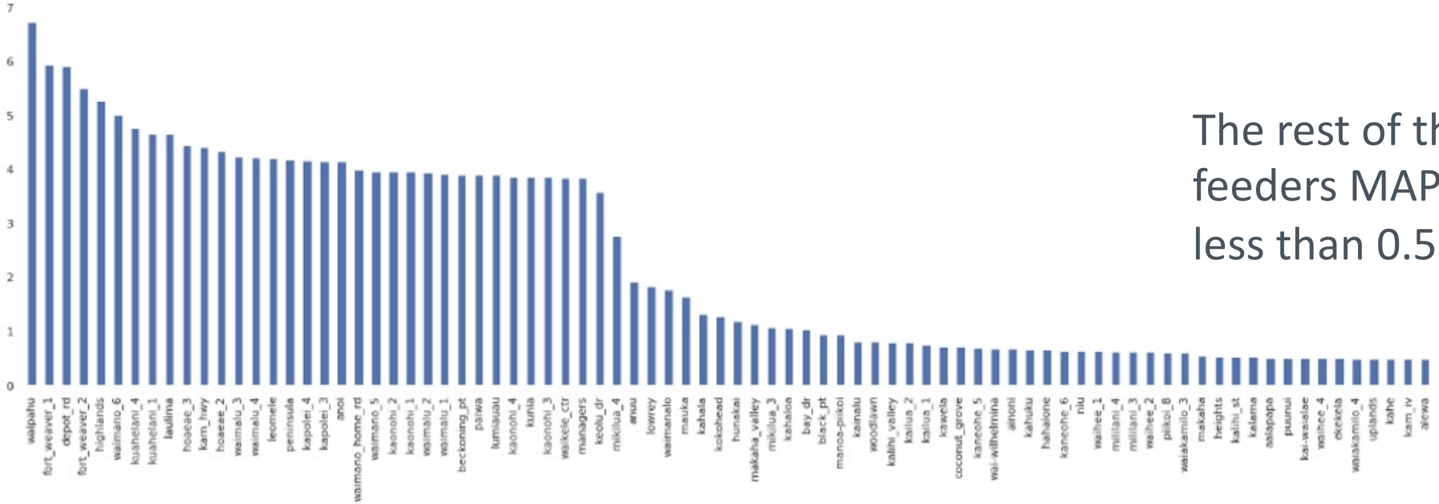
State Estimator

- Generally, the state estimator MAPE results are good but there are number of feeders with very large average MAPE which is driven by tuning of the GO-Solar OMOO. The feeders with the most difficulty are Waipahu, Manoa-Piikoi, and Waimanalo which have a correspondingly large voltage swing from the OMOO control points.



The rest of the feeders MAPE average is less than 0.5

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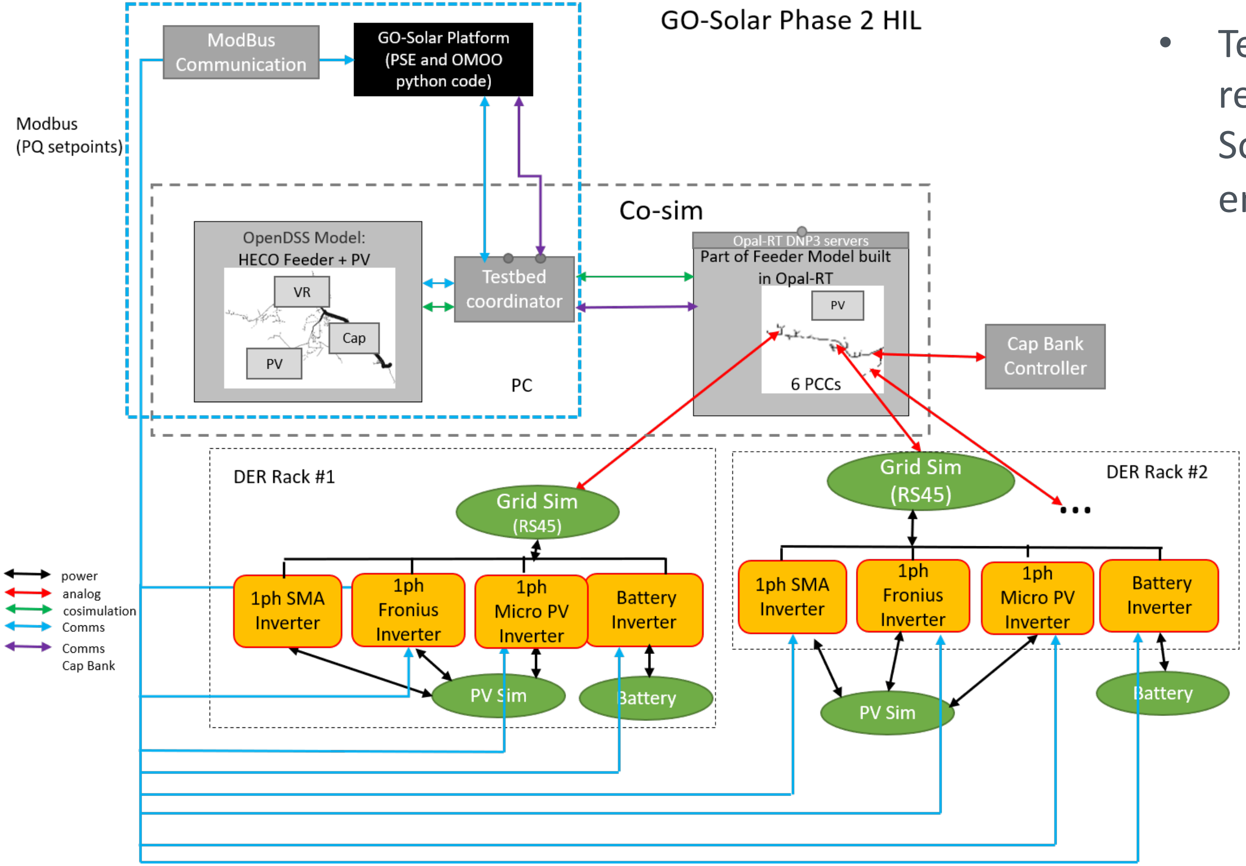
Hardware-in-the-Loop

