Model-Free Hosting Capacity Analysis

Matthew Reno, Ph.D

Presented by Abraham Ellis

Sandia National Laboratories

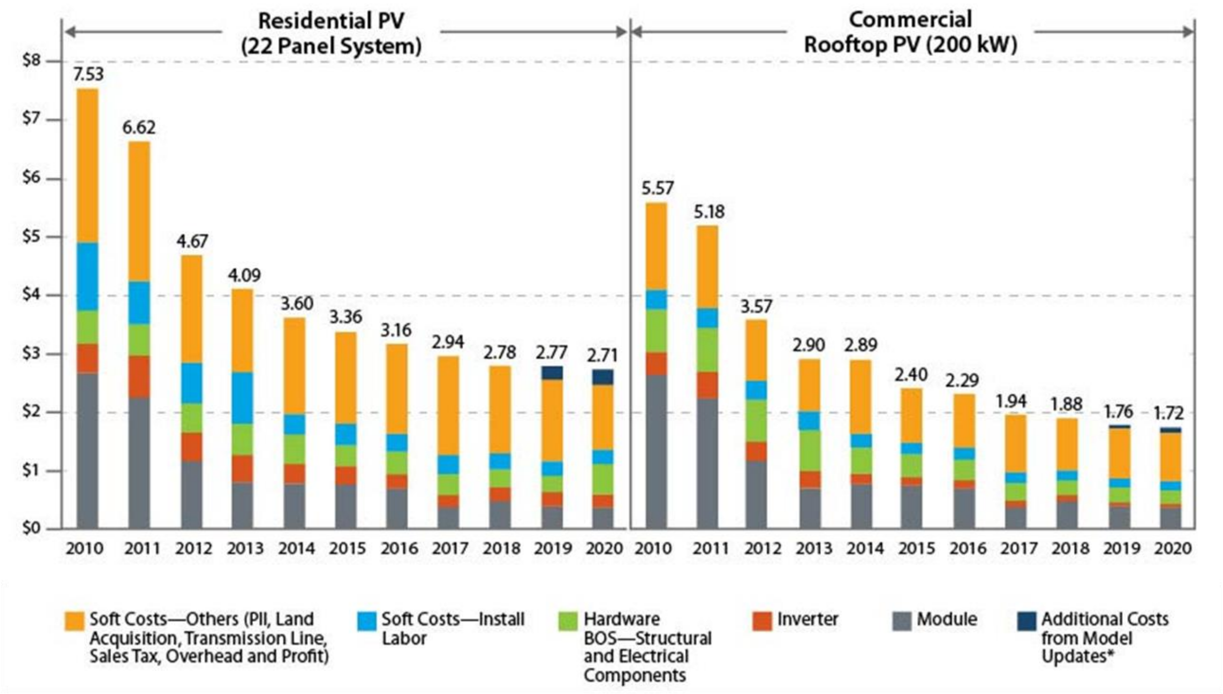
U.S. DEPARTMENT OF ENERGY

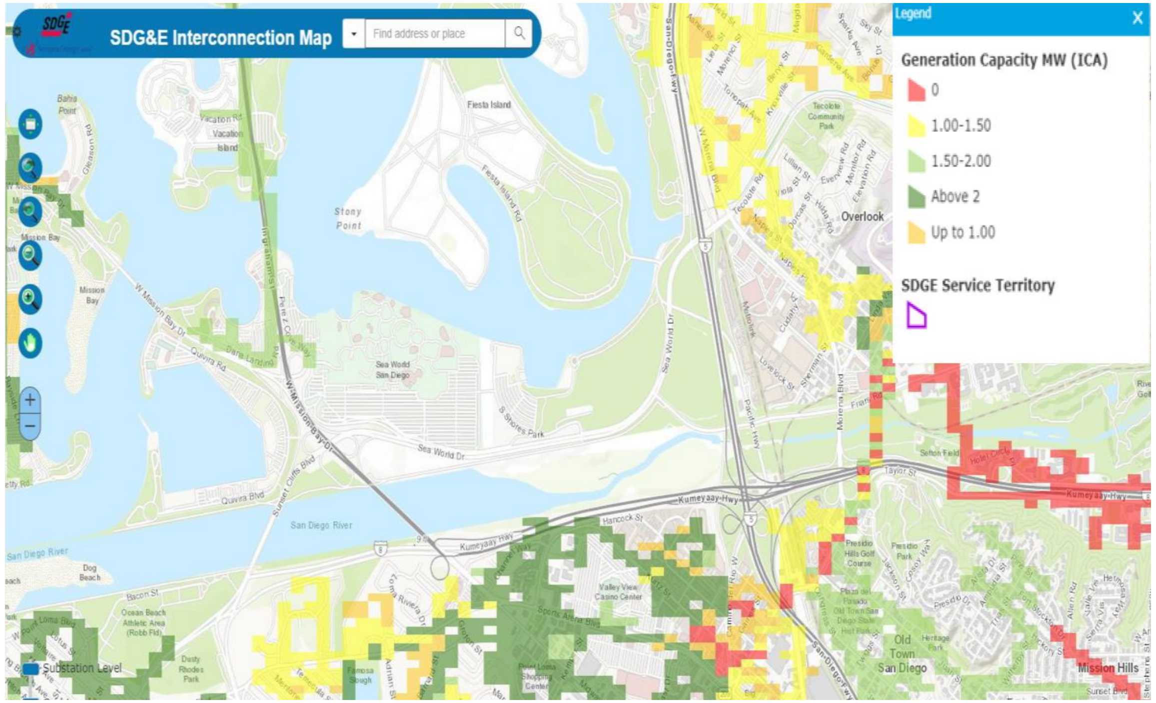
NNSA National Nuclear Security Administration

Sandia National Laboratories is a multimission laboratory managed and operated by National Technology & Engineering Solutions of Sandia, LLC, a wholly owned subsidiary of Honeywell International Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525.

