Model-Free Hosting Capacity Analysis (MoHCA)

DOE SETO Award # DE-EE0038426: "Smart Meter Data: A Gateway for Reducing Solar Soft Costs with Model-Free Hosting Capacity Maps"

SNL: Matthew Reno, Joe Azzolini
NRECA: David Pinney, Jennifer Thakkar

Table of Contents

- Task 1 - Problem Statement and Approach
- Task 2 - Develop Algorithms for Voltage-Constrained Hosting Capacity Analysis
- Task 3 - Develop Algorithms for Thermal-Constrained Hosting Capacity
- Task 4 - Integrate Algorithms into an OMF Application
- Task 5 - Develop Algorithms for Assessing the Impact of Advanced Inverter Operation Modes
- Task 6 - Engage Project Stakeholders, Result Dissemination, and Outreach

75 Years of Service
NRECA
America's Electric Cooperatives

Task 1 - Problem Statement and Approach

Background and Problem Statement

- Background
  - Hosting capacity analysis (HCA) determines the maximum amount of PV that can be installed at various locations on the grid without adverse effects on the distribution network and without requiring network upgrades. The outputs are often published in hosting capacity (HC) maps: a visual representation of the hosting capacity across the system.
- Problem 1: rapidly growing DER interconnection requests
  - Some Co-ops are seeing 1-2 solar interconnection requests per day.
  - These Solar photovoltaic (PV) system costs are now dominated by non-hardware or “soft” costs - e.g. customer acquisition, permitting, and interconnection costs.
  - Heavy work-load and time-consuming for consumers & engineering to process interconnections
- Problem 1: increasing interest & mandates around generation of hosting capacity maps
  - Public-facing hosting capacity (HC) maps have been key factors to reducing solar soft costs
  - They enable streamlined interconnection processes and direct access to siting and permitting data for stakeholders and decision-makers
  - Incoming mandates for utilities to create them from state regulators

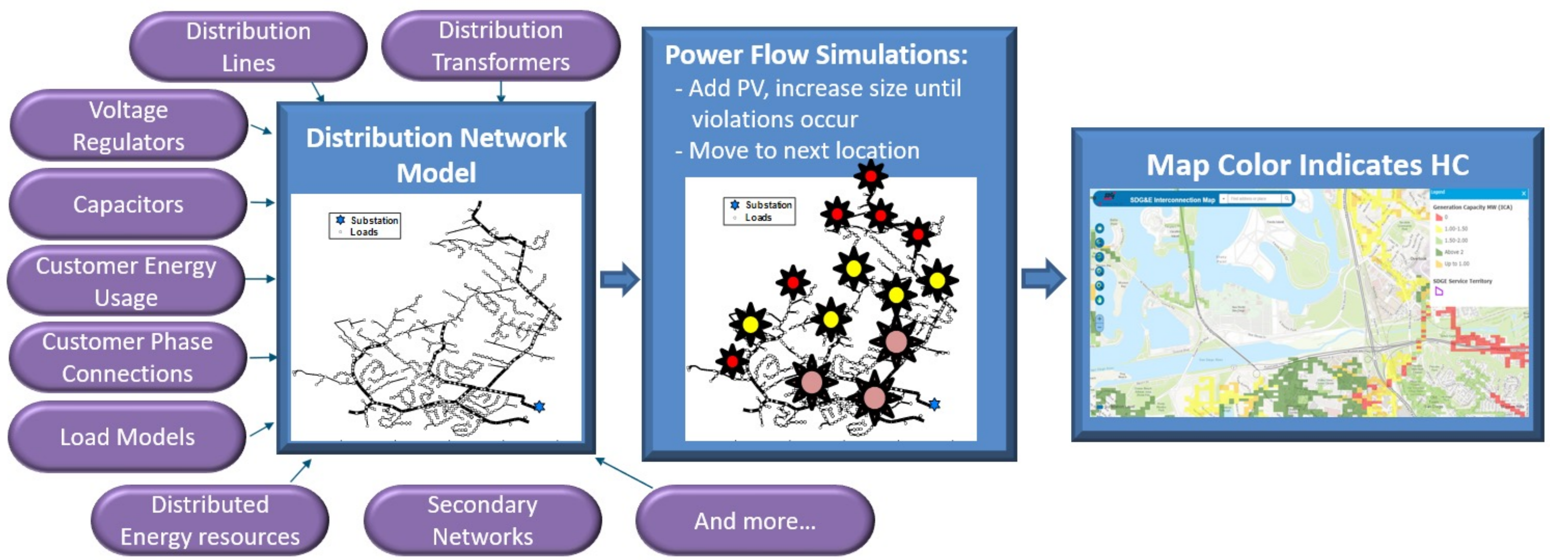
The Problem With Traditional Hosting Capacity

- Conventional model-based HCA methods are time-consuming and computationally intensive, making them impractical for many utilities and coops
- Require iterative simulations on detailed distribution system models = long computation times
- “*The time needed for distribution analysis models doing any type of iterative analysis takes too long to run.*” - California Public Utility Commission
- Accuracy of the HC solution is dependent upon the accuracy of the model, which are prone to errors
- Lack the necessary resolution and functionality to evaluate advanced inverter capabilities or flexible PV interconnections

Model–Based HC Definition

Conventional model-based HCA:

- Model – Based HCA accuracy depends on accuracy of distribution network model
- Network model consists of various components that all must be modeled accurately
  - Component models each have a variety of parameters and assumptions
  - Models rely on human input and are prone to errors (e.g., network upgrades don’t make it into the model or customers are connected to the wrong phases)
  - Secondary networks models are often unavailable or oversimplified
  - Modern distribution networks are becoming increasingly complex, making it more difficult to maintain model fidelity



75 Years of Service NRECA America's Electric Cooperatives

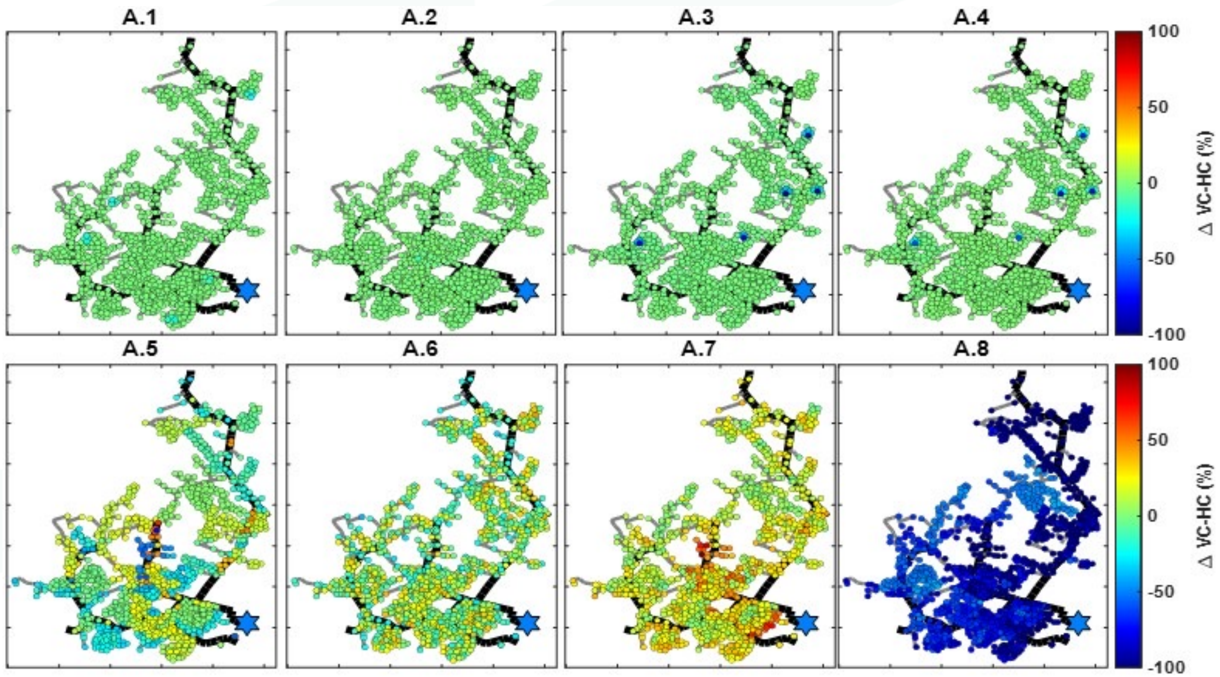
Model-Based Hosting Capacity Error Potential

Conventional model-based HCA:

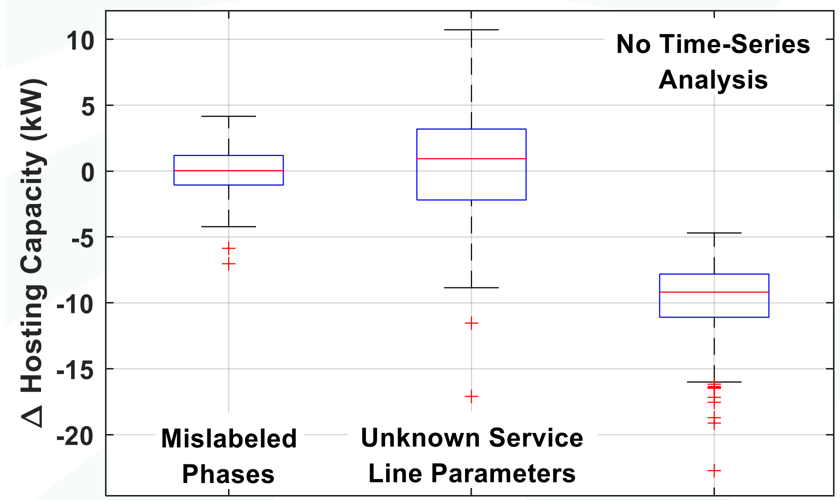
- HCA accuracy is *highly sensitive* to modeling errors [1]
  - Errors can have local or feeder-wide impacts
- Worst-case “snapshot” style analyses can significantly underestimate PV hosting capacity

Model Error Scenarios

#	Error Type
A.1	Service Xfmr Size
A.2	Xfmr/Customer Pairing
A.3	Missing Existing PV
A.4	Missing Existing PV w/ Volt-VAR
A.5	Phase Labeling Errors
A.6	Service Line Lengths
A.7	Substation LTC Malfunction
A.8	Capacitor Malfunction



Percent Error in Hosting Capacity



Impact of poor distribution models on hosting capacity estimates for each residential customer (generally 10-30 kW hosting capacity)

75 Years of Service
NRECA
America's Electric Cooperatives

Our Solution: AMI-Based Hosting Capacity

Can we extract locational HC limitations from smart meter data without a network model?

- Yes: scalable, data-driven algorithms based on statistical analytics and physics-informed machine learning techniques can calculate the voltage- and thermal-constrained HC at smart meter locations
- Needs only P,Q,V readings from each input smart meter (can work at lower fidelity without Q)
- 1 year of data required, 15-minute intervals are ideal but 1-hour intervals will work
- Software developed to calculate capacity and generate hosting capacity maps

How does this help the issues with model-based methods?

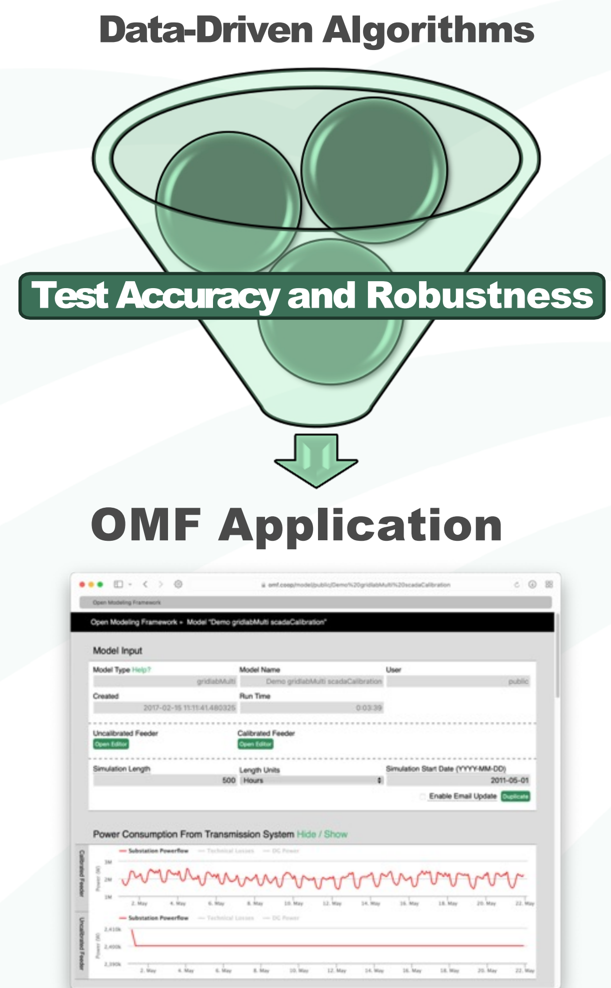
- No power-flow circuit model required
- Not impacted by modeling assumptions/errors
- No simulations required => faster and more scalable than model-based methods
    - Reduced computational burden means HC maps updated more frequently
    - More practical to implement
    - Any changes to the distribution network are inherently captured in the smart meter data
- Historical AMI provides time-series hosting capacity analysis of operations during the entire year instead of just extreme points

AMI-Based Hosting Capacity Benefits

- Smart meter data is passed directly into the model-free HCA tool
  - Entirely Data-driven algorithms are applied to calculate locational solar HC subject to voltage and thermal constraints, HC map can then be generated for that location
- Any changes to the distribution network are inherently captured in the smart meter data
  - I.e., the approach is robust to phase changes, network upgrades, etc. *without user intervention*
  - Captures low-voltage secondary network characteristics, which are often missing or over-simplified in utility models
- No simulations are required = much faster than model-based methods
  - Reduced computational burden means HC maps can be updated more frequently to keep pace with increasing levels of interconnection requests
- Can accommodate both **static** and **timeseries** hosting capacity analysis
  - **Static:** limited by any violation at any time during the year
  - **Timeseries:** relaxes constraints to allow for some violations to occur (aligned with standards that allow temporary violations)
- Useful for streamlining behind-the-meter (BTM) interconnection requests
  - Model-free HCA results can be used as a screening method (as opposed to existing “rules of thumb”)

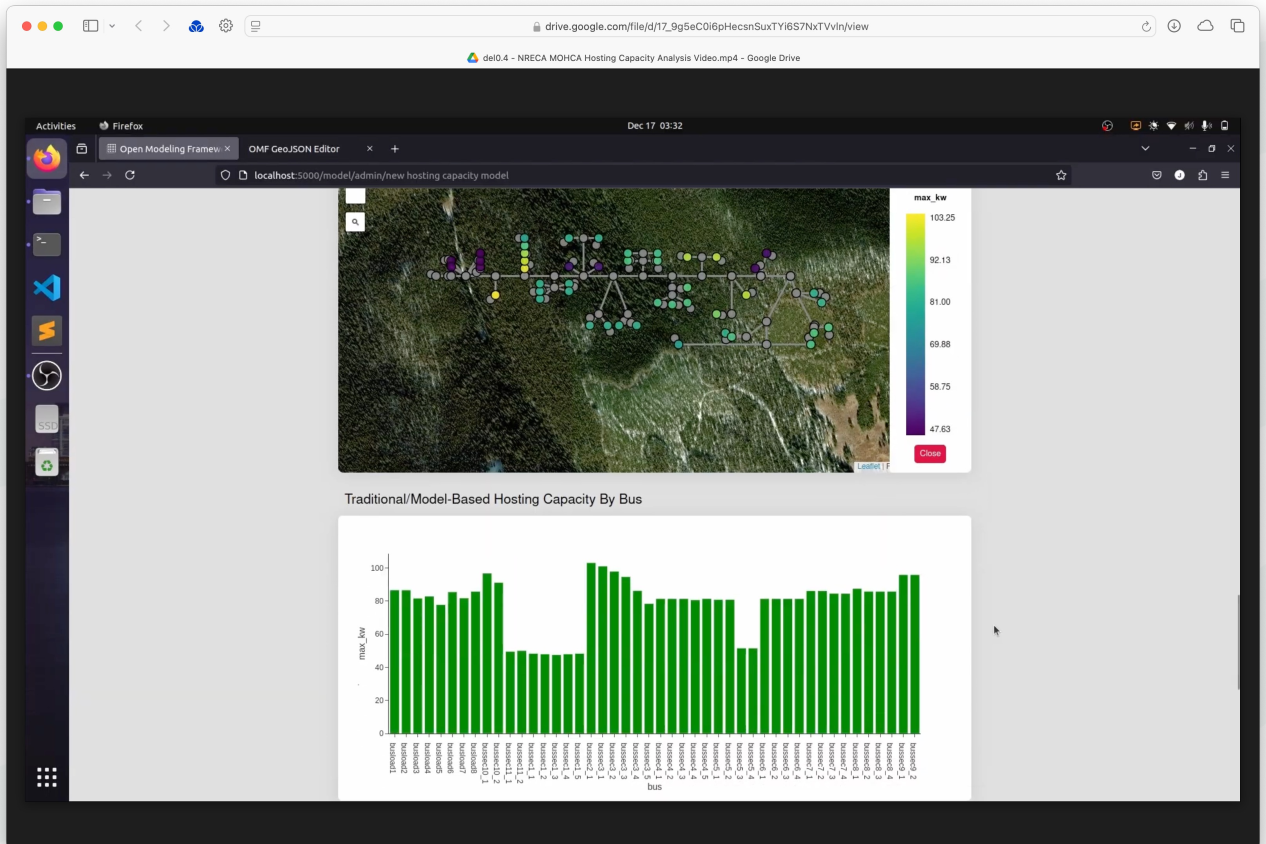
Project Software Available on OMF.coop

- Algorithms developed for the project have been incorporated in the web-based modeling platform Open Modeling Framework (OMF) at omf.coop.
  - OMF.coop allows utility access to advanced algorithms and modeling tools via easy graphical interface
  - Free and open source
  - Can run algorithm on-demand
  - Input via file upload
- Visualization, data conversion, and model management tools in place.
- 250+ utilities and vendors throughout the US already active on the platform

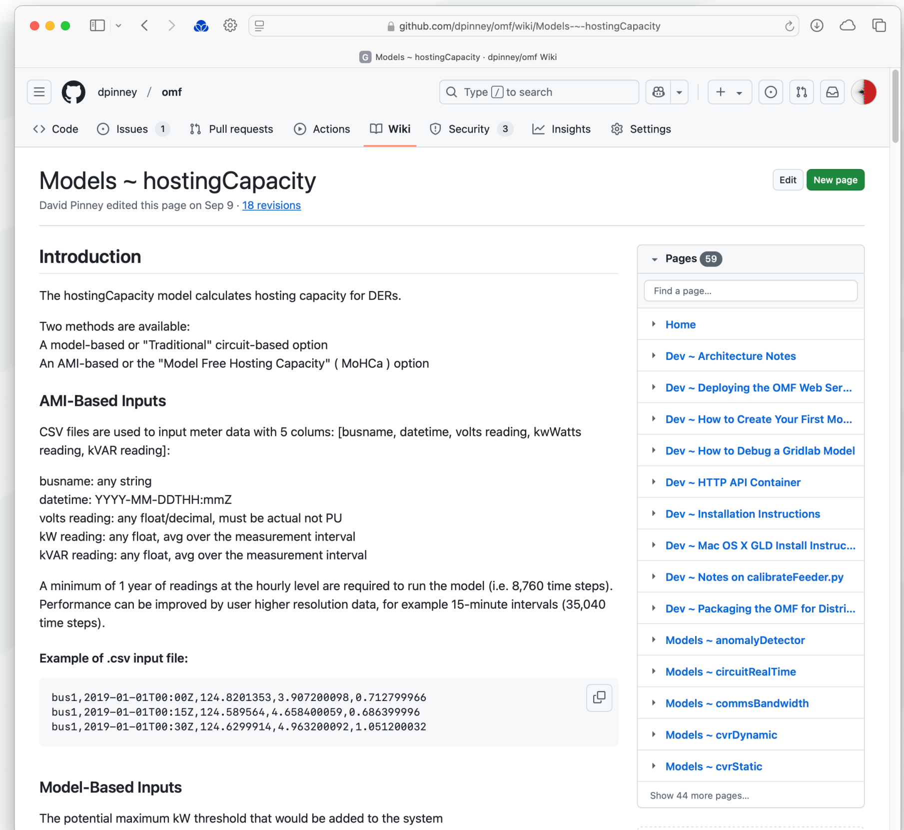


Video Demonstration and Documentation of Software

Video Demonstration [1]



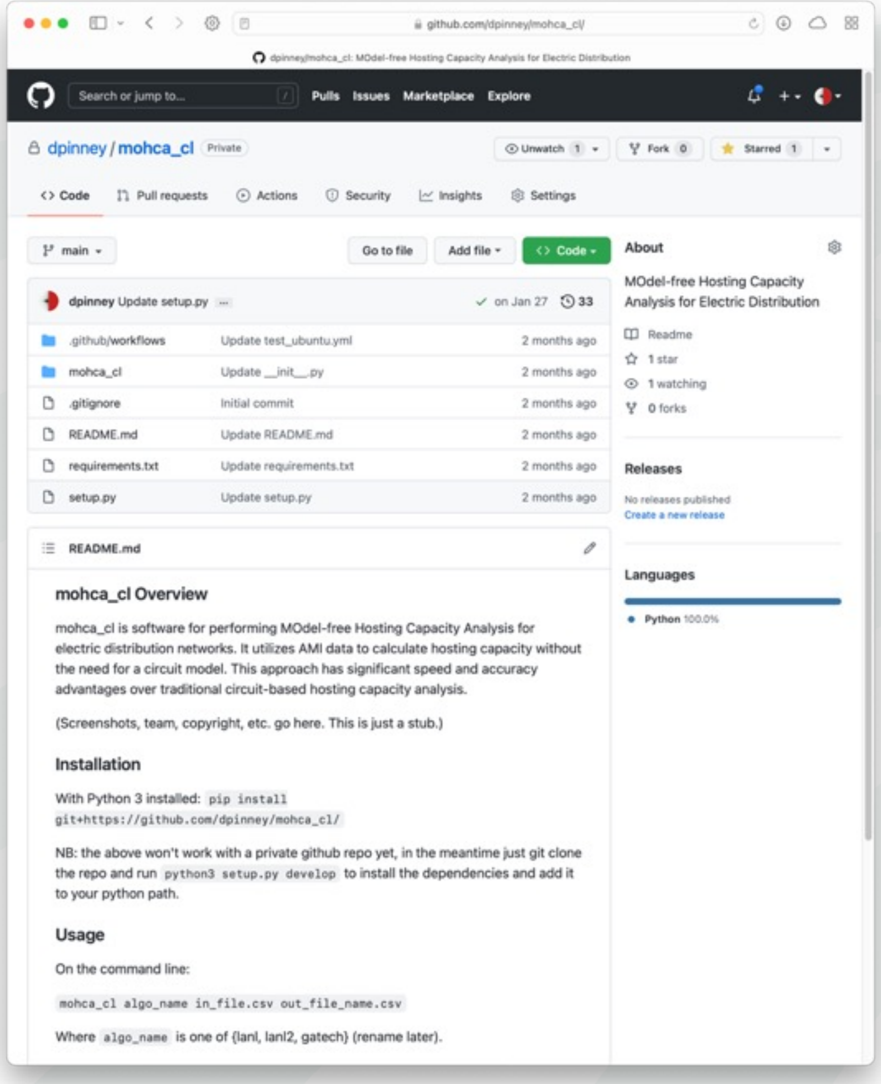
Documentation [2]



[1] https://drive.google.com/file/d/17_9g5eC0i6pHecsnSuxTYi6S7NxTVvln/
[2] https://github.com/dpinney/omf/wiki/Models-~-hostingCapacity

Core MOHCA Algorithms also Available in mohca_cl

- Simple python package with command line interface implementing core algorithms
- Hosted on GitHub at https://github.com/dpinney/mohca_cl
- Allows easy integration into commercial and existing tools.
- Project team open to moving additional functionality into this package (e.g. support for circuit models).



75 Years of Service
NRECA
America's Electric Cooperatives

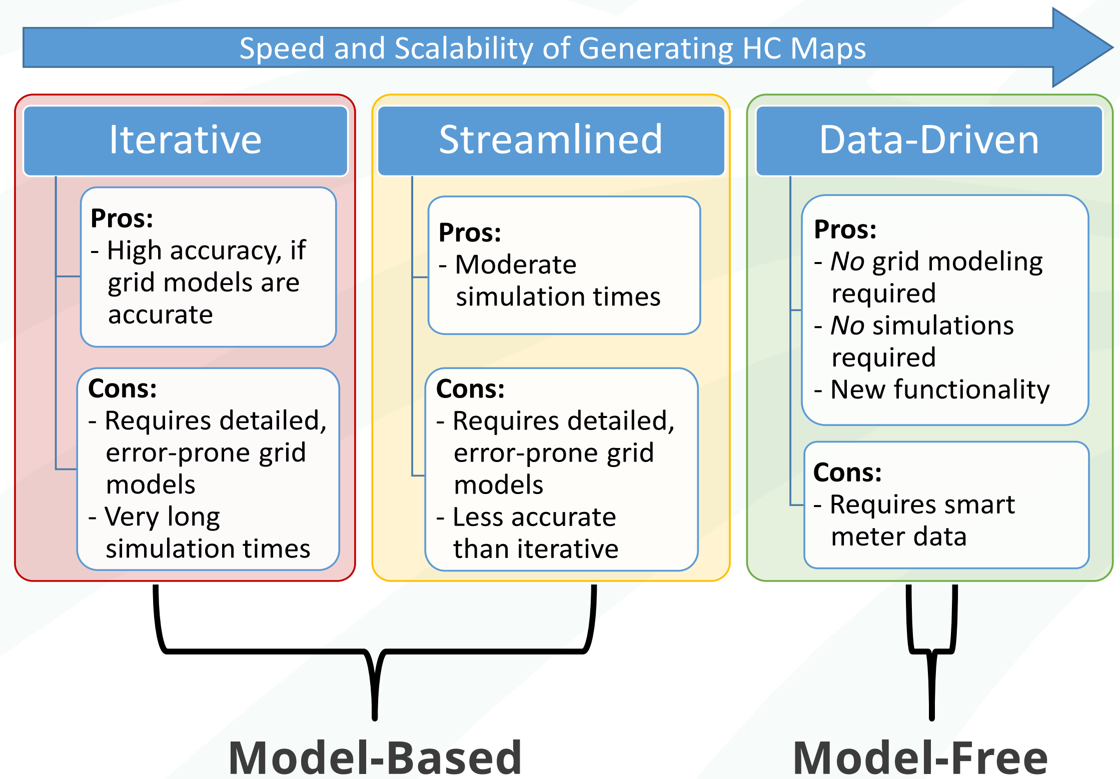
The MOHCA Project, Federally-Funded Research

3-Year Project funded by DOE SETO "Smart Meter Data: A Gateway for Reducing Solar Soft Costs with Model-Free Hosting Capacity Maps"

aka, Model-free Hosting Capacity Analysis (MoHCA)

Objectives Achieved

- Develop scalable algorithms for estimating the voltage- and thermal-constrained HC at smart meter locations
- Algorithms for identifying optimal inverter settings
- Evaluating hosting capacity as a time-series, instead of considering a handful of worst-case scenarios that may underestimate HC



Timeline of MOHCA Project Tasks

2022 — Year 1 — Task 1-4

- Form Industry Advisory Board
- Identify 5 test circuits
- Initial development of voltage-constrained and thermal-constrained algorithms
- Initial integration into the OMF and mohca_cl to allow utilizes to run algorithms with their own data

2023 — Year 2 — Task 2-5

- Perform hosting capacity analysis for co-ops on circuits
- Continuous updates and integration of hosting capacity algorithms as testing goes on
- Comparison of model-free and model-based
- Upgrade front-end integration for comparison analysis

2024 — Year 3+ — Task 4-6

- Further testing for refinements and enhancements
- Get stable version of model-free hosting capacity
- Develop algorithms for assessing impact of advanced inverter functions
- Upgrade frontend for advanced inverter operations
- Introduce continuous analysis of hosting capacity for coops

Task 2 - Develop Algorithms for Voltage-Constrained Hosting Capacity Analysis

75 Years of Service
NRECA
America's Electric Cooperatives

Conventional Model-based HCA Method I

Main Objective: Calculate baseline locational* HC results using a conventional, model-based approach

Feeder Model in Native Format

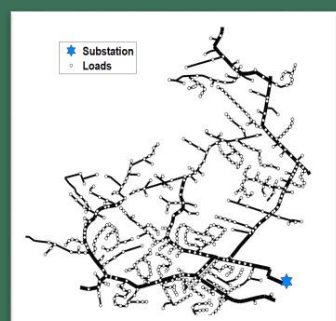
Raw AMI Dataset

Meter *n*:
P, Q measurements
(>=1 yr @ <=15 min. res.)