The GO-Solar Platform HIL Setup



- Test objective: evaluate voltage regulation performance of the GO-Solar Platform in a realistic testing environment
  - Accurate modeling of a full-scale distribution system of Mikulua 3 and sub-transmission system
  - Software control algorithm
  - 90 hardware PV and Battery inverters
  - Standard communication protocols

Schematic Diagram of the HELICS Architecture

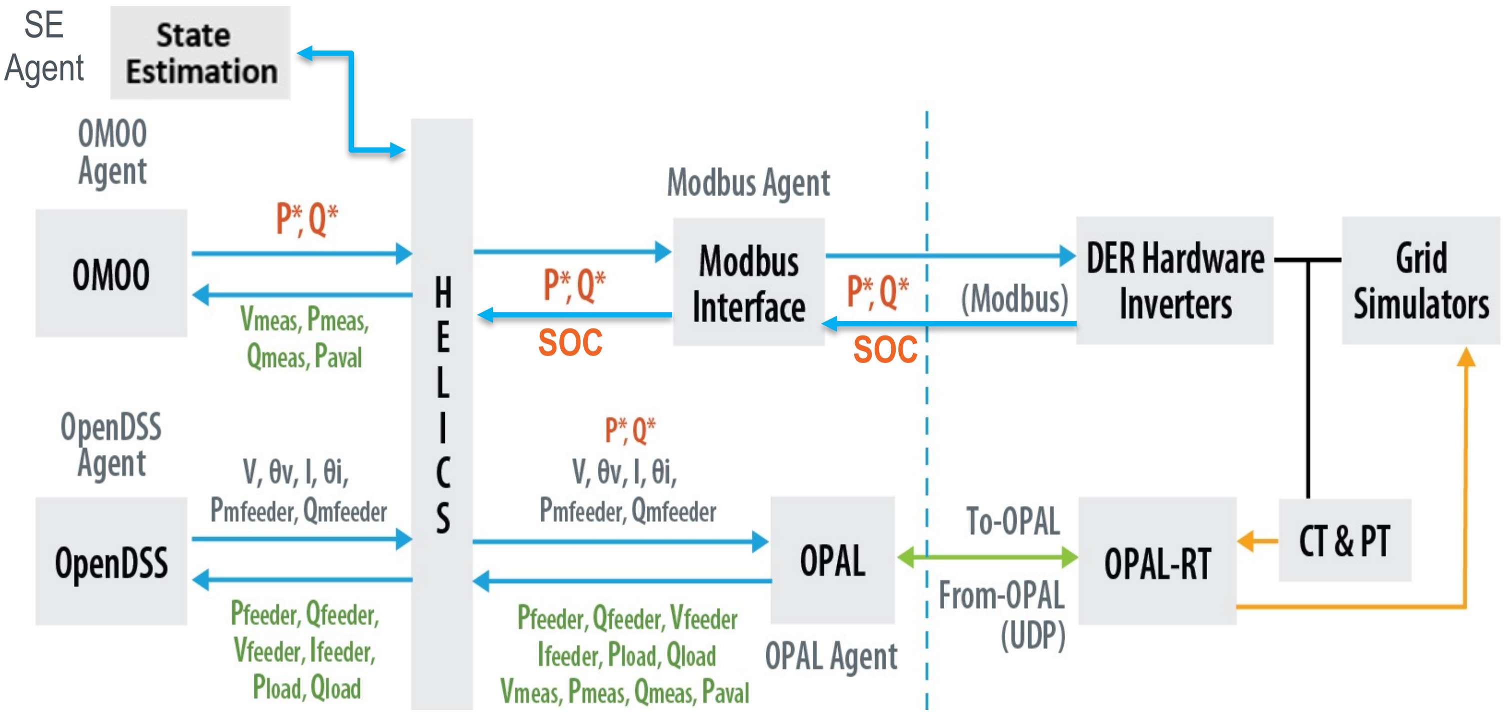
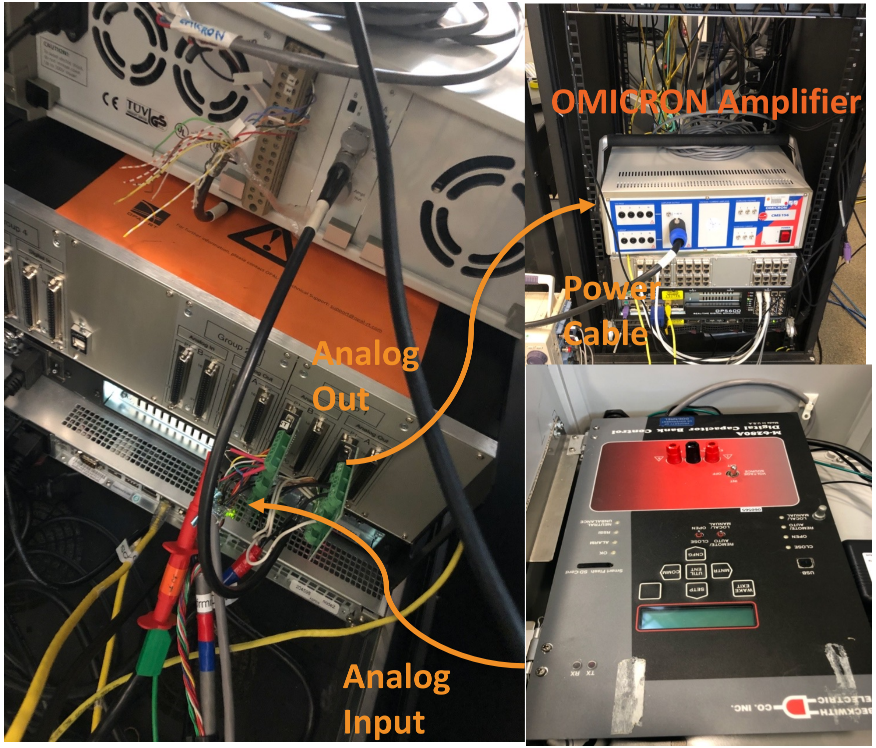