Motivation

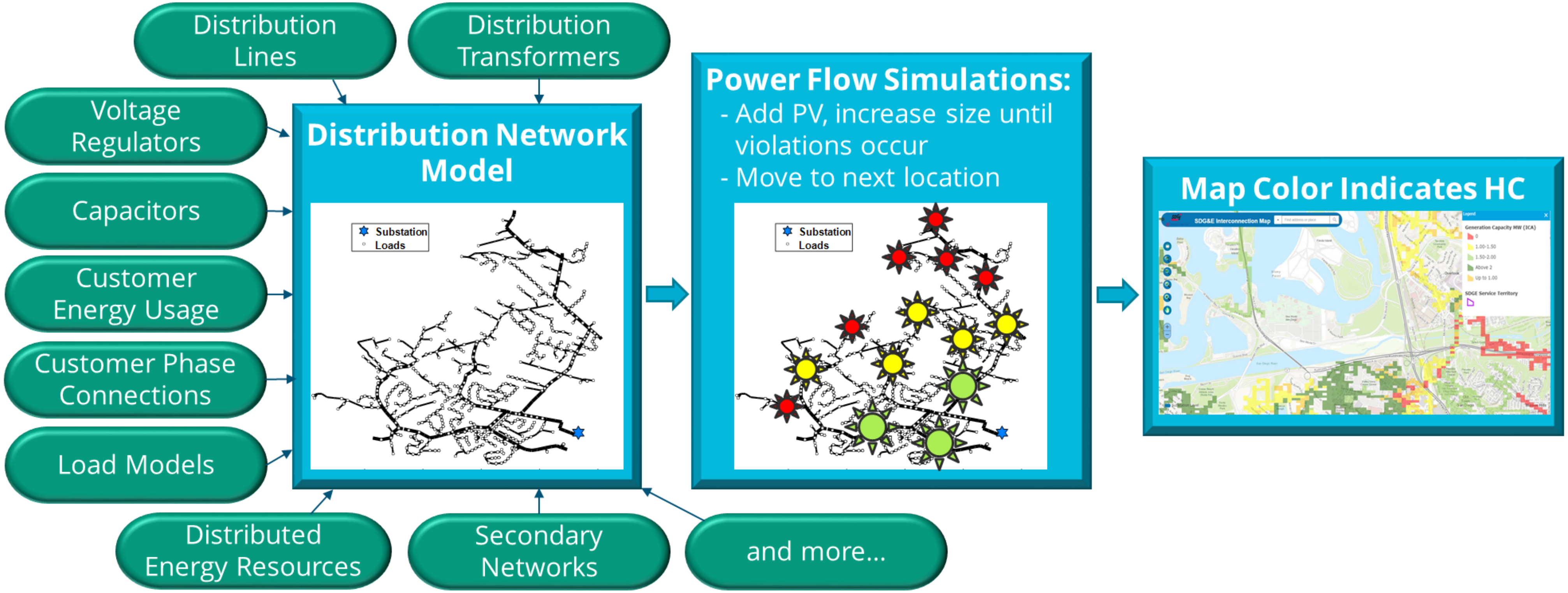
- Installed cost of distributed PV is increasingly dominated by “soft costs”
  - Customer acquisition, permitting, and interconnection costs
- Public-facing **hosting capacity (HC) maps** are part of the solution to reduced soft costs
  - Visual representations of hosting capacity per node (i.e., locational HC)
  - Enable streamlined interconnection processes, inform stakeholders about siting options
- Challenge: How do we compute and update HC maps faster and accurately?