Convert to OpenDSS

Clean data, Create *n* profiles from P and Q data

Model w/ AMI profiles for all loads



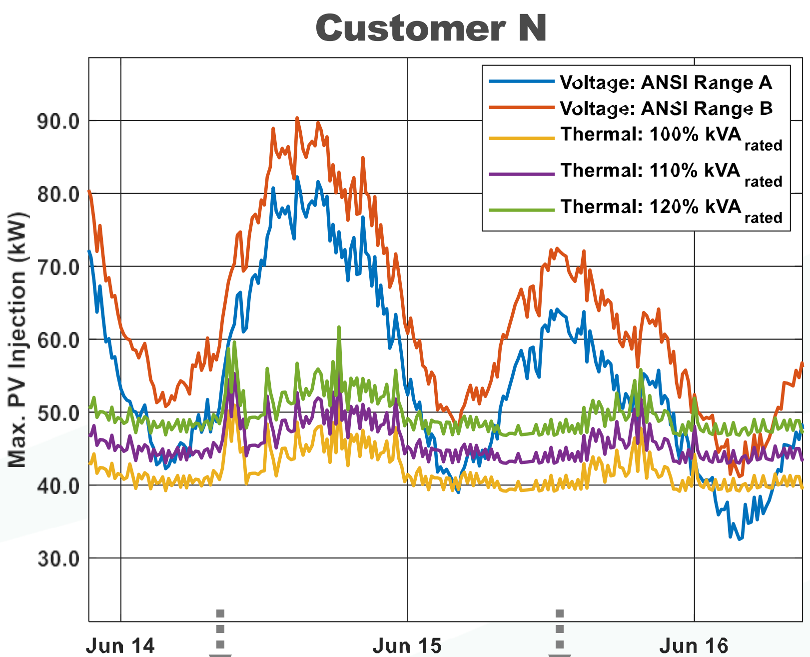
Model-based Locational HCA:

1. **Run yearlong quasi-static time-series (QSTS) simulation without PV**
   a) Record customer voltages and transformer loading time-series
2. **Add PV to any customer premise**
3. **At t=0:**
   a. Iteratively increase PV size, solving the power flow each time
   b. Record max PV size w/o any voltage or thermal violations
4. **Move to next time point (e.g., t=t+15 minutes) if there is one**
   a) Repeat steps 3a and 3b
5. **Repeat steps 2 through 4 for all customer premises**

*Determines how much PV can be installed at any customer premise before voltage or thermal issues occur, providing actionable data to streamline interconnection requests. If the system changes (e.g., due to equipment upgrades or PV installations), the locational HCA must be re-run.

75 Years of Service
NRECA
America's Electric Cooperatives

Conventional Model-based H-CA Method 2



The time-series results can then be post-processed in various ways (see table) to determine a final HC value for each customer premise

Model-based Locational H-CA Objective:

1. **Run yearlong quasi-static time-series (QSTS) simulation without PV**
   a) Record customer voltages and transformer loading time-series
2. **Add PV to any customer premise**
3. **At t=0:**
   a. Iteratively increase PV size, solving the power flow each time
   b. Record max PV size w/o any voltage or thermal violations
4. **Move to next time point (e.g., t=t+15 minutes) if there is one**
   a) Repeat steps 3a and 3b
5. **Repeat steps 2 through 4 for all customer premises**

Example HCA Constraints

Scenario	Only Daylight PV*	V_{lim1} (V_{pu})	Hrs Outside V_{lim1}	V_{lim2} (V_{pu})	Hrs Outside V_{lim2}	T_{lim1} (%kVA)	Hrs Outside T_{lim1}	T_{lim2} (%kVA)	Hrs Outside T_{lim1}
1	False	1.05	0	1.058	0	120	0	150	0
2	True	1.05	0	1.058	0	120	0	150	0
3	True	1.05	87.6	1.058	0	120	87.6	150	0

** True = only consider time between 09:00 – 15:00*

Model-Free Regression Algorithm Overview

Main Objective: Develop algorithms that derive a customer's maximum PV interconnection size, according to voltage and thermal constraints, using only that customer's smart meter data.

Algorithm Inputs:

- **Customer smart meter measurements**
  - (P, Q, V) starting with 1-year at 15-min resolution
  - Meter location info
- **Utility thresholds**
  - Voltage limit (e.g., ANSI)
  - Threshold limits (e.g., overload capability)

Algorithm Outputs:

- **Voltage-constrained HC (V-HC)**
  - kW of PV that can be installed before that customer will experience voltages outside of limits
- **Thermal-constrained HC (T-HC)**
  - kW of PV that can be installed before the service transformer will be overloaded

Assumptions:

- No system model or topology information is available
- Purely data-driven methods to determine transformer groupings and secondary system topology can be leveraged
  - Some now included in the OMF already

Limitations:

- Customer's AMI data only provides information on the potential local impacts of the interconnection. Things like substation transformer rating and transmission hosting capacity constraints have to be brought in separately.
  - Other impacts, such as protection, are not considered

75 Years of Service
NRECA
America's Electric Cooperatives

Input and Output Schema

Regression Model-Free Algorithm

Input Schema

busname	datetime	v_reading	kw_reading	kvar_reading
50061	2019-12-31T20:00Z	249.3867	0.6474	1.282715
50061	2019-12-31T20:15Z	248.9600	0.6696	0.292835
50061	2019-12-31T20:30Z	249.1022	0.6588	1.395352

Output Schema

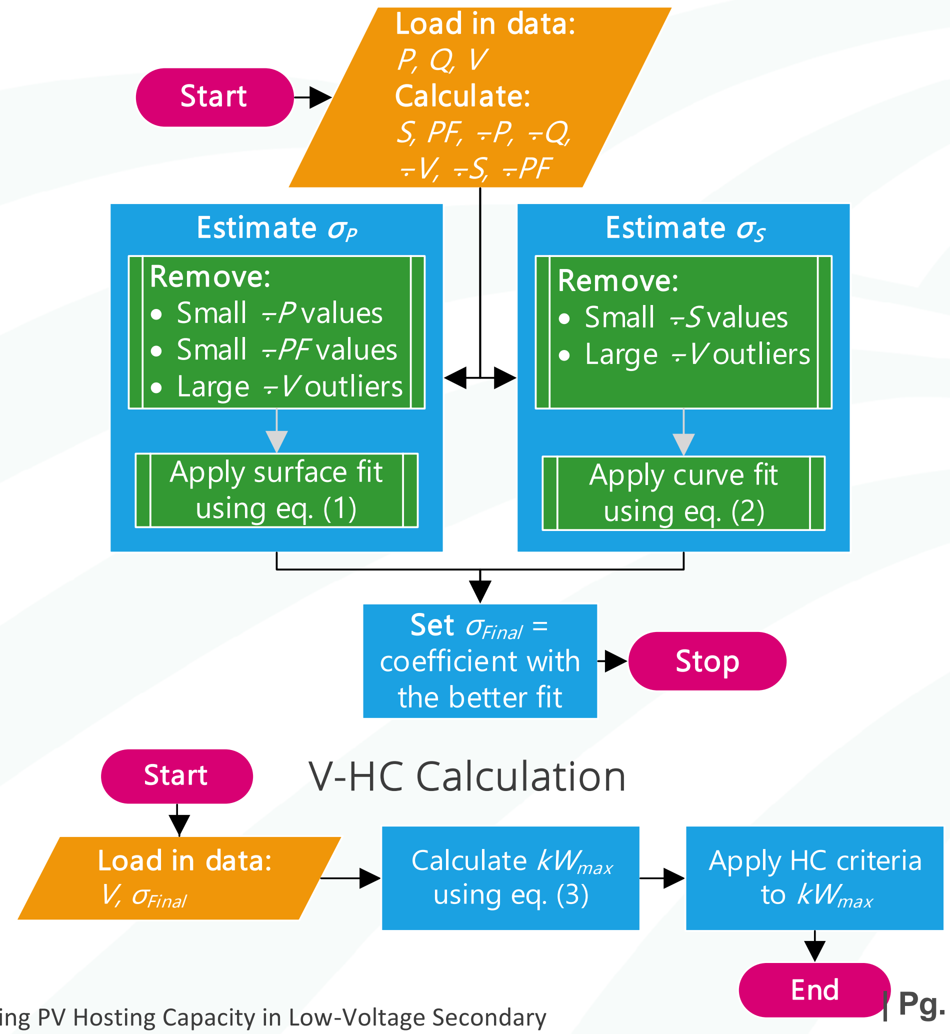
busname	kw_hostable
50061	2019-12-31T20:00Z
50061	2019-12-31T20:15Z
50061	2019-12-31T20:30Z

Model-Free Regression VHC Introduction

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 (i.e., V-HC)

Voltage Sensitivity Calculation



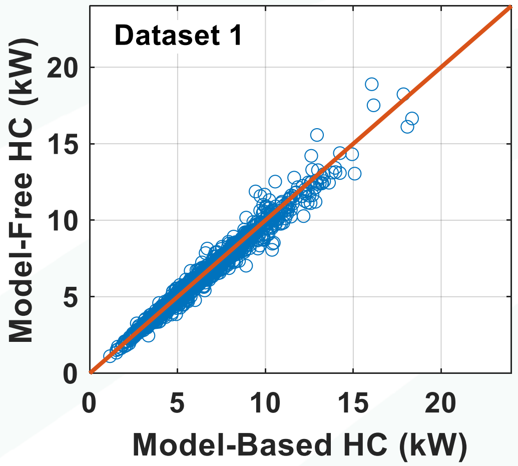
75 Years of Service NRECA America's Electric Cooperatives

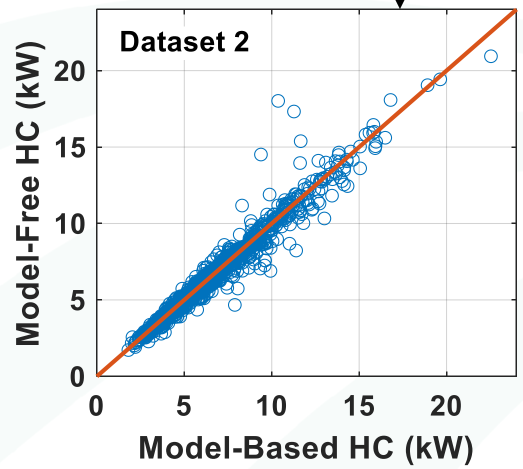
[2] J. Azzolini, M. Reno, J. Yusuf, S. Talkington, and S. Grijalva, "Calculating PV Hosting Capacity in Low-Voltage Secondary Networks Using Only Smart Meter Data," *IEEE Innovative Smart Grid Technologies Conference* (ISGT), 2023.

Regression Results Against 2 Datasets

- Regression-based V-HC algorithm developed and tested on 2 different smart meter datasets
- The model-free algorithm was **within 0.3 kW** of the model-based HC results, on average
  - **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

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%



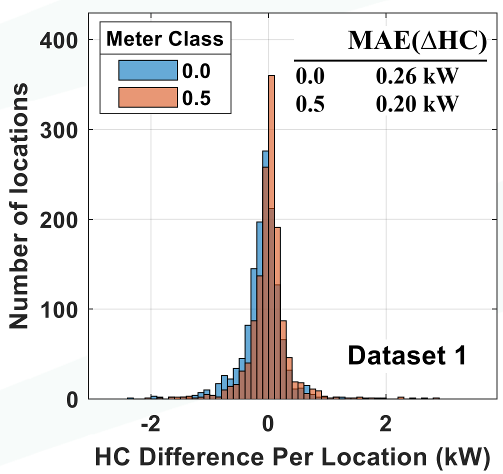


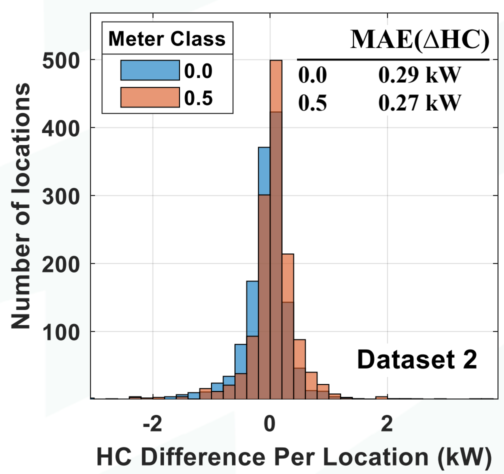
75 Years of Service
NRECA
America's Electric Cooperatives

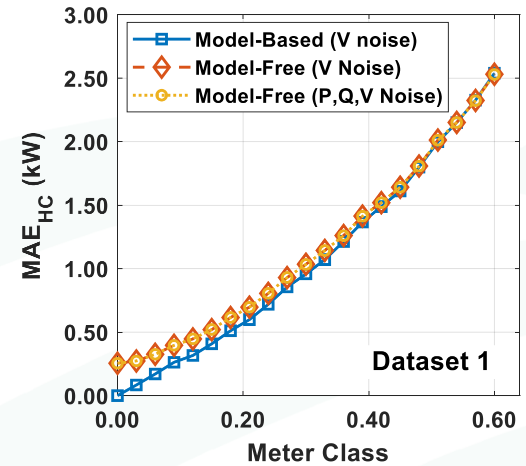
[2] J. Azzolini, M. Reno, J. Yusuf, S. Talkington, and S. Grijalva, "Calculating PV Hosting Capacity in Low-Voltage Secondary Networks Using Only Smart Meter Data," *IEEE Innovative Smart Grid Technologies Conference* (ISGT), 2023.

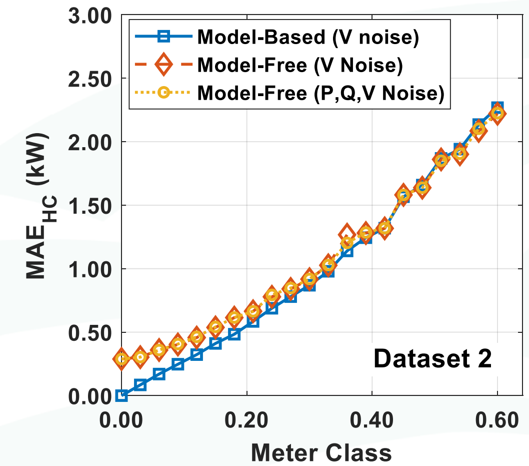
Regression Results – Measurement Noise

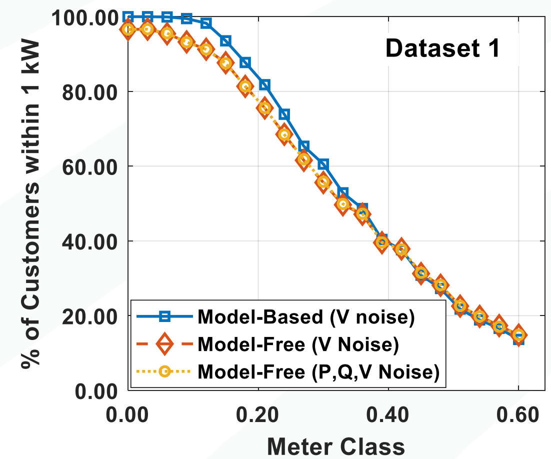
- Both the model-based and model-free approaches were highly sensitive to measurement noise
- Errors introduced by the model-free method (ΔHC) were consistent even as noise increased

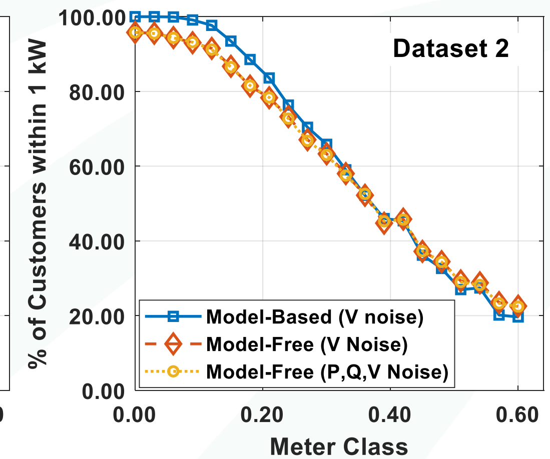








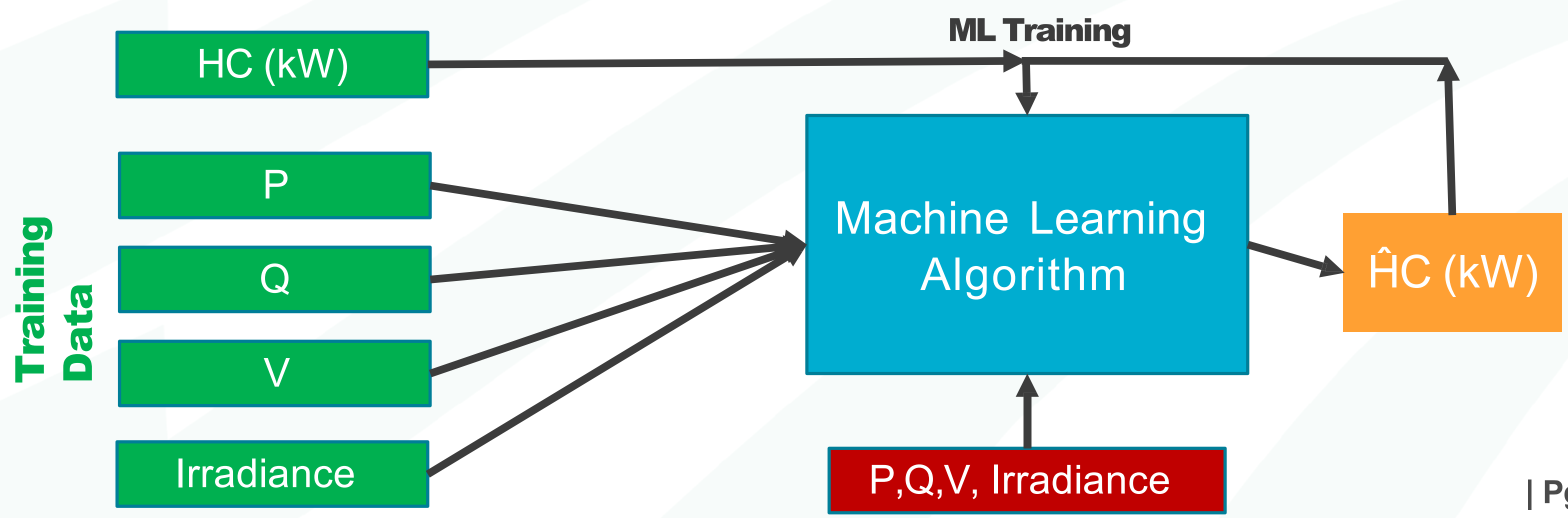




[2] J. Azzolini, M. Reno, J. Yusuf, S. Talkington, and S. Grijalva, "Calculating PV Hosting Capacity in Low-Voltage Secondary Networks Using Only Smart Meter Data," *IEEE Innovative Smart Grid Technologies Conference* (ISGT), 2023.

Model-Free DNN V-HC Algorithm Introduction

- Data-driven models learn how changes in power consumption impact the voltage
  - Correlations between historical P, Q, V data and hosting capacity
- Use that model to predict the max PV size that customer can install without voltage violations
  - Utilizing Convolutional Neural Network + possible physical-informed elements
  - Inputs – an “image” per customer
    - 3x35040 (p, q, v by time) or some other method to compress time into more meaningful physics-based statistics
    - For timeseries HC – provide irradiance timeseries
- Training data – baseline hosting capacity for 10, 000 customer training samples
- Repeat prediction for all customer locations on a feeder



DNN V-HC Objective and Steps

Model-Free DNN V-HC Algorithm Objective

- Train a deep neural network (DNN) to predict ΔV given ΔP and ΔQ
- DNN can be trained for
  - **1)** a group of customers served by the same transformer
  - **2)** a single customer
- After training, the DNN can predict voltage impacts from PV injections, which can then be used to calculate V-HC

Step 1

dP, dQ and dV for the customers

Data Preprocessing

Training and Validation Split

Step 2

dP, dQ (model input)

dV (model output)

Hyperparameter Tuning

Parameter Selection

Step 3

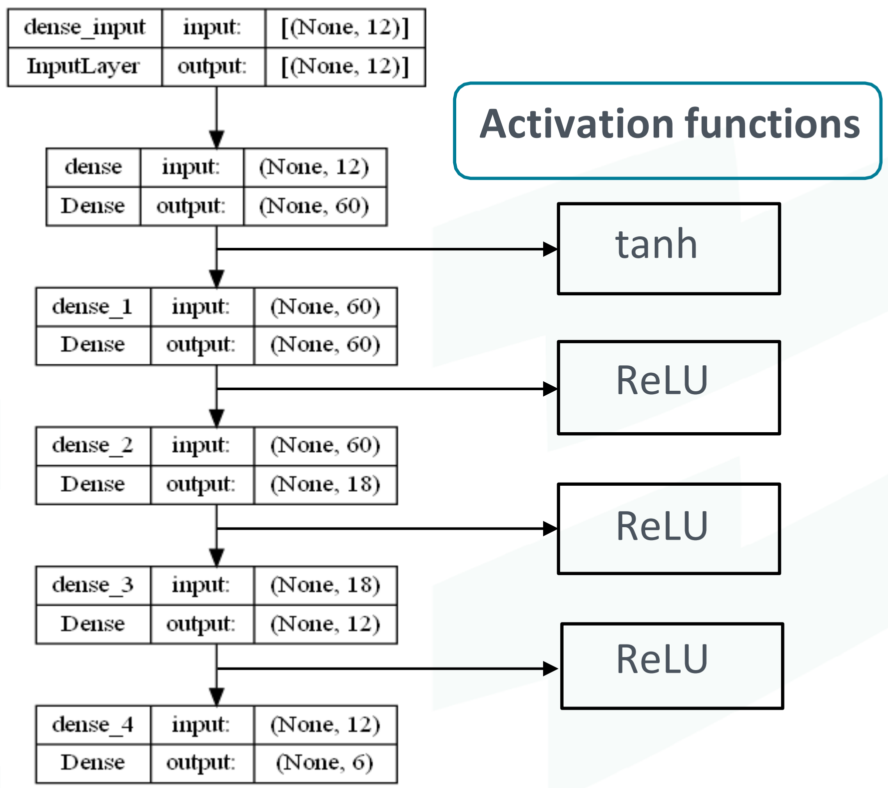
Predicting dV for the test data

Post Processing

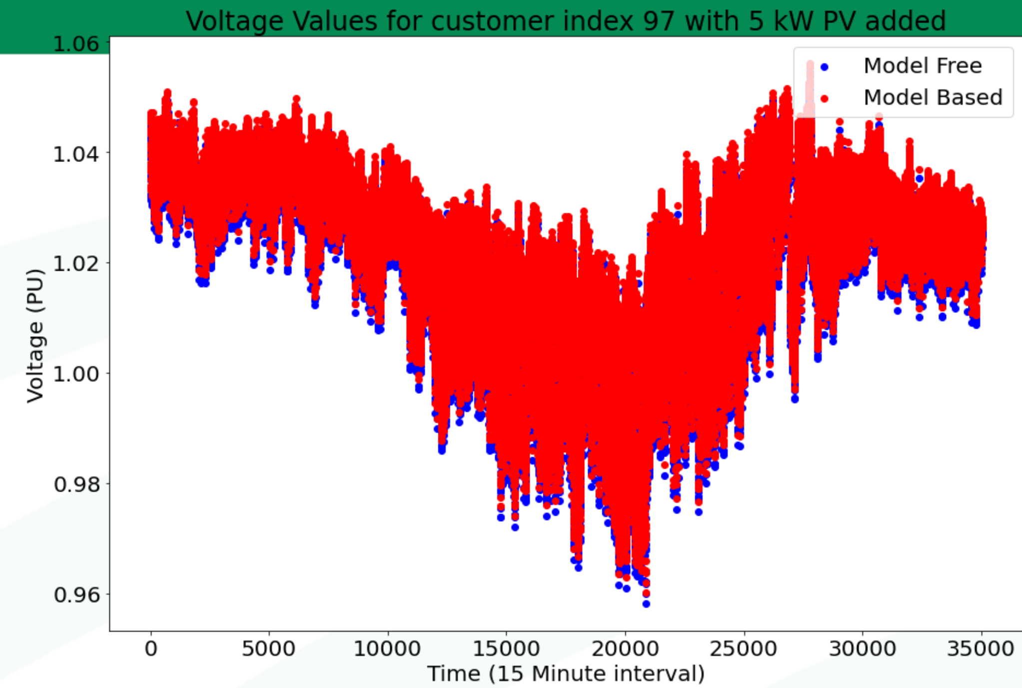
[3] J. Yusuf, J. Azzolini, and M. Reno, "Predicting Voltage Changes of Low-Voltage Secondary Networks Using Deep Neural Networks," *IEEE Power and Energy Conference at Illinois* (PECI), 2023. *Under Review.*

DNN V-HC Algorithm Architecture

DNN Architecture:



*The number of neurons in dense layers corresponds to the number of customers sharing a transformer (6 in this case)



Using DNN to predict Voltages:

- Model trained for 6 customers connected to the same transformer
- Voltages were predicted for constant 5 kW PV injection at one customer location (customer 97)
- Predicted voltages compared to model-based results

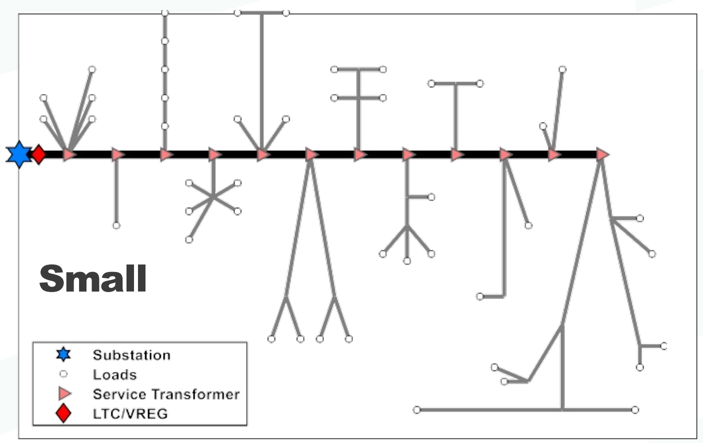
[3] J. Yusuf, J. Azzolini, and M. Reno, “Predicting Voltage Changes of Low-Voltage Secondary Networks Using Deep Neural Networks,” *IEEE Power and Energy Conference at Illinois* (PECI), 2023. *Under Review.*

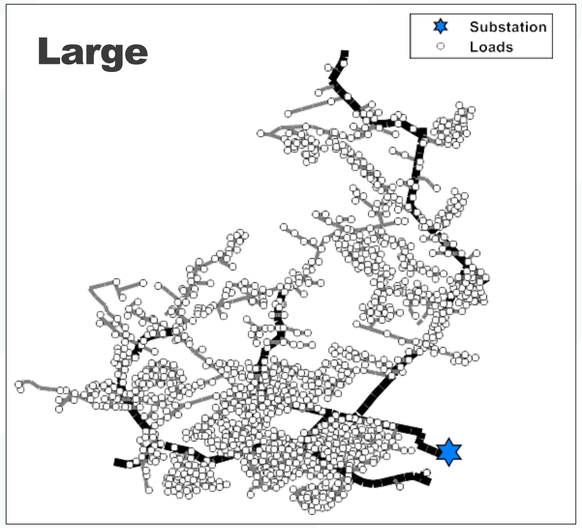
DNN V-HC Algorithm Setup

Algorithm 1
- Train a DNN for each group of customers sharing a transformer

Algorithm 2
- Train a DNN for each customer

Testing
- Use each DNN to predict voltage changes associated with a variety of PV injections





Mean Abs. Percent Errors (MAPE) of Voltage Predictions

Interpolation Errors

Test Case	Alg. 1	Alg. 2
A. Small (constant source voltage)	2.39%	6.89%
B. Small (varying source voltage + LTC)	11.21%	12.04%
C. Large (varying source voltage)	17.22%	17.62%

Extrapolation Errors

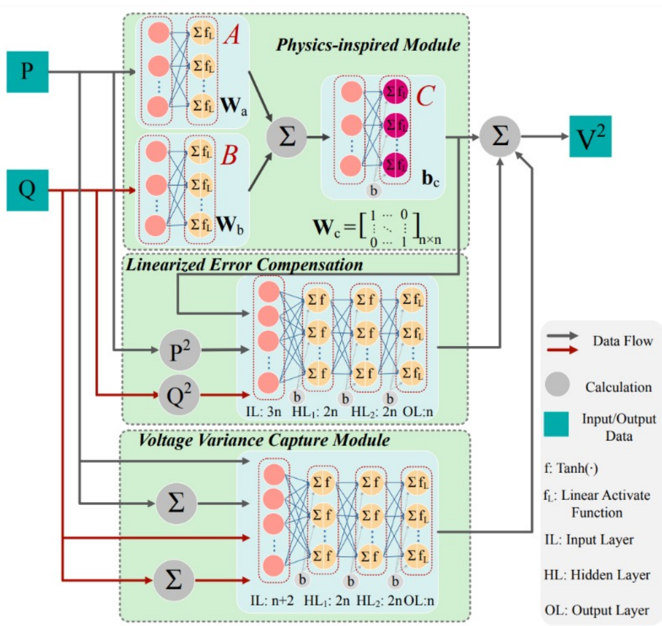
Test Case	Alg. 1	Alg. 2
A. Small (constant source voltage)	1.78%	4.33%
B. Small (varying source voltage + LTC)	5.29%	8.70%
C. Large (varying source voltage)	13.50%	19.14%