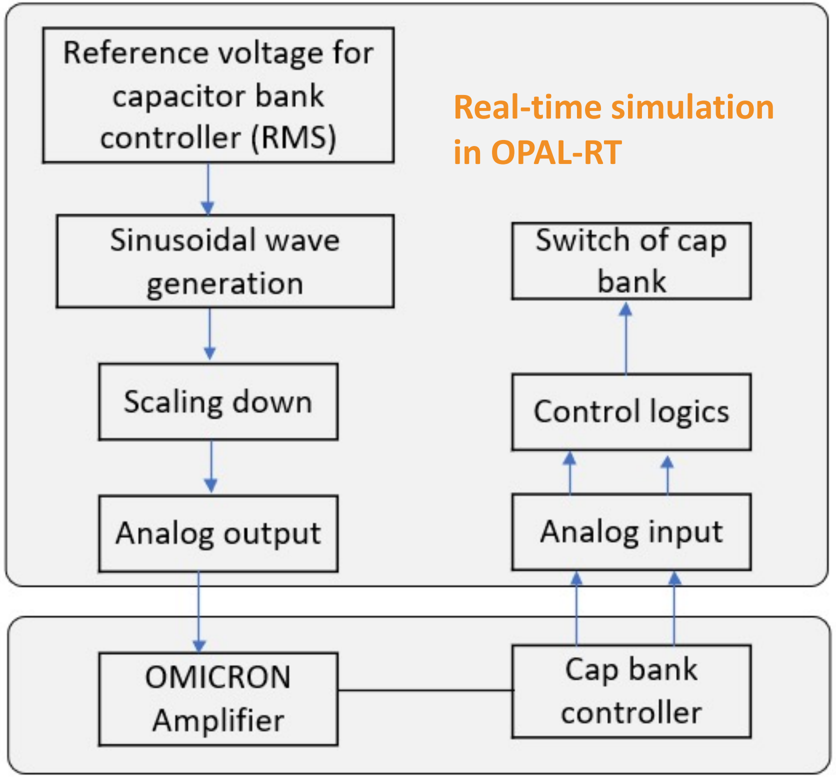
Photo of Hardware Setup for Six DER Racks/PCCs