Model-Based Hosting Capacity Analysis (HCA)

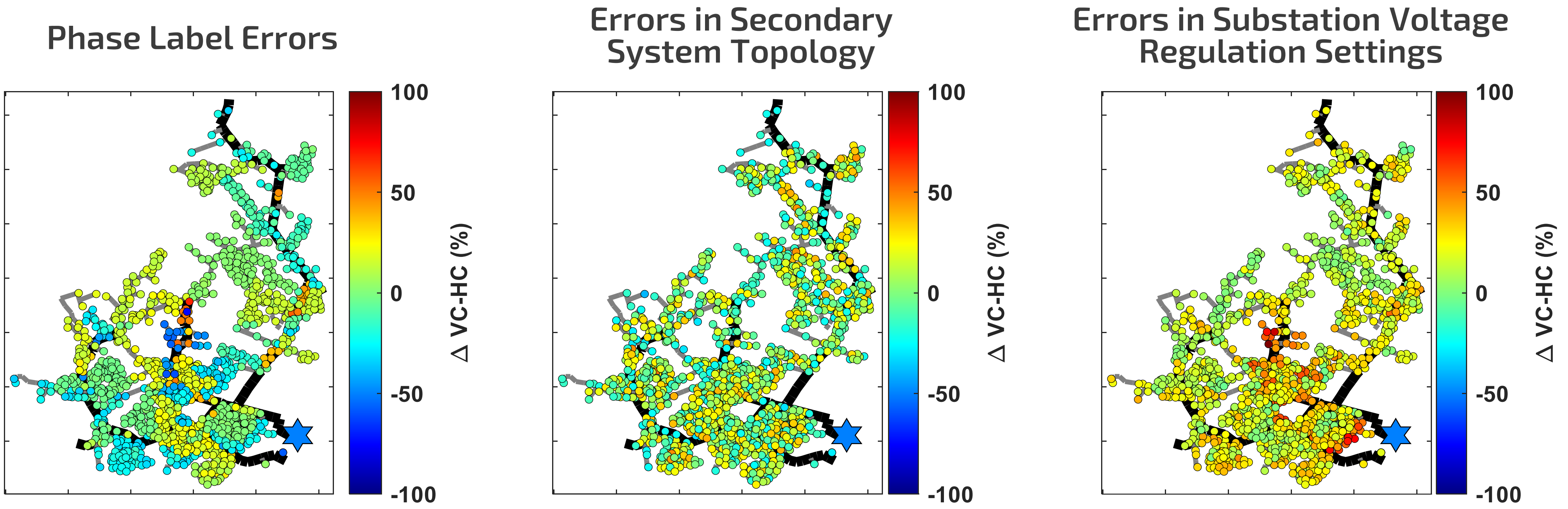
- Conventional method is computationally intensive and/or data challenged
  - Iterative simulations using detailed distribution system models, not necessarily accurate
- Not universally practical or scalable