[3] J. Yusuf, J. Azzolini, and M. Reno, “Predicting Voltage Changes of Low-Voltage Secondary Networks Using Deep Neural Networks,” *IEEE Power and Energy Conference at Illinois* (PECI), 2023. *Under Review.*

PINN Algorithm Overview

Physics-Inspired Neural Network (PINN) for voltage-constrained HC [2]

Model



Structure of Physics-inspired Neural Network

Training

Algorithm 1 PINN Model Training Algorithm

Require: Training set $\mathcal{D}_{tr} = \{\boldsymbol{V}_{sm}, \boldsymbol{P}_{sm}, \boldsymbol{Q}_{sm}\}$, initial learning rate (LR) α_0, decay factor k, momentum ζ , mini-batch size N_b, number of epochs $\mathcal{T}$

Initialize the parameters of network $F_{\boldsymbol{\theta}}$ as $\Theta = \left\{\theta_\eta^0, \theta_\phi^0\right\}$ by designed rules; update initial LR as $\alpha \leftarrow \alpha_0$

for *epoch* $= 1$ to $\mathcal{T}$ **do**

  for $i = 1$ to $\lceil N/N_b \rceil$ **do**

    Select N_b example pairs from shuffled $\mathcal{D}_{tr}$ forming mini-batch $S_i = \{\boldsymbol{p}_b^{c_n}, \boldsymbol{q}_b^{c_n}, \boldsymbol{v}_b^{c_n}\}_{b=1}^{N_b}$

    Compute gradient of the loss function with respect to network parameters as

$$\nabla_\theta \mathcal{J}(\Theta; S_i) = \{\ \nabla_{\theta_\eta}\mathcal{J}, \nabla_{\theta_\phi}\mathcal{J}\}$$

    Editing gradient of physics-inspired module based on weight symmetry averaging as

$$\nabla_{\theta_\eta}\mathcal{J} \leftarrow \tfrac{1}{2}\left(\nabla_{\theta_\eta}\mathcal{J} + \nabla_{\theta_\eta}\mathcal{J}^T\right)$$

    Update the parameters using SGD update rule:

$$\bar{\boldsymbol{v}} \leftarrow \zeta \boldsymbol{v} + (1-\zeta)\nabla_\theta \mathcal{J}(\Theta; S_i)$$
$$\Theta \leftarrow \Theta - \alpha\bar{\boldsymbol{v}} \qquad \triangleright\, v \leftarrow \nabla_\theta \mathcal{J}(\Theta; S_{i-1}).$$

    if $\lceil \alpha/e \rceil == 0$ **then**

      $\alpha \leftarrow k\alpha$ ▷ decays LR α by k every e epochs

    end if

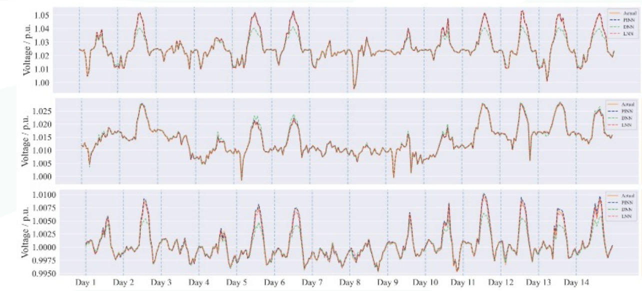
  end for

end for

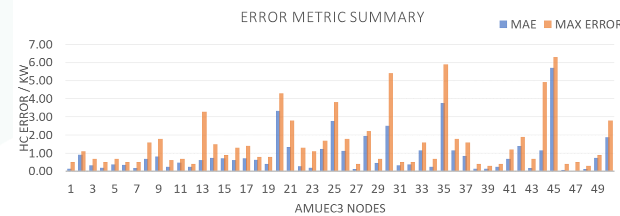
return F_{θ_f}

Customized training algorithm of the designed model

Results



Customer node voltage calculation results



Error Metrics	MAE(kW)	Max MAE(kW)	Locations(%) <1 kW Error
Nodes Avg	*0.89*	*1.57*	*87.72%*

Maximum accessible PV Capacity estimation results (taking AMU model as an example)

75 Years of Service
NRECA
America's Electric Cooperatives

[2] L. Liu, N. Shi, D. Wang, Z. Ma, Z. Wang, M. J. Reno, J. A. Azzolini, "Voltage Calculations in Secondary Distribution Networks via Physics-Inspired Neural Network Using Smart Meter Data," under review.

Model-free Algorithms Accuracy

- More data = better accuracy
- Regression-based[2] and PINN-based[3] methods integrated in OMF

Algorithms	Required Inputs	MAE (kW)	Max Error (kW)	% of Locations >1kW Error
Constant Sensitivity[5]	Max V	1.49	20.74	50.88%
Statistics-based AdaBoost – V[5]	Min, Max, Std of (V)	1.25	15.57	22.50%
Statistics-based AdaBoost – PV[5]	Min, Max, Std of (P, V)	0.98	14.80	17.74%
Statistics-based AdaBoost – PQV[5]	Min, Max, Std of (P, Q, V)	0.95	14.35	17.83%
Model-Free Approach - DNN-based[4]	Time-series (P, Q, V)	0.78	2.49	30.40%
Regression-based[2]	**Time-series (P, Q, V)**	**0.26**	**2.84**	**3.40%**
PINN-based[3]	**Time-series (P, Q, V)**	**0.89**	**1.57**	**12.28%**

[2] J. A. Azzolini, M. J. Reno, J. Yusuf, S. Talkington, S. Grijalva, "Calculating PV Hosting Capacity in Low-Voltage Secondary Networks using Only Smart Meter Data" in *IEEE Innovative Smart Grid Technologies (ISGT-NA)*, Washington, DC, 2023.

[3] L. Liu, N. Shi, D. Wang, Z. Ma, Z. Wang, M. J. Reno, J. A. Azzolini, "Voltage Calculations in Secondary Distribution Networks via Physics-Inspired Neural Network Using Smart Meter Data," *IEEE Transactions on Smart Grid*, 2024.

[4] J. Yusuf, J. A. Azzolini, M. J. Reno, "Predicting Voltage Changes in Low-Voltage Secondary Networks using Deep Neural Networks" in *IEEE Power and Energy Conference at Illinois (PECI)*, Champaign, IL, 2023

[5] J. Yusuf, J. A. Azzolini, M. J. Reno, "PV Hosting Capacity Estimation in Low-Voltage Secondary Networks Using Statistical Properties of AMI Data," *IEEE Innovative Smart Grid Technologies Latin America (ISGT-LA)*, 2023.

Model Free Additional Enhancements

Leveraging Statistical Properties of AMI data for model-free HC calculation [1]

- **Challenges:**
  - Data available for limited timestamps
  - Unavailability of all P, Q and V measurements
  - Unavailability of AMI devices for all the locations
- **Solution:**
  - A simple, easy-to-implement yet reliable method is needed that can provide a ballpark PV HC estimation for any customer and overcome these limitations.

Constant Sensitivity Approach

Input: Maximum Voltage

Output: Hosting Capacity

Ensemble Approach

Input: Statistical Properties (min, max, std, mean) of Available AMI Data

Output: Hosting Capacity

[1] J. Yusuf, J. A. Azzolini, M. J. Reno, "PV Hosting Capacity Estimation in Low-Voltage Secondary Networks Using Statistical Properties of AMI Data," *IEEE Innovative Smart Grid Technologies Latin America (ISGT-LA)*, 2023.

Model-Free V-HC – Ensemble Approach

Ensemble Approach

Split the dataset into training and testing

↓

Generate the predictors (selected features) and responses (sensitivity values) for training data

↓

Use the AdaBoost algorithm to develop the model

↓

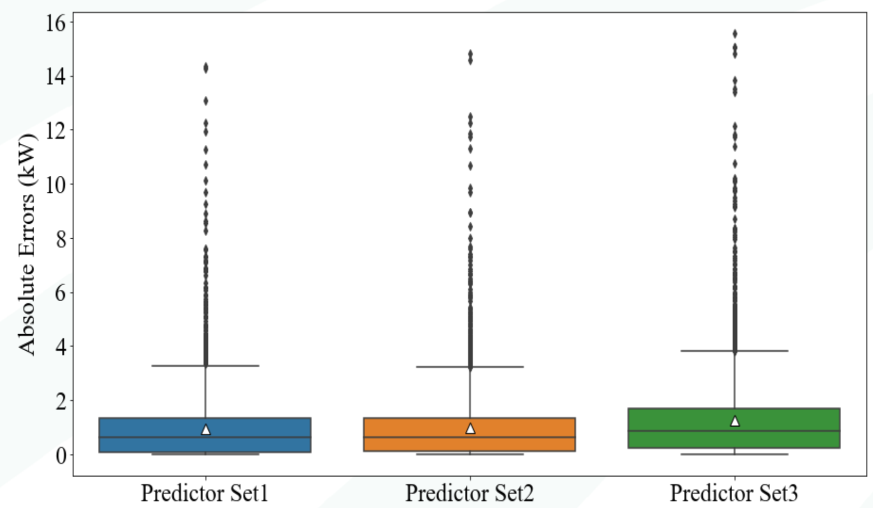
Deploy the model for testing data and estimate the predicted HC where HC=predicted sensitivity× abs(1.05-Vmax)

Divided into 3 categories:

Predictor Set 1: Smart meter has all P, Q, and V measurements; so all 12 features are used

Predictor Set 2: Smart meter has only P and V measurements; so 11 of 12 features are selected; removing $^{\Delta V}/_{\Delta S}$ (mean)

Predictor Set 3: Smart meter has only V measurements; so 5 of 12 features are selected; only utilizing the ΔV (mean, max, std), V (mean, std)

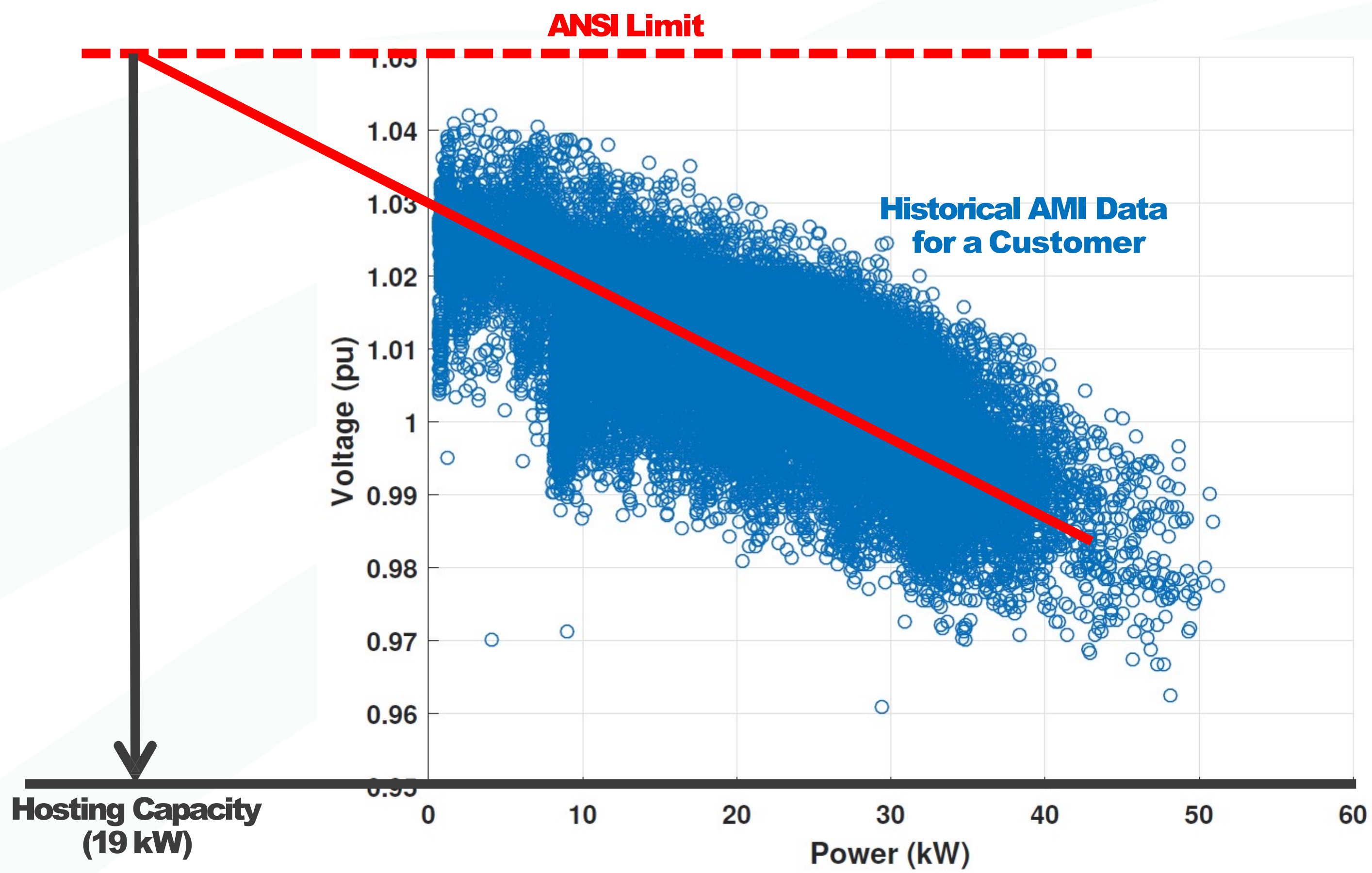


75 Years of Service NRECA America's Electric Cooperatives

[1] J. Yusuf, J. A. Azzolini, M. J. Reno, "PV Hosting Capacity Estimation in Low-Voltage Secondary Networks Using Statistical Properties of AMI Data," *IEEE Innovative Smart Grid Technologies Latin America (ISGT-LA)*, 2023.

Model-Free V-HC - Irradiance

- Static hosting capacity worst case assuming irradiance is always full:
  - (1.05 – max(V(t))) / dV/dP
- Timeseries Hosting Capacity
  - V_withPV(t) = V(t) +
    - PVsize*Irradiance(t)*dV/dP
  - Increase PV size until you reach amount of allowed violations during the year for V_withPV



Model-Free Discussion

- Promising initial results for the model-free approaches
- Significantly reduced computational time. Results were generated in *minutes,* where model-based results required multiple *days* of simulations
- Regression **V-HC:**
  - Comparable accuracy to model-based results
  - Much faster than model-based approach
  - Tested on two different feeder models with several different AMI datasets
- DNN V-HC:
  - Tested on multiple circuits and datasets
  - More accurate when customer-transformer groupings are known
  - Scalability concerns, less accurate for larger or more complex circuits
- Service Transformer Estimation:
  - Potential for high accuracy
  - R estimates were slightly better predictors than X estimates

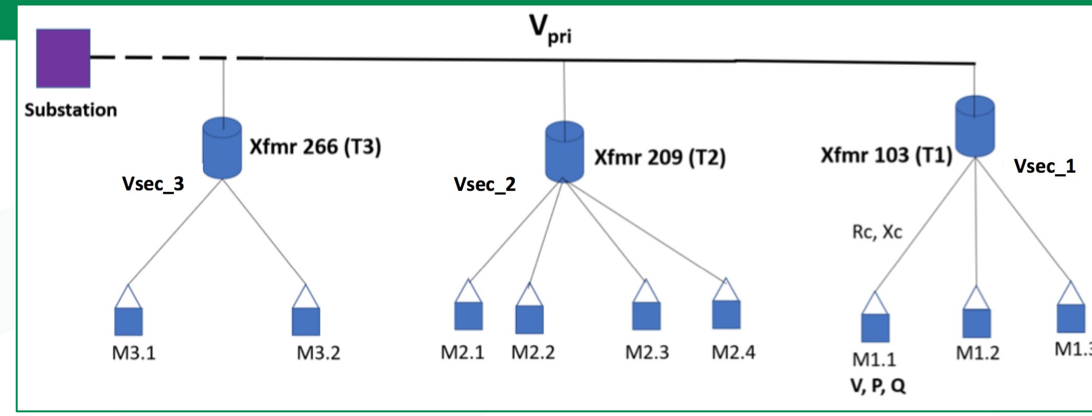
Task 3 - Develop Algorithms for Thermal-Constrained Hosting Capacity

75 Years of Service
NRECA
America's Electric Cooperatives

Thermal-Constrained Hosting Capacity (T-HC)

Two Methods:

- **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.
- **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



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

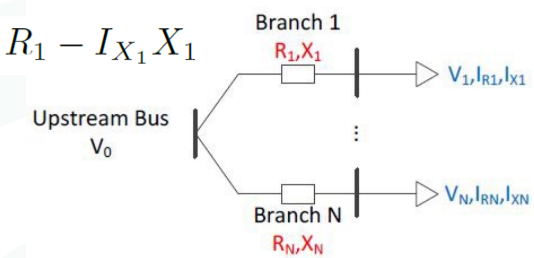


TABLE VIII
TRANSFORMER IMPEDANCE ESTIMATION

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

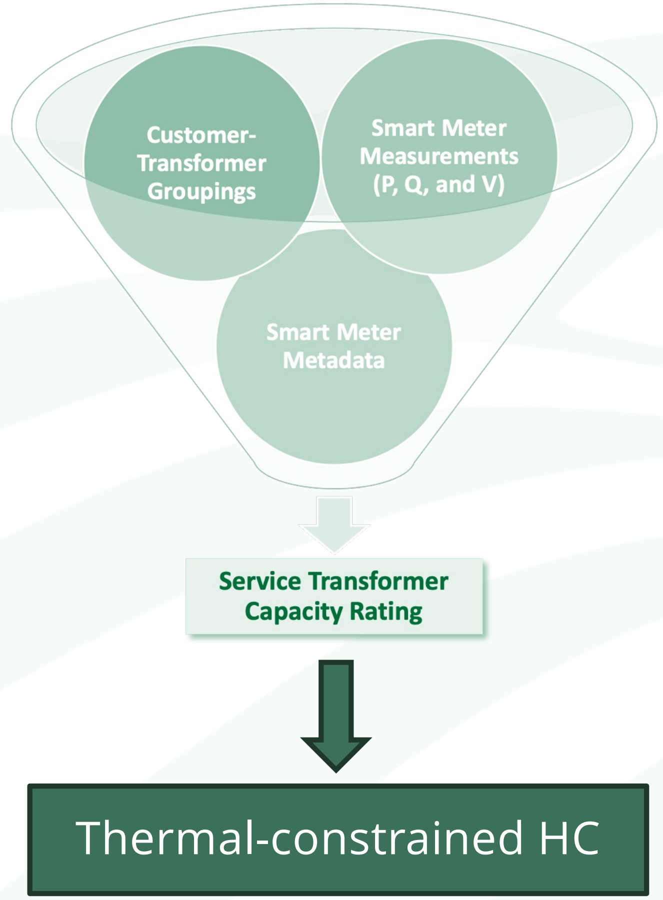
T-HC Problem Statement and Solution Steps

Problem Statement

- Develop and validate data-driven algorithms to determine the maximum amount of solar that can be installed before exceeding the loading capacity of power delivery equipment.

Three main steps:

1. Identify **Transformer-Customer Groupings**[3,7,8]
   - Determine which customers are connected to each transformer
2. Determine the **Transformer kVA Ratings**[6]
3. Calculate the **Thermal-Constrained hosting capacity** based on the total load on the transformer and the power rating
   - How much PV can be installed without over-loading the transformer

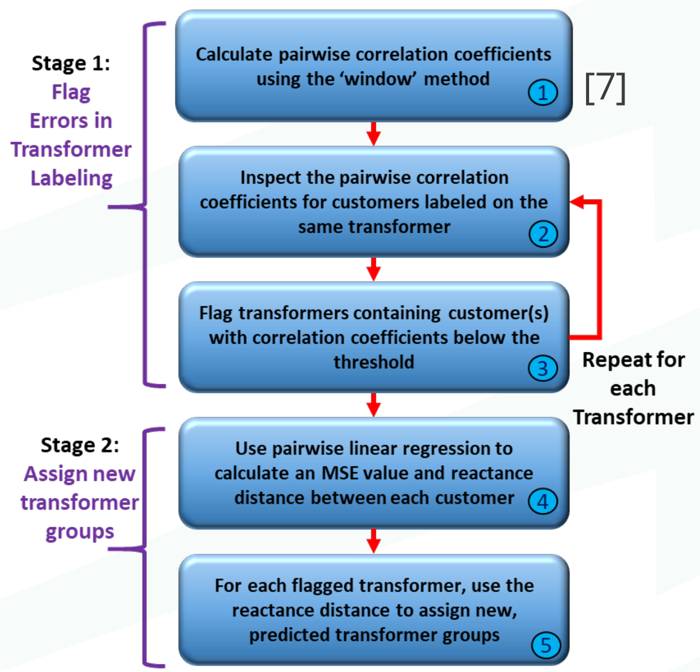


75 Years of Service NRECA America's Electric Cooperatives

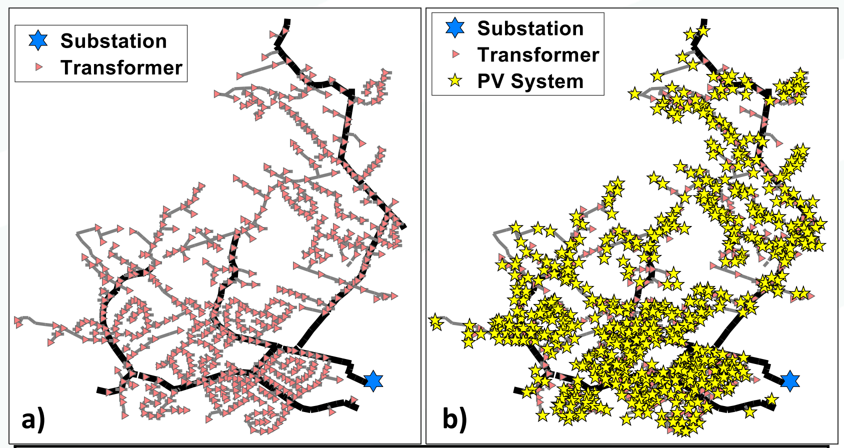
[3] L. Liu, N. Shi, D. Wang, Z. Ma, Z. Wang, M. J. Reno, J. A. Azzolini, "Voltage Calculations in Secondary Distribution Networks via Physics-Inspired Neural Network Using Smart Meter Data," *IEEE Transactions on Smart Grid*, 2024.
[6] J. A. Azzolini, M. J. Reno, J. Yusuf, "A Model-free Approach for Estimating Service Transformer Capacity Using Residential Smart Meter Data," *IEEE Photovoltaic Specialists Conference* (PVSC), 2023.
[7] L. Blakely and M. J. Reno, "Identification and Correction of Errors in Pairing AMI Meters and Transformers," *IEEE Power and Energy Conference at Illinois* (PECI), 2021.
[8] M. Reno et al., "IMoFi - Intelligent Model Fidelity: Physics-Based Data-Driven Grid Modeling to Accelerate Accurate PV Integration Final Report," *Sandia National Laboratories*, SAND2022-0215, 2022.

T-HC Detailed Step Solution Form

- Similar to the V-HC algorithms, the thermal algorithms accept a range of input variables to accommodate different levels of data availability
- Some methods require additional GIS data[6,8], (customer address or transformer latitude/longitude)



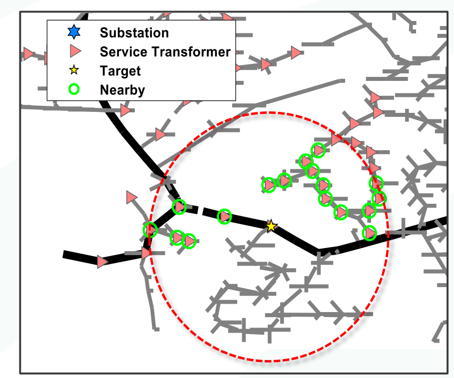
[7]



	Correct Predictions	Prediction Accuracy
Ckt5	583 / 591	98.65%
Ckt5 w/PV	584 / 591	98.82%

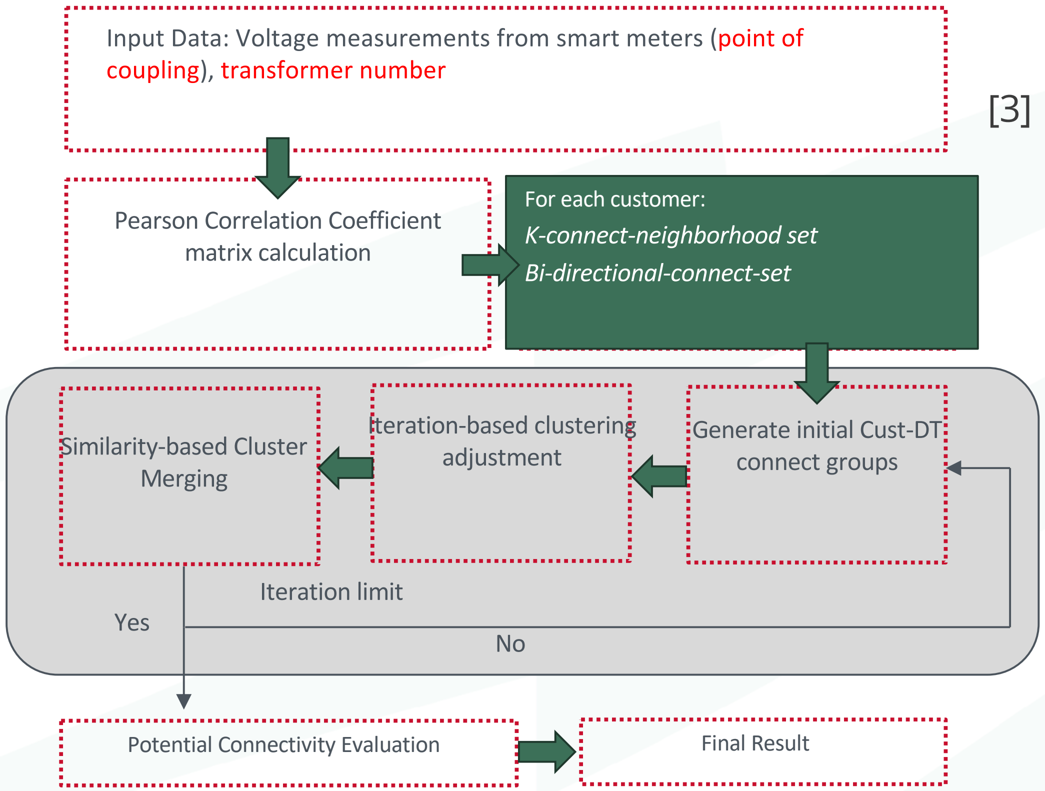
[6] J. A. Azzolini, M. J. Reno, J. Yusuf, "A Model-free Approach for Estimating Service Transformer Capacity Using Residential Smart Meter Data," *IEEE Photovoltaic Specialists Conference* (PVSC), 2023.
[7] L. Blakely and M. J. Reno, "Identification and Correction of Errors in Pairing AMI Meters and Transformers," *IEEE Power and Energy Conference at Illinois* (PECI), 2021.
[8] M. Reno et al., "IMoFi - Intelligent Model Fidelity: Physics-Based Data-Driven Grid Modeling to Accelerate Accurate PV Integration Final Report," *Sandia National Laboratories*, SAND2022-0215, 2022.

[6]



75 Years of Service NRECA America's Electric Cooperatives

T-HC Voltage Correlation and Clustering



[3]

- The accurate **number of service transformers** in the system is **not known** a priori.
- We utilized the voltage correlation between customers to develop a customer clustering algorithm. Customers within one cluster are connected to the same transformer.
- Cluster adjustment and merging process guided the algorithm to estimate the transformer number based on clustering constraints.

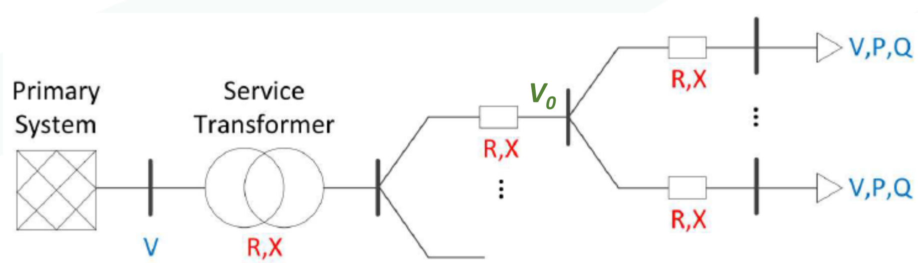
[3] L. Liu, N. Shi, D. Wang, Z. Ma, Z. Wang, M. J. Reno, J. A. Azzolini, "Voltage Calculations in Secondary Distribution Networks via Physics-Inspired Neural Network Using Smart Meter Data," *IEEE Transactions on Smart Grid*, 2024.