Capacitor bank controller setup



OPAL-RT

Beckwith Cap Bank Controller

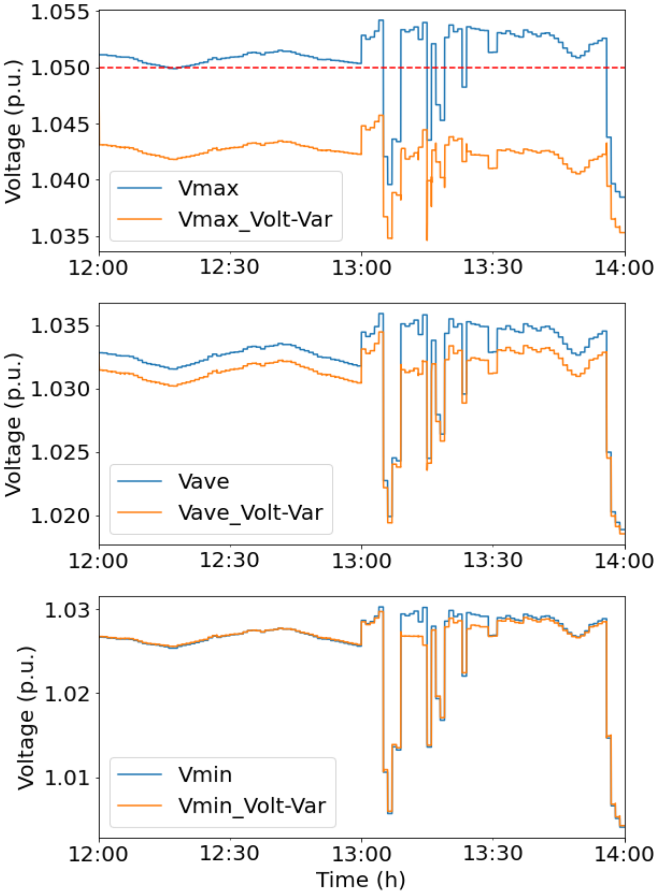


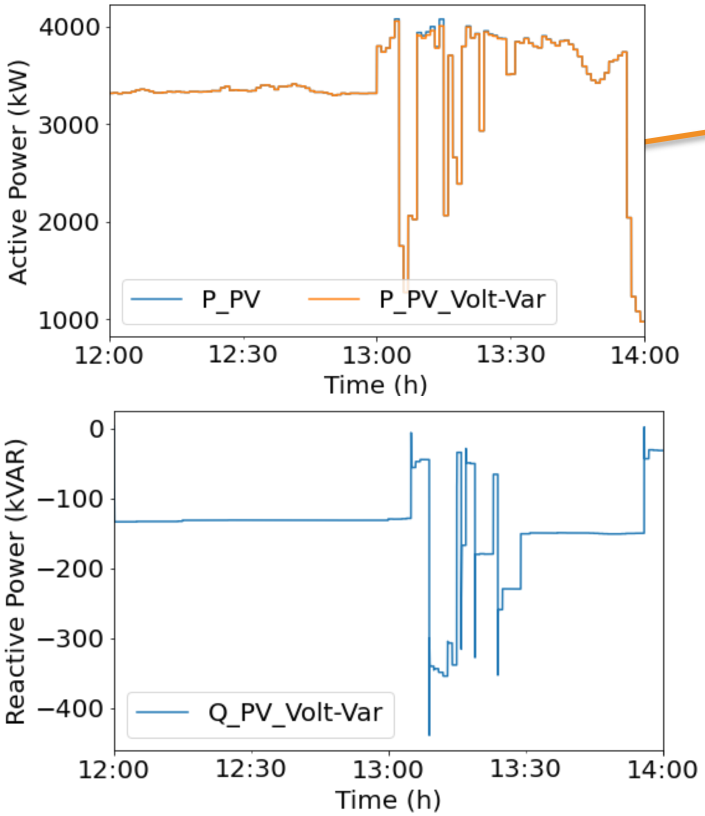
Controller to be tested

List of PHIL DER Inverters of Each PCC

Rack	# Devices	Physical Devices	Total capacity	Simulated PV capacity
PHIL-1	15	(1) 3 kVA PV, (1) 5 kVS PV, (12) 320 VA µPV, (1) 5 kVA / 10 kWh Li-ion Batt	16.84 kVA	23.5 kVA
PHIL-2	15	(1) 3 kVA PV, (1) 5 kVA PV, (12) 320 VA µPV, (1) 5 kVA / 10 kWh Li-ion Batt	16.84 kVA	19 kVA
PHIL-3	15	(1) 3 kVA PV, (1) 5 kVA PV, (12) 320 VA µPV, (1) 5 kVA / 10 kWh Li-ion Batt	16.84 kVA	93.9 kVA
PHIL-4	15	(1) 3 kVA PV, (1) 5 kVA PV, (12) 320 VA µPV, (1) 5 kVA / 10 kWh Li-ion Batt	16.84 kVA	67.6 kVA
PHIL-5	15	(1) 3 kVA PV, (1) **3 kVA PV**, (12) 320 VA µPV, (1) 5 kVA / 10 kWh Li-ion Batt	14.84 kVA	119.2 kVA
PHIL-6	15	(1) 3 kVA PV, (1) **3 kVA PV**, (12) 320 VA µPV, (1) 5 kVA / 10 kWh Li-ion Batt	14.84 kVA	54 kVA
Total	90	6 PCCs		