"The time needed for distribution analysis models doing any type of iterative analysis takes too long to run."
California Public Utility Commission

More Than a Few Challenges

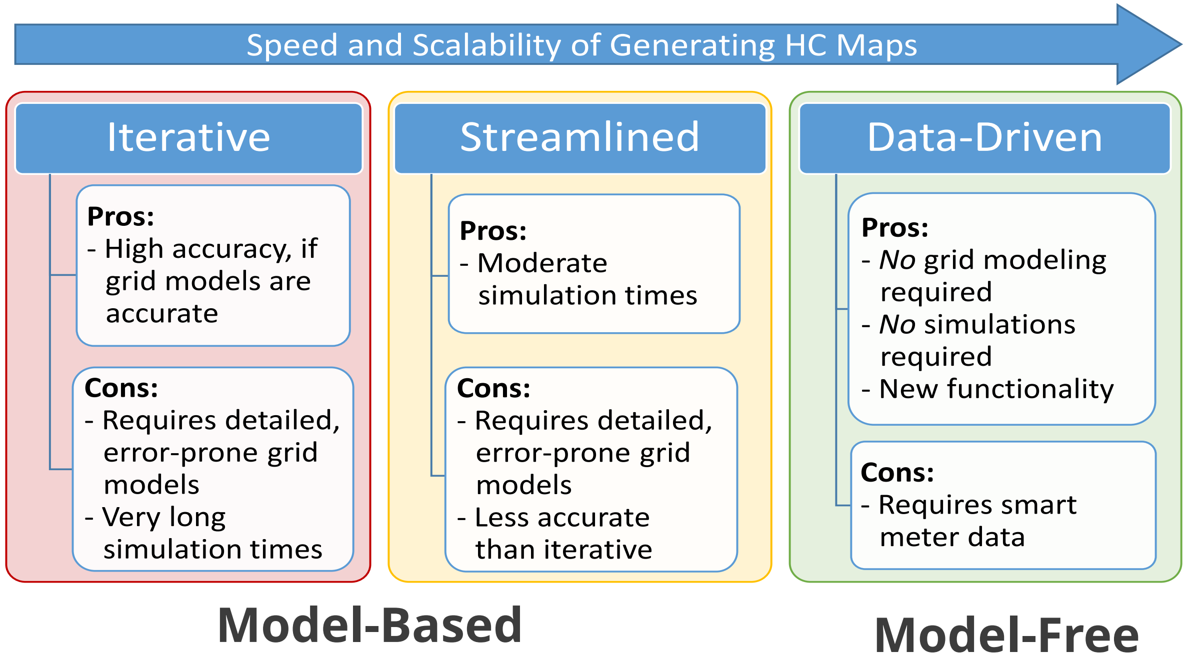
- Few utilities have good secondary LV network models
- Process relies on human input – error prone (e.g., wrong service transformer or phase)
- Hard to keep updated for network and DER changes
- Default answer: HC based on worst-case scenario, no time-series analysis