T-HC Algorithm Details

1. **Determine kVA rating of upstream service transformer:**
   1. Estimate the low-side voltage of the service transformer [4]
   2. Identify nearby service transformers connected to the same phase
   3. Apply parameter estimation to determine the transformer's impedance [5]
   4. Use look-up table to convert transformer impedance to kVA rating [5]
2. **Calculate Thermal-Constrained HC:**
   1. Calculate net kVA timeseries by summing customer AMI measurements
   2. Subtract net kVA from kVA rating to find kVA headroom
   3. Calculate T-HC from the daytime minimum kVA headroom value

[4] J. Peppanen, M. J. Reno, R. J. Broderick, and S. Grijalva, "Distribution System Secondary Circuit Parameter Estimation for Model Calibration," Sandia National Laboratories, SAND2015-7477, 2015.

[5] K. Ashok, M. J. Reno, and D. Divan, "Secondary Network Parameter Estimation for Distribution Transformers," in 2020 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT), 17-20 Feb. 2020.



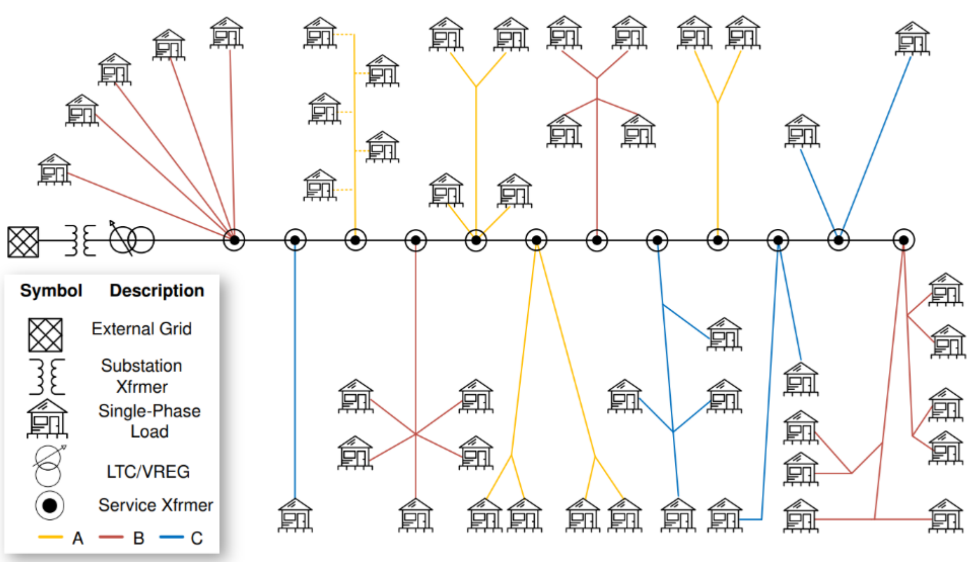
$$
\begin{cases}
V_0 = V_1 + R_1 I_{R1} + X_1 I_{X1} + \epsilon_1 \\
V_0 = V_2 + R_2 I_{R2} + X_2 I_{X2} + \epsilon_2 \\
\vdots \\
V_0 = V_N + R_N I_{RN} + X_N I_{XN} + \epsilon_N
\end{cases}.
$$

Figure 15. Secondary circuit tree for parameter estimation

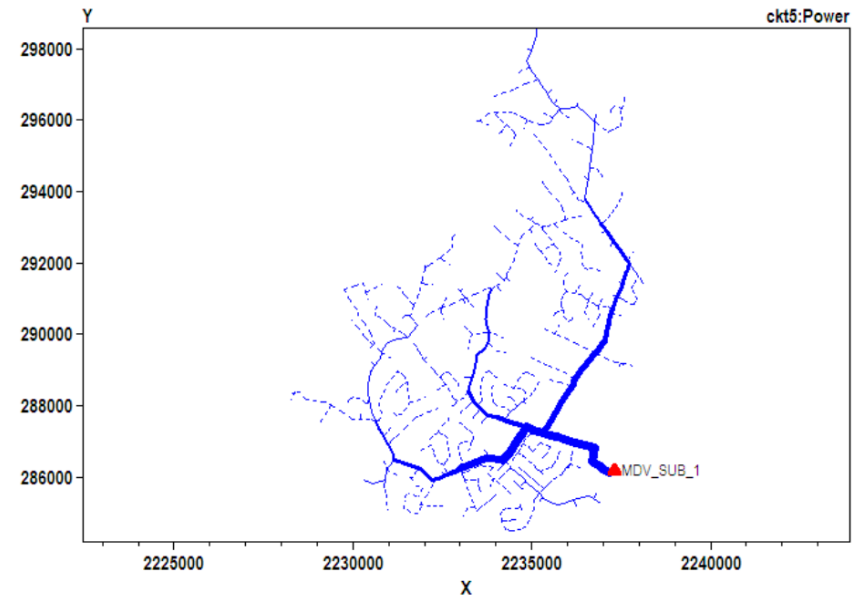
Test Sets for T-HC Development

- Model Test Dataset: ***EPRI Secondary Topology Model*** and ***EPRI Ckt5 Model***
- Input Data: One year of customer smart meter voltage measurements at 15-mins resolution.

EPRI Secondary Topology Model



EPRI Ckt5 Model



75 Years of Service
NRECA
America's Electric Cooperatives

T-HC Results for Test Sets

EPRI Secondary Topology Model

Fig: Voltage correlation heatmap for EPRI ST model

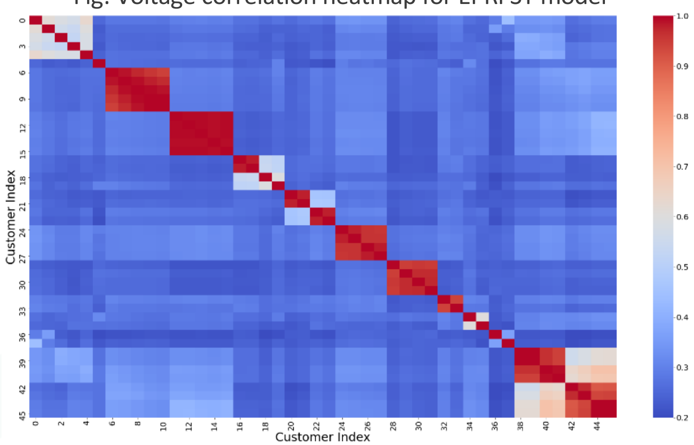
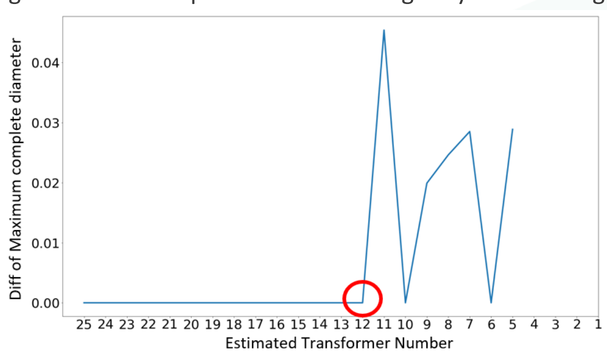


Fig: Maximum complete diameter changes by cluster merging



Simulated Results

0	list	5	[1, 2, 3, 4, 5]
1	list	1	[6]
2	list	5	[7, 8, 9, 10, 11]
3	list	5	[12, 13, 14, 15, 16]
4	list	4	[17, 18, 19, 20]
5	list	4	[21, 22, 23, 24]
6	list	4	[25, 26, 27, 28]
7	list	4	[29, 30, 31, 32]
8	list	2	[33, 34]
9	list	2	[35, 36]
10	list	2	[37, 38]
11	list	8	[39, 40, 41, 42, 43, 44, 45, 46]

Ground Truth

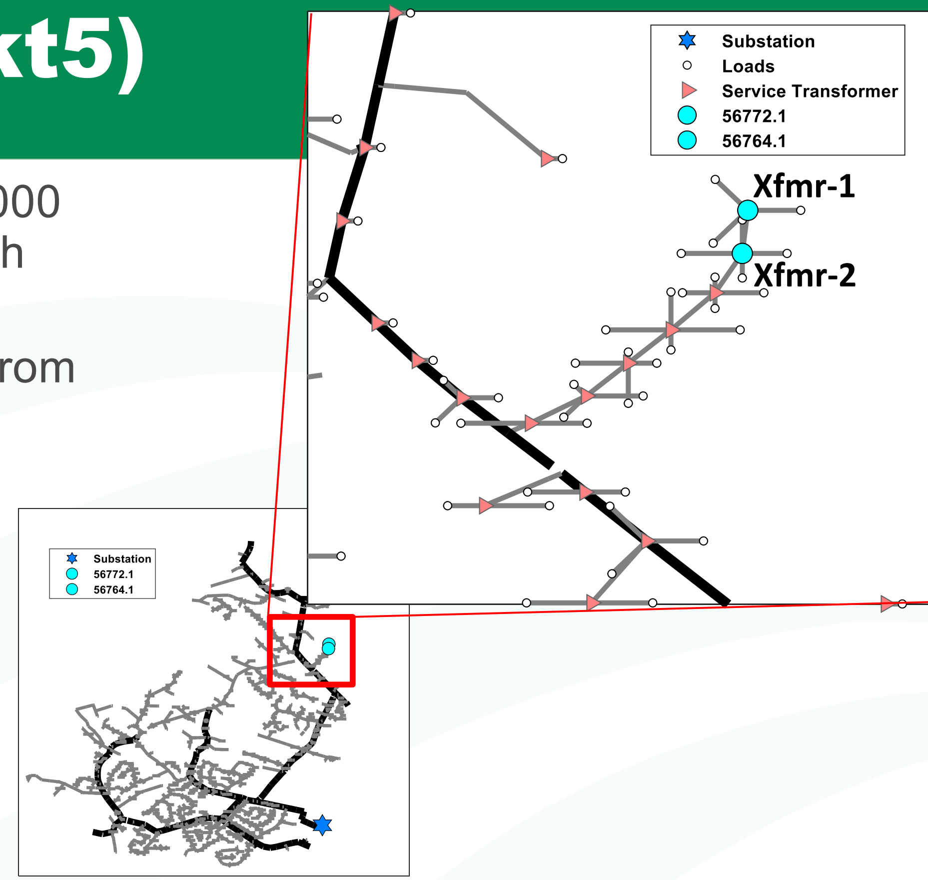
0	list	5	[1, 2, 3, 4, 5]
1	list	1	[6]
2	list	5	[7, 8, 9, 10, 11]
3	list	5	[12, 13, 14, 15, 16]
4	list	4	[17, 18, 19, 20]
5	list	4	[21, 22, 23, 24]
6	list	4	[25, 26, 27, 28]
7	list	4	[29, 30, 31, 32]
8	list	2	[33, 34]
9	list	2	[35, 36]
10	list	2	[37, 38]
11	list	8	[39, 40, 41, 42, 43, 44, 45, 46]

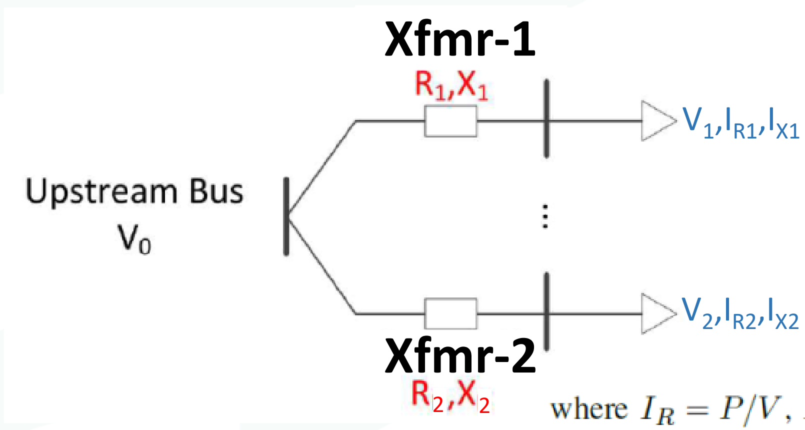
- Connecting results of 46 customers to 12 transformers
- Transformer estimation Error Margin = **0**
- Customer Connectivity Accuracy = **100%**

Accuracy = *number of totally identified transformers/transformer number*

kVA estimation example (Ckt5)

- Solve the linear regression problem in [5] using the first 1000 AMI measurements to estimate the X and R values of each service transformer
- Compare the estimated impedances to the actual values from the model





where $I_R = P/V$, $I_X = Q/V$;

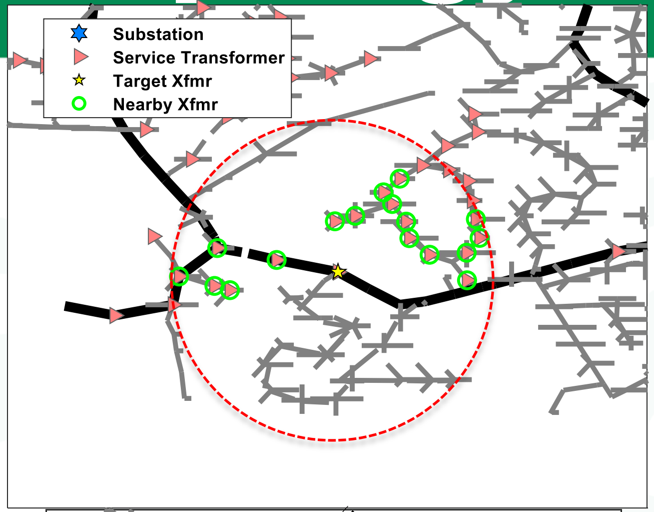
	R_{Actual}	$R_{Estimated}$	Error	X_{Actual}	$X_{Estimated}$	Error
Xfmr-1	0.034560 Ω	0.034819 Ω	**+0.75%**	0.04608 Ω	0.04596 Ω	**-0.26%**
Xfmr-2	0.021504 Ω	0.021585 Ω	**+0.38%**	0.03072 Ω	0.03063 Ω	**-0.28%**

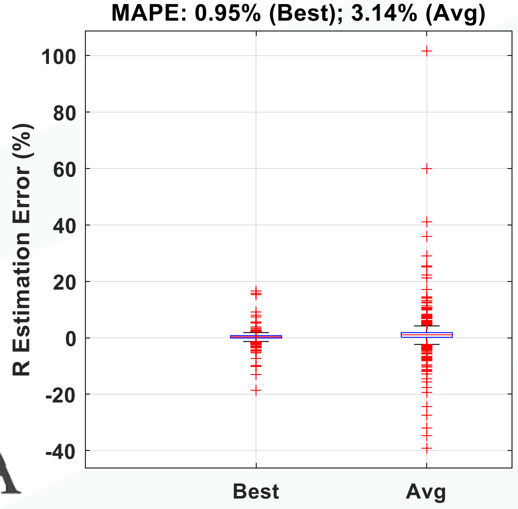
OpenDSS Actual

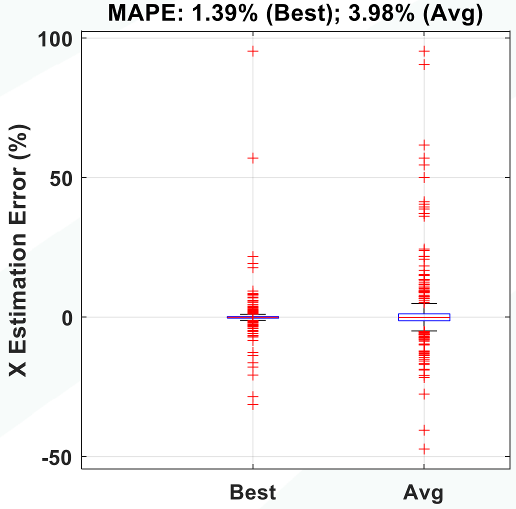
kVA	R_ohms_sec	X_ohms_sec
10	0.0979	0.1152
15	0.0634	0.0768
25	0.0346	0.0461
37.5000	0.0215	0.0307
50	0.0150	0.0230
75	0.0092	0.0154

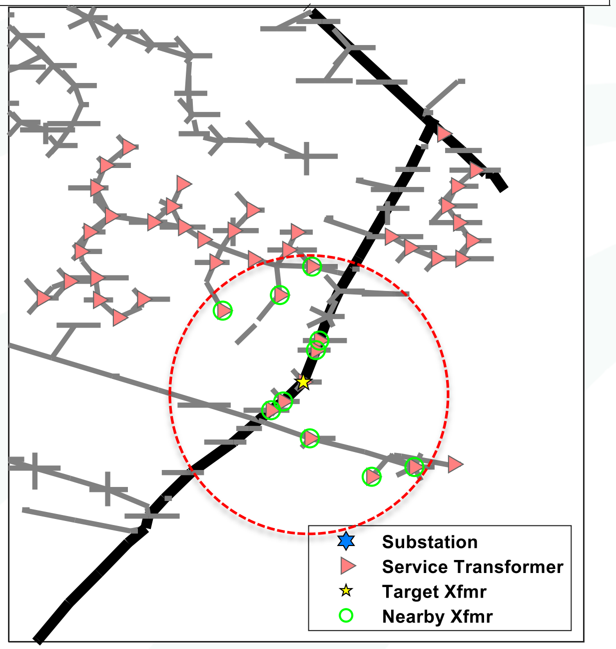
Transformers with Unknown Topology

- Assuming the topology was unknown, estimates of each transformer were calculated from "nearby" transformers on the same phase
  - Geographic distance is a proxy for electrical distance; multiple estimates limit the impact of pairing a transformer served by a different branch
- kVA selections for each transformer were made using
  - Avg. R estimate: **584/591 correct predictions** (98.82% accuracy)
  - Avg. X estimate: **569/591 correct predictions** (96.28% accuracy)
  - Best R estimate: **591/591 correct predictions** (100% accuracy)
  - Best X estimate: **584/591 correct predictions** (98.82% accuracy)





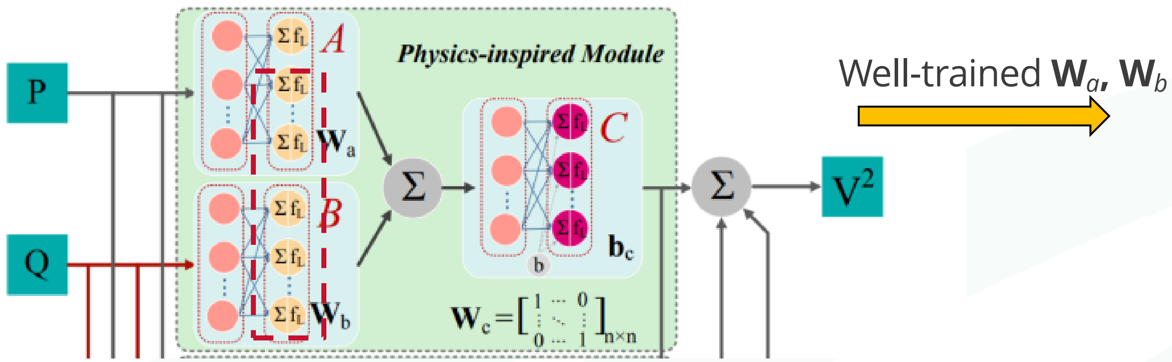


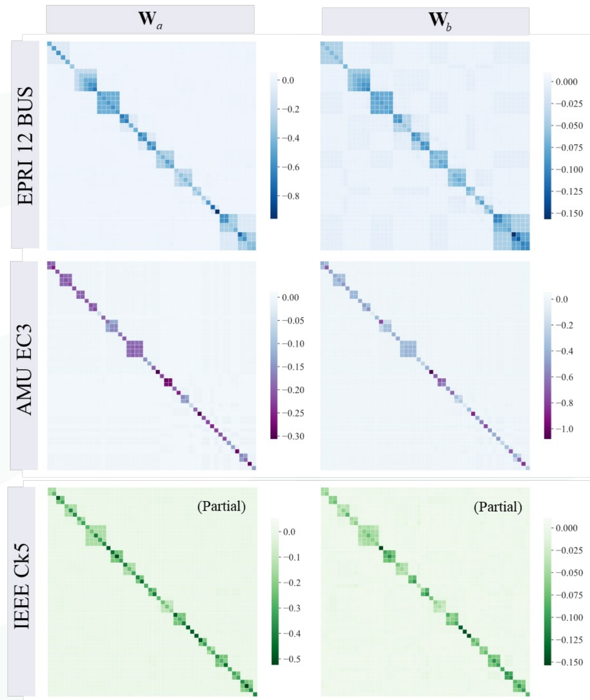


75 Years of Service NRECA America's Electric Cooperatives

[6] J. Azzolini, M. Reno, J. Yusuf, "A Model-free Approach for Estimating Service Transformer Capacity Using Residential Smart Meter Data," *IEEE Photovoltaic Specialists Conference (PVSC)*, 2023. *Under Review*.

PINN Model for Transformer-Cust. Connectivity





- Due to the designed structure, physics information, including the transformer-customer (TC) connection, can be learned by the "Physics-inspired Module."
- The simulation results of matrices W_a, W_b , which contain the physics information, are shown on the right.
- According to the W_a, W_b , a TC Connectivity Identification method is designed as an Application of the PINN model.

Simulation Results

- The method considers both load and voltage data together.
- The method is straightforward while showing good performance.

TC Connectivity Identification Results

Model	EPRI 12 Bus	AMU EC3	IEEE Ck5
Xfmr Number	12	40	584
Customer Number	46	50	1379
Correctly Identified	12	40	568
Accuracy Rate	100%	100%	97.3%

75 Years of Service
NRECA
America's Electric Cooperatives

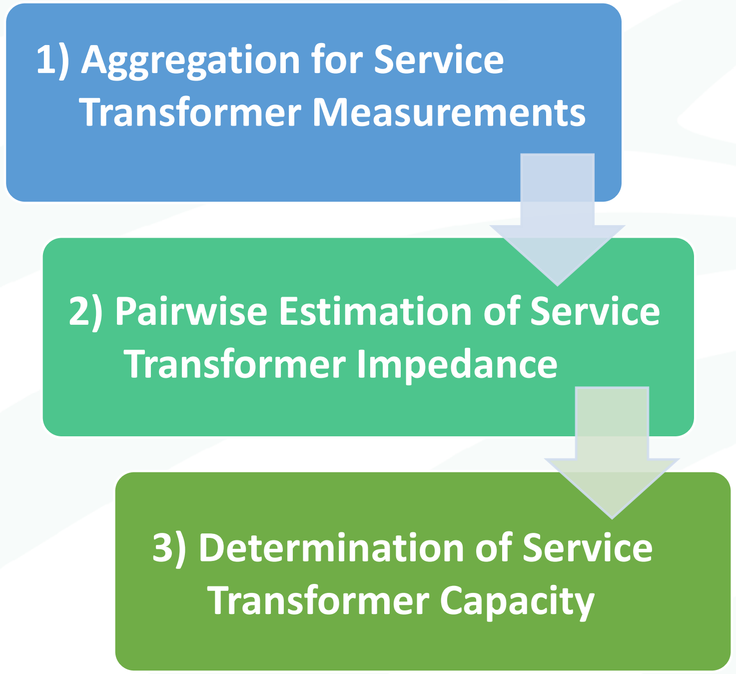
Model-free PINN Transformer Capacity Estimation

Objective:

- Determine the rated capacity (in kVA) of all service transformers on a given radial distribution feeder *without* any topology information or grid models

Inputs:

- Smart meter data for all customers
  - Includes historical P, Q, V measurements
  - Metadata (e.g., location, phase)
- Customer-transformer groupings
- Lookup table of known transformer types
  - kVA, R, and X for each transformer type

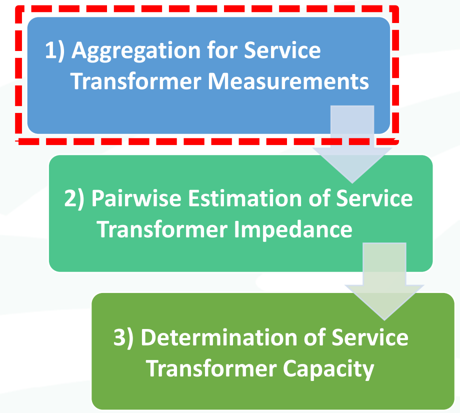


75 Years of Service
NRECA
America's Electric Cooperatives

[5] J. A. Azzolini, M. J. Reno, J. Yusuf, "A Model-free Approach for Estimating Service Transformer Capacity Using Residential Smart Meter Data," IEEE Photovoltaic Specialists Conference (PVSC), 2023.

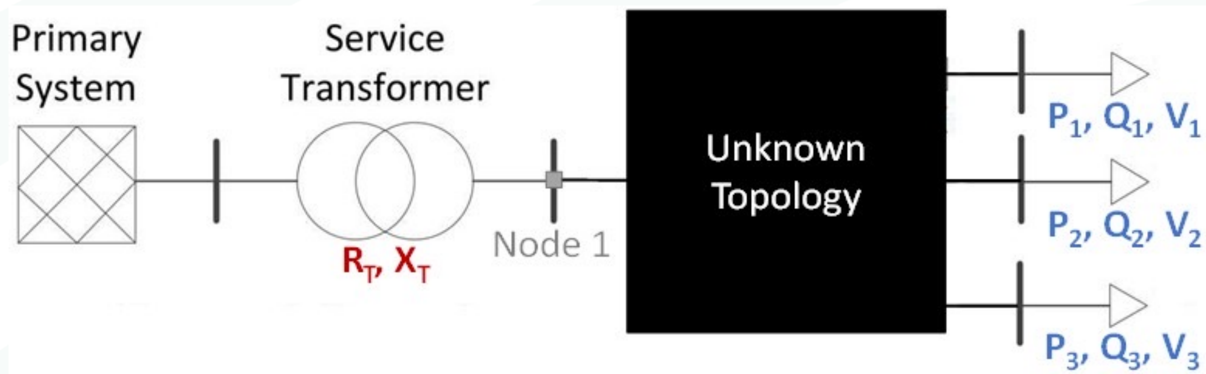
Aggregation for Transformer Measurements

- Apply filter to ensure uni-directional power flow from the transformer to the customers
  - This guarantees that LV terminal voltage will be highest
- Estimate Node 1 voltage iteratively using every possible combination of customer pairs
- Whichever pair has the highest average estimated voltage is selected



$$(V_1 - V_2) = -R_1 I_{R1} - X_1 I_{X1} + R_2 I_{R2} + X_2 I_{X2}$$

$$V_{Node1} = \frac{1}{N} \sum_{i=1}^{N} \left| \left| V_i + (R_i + jX_i)(I_{Ri} + jI_{Xi}) \right| \right|$$

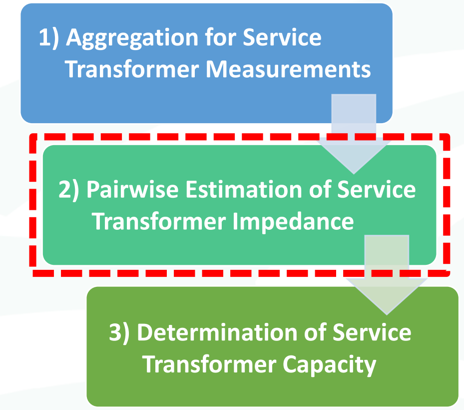


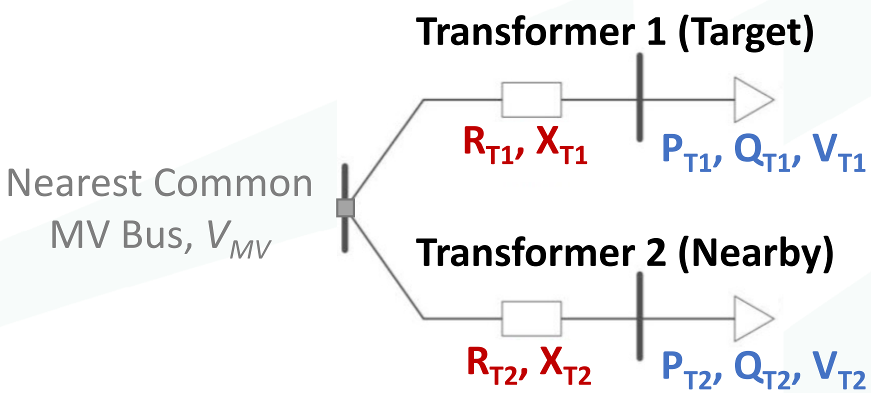
75 Years of Service NRECA America's Electric Cooperatives

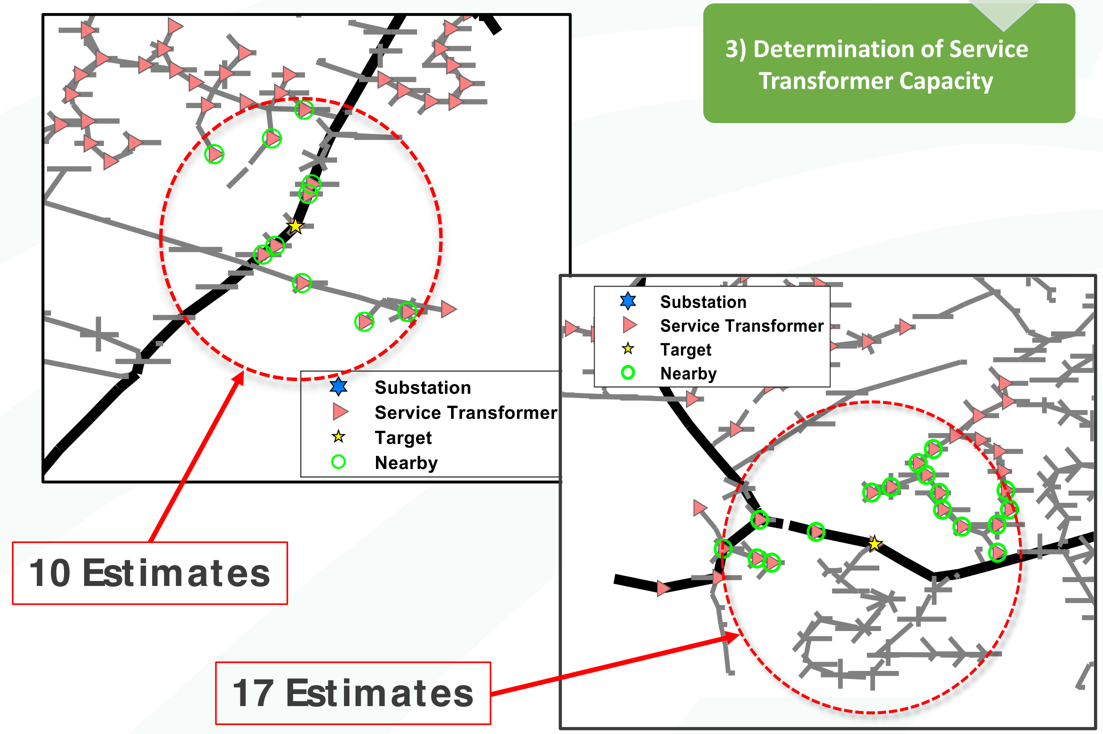
[5] J. A. Azzolini, M. J. Reno, J. Yusuf, "A Model-free Approach for Estimating Service Transformer Capacity Using Residential Smart Meter Data," IEEE Photovoltaic Specialists Conference (PVSC), 2023.