HIL Testing Results – Scenario #1: Baseline Scenario

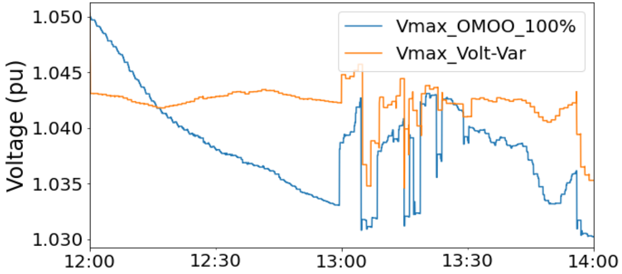


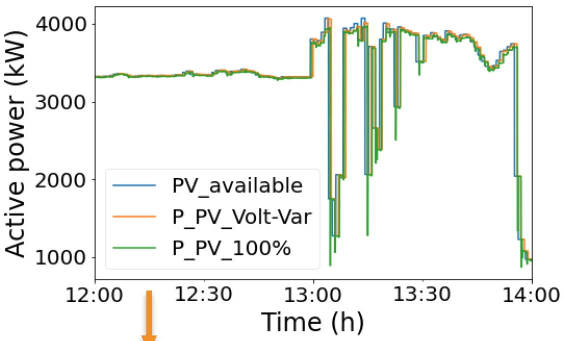


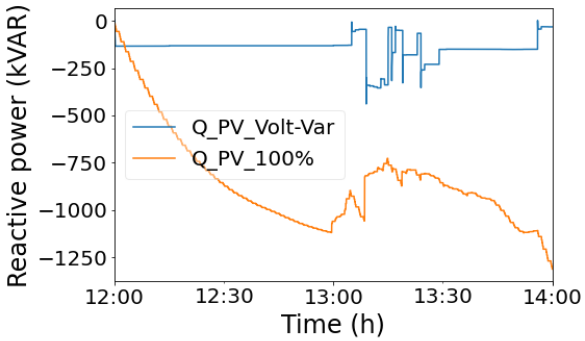
0.081% of total curtailment

Total PV measurements

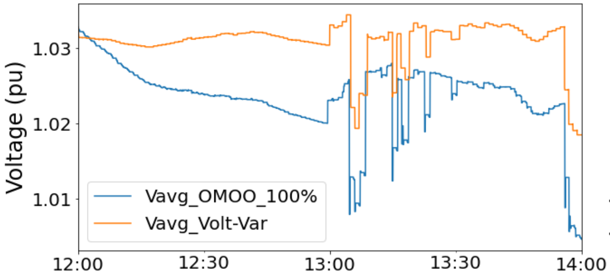
HIL Testing Results – Scenario #2: Control 100% PVs