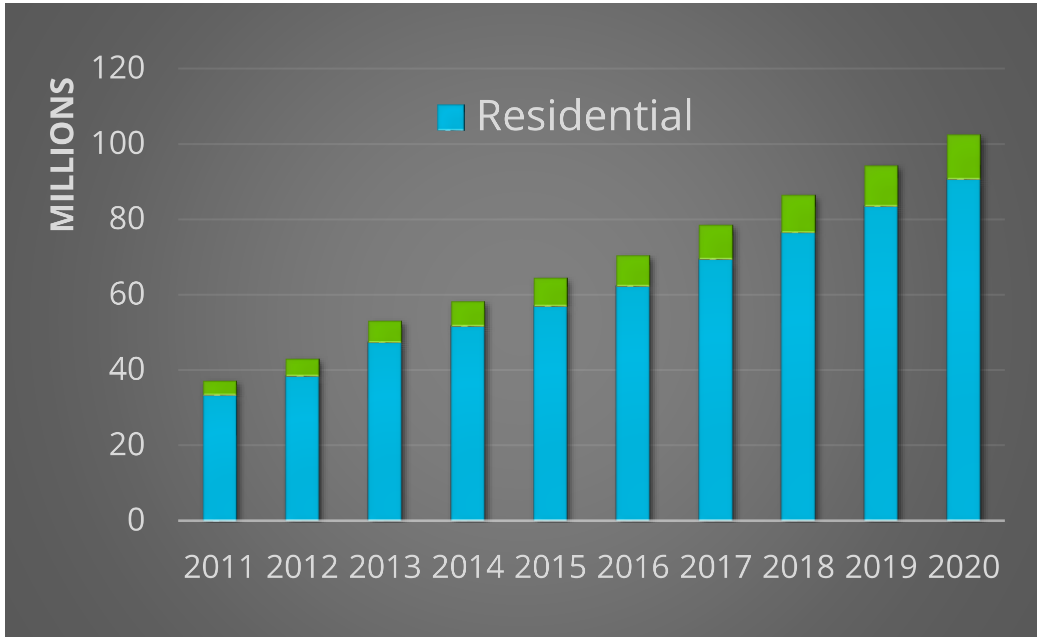


Percent error in estimated locational voltage-constrained hosting capacity (VC-HC) when there are errors in the distribution system model

Model-free Hosting Capacity Analysis (MoCHA)

- Develop scalable method for voltage- and thermal-constrained HC based on smart meter data
- Identify optimal inverter settings based on $\Delta V / \Delta Q_L$
- Support static (worst-case scenario) or dynamic HC with confidence intervals
- Inherently capture any changes to the distribution network
- Validation against reference utility data; incorporated into the Open Modeling Framework (OMF.coop)





U.S. Energy Information Administration (EIA)

Project Approach

Inputs

- Historical customer smart meter measurements (P, Q, V) – starting with 1-year at 15-minute resolution
- Reliability limits such as ANSI voltage limits and thermal rating

Outputs

- Voltage-constrained hosting capacity (V-HC) and Thermal-constrained hosting capacity (T-HC)
- Station and protection impacts need to be considered separately

Complementary approach

- Data-driven methods to determine transformer groupings and secondary system topology

Voltage-Constrained Hosting Capacity (V-HC)

Regression analysis of historical load power and voltage measurements, gives you dV/dP, dV/dQ