Pairwise Estimation of Service Transformer Impedance

- The same parameter estimation approach can be applied to calculate the service transformer R and X values
- Since the topology is unknown, multiple impedance estimates are generated for the target transformer by iteratively pairing it with nearby transformers (physically close)







[5] J. A. Azzolini, M. J. Reno, J. Yusuf, "A Model-free Approach for Estimating Service Transformer Capacity Using Residential Smart Meter Data," IEEE Photovoltaic Specialists Conference (PVSC), 2023.

Determination of Service Transformer Capacity

1) Aggregation for Service Transformer Measurements

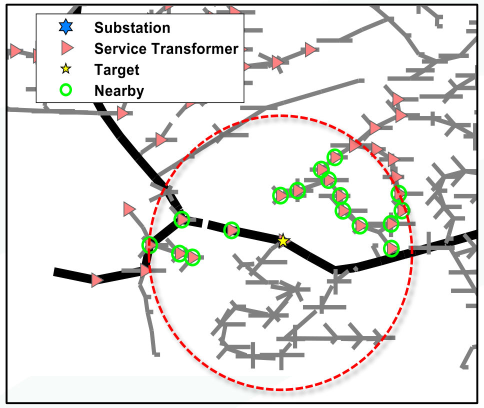
2) Pairwise Estimation of Service Transformer Impedance

3) Determination of Service Transformer Capacity

- The algorithm then uses a **weighted voting scheme** to combine the multiple estimates into a single kVA prediction, where the best matching R and X values from the lookup table receives a vote

$$Error = \min(|R_{est} - R_{Lookup}| + |X_{est} - X_{Lookup}|)$$

- The votes are then weighted according to the RMSE of the linear regression models
- After tallying the votes from the table and the remaining 11 estimates (not shown):
  - Transformer Type 3 = 79%
  - Transformer Type 4 = 14%
  - Transformer Type 5 = 7%
- The algorithm was correct since the target transformer was Type 3



$$WF_t = \frac{1/(RMSE_t)}{sum(1/RMSE_T)}$$

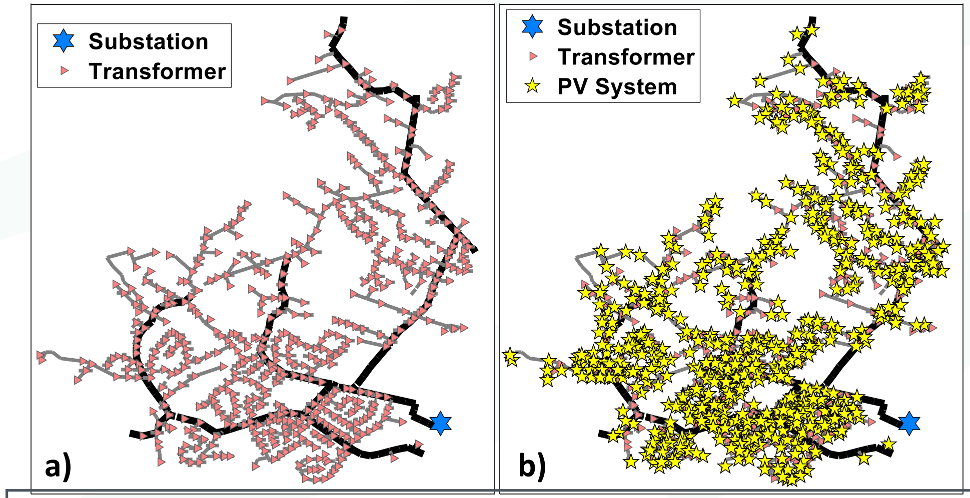
Distance from Target (ft)	R_{est} (Ω)	X_{est} (Ω)	Predicted ID (Table I)	WF (8)
375	0.0396	0.0566	3	0.107
486	0.0561	0.0291	4	0.046
529	0.0576	0.0300	4	0.042
540	0.0525	0.0361	3	0.050
544	0.0525	0.0343	3	0.057
587	0.0596	0.0227	5	0.038

75 Years of Service NRECA America's Electric Cooperatives

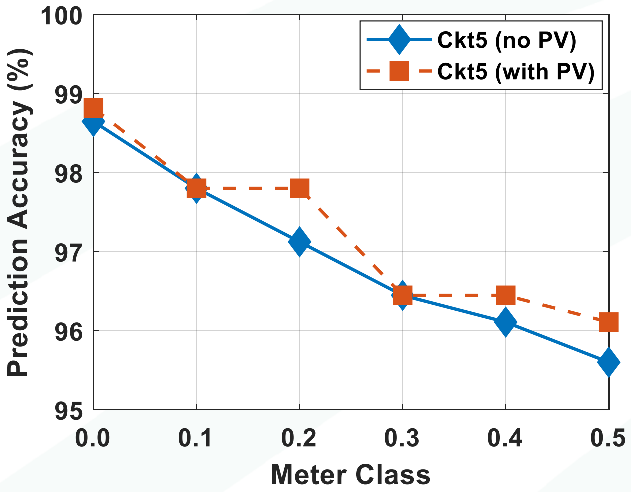
[5] J. A. Azzolini, M. J. Reno, J. Yusuf, "A Model-free Approach for Estimating Service Transformer Capacity Using Residential Smart Meter Data," IEEE Photovoltaic Specialists Conference (PVSC), 2023.

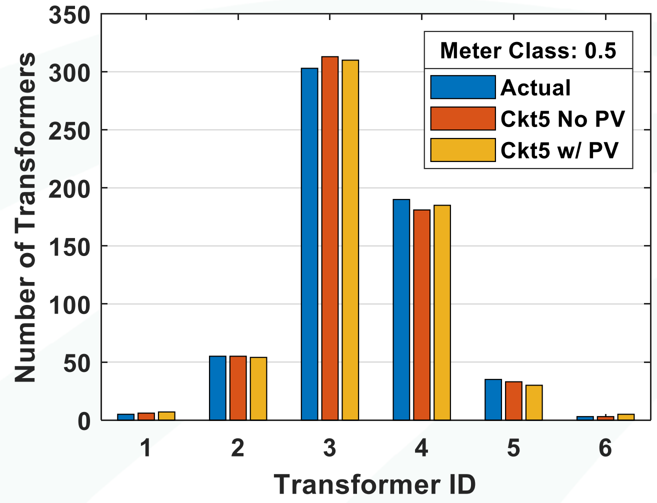
Thermal Hosting Capacity Summary

- Overall, the algorithm was accurate regardless of existing PV penetration and robust to noise
  - (Meter class 0.5 means all measurements were within ±0.5% of actual value)
  - Class 0.5 corresponds to lowest accuracy allowed by ANSI C12.1-2022
- Errors were distributed across different transformer types
- Total predicted cumulative thermal capacity was accurate within 1.01%



	Correct Predictions	Prediction Accuracy
Ckt5	583 / 591	98.65%
Ckt5 w/PV	584 / 591	98.82%





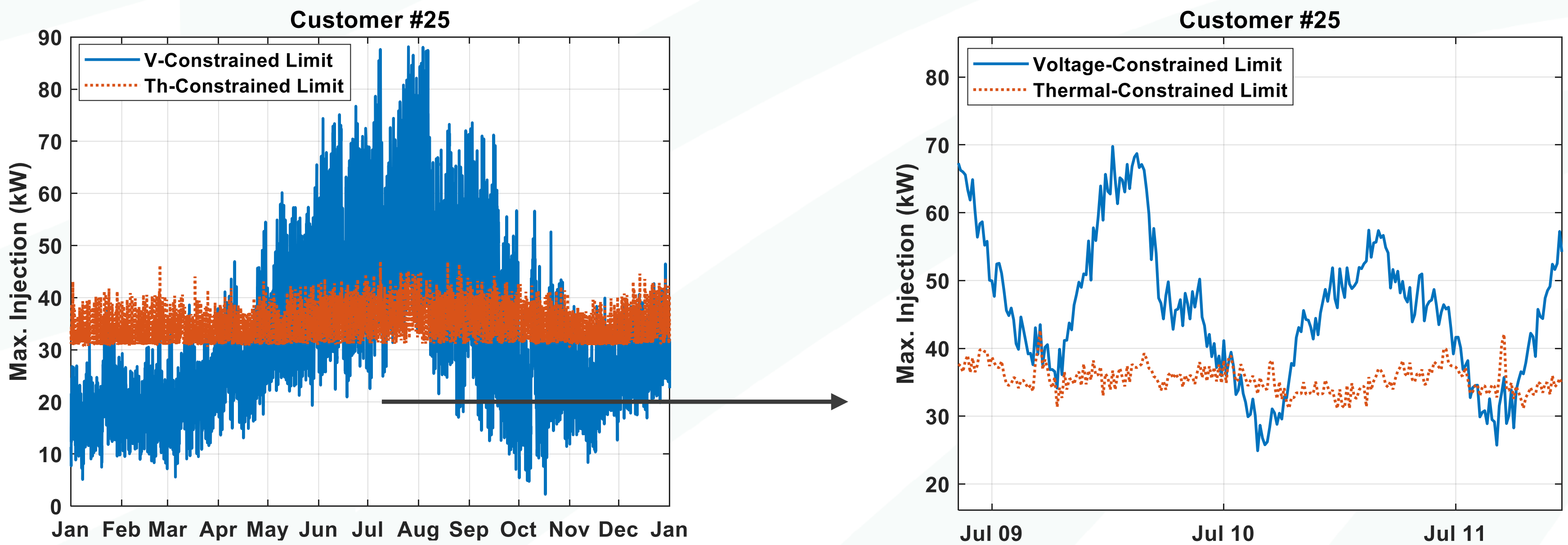
[5] J. A. Azzolini, M. J. Reno, J. Yusuf, "A Model-free Approach for Estimating Service Transformer Capacity Using Residential Smart Meter Data," IEEE Photovoltaic Specialists Conference (PVSC), 2023.

Subtask – Timeseries Analysis of Hosting Capacity

75 Years of Service
NRECA
America's Electric Cooperatives

Timeseries Modeling Introduction

- First, determine the largest magnitude of real power (kW) injections that can be accommodated at each time point
  - This step can be accomplished via model-based or model-free methods
- For this example, the voltage constraint was often the most limiting factor, but some days were limited by the thermal constraint

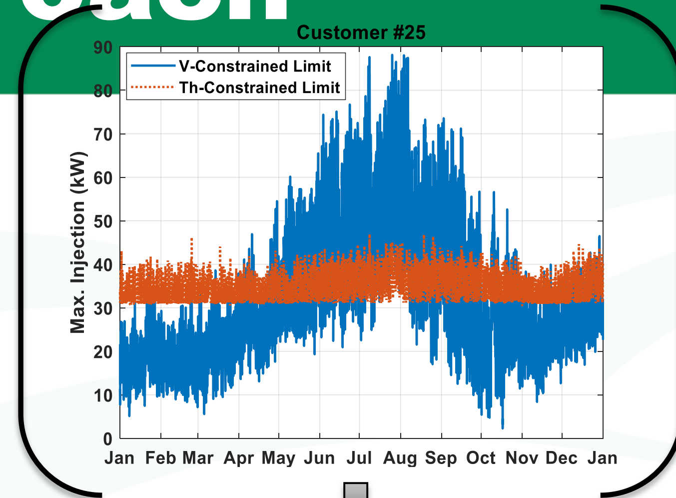


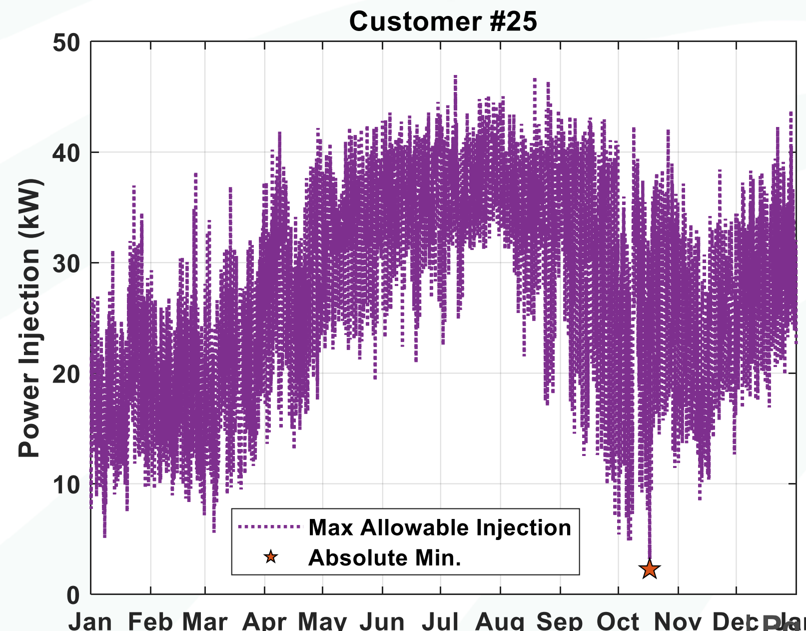
75 Years of Service NRECA America's Electric Cooperatives

Timeseries Modeling Approach

- We can simply look at the minimum of the two plots
- This is the upper limit of kW injections for any DER throughout the whole year
- To create a hosting capacity map, we have to distill this time-series down to a single value
- The most conservative approach would be to use the absolute min value to represent DER hosting capacity
  - Absolute min = **2.26 kW @ 4:30 am** in this case

min

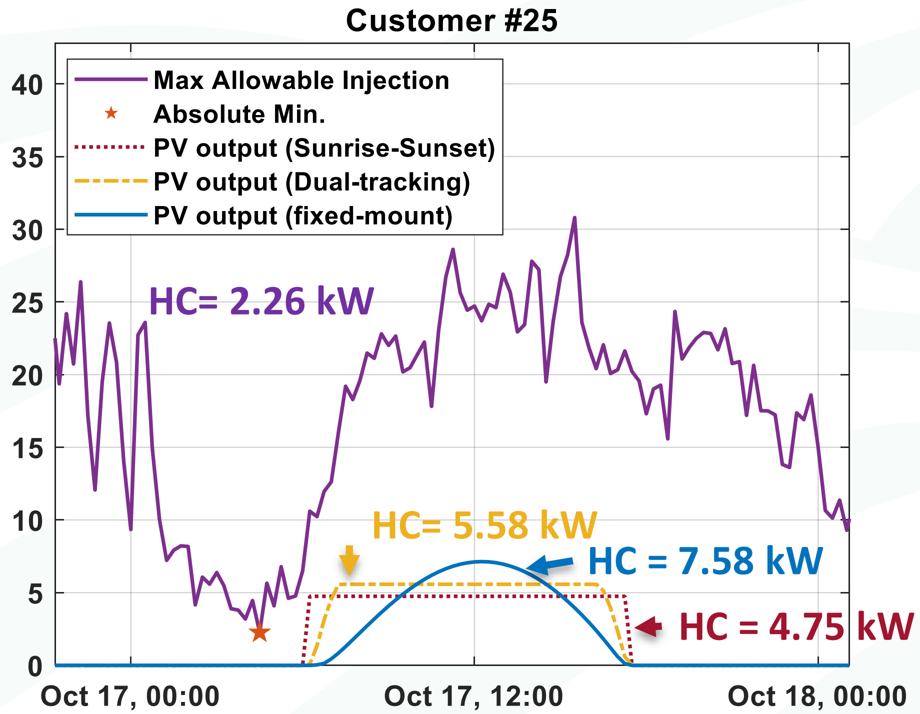




75 Years of Service
NRECA
America's Electric Cooperatives

Timeseries Approach Provides More Realistic Limits

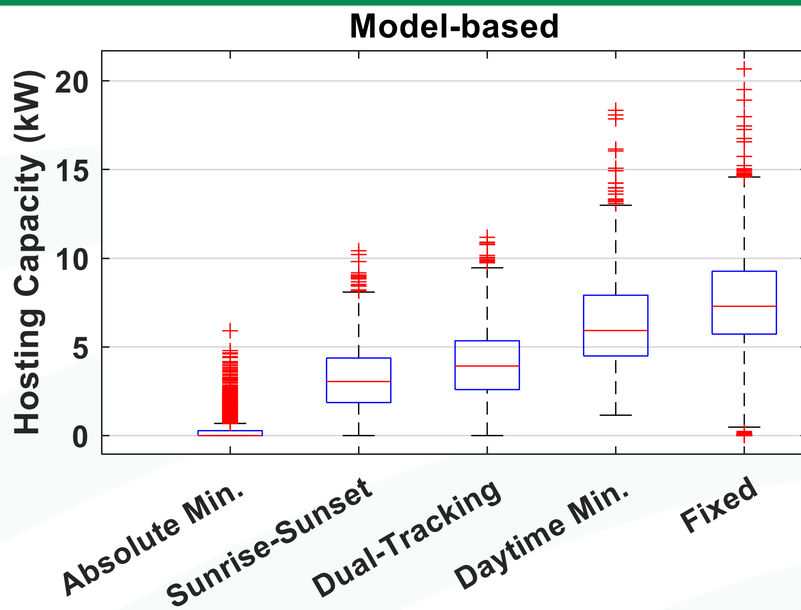
- Taking the absolute min value is likely overly conservative for PV HC
- We can still model the PV output conservatively in several ways (e.g., exclude losses, clear-sky, assume sun-tracking)
- The more info we have about the PV system means we can reduce the number of "worst-case" parameters, and get a more accurate HC value

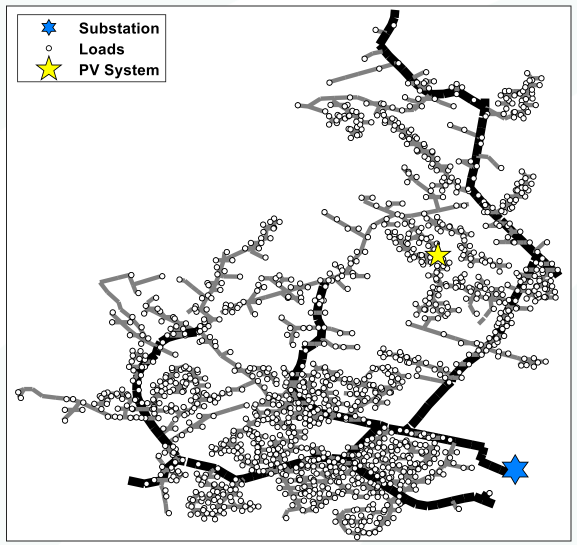


75 Years of Service NRECA America's Electric Cooperatives

Applying Timeseries Analysis to Full Circuit

- Repeating this process for all locations in modified version of EPRI Ckt5 using the **model-based** HC approach:
  - Mean(HC_absoluteMin) = **0.40 kW**
  - Mean(HC_sunrise-sunset) = **3.26 kW**
  - Mean(HC_dual) = **4.04 kW**
  - Mean(HC_daytimeMin) = **6.37 kW**
  - Mean(HC_fixed) = **7.55 kW**
- In practice, maybe conservative approach is fine for general HC maps but bringing in more details is needed for interconnections





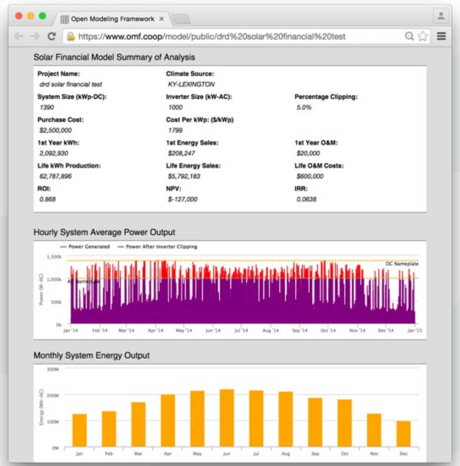
75 Years of Service
NRECA
America's Electric Cooperatives

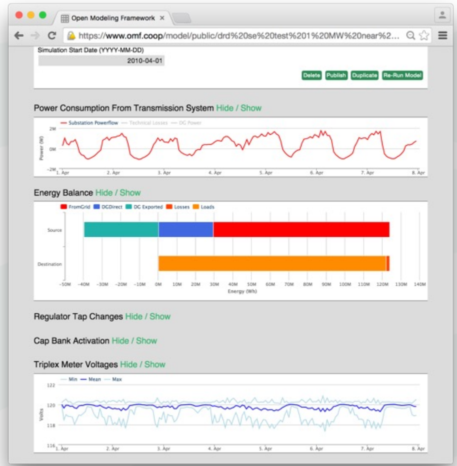
Task 4 - Integrate Algorithms into an OMF Application

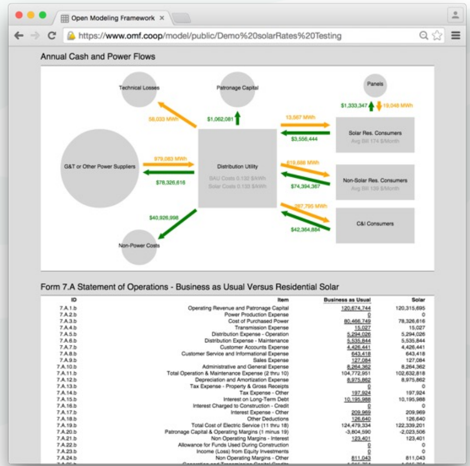
75 Years of Service
NRECA
America's Electric Cooperatives

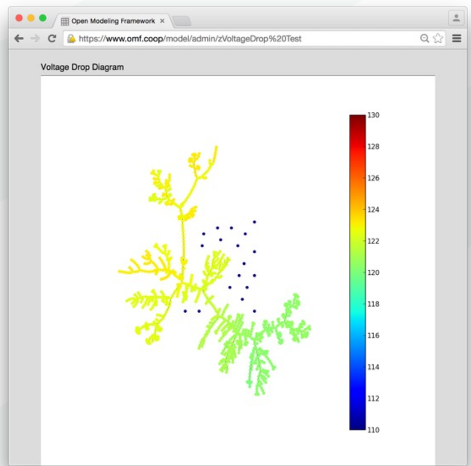
Open Modeling Framework – https://www.omf.coop

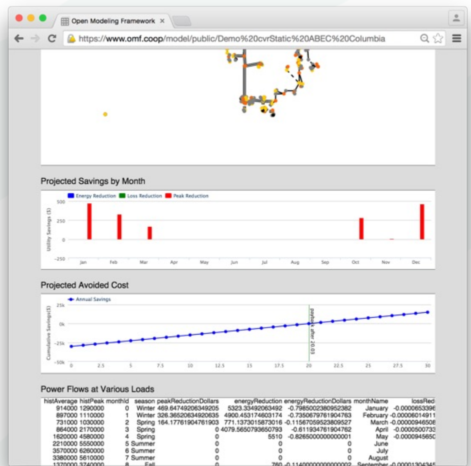
- Free and open source electric utility modeling software
- Built by the co-ops and the US Department of Energy (OE, EERE, ARPA-E)
- Offers models to determine:
  - Benefits of energy storage for arbitrage, peak demand reduction and asset upgrade deferral
  - Cost and financing options for utility-scale solar
  - Cashflow and engineering impacts of distributed generation
  - Full distribution dynamic powerflow simulation (for the ambitious)
- Users from 176 organizations (utilities, vendors, universities) as of June 2017.