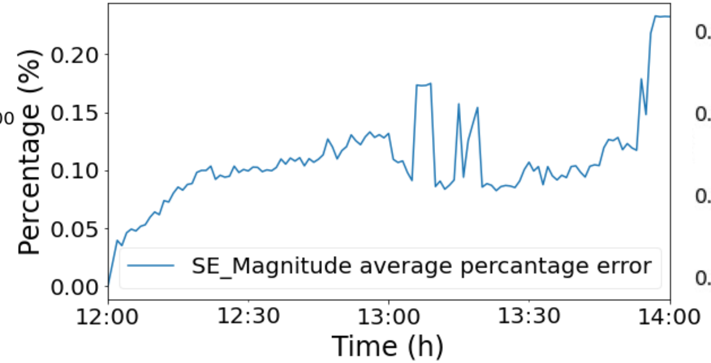


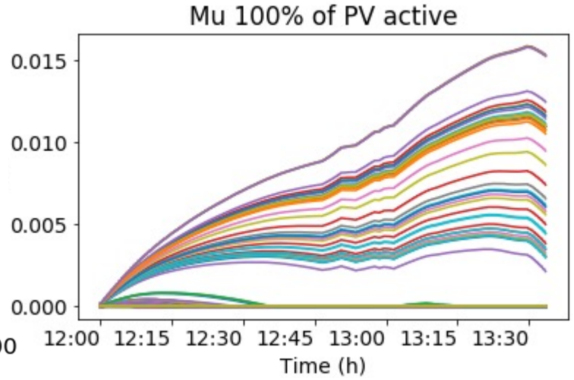


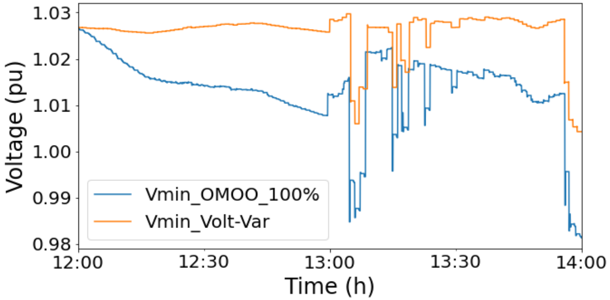


0.4% of total curtailment for OMOO and 0.081% for Volt-Var

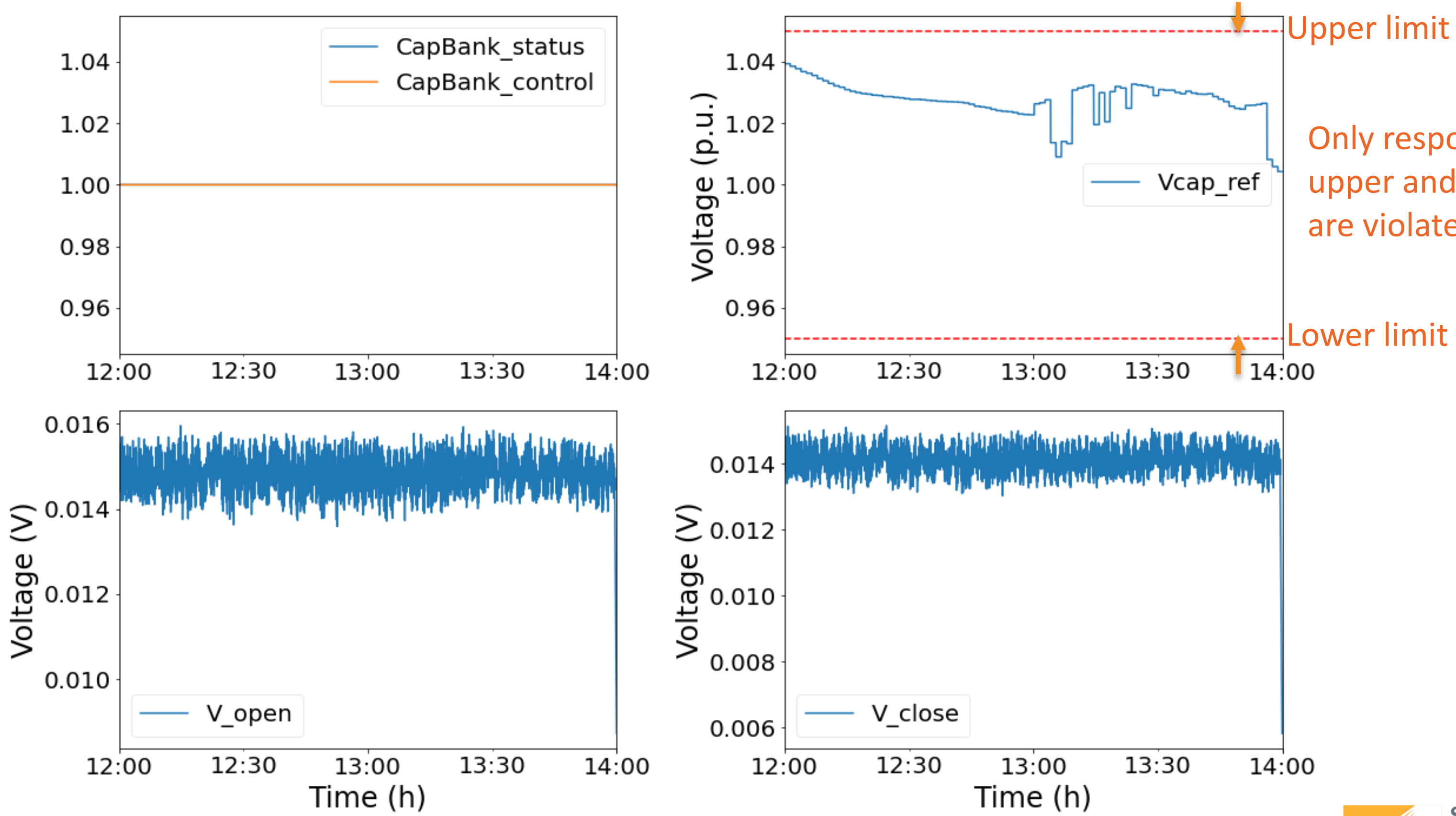






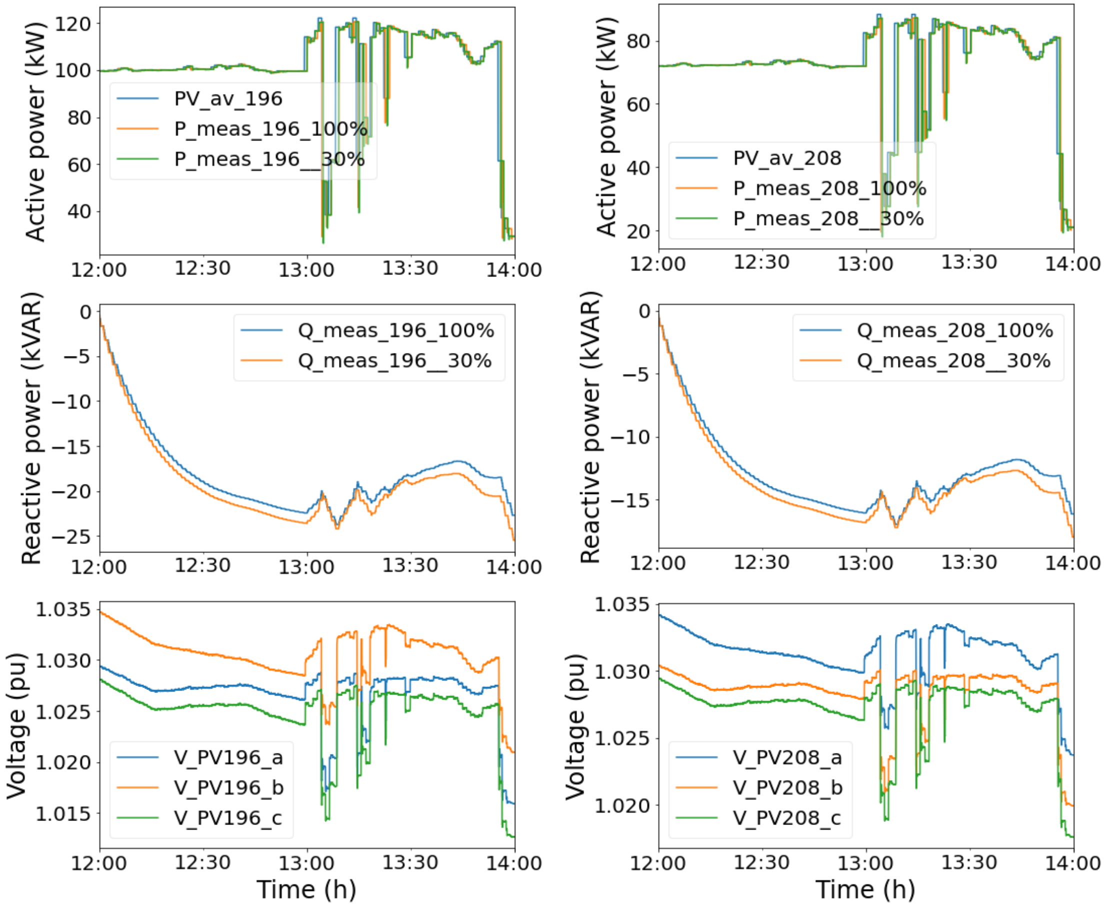


HIL Testing Results – Scenario #2: Control 100% PVs



Only respond when the upper and lower limits are violated

HIL Testing Results – Scenario #3: Control 30% PVs



- The simulated PV inverters have similar responses in active and reactive power as the inverters in Rack #1, #2, #4, and #5.
- Confirm the simulated and hardware inverters work correctly.
- Higher reactive power outputs than the 100% PV scenario