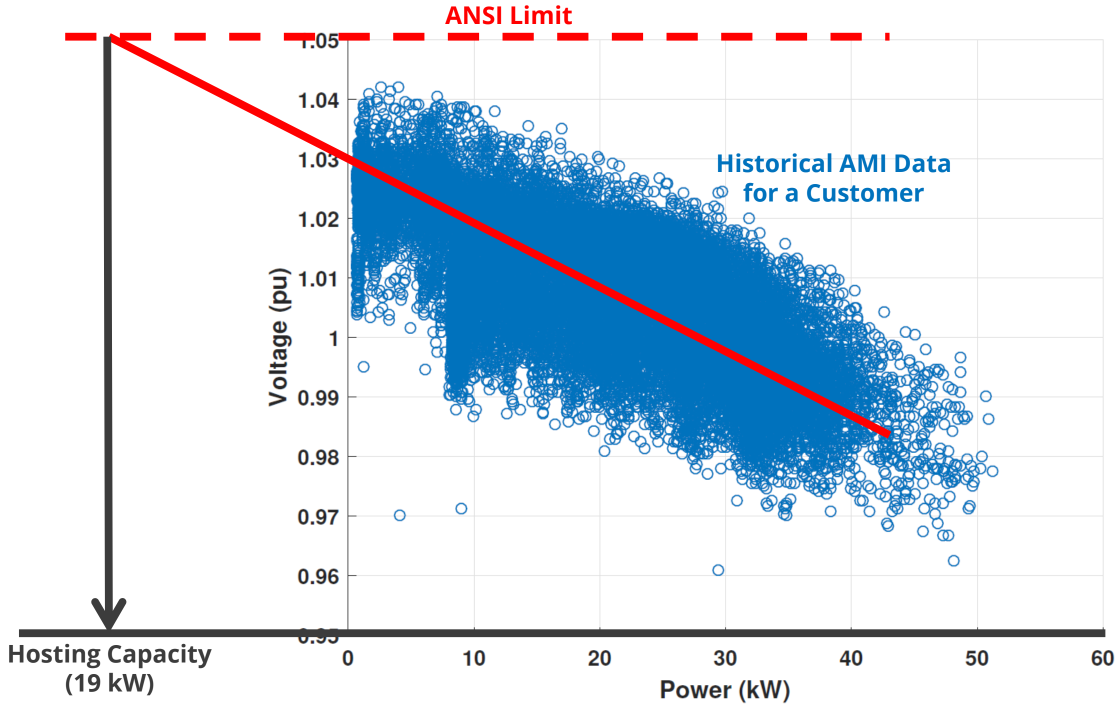
- I.e., sensitivity of the customer's voltage to changes in power

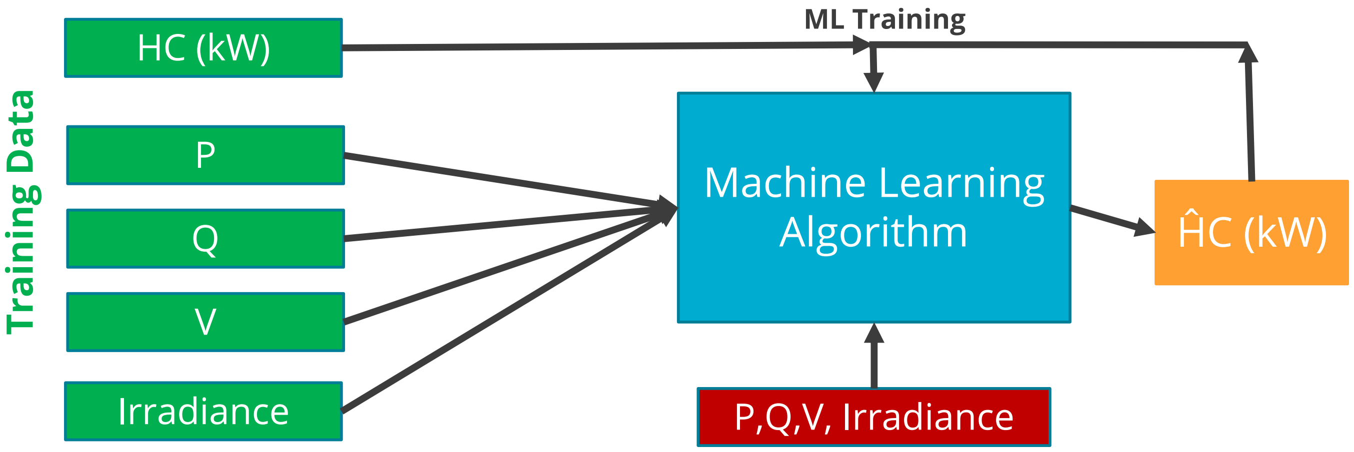
Use that sensitivity to determine the max allowable PV injection before a voltage violation occurs for that customer

Supervised Machine Learning of correlations between historical P, Q, V data and hosting capacity

Train the machine learning using sample data from model-based hosting capacity and the corresponding smart meter data (green)