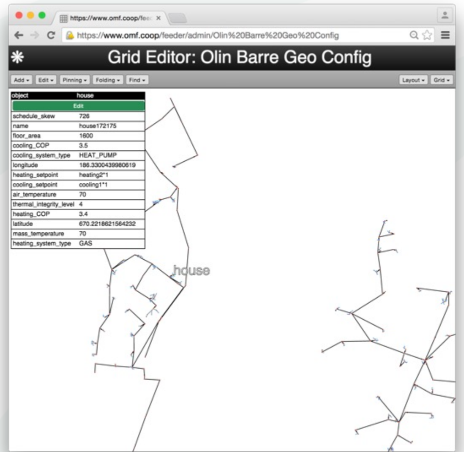












75 Years of Service
NRECA
America's Electric Cooperatives

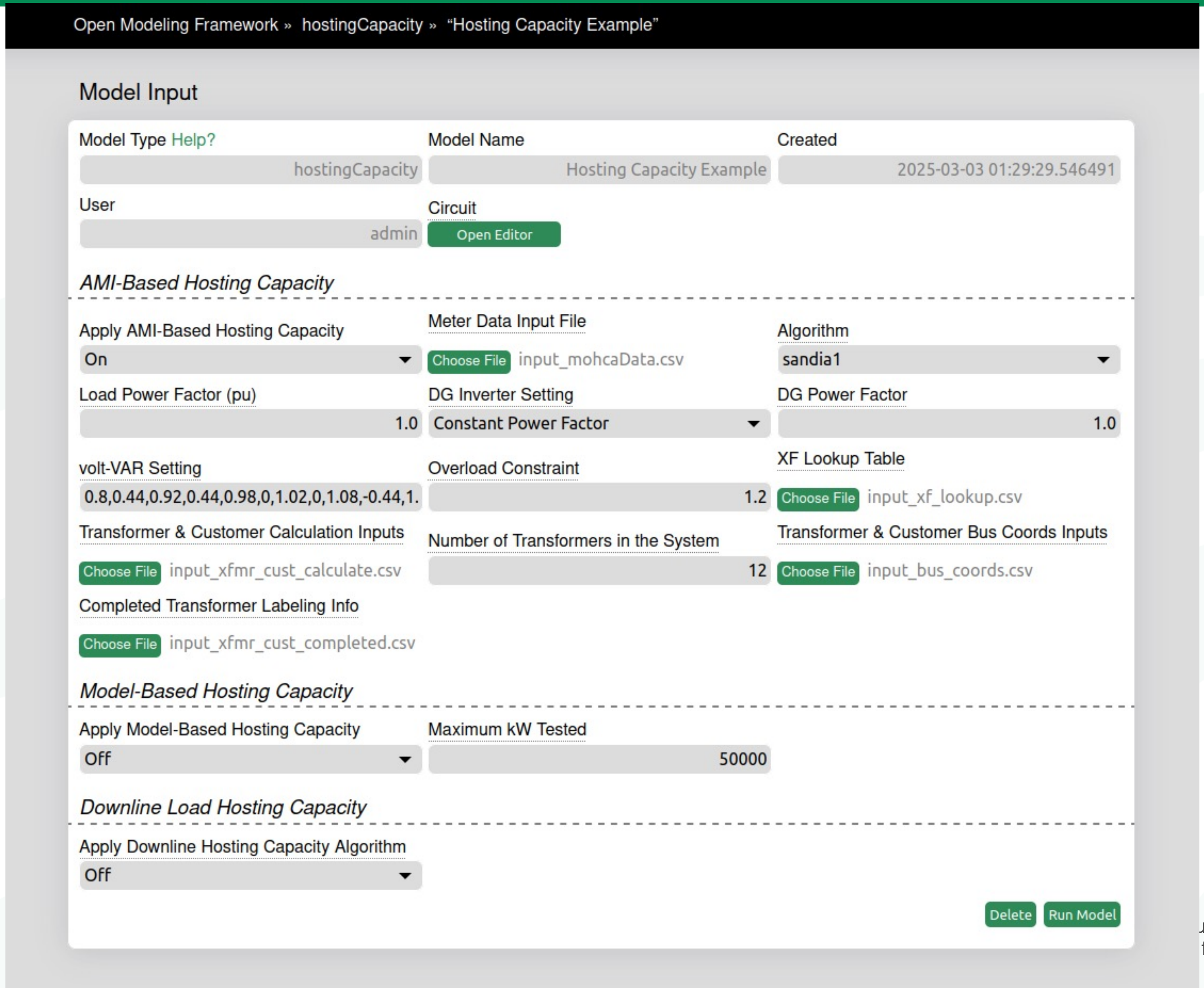
OMF Integration – Hosting Capacity

Users can create an instance of the model in the OMF

Circuit File Input

Standard Advanced Inverter Default Inputs

Model-Based Inputs



Model Inputs for Model-Free HC

Model-Free Thermal Hosting Capacity Arguments

Downline Load Algorithm (needs circuit to run)

urrent placeholders
future functionality

75 Years of Service NRECA America's Electric Cooperatives

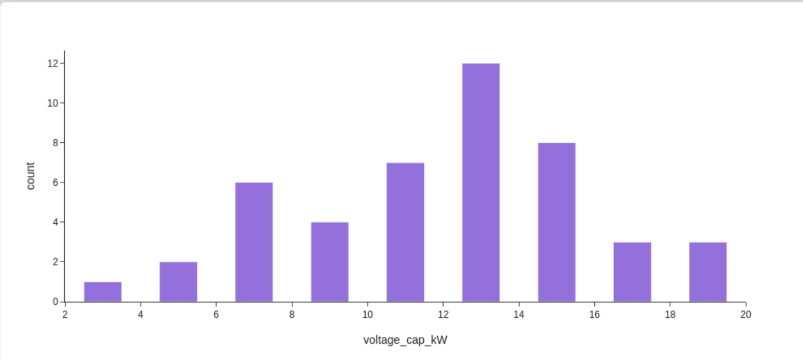
Model-Free V-HC Results Display

AMI-Based Hosting Capacity Runtime (H:M:S:MS)

00:00:03.563

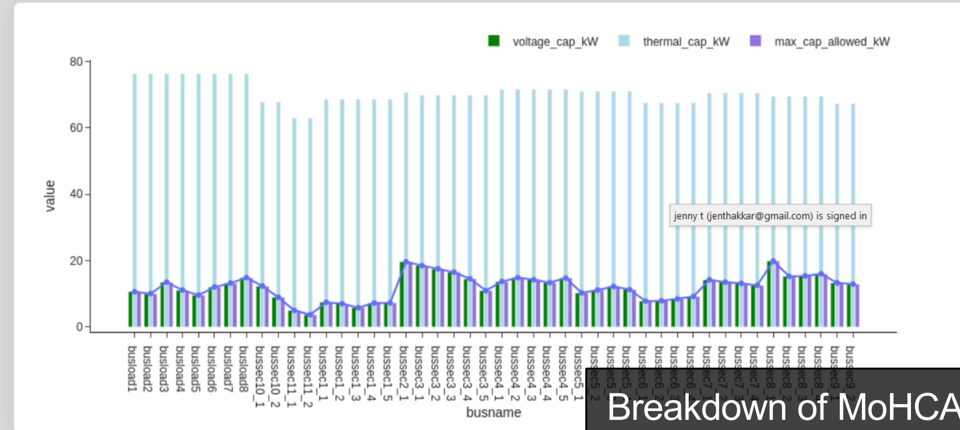
Runtime Tracking

AMI-Based Hosting Capacity Distribution



Distribution of MoHCA hosting capacities.

AMI-Based Hosting Capacity By Bus



Breakdown of MoHCA voltage versus thermal limits

AMI-Based Full Hosting Capacity Data Table

busname	voltage_cap_kW	thermal_cap_kW	max_cap_allowed_kW
busload1	10.673748084712866	76.34830831104881	10.673748084712866
busload2	10.03274271595919	76.34830831104881	10.03274271595919
busload3	13.51303516196088	76.34830831104881	13.51303516196088
busload4	11.121959384844097	76.34830831104881	11.121959384844097
busload5	9.600178982441768	76.34830831104881	9.600178982441768
busload6	12.062887194881814	76.34830831104881	12.062887194881814
busload7	13.216178166722733	76.34830831104881	13.216178166722733
busload8	14.909682412917368	76.34830831104881	14.909682412917368
bussec10_1	12.33987290842344	67.7761225967042	12.33987290842344

Model-Free Full Raw Data Table

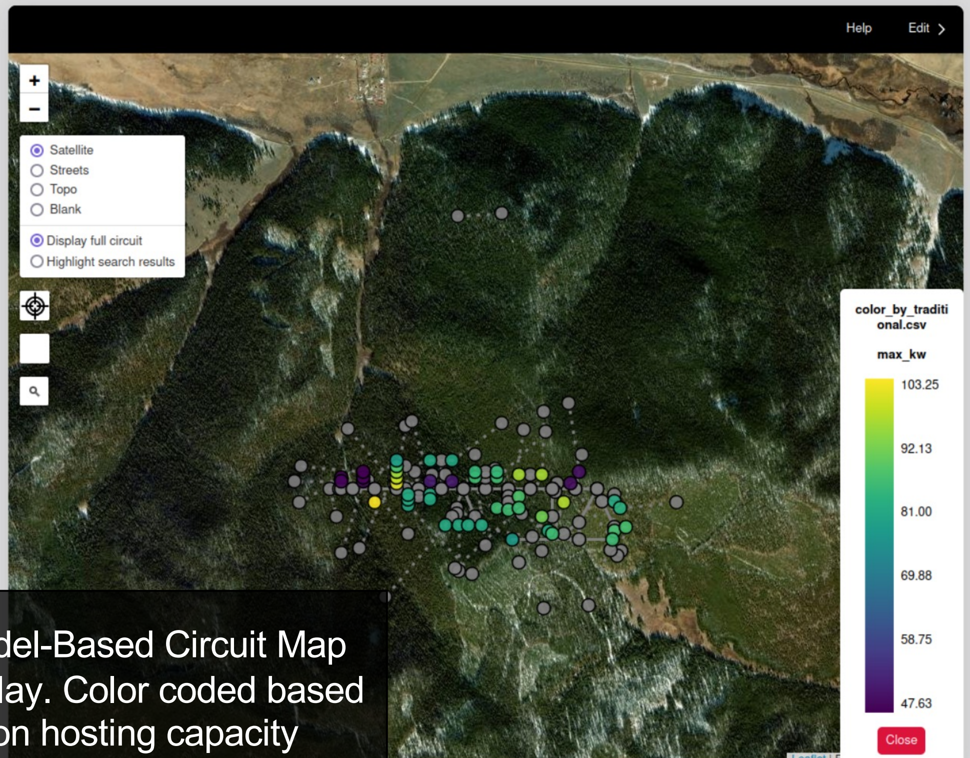
Hosting Map Generation and Export

Traditional/Model-Based Hosting Capacity Runtime (H:M:S:MS)

00:00:10.958

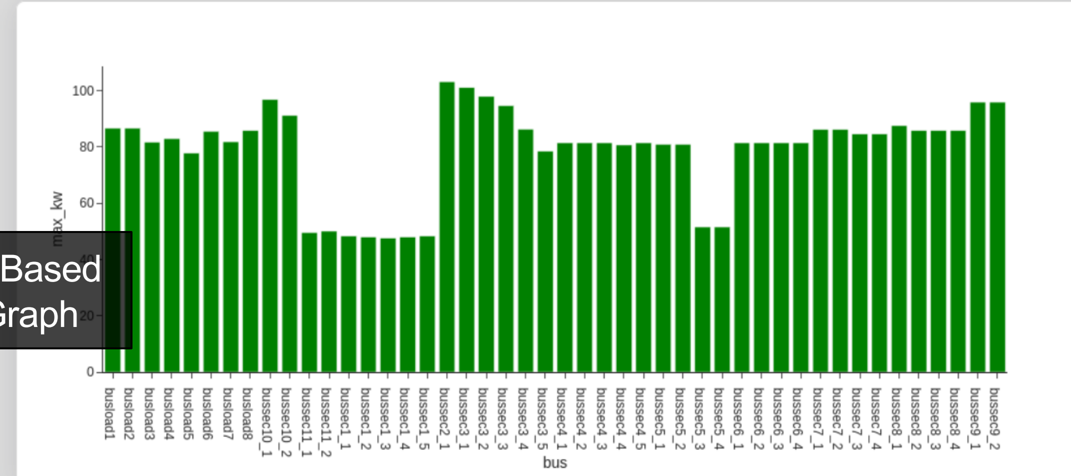
Model-Based Runtime

Traditional Hosting Capacity Map



Model-Based Circuit Map Display. Color coded based on hosting capacity

Traditional/Model-Based Hosting Capacity By Bus



Model-Based Bar Graph

Traditional/Model-Based Hosting Capacity Full Data Table

bus	max_kw	reached_max	thermally_limited	voltage_limited
bussec7_2	86.25	True	True	False
bussec7_3	84.625	True	True	False
bussec7_4	84.625	True	True	False
bussec8_1	87.625	True	True	False
bussec8_2	85.875	True	True	False
bussec8_3	85.875	True	True	False
bussec8_4	85.875	True	True	False
bussec9_1	96.0	True	True	False
bussec9_2	96.0	True	True	False

Model-Based Full Raw Data Table

75 Years of Service

NRECA

America's Electric Cooperatives

Downline Load Comparison Option

Downline Load Hosting Capacity Runtime (H:M:S:MS)

00:00:00.003

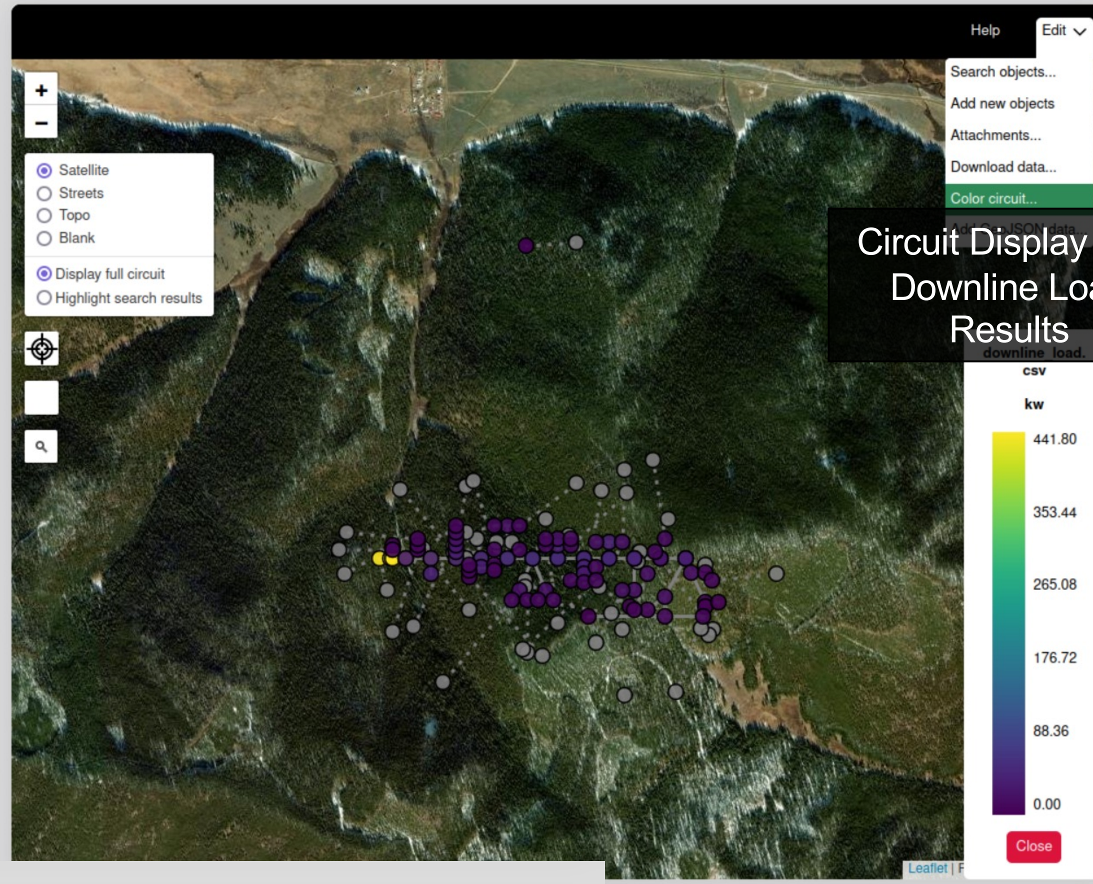
Downline Load Hosting Capacity Full Data Table

Load = generation - storage - pvsystem

bus	kw
busload1	1.6
busload2	1.2
busload3	5.2
busload4	8.3
busload5	2.6
busload6	8.4
busload7	1.8
busload8	5.7
buslv1	16.3

Downline Load Runtime and Full Raw Data Table

Traditional Hosting Capacity Map



Circuit Display with Downline Load Results

Raw Input and Output Files

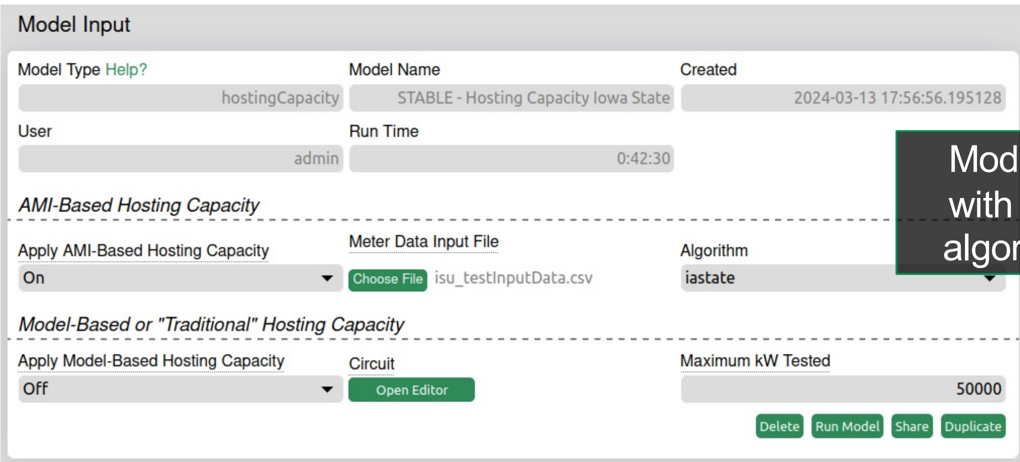
secondary.dss — volts.csv — HOSTCAP.dss — input_mohcaCustom.csv — allInputData.json — geoJson_offline.html — output_tradHC.csv — downlineLoad.dss — secondarytestcircuit_EXP_VOLTAGES.csv — protractor-colored.png — secondary.omd — output_downline_load.csv — output_MoCHa.csv — color_by_traditional.csv — circuit.dss — spinner.gif — color_test.omd — overloads.csv — PPID.txt — protractor.png — allOutputData.json

Raw Files for Download

75 Years of Service NRECA America's Electric Cooperatives

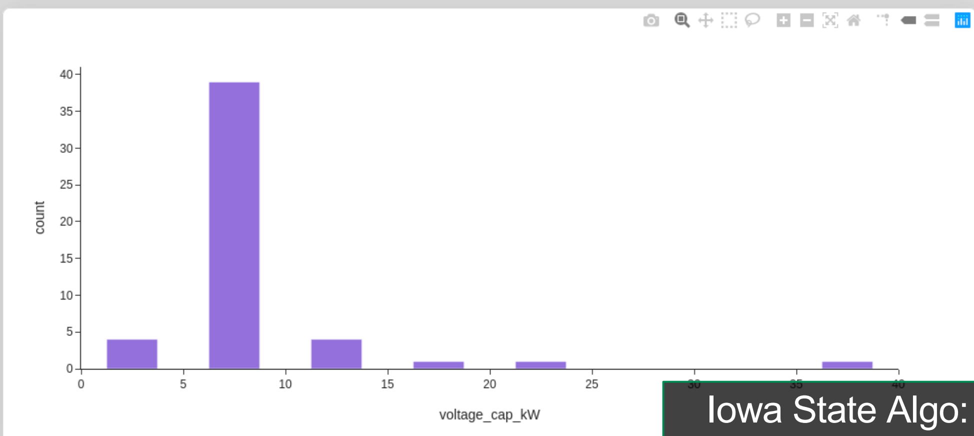
DNN HC – Iowa State Results Display

Model-free PINN-based algorithm



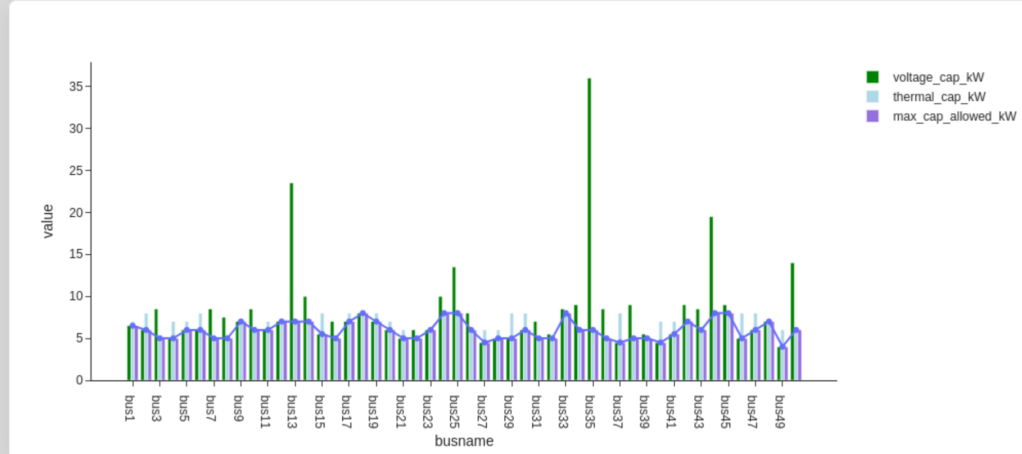
Model Creation with Iowa State algorithm option

AMI-Based Hosting Capacity Distribution



Iowa State Algo: Runtime and distribution outputs

AMI-Based Hosting Capacity By Bus



AMI-Based Full Hosting Capacity Data Table

busname	voltage_cap_kW	thermal_cap_kW	max_cap_allowed_kW
bus24	10.0	8	8.0
bus33	8.5	8	8.0
bus45	9.0	8	8.0
bus44	19.499999999999996	8	8.0
bus18	8.0	8	8.0
bus25	13.5	8	8.0
bus48	7.0	7	7.0
bus19	7.0	8	7.0
bus42	8.999999999999998	7	7.0
bus9	7.0	7	

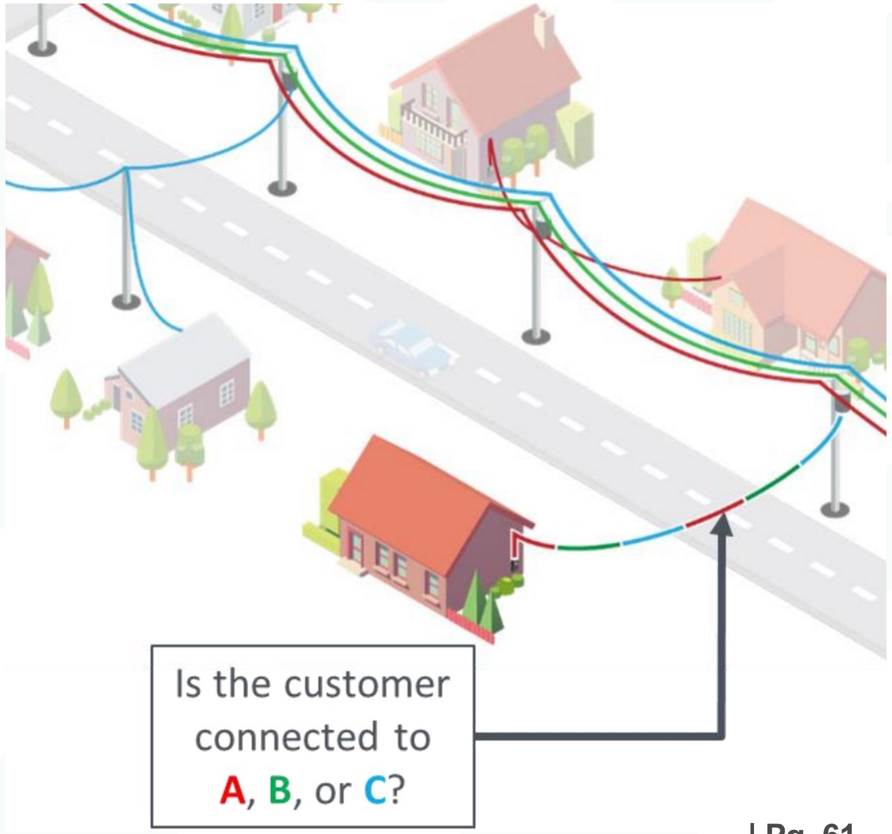
Iowa State Algo: Output by bus visual and data table

75 Years of NRECA America's Electric Cooperatives

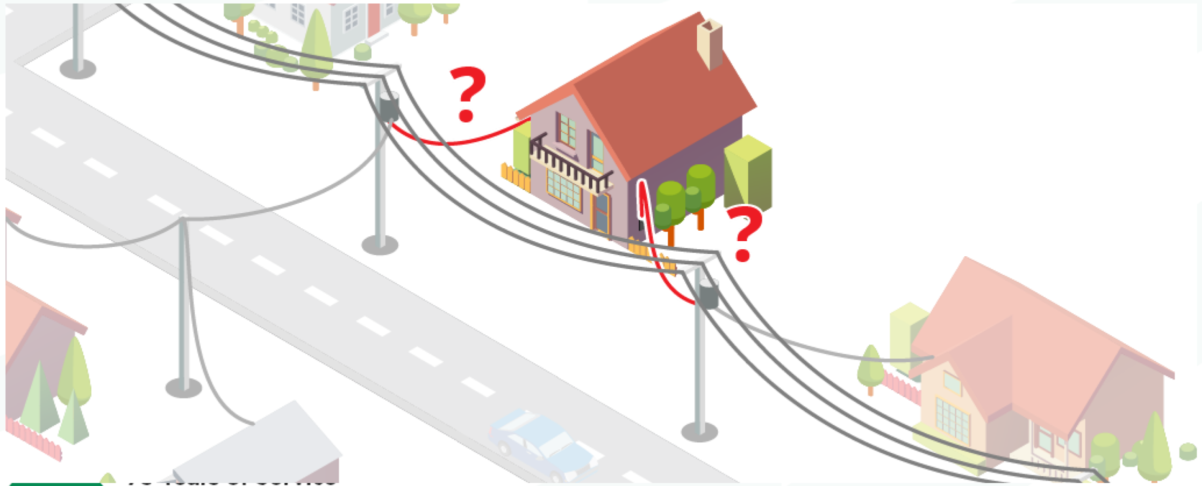
Transformer Pairing and Phase ID Background

- Accurate information regarding customer-to-transformer groupings and customer phase connections can improve the performance of the MoHCA algorithms
- Data-driven algorithms for both tasks have been integrated with OMF

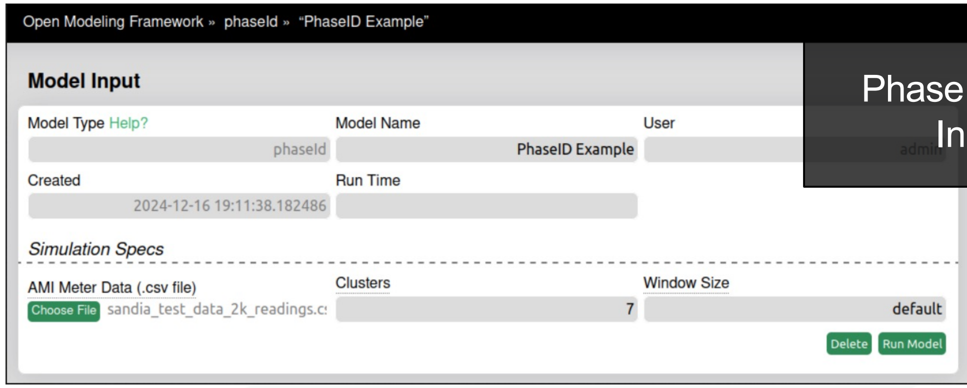
Phase Identification



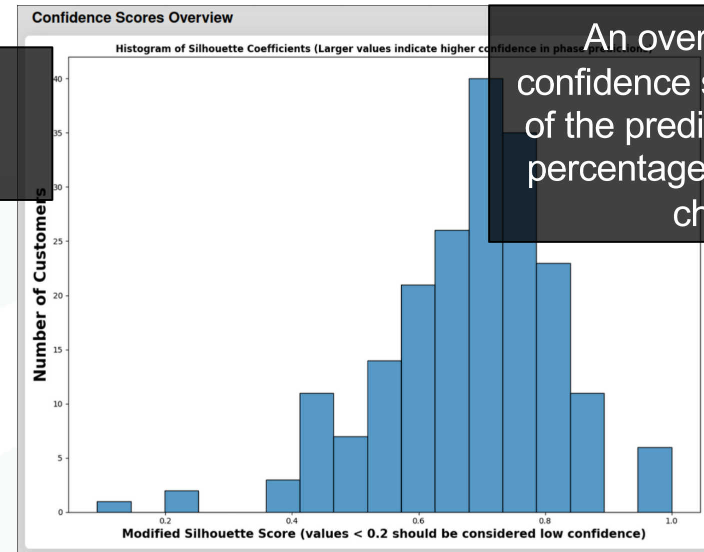
Customer-to-Transformer Mapping



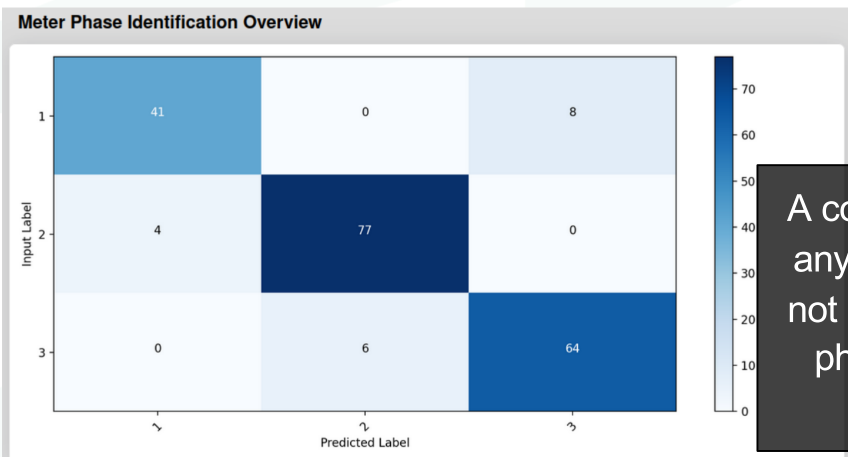
OMF Integration – PhaseID Results



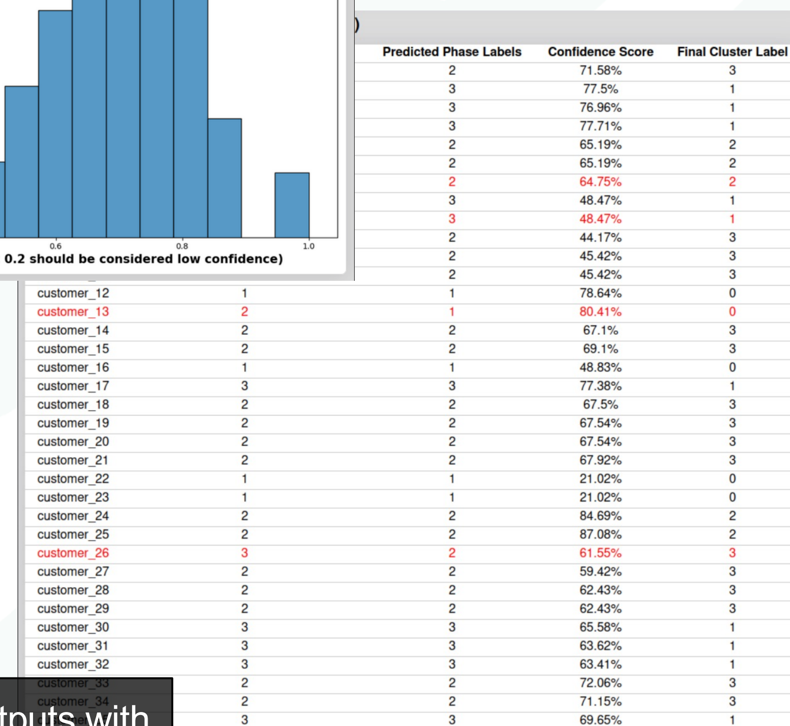
PhaseID Model Inputs



An overview of the confidence scores for each of the predictions, and the percentage of meters that change