Summary of HIL Test

- Successful Power-hardware-in-the-loop (PHIL) testing with GO-Solar platform
  - 90 hardware DER inverters
  - standard communication protocols
  - real responses of hardware inverters
  - stability and dynamics of the GO-Solar platform
- Evaluated voltage regulation performance of the GO-Solar platform in real-time simulation (ensures computational time is fast enough)
- HIL captures key real-world aspects and forced us to refine the approaches taken for GO-Solar that were not seen with the artificially tight data coupling from single feeder simulation.
- Results: Once tuned, GO-Solar Platform performs better than the smart inverter volt-var:
  - fewer voltage violations
  - reduced system voltages and improved energy savings (CVR),
  - precise voltage regulation, etc.

Summary

- GO-solar developed state-of-art centralized visibility and controllability for DERs
- Scalable solution for heterogenous measurements and controllers
- Large scale co-simulation and large scale HIL for extended performance testing

Completing the Picture

Cybersecurity

Cybersecurity Scenarios

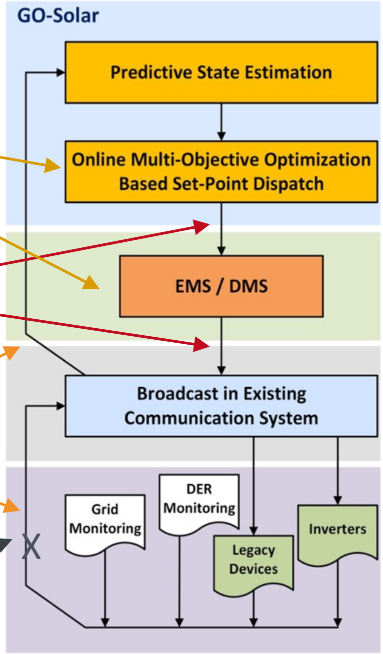
2. Control node compromise

1. Control signal spoofing

3. Sensor data spoofing

4. Communication Denial of Service

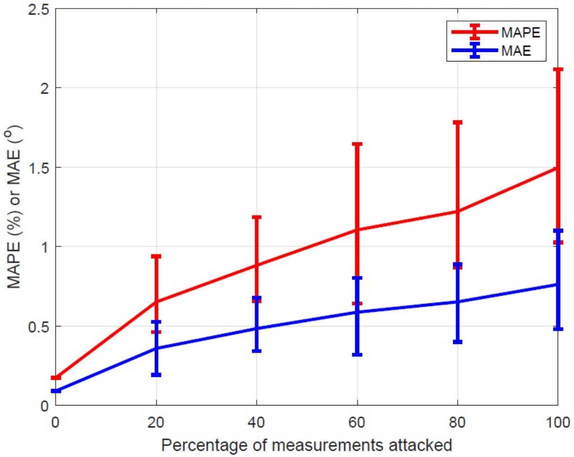
5. Communication Latency Margin



Cyber Vulnerability Exercise

- Focus on state estimation
- Cyber attack scenarios

FDI Attack on |V|



Achievement Highlights

- **Publications**

1. A. Bernstein, C. Wang, and J.-Y. Le Boudec, “Multiphase Optimal and Non-Singular Power Flow by Successive Linear Approximations,” Power Systems Computation Conference (PSCC), Dublin, Ireland, June 11-15, 2018. (Partly funded by the ENERGISE Go-Solar project and partly by the GMLC 1.4.10 [Control Theory] project.)
2. 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.
3. 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.
4. Y. Zhang, A. Bernstein, and A. Schmitt, “State Estimation in Low-Observable Distribution Systems Using Matrix Completion,” HICSS-52 conference, Jan. 2019.
5. B. Liu, H. Wu, Y. Zhang, R. Yang, and A. Bernstein, “Robust Matrix Completion State Estimation in Distribution Systems,” IEEE PES General Meeting, Atlanta, GA, Aug. 4-8, 2019.
6. P. L. Donti, Y. Liu, A. J. Schmitt, A. Bernstein, R. Yang, and Y. Zhang, “Matrix Completion for Low-Observability Voltage Estimation,” IEEE Transactions on Smart Grid, IEEE Transactions on Smart Grid, vol. 11, no. 3, May 2020.
7. M. Emmanuel and J. Giraldez, “Net Electricity Clustering at Different Temporal Resolutions Using a SAX-Based Method for Integrated Distribution System Planning,” IEEE Access, vol. 7, pp. 123689-123697, 2019.
8. G. Cavraro, A. Bernstein, V. Kekatos and Y. Zhang, "Real-Time Identifiability of Power Distribution Network Topologies With Limited Monitoring," IEEE Control Systems Letters, vol. 4, no. 2, pp. 325-330, April 2020.
9. X. Zhu, M. Emmanuel, G. Julieta, I. Krad, B. Palmintier, W.-H. Chen, A. Hirayama, and M. Asano “Realistic Distribution System Model Development for Integrated Transmission-Distribution Simulation,” the 47th IEEE Photovoltaic Specialists Conference (PVSC 47), June 14-19, 2020.
10. Y. Liu, A. Sagan, A. Bernstein, R. Yang, X. Zhou, and Y. Zhang, “Matrix Completion Using Alternating Minimization for Distribution System State Estimation,” IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids, October 6-9, 2020.
11. A. Sagan, Y. Liu, and A. Bernstein, “Decentralized low-rank state estimation for power distribution systems,” IEEE Transactions on Smart Grid, 2021.
12. J. Wang, J. Simpson, R. Yang, B. Palmintier, S. Tiwari, and Y. Zhang, “Hardware-in-the-Loop Evaluation of an Advanced Distributed Energy Resource Management Algorithm,” the Twelfth Conference on Innovative Smart Grid Technologies, February 15-18, 2021.