Useful when hosting capacity analysis does not converge for a portion of a utility feeders

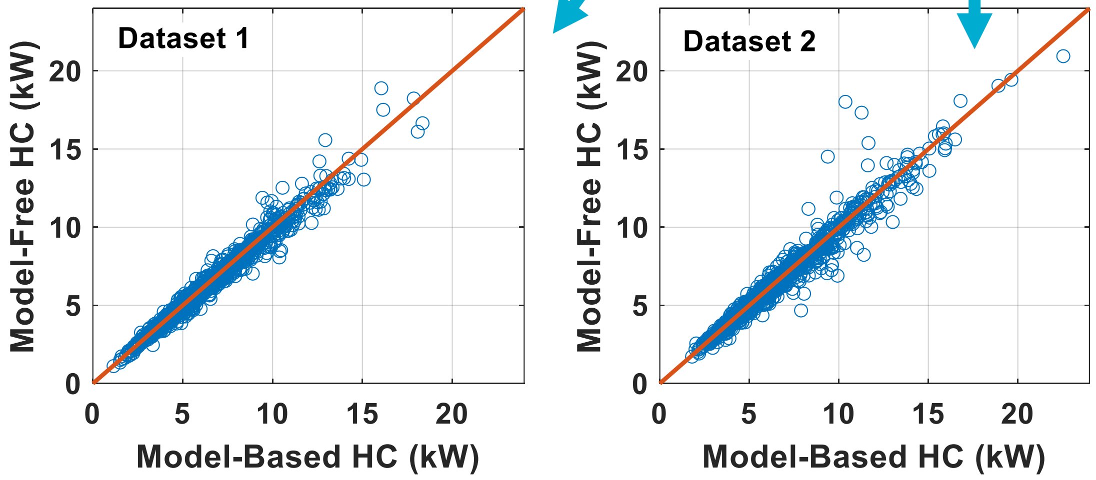


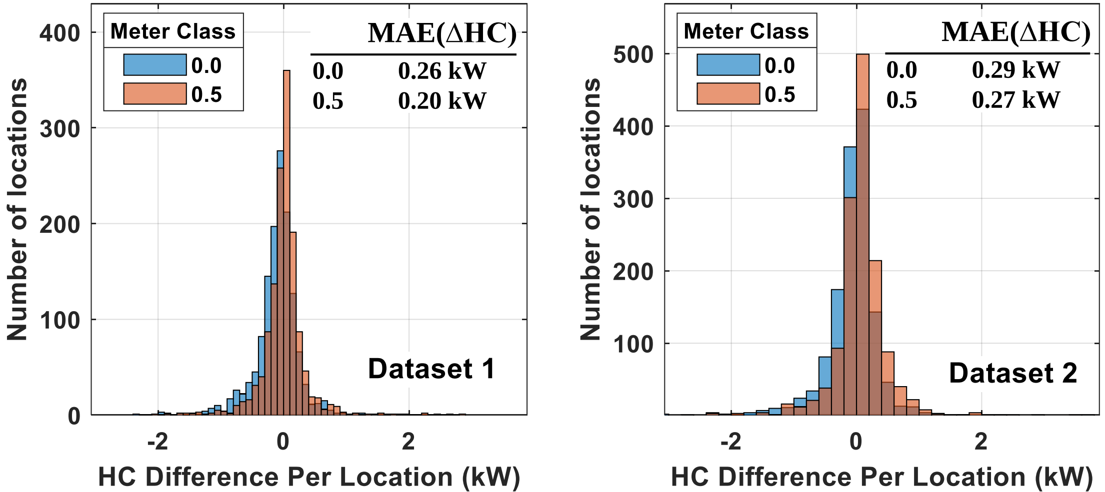


V-HC Results

- Regression-based V-HC algorithm developed and tested on 2 different smart meter datasets
- On average, the model-free algorithm was **within 0.3 kW** of the model-based HC results
  - **Within 1 kW** at **96.6%** and **95.8%** of customer locations for the two datasets
- Higher errors were observed for some locations
  - Confidence metrics can be used to flag locations with poor fits
- Consistent performance for two different datasets
- Stable under increasing levels of measurement noise