A confusion matrix, showing any meters whose label did not match the predicted true phase in the off-diagonal entries



		Predicted Phase Labels	Confidence Score	Final Cluster Label
		2	71.58%	3
		3	77.5%	1
		3	76.96%	1
		3	77.71%	1
		2	65.19%	2
		2	65.19%	2
		2	64.75%	2
		3	48.47%	1
		3	48.47%	1
		2	44.17%	3
		2	45.42%	3
		2	45.42%	3
customer_12	1	1	78.64%	0
customer_13	2	1	80.41%	0
customer_14	2	2	67.1%	3
customer_15	2	2	69.1%	3
customer_16	1	1	48.83%	0
customer_17	3	3	77.38%	1
customer_18	2	2	67.5%	3
customer_19	2	2	67.54%	3
customer_20	2	2	67.54%	3
customer_21	2	2	67.92%	3
customer_22	1	1	21.02%	0
customer_23	1	1	21.02%	0
customer_24	2	2	84.69%	2
customer_25	2	2	87.08%	2
customer_26	3	2	61.55%	3
customer_27	2	2	59.42%	3
customer_28	2	2	62.43%	3
customer_29	2	2	62.43%	3
customer_30	3	3	65.58%	1
customer_31	3	3	63.62%	1
customer_32	3	3	63.41%	1
customer_33	2	2	72.06%	3
customer_34	2	2	71.15%	3
[illegible]	3	3	69.65%	1

PhaseID Outputs with Original and Predicted Correct Phases

75 Years of Service NRECA America's Electric Cooperatives

OMF Integration – Transformer Pairing Results

Customer to Transformer Pairing Analysis

Model Input

Model Type Help?: transformerPairing
Model Name: STABLE - Default Trans Pairing Customer DI
Created: 2024-03-13 18:01:17.371135
User: admin
Run Time: 0:00:55
Voltage AMI - Data Input File: Choose File voltageData_AMI.csv
Real Power - AMI Data Input File: Choose File realPowerData_AMI.csv
Customer ID Data - AMI Data Input File: Choose File CustomerIDs_AMI.csv
Choose Algorithm: Customer Distance Based or Reactive Power Based: Customer LatLong
Customer Latitude & Longitutde - AMI Data Input File: Choose File CustomerLatLon.csv
Reactive Power - AMI Data Input File: Choose File reactivePowerData_AMI.csv

Delete | Run Model | Share | Duplicate

OMF Model inputs: AMI Data

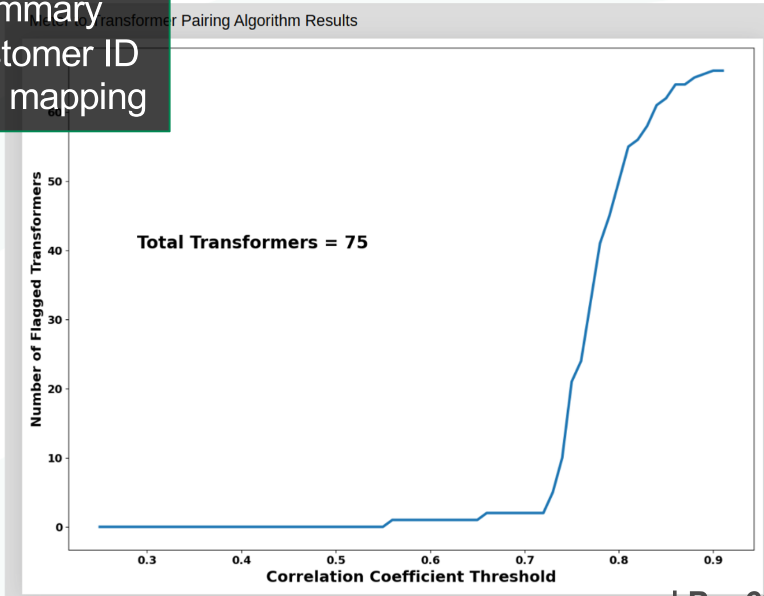
Customers Whose Transformer Labels/Groupings Have Changed

customer ID	Original Transformer Labels (with Errors)	Predicted Transformer Labels
customer_0	1.0	-2.0
customer_1	1.0	-2.0
customer_2	449.0	-2.0
customer_31	59.0	-1.0
customer_32	59.0	-1.0
customer_33	124.0	-1.0

Improvement Stats

Num of incorrect transformers before	Num of incorrect transformers after	Total transformer improvement	Improvement percentage
4	0	4	100.0

Results summary based on customer ID and corrected mapping



75 Years of Service NRECA America's Electric Cooperatives

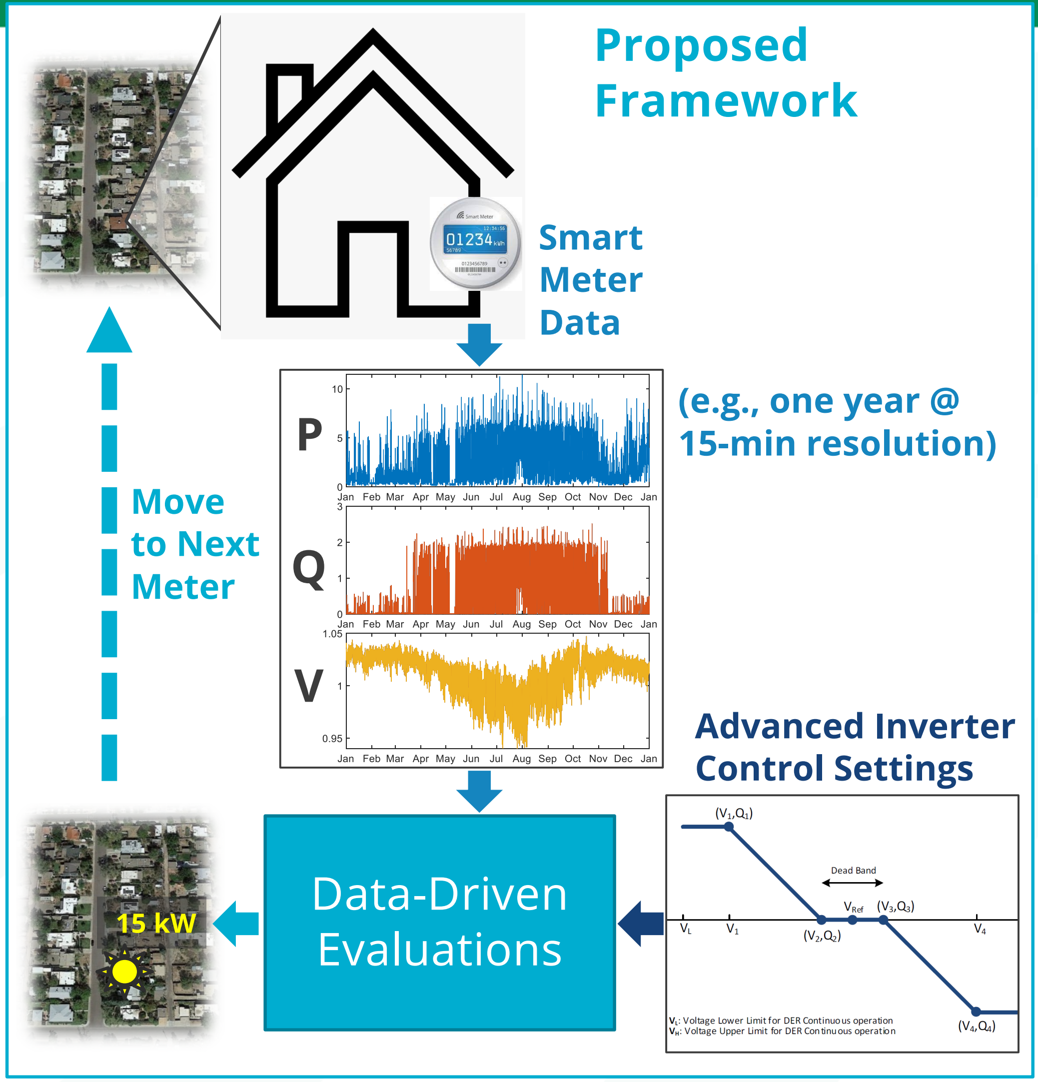
Task 5 - Develop Algorithms for Assessing the Impact of Advanced Inverter Operation Modes

75 Years of Service
NRECA
America's Electric Cooperatives

Evaluating Advanced Inverter Functions

Background / Methodology

- Advanced inverter functions like **Volt-VAR** are **required** by IEEE 1547 and becoming standardized by many utilities/PUCs to:
  - Mitigate voltage & thermal issues
  - Prevent excess reverse power flows
  - Increase PV hosting capacity (HC)
  - Improve the dispatchability of PV
  - Offset the need for grid upgrades



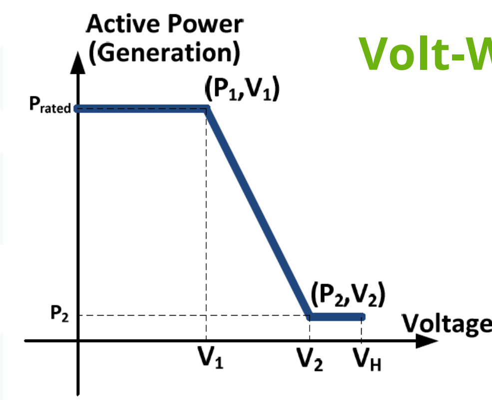
75 Years of Service NRECA America's Electric Cooperatives

1. J. A. Azzolini, M. J. Reno, J. Yusuf, S. Talkington, and S. Grijalva, "Calculating PV Hosting Capacity in Low-Voltage Secondary Networks Using Only Smart Meter Data," in IEEE Innovative Smart Grid Technologies NA, 2023.

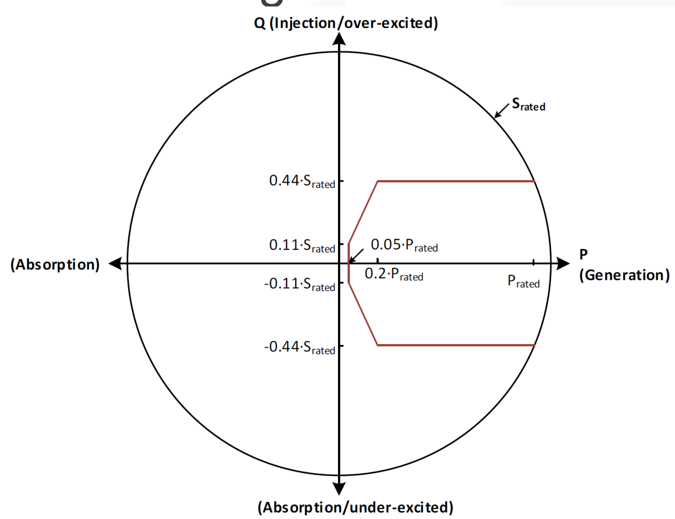
Prior Work to Future Goals

- We built on prior work[1] to include the capability of evaluating advanced inverter control functions
  - **Constant power factor (PF)** and **autonomous Volt-VAR**
  - Framework can be applied to **any function** that manipulates PV real and reactive power outputs
  - Applicable to any inverter-based DER, such as **energy storage** or **electric vehicles**
- The goal of out methods is to evaluate the effects on PV HC, not determining optimal settings

Volt-WATT

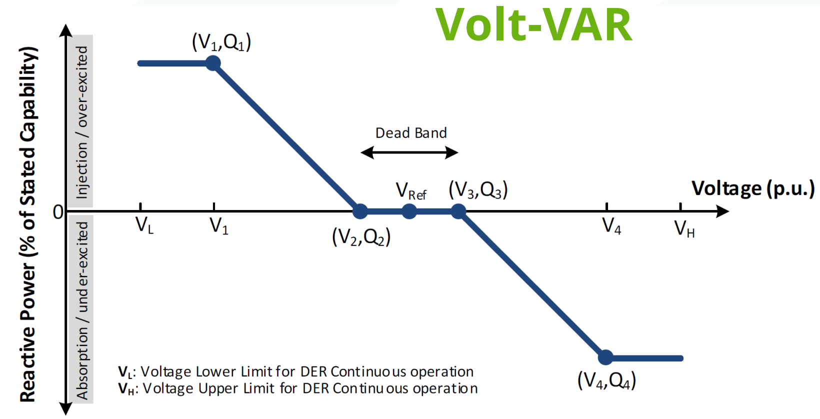


Minimum Q capability



Category B

Volt-VAR

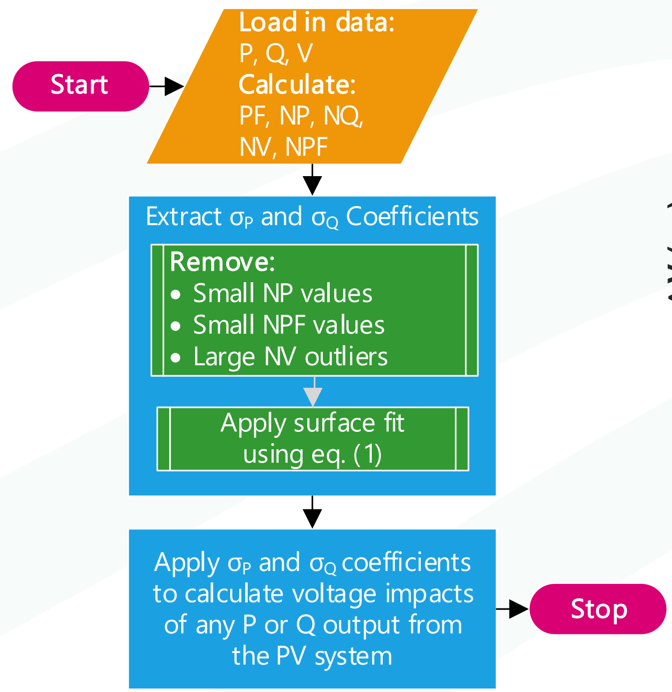


Evaluating Advanced Inverter Functions

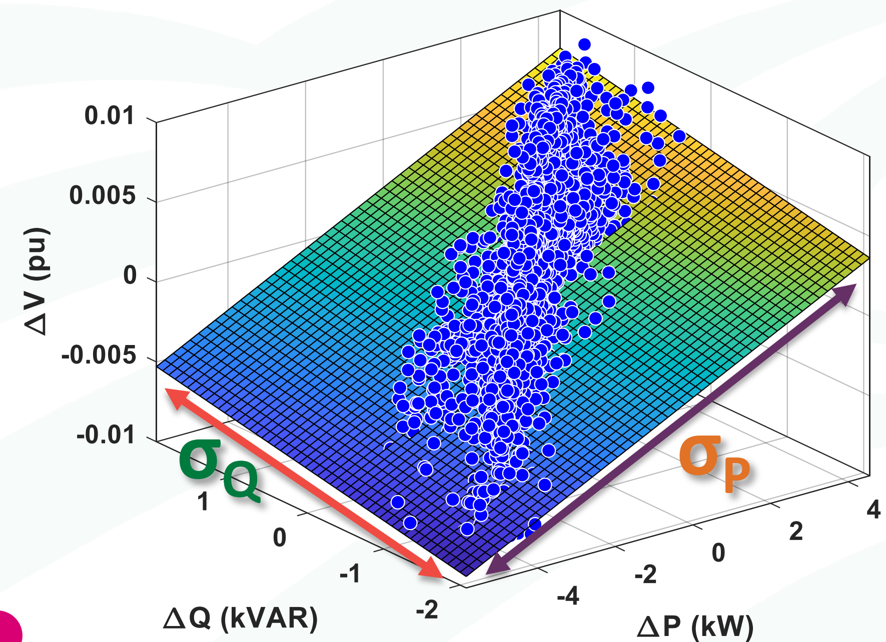
Methodology

The main steps are to:

1. **Load** in the yearlong time-series data from a smart meter and calculate additional variables
2. **Filter** the data and apply the surface fit to extract the coefficients of voltage changes due to real and reactive power changes, σ_P and σ_Q
3. **Use** those coefficients for DER impact analyses, such as voltage-constrained hosting capacity (VCHC)



$$\Delta V = (\sigma_P \times \Delta P) + (\sigma_Q \times \Delta Q) \qquad (1)$$

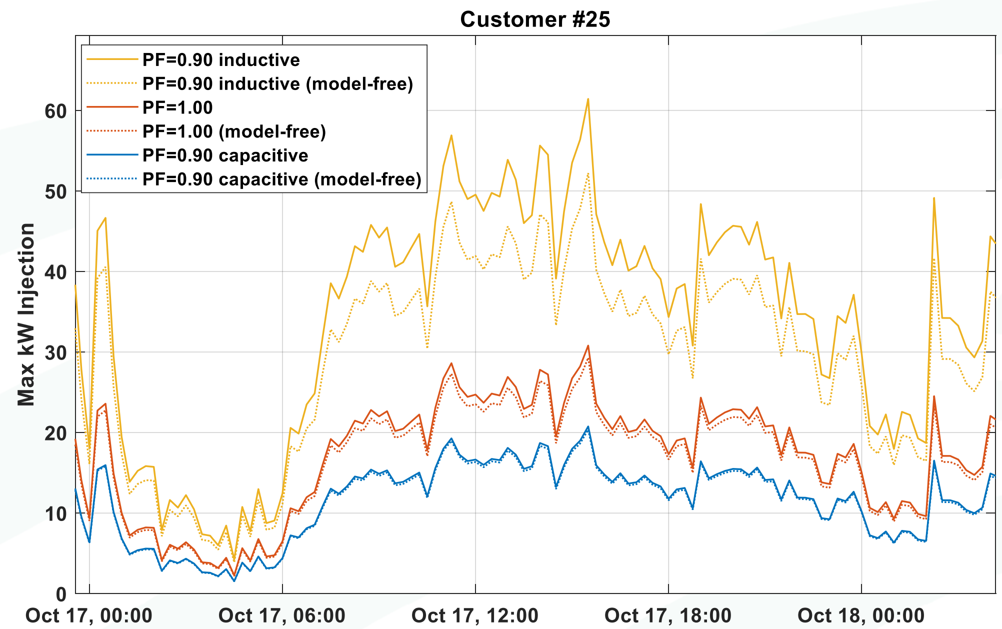


Blue dots are one year of filtered smart meter data

75 Years of Service NRECA America's Electric Cooperatives

Constant Power Factor Mode Results

- The maximum PV kW injections (not causing 1.05 Vpu) were calculated using both methods
- As anticipated, the capacitive PF resulted in the lowest values of kW_{Max}
- More extrapolation led to more errors, but more accurate at times when PV is most limited
- The data-driven method was able to determine the HC within 1 kW of the model-based results for all cases

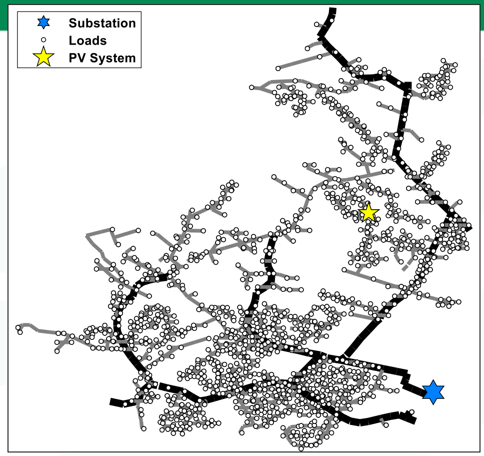


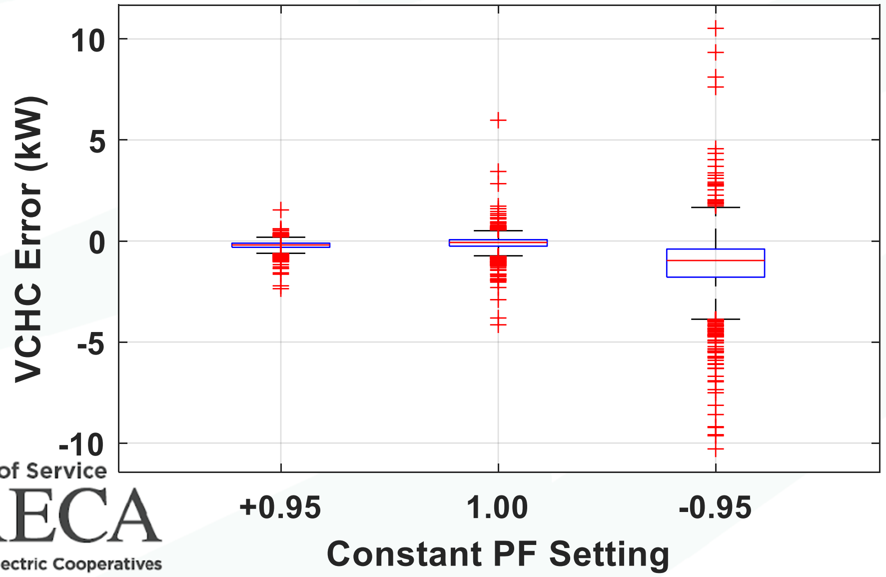
PV PF	HC Model-based	HC Data-Driven	Error
PF = 0.9 capacitive	3.24 kW	3.18 kW	-0.06 kW
PF = 1.0 unity	4.75 kW	4.58 kW	-0.17 kW
PF = 0.9 inductive	9.04 kW	8.16 kW	-0.88 kW

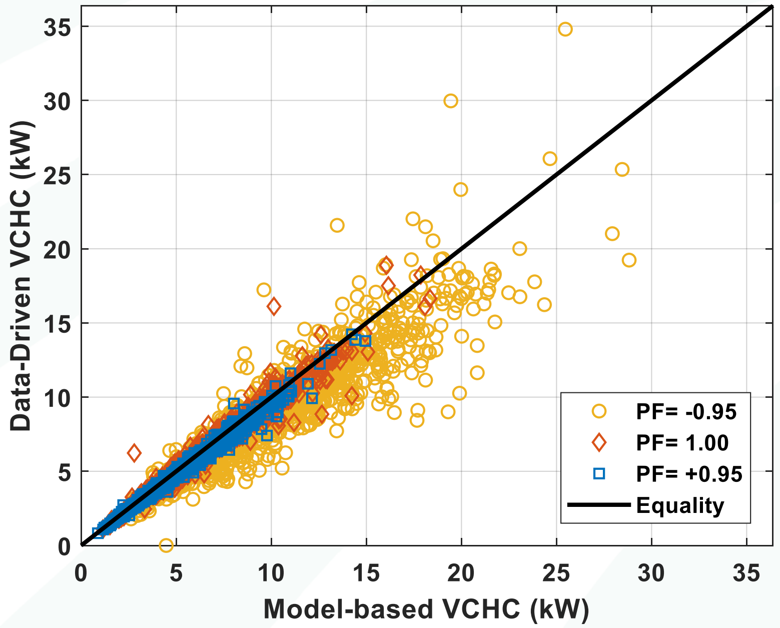
75 Years of Service NRECA America's Electric Cooperatives

Model-Free HC Leads to Large Performance Improvements

- For all 1379 customer locations, **the average** VCHC results were **[4.93, 6.26, 8.89] kW**, which correspond to inverter ratings of **[5.19, 6.26, 9.36] kVA** for the **[+0.95, 1.00, -0.95] PFs**
- Compared to the model-based results, the mean absolute errors (MAEs) were **[0.25, 0.27, 1.62] kW**
- The proposed framework took **<6 minutes** to calculate all results, whereas the model-based results required ***days*** of simulation time **for each PF case** using the same computer



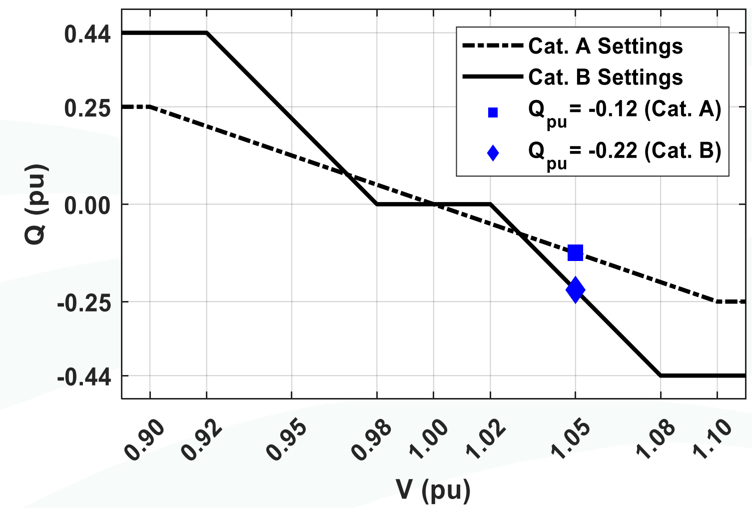


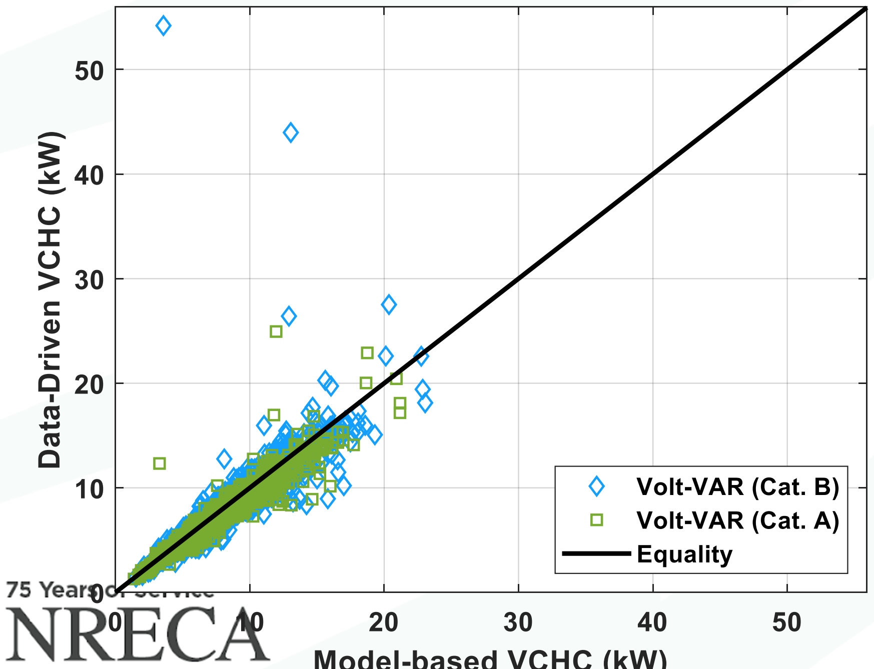


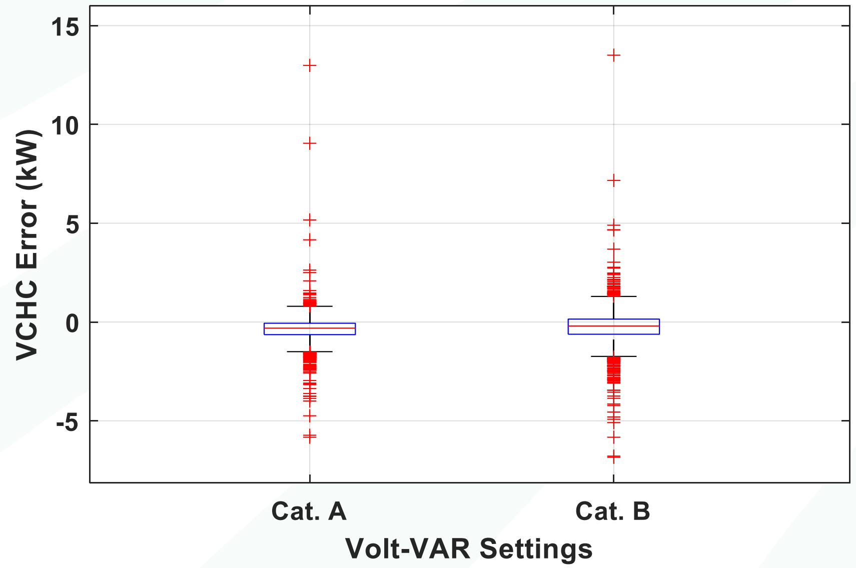
75 Years of Service
NRECA
America's Electric Cooperatives