- **Presentations**

13. R. Yang, “Machine Learning-based Predictive State Estimation,” Virtual Workshop on Distribution and Transmission System Monitoring, U.S. Department of Energy, Solar Energy Technologies Office, Oct. 2020.
14. R. Yang, “Predictive Analytics for Power Systems Decision Making,” IEEE Smart Grid Webinar, April 25, 2019. [Online].
15. B. Palmintier, “Grid Optimization with Solar (GO-Solar) Experiences with: Data-driven and Machine Learning Approaches for High-pen PV Grids,” Workshop on Challenges for Distribution Planning, Operational and Real-time Planning Analytics for Small Scale PV Integration, U.S. Department of Energy, Solar Energy Technologies Office, Washington DC, May 15-16, 2019.
16. R. Yang, “Data and Algorithms for Grid Optimization with Solar (GO-Solar),” Big Data Analytics Workshop, SLAC National Accelerator Laboratory, Dec. 10, 2018.
17. Y. Zhang, “Predictive State Estimation – a Step Towards Proactive Operation of Power systems,” IEEE PES 2018.

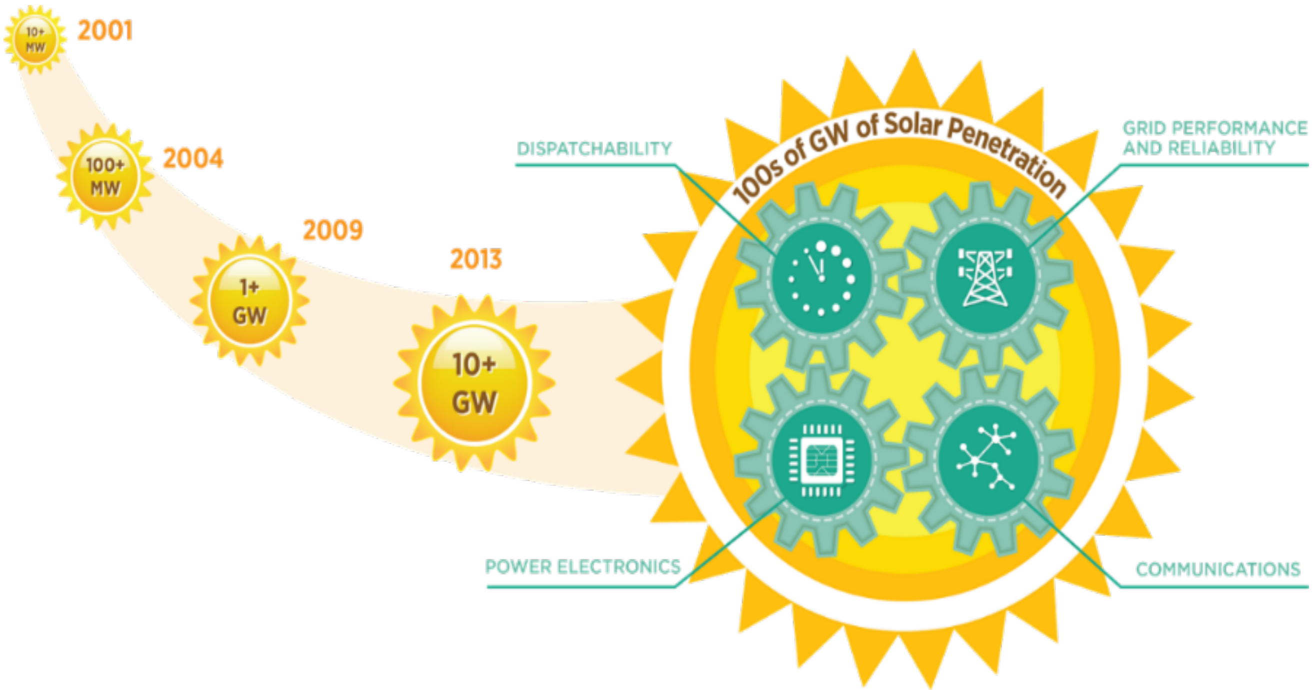
- **Book Chapter**

18. R. Yang and Y. Zhang, “Predictive Analytics for Coordinated Optimization,” to appear in Intelligent Power Grid of Tomorrow: Modeling, Planning, Control, and Operation, Springer.

- **Patent**

19. R. Yang, Y. Liu, A. Bernstein, Y. Zhang, “Low-observability matrix completion” US Patent App. 16/246,998

Questions?



10+ MW
2001
100+ MW
2004
1+ GW
2009
10+ GW
2013
100s of GW of Solar Penetration
DISPATCHABILITY
GRID PERFORMANCE AND RELIABILITY
POWER ELECTRONICS
COMMUNICATIONS