HC Metric	Dataset 1	Dataset 2
MAE_{HC}	0.26 kW	0.29 kW
Max. Error	2.84 kW	7.65 kW
Locations <1kW Error	96.6%	95.8%





Thermal-Constrained Hosting Capacity (T-HC)

Two Methods:

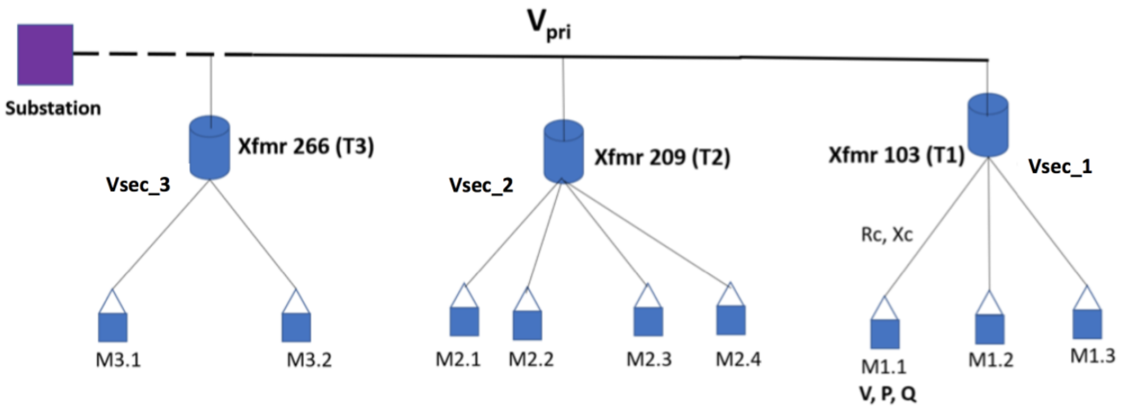
1. Parameter Estimation Approach

- Use measurements from multiple customers to estimate low-voltage topology and impedances, along with the distribution service transformer impedances
- Transformer impedances can then be used to estimate transformer size (kVA)

K. Ashok, M. J. Reno, D. Divan, "Secondary Network Parameter Estimation for Distribution Transformers," IEEE Innovative Smart Grid Technologies (ISGT), 2020.

2. Machine Learning Approach

- Same as other slide where supervised ML algorithms learn to correlate timeseries data with hosting capacity – this time the training data is the thermal-constrained hosting capacity



$$V_1 - V_2 = V = I_{R_2}R_2 + I_{X_2}X_2 - I_{R_1}R_1 - I_{X_1}X_1$$

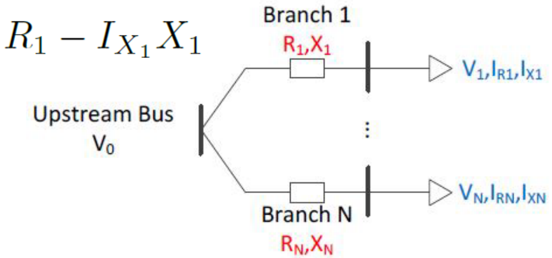


TABLE VIII
TRANSFORMER IMPEDANCE ESTIMATION

Transformer ID	Resistance (Ω)		Reactance (Ω)	
	Actual	Estimate	Actual	Estimate
103	0.0346	0.0370	0.0461	0.0492
209	0.0215	0.0219	0.0307	0.0292
266	0.0346	0.0338	0.0461	0.4394

Conclusions

Promising initial results for the model-free approach:

- Comparable accuracy to model-based results (assuming you have 100% correct distribution system models)
- Significantly reduced computational time:
  - Results were generated in *minutes*, where model-based results required multiple *days* of simulations

Thank You!

Contact:

Matt Reno

mjreno@sandia.gov