Similar Results for Volt-VAR Mode Inverters

- The average VCHC results were **[7.01, 7.80] kW**, which correspond to inverter ratings of **[7.06, 8.00] kVA,** with MAEs of **[0.56, 0.72] kW**
- The proposed framework took **<4 minutes** to calculate all results, whereas the model-based results required ***days*** of simulation time **for each Volt-VAR case** using the same computer



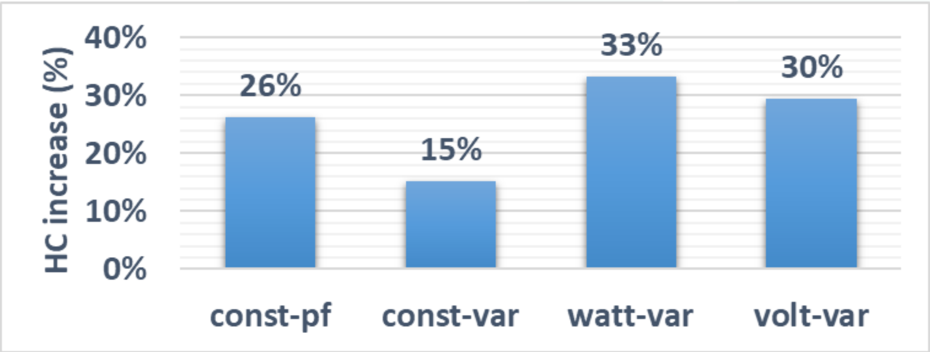




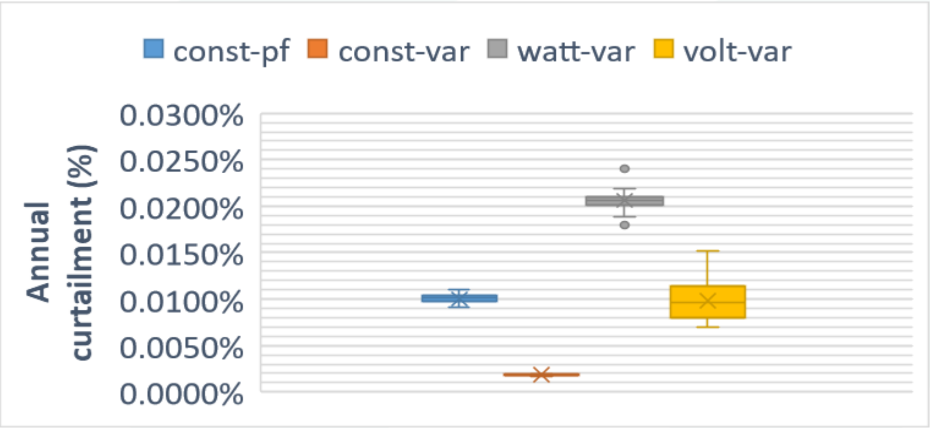
75 Years of Service
NRECA
America's Electric Cooperatives

Advanced Inverters Greatly Increased Hosting Capacity

- Compared to unity PF, grid-support functions can significantly increase HC
- Under default settings, only minimal impact to annual energy yields (i.e., no significant curtailment of real power)
- Ultimately, the user will be able to toggle these functions to see the impacts on HC and PV energy yields



HC increases when applying different control modes



PV inverter generation curtailment (compared to the total PV generation) under different control modes

75 Years of Service

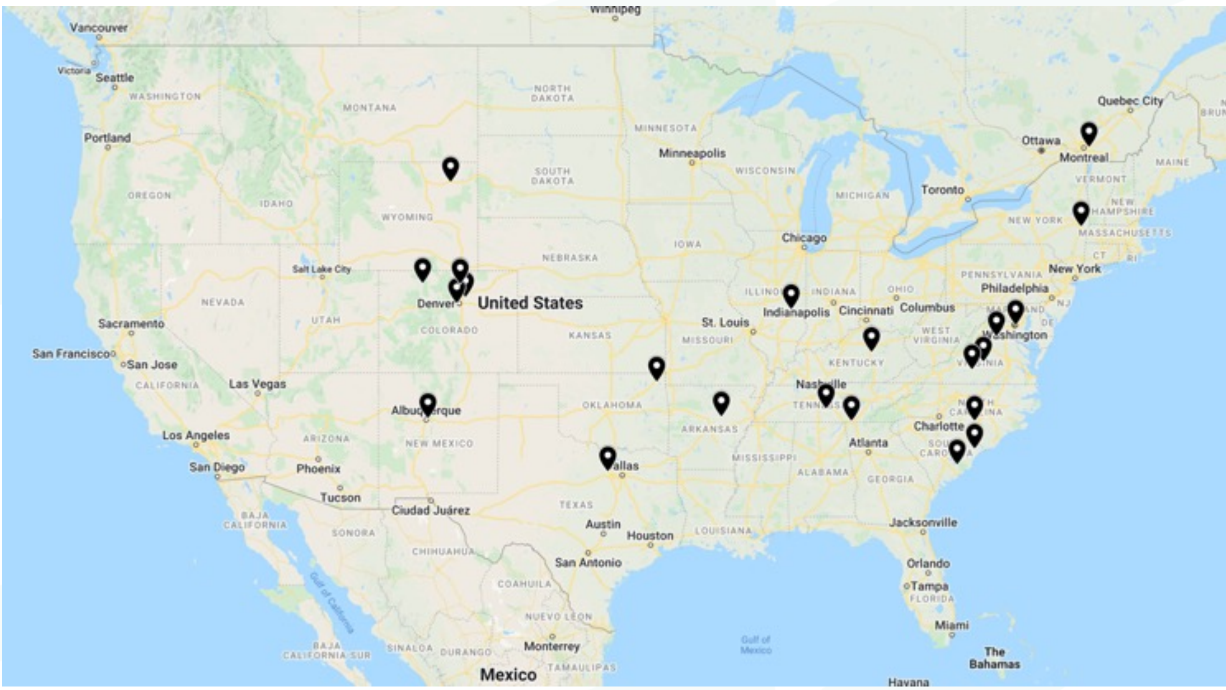
America's Electric Cooperatives

Task 6 - Engage Project Stakeholders, Result Dissemination, and Outreach

75 Years of Service
NRECA
America's Electric Cooperatives

Industry Advisory Board Formed

- Meetings ran 2022 through 2024
- Approx. 35 individuals make up the advisory board, representing electric utility staff, research organizations, and vendors



Name	Organization
Jared Weeks	United Power Colorado
Brian Lydic	Interstate Renewable Energy Council (IREC), Albany, NY
Shibani Ghosh	NREL
Andrea Pinceti	Virginia Dominion Energy, Inc.
Jon Hawkins	PNM Resources, Albuquerque, NM
Jeremiah Miller	Solar Energy Industries Association, Washington, DC
Jim Cross	Yampa Valley Electric Association
Jeffrey Wadsworth	Poudre Valley REA
Jim Glass	EPB Chattanooga
Francis Therrien	Eaton, CYME International T&D
Joshua Noel	Poudre Valley REA
Jakob Lowman	Southside Electric Cooperative
Chuck Gill	Owen Electric Coop, Kentucky
Dion Cooper	Southwest Arkansas Rural Electric Administration
Philip Lim	Middle Tennessee Electric Coop
Kelsey Gustainis	Tri-County Electric Coop Texas
Eugene Hamrick	Rappahannock Electric Coop
Brian Swart	Horry Electric Coop
Shaun Vester	Coles-Moultrie Electric Coop
Anthony J. Capobianco	Berkeley Electric Cooperative
Brett Kinlaw	Lumbee River Electric Coop
Lacy Frazier	Northeast Oklahoma Electric Coop
Quentin Rogers	Powder River Energy Corporation

75 Years of Service
NRECA
America's Electric Cooperatives

Stakeholders

- Who are the relevant stakeholders in your area?
  - Relevant stakeholders include **utilities, co-ops, software vendors**, and **solar developers**
  - We have established (and met with) an industry advisory board (IAB)
    - Members include IREC, EPRI, SEIA, CYME, NREL, PNM, EPB Chattanooga, and 18 co-ops (e.g., Poudre Valley REA, Owen Electric, Lumbee River, Rappahannock, …)
  - The work has also been presented through conferences (IEEE T&D) and workshops (GridTECH Connect)
- What reactions have you heard from stakeholders about outputs or findings?
  - We continue to hear that conducting conventional hosting capacity analyses are challenging given the status of utility models and the pace of interconnection requests leading to long queues.
  - Utilities are interested in the ability to run algorithms locally due to data privacy concerns
  - Lots of interest in leveraging these algorithms

United Power Testing

<u>United Power Test System</u>

8 different feeders of varying sizes with different types and numbers of customers

Feeders 6, 7, and **9** are much smaller than other feeders

Feeder 4 smaller than **2, 3, 5,** and **8**

Feeder 9 has no secondary

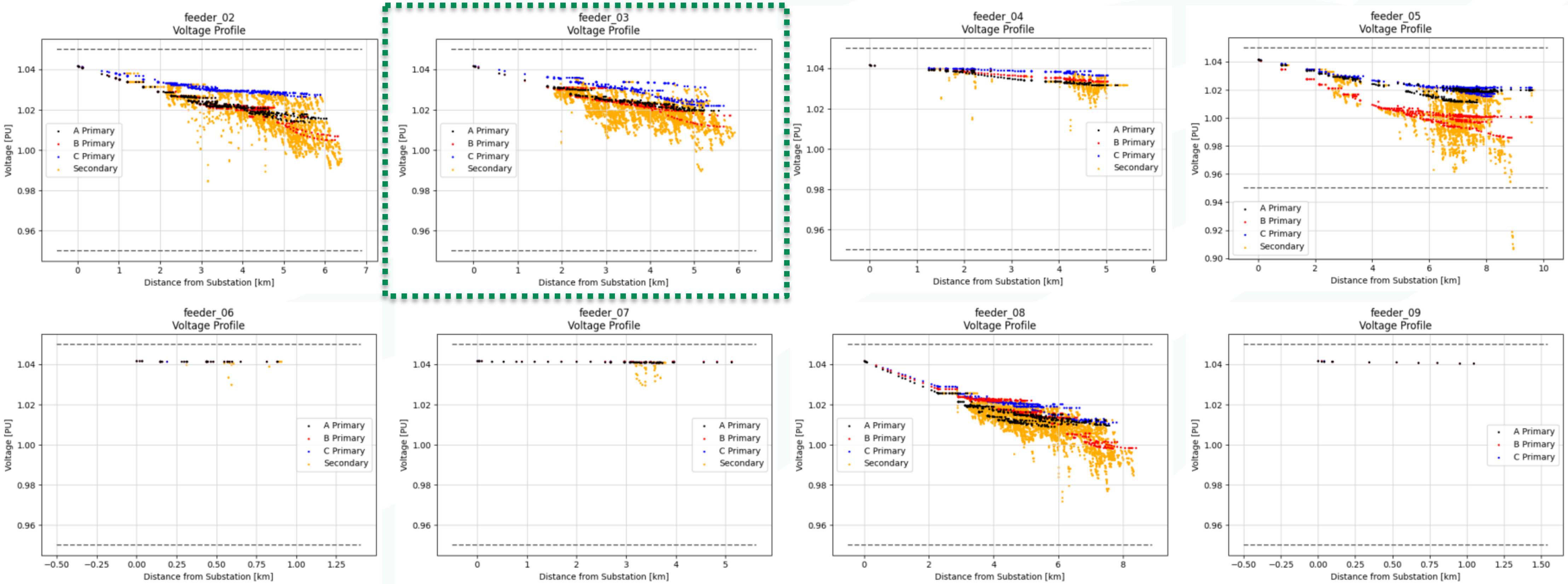
We focused our modeling and analysis on **Feeder 3**

	02	03	04	05	06	07	08	09
source_pu	1.04167	1.04167	1.04167	1.04167	1.04167	1.04167	1.04167	1.04167
source_kv	12.47077	12.47077	12.47077	12.47077	12.47077	12.47077	12.47077	12.47077
init_kw	6592.936391	6570.037629	1829.747615	6545.92479	219.343195	229.916797	7467.170408	2868.47998
init_kvar	1702.22599	1247.663198	647.208794	1761.771997	74.050801	70.674799	1900.118403	380.160004
feeder_max_length_km	6.382165	5.863739	5.265643	9.584368	0.904401	5.122013	8.317869	1.045164
n_bus	2965	3222	806	3088	57	129	4554	12
n_lines	2538	2856	695	2632	39	95	4000	9
n_primary_lines	742	607	253	851	32	76	947	9
length_primary_lines_km	37.855196	42.658003	11.857132	59.725156	2.003133	7.0015	65.748788	1.045164
n_secondary_lines	1796	2249	442	1781	7	19	3053	0
length_secondary_lines_km	42.728553	54.513597	9.961395	44.330104	0.156972	0.431292	76.165209	0.0
n_cust	0	0	0	0	0	0	0	0
n_loads	2733	3131	555	2890	13	19	4635	1
n_primary_loads	1	0	1	1	0	0	0	1
n_secondary_loads	2732	3131	554	2889	13	19	4635	0
n_capacitors	0	0	0	0	0	0	0	0
n_fuses	0	0	0	0	0	0	0	0
n_generators	0	0	0	0	0	0	0	0
n_pv	0	0	0	0	0	0	0	0
n_transformers	319	307	57	339	12	14	434	3
n_reactors	111	60	55	118	7	21	121	1
n_regulators	0	0	0	0	0	0	0	0
n_storages	0	0	0	0	0	0	0	0
n_switches	0	0	0	0	0	0	0	0

United Power Testing

- Most feeders had **no violations**
- Over-loaded transformers in **feeders 5** and **8**

- **Under-voltages** on **feeder 5**
- Each feeder model was **reduced** 2-14 times by merging neighboring lines to minimize the number of buses while maintaining the topology
  - Cuts down on computational time and are mathematically equivalent



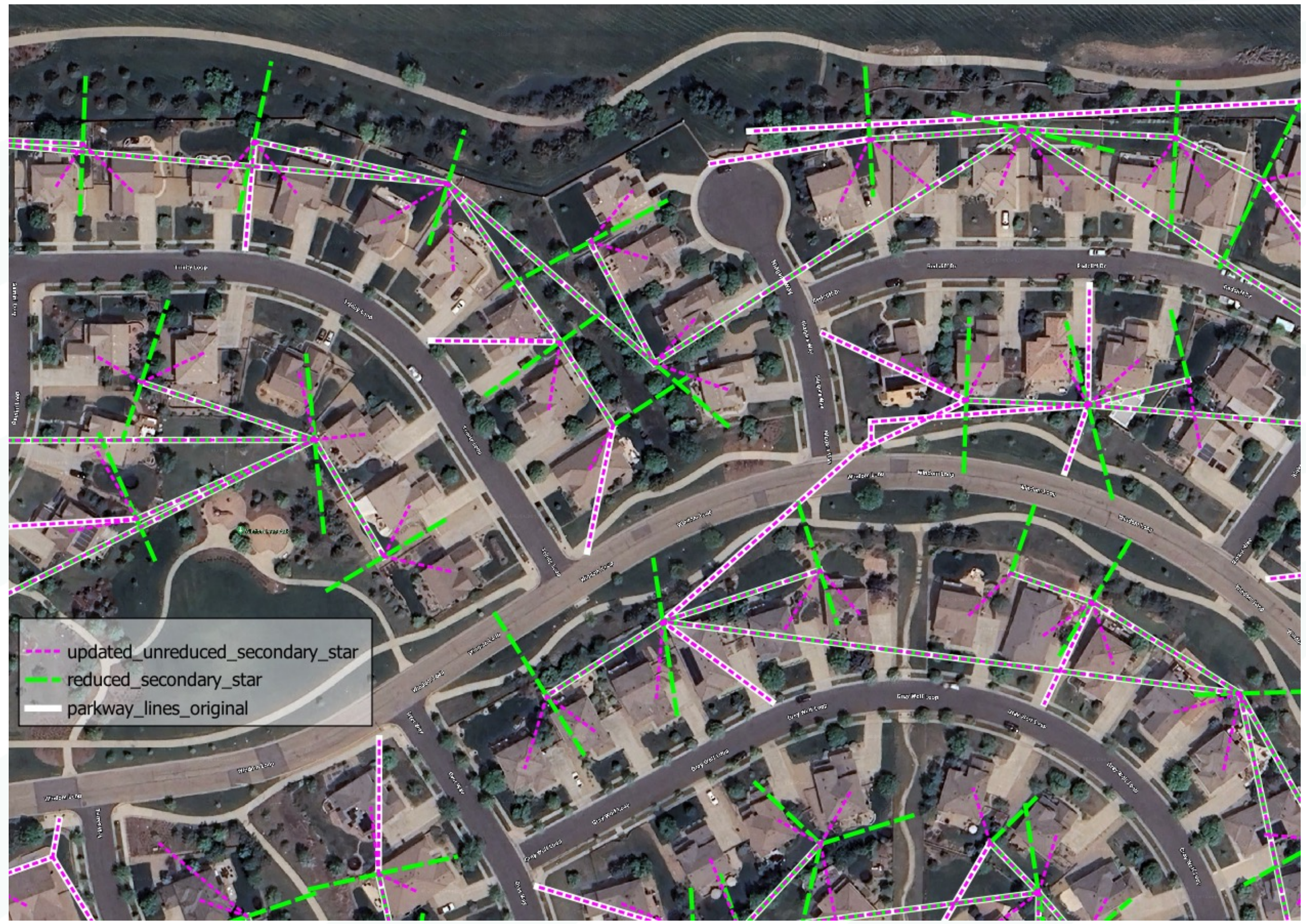
United Power Testing

Feeder 3

Incorporated load locations from new models, but many line codes and line ratings did not convert (just zeros)

Used secondary star approach to reduce excess lines and add line length diversity

Loads modified to connect across 240V LV terminals of split-phase transformer (instead of splitting each load in half on each leg)



75 Years of Service NRECA America's Electric Cooperatives

United Power Testing

<u>Feeder 3</u>

304 single-phase service transformers

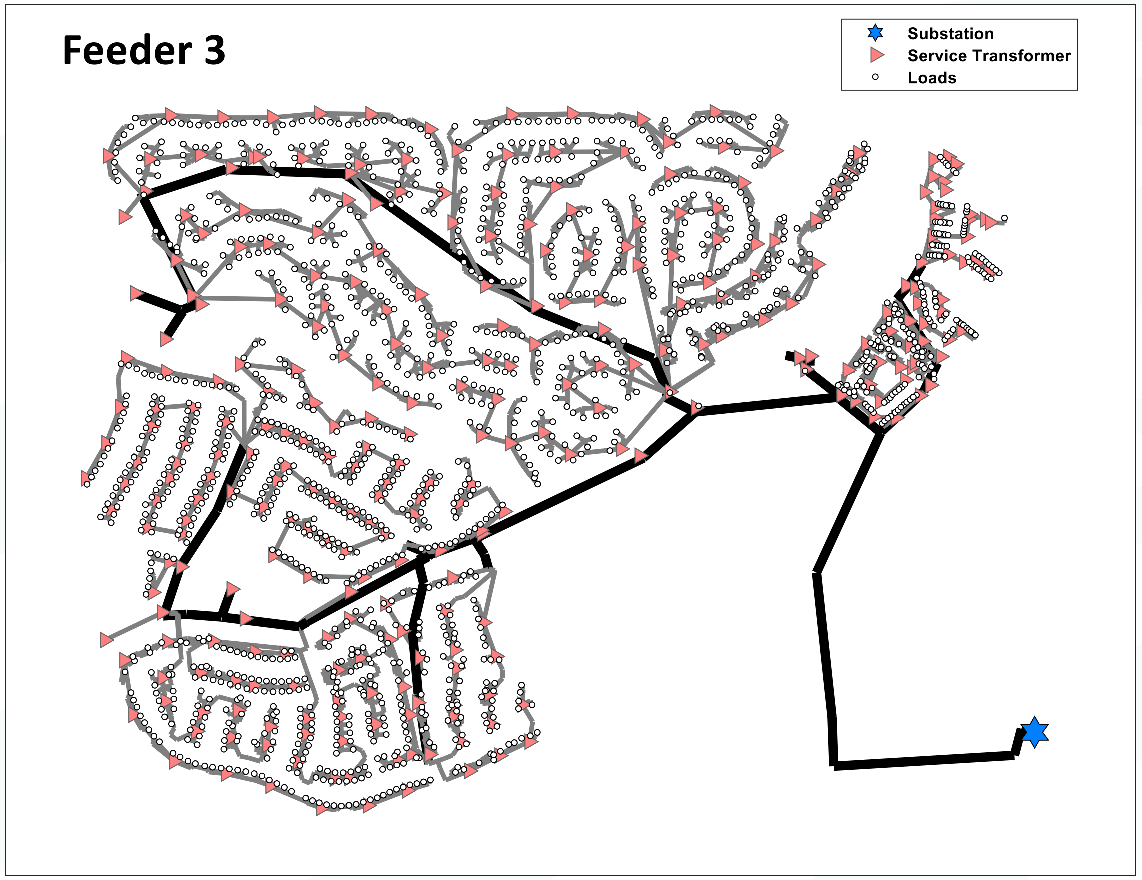
- **277 with downstream loads that had AMI data**

Low-voltage networks from United Power are included in the analysis

1,563 residential customers with AMI data

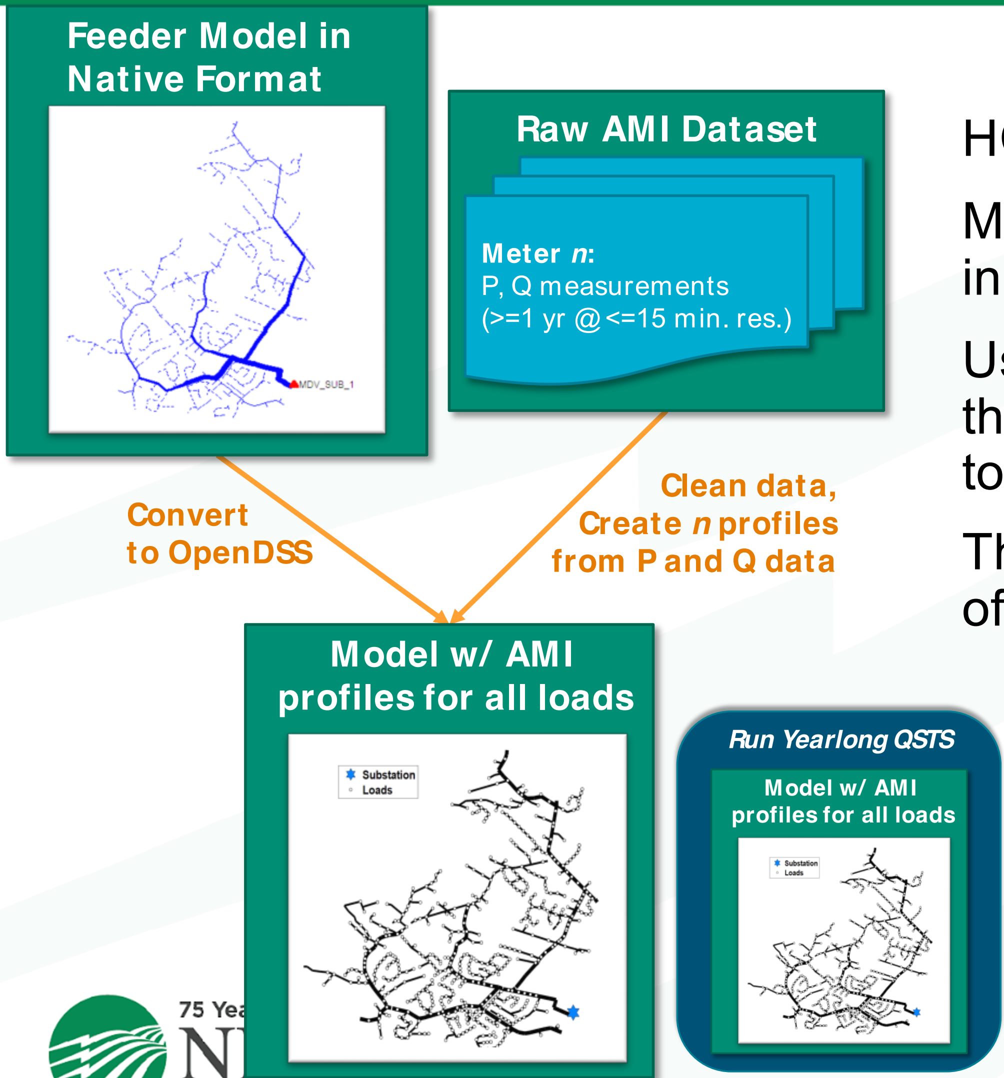
Each customer has smart meter data

- **P, Q, and V measurements @ 15-min resolution**
- **Most customers have a full year of measurements, but some are missing parts of the year**
- **Could be due to meter outages, new customers being added, inactive customers that were removed**



75 Years of Service NRECA America's Electric Cooperatives

Validation Methodology

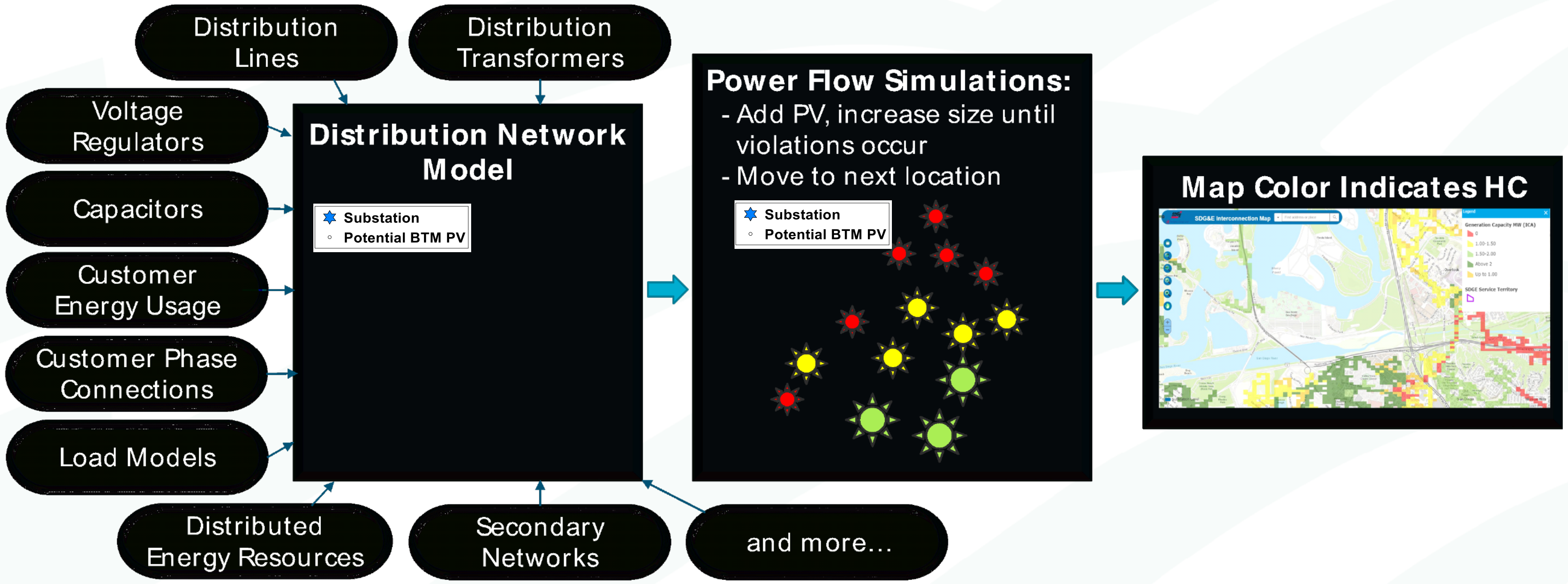


- HCA conducted on Feeder 3 for algorithm validation
- Modifications made to align the model-based and MoHCA inputs, that way we can quantify algorithm errors
- Use actual P and Q from smart meters to model the loads, then run yearlong quasi-static time-series (QSTS) simulation to calculate the synthetic voltages
- This means that the HCA results may **not** be representative of field results

HCA Methodology, Model-based

Model-based Locational HCA:

1. **Run yearlong quasi-static time-series (QSTS) simulation without PV**
   a. Record customer voltages and transformer loading time-series
2. **Add PV to any customer premise**
3. **At t=0:**
   a. Iteratively increase PV size, solving the power flow each time
   b. Record max PV size w/o any voltage or thermal violations
4. **Move to next time point (e.g., t=t+15 minutes) if there is one**
   a. Repeat steps 3a and 3b
5. **Repeat steps 2 through 4 for all customer premises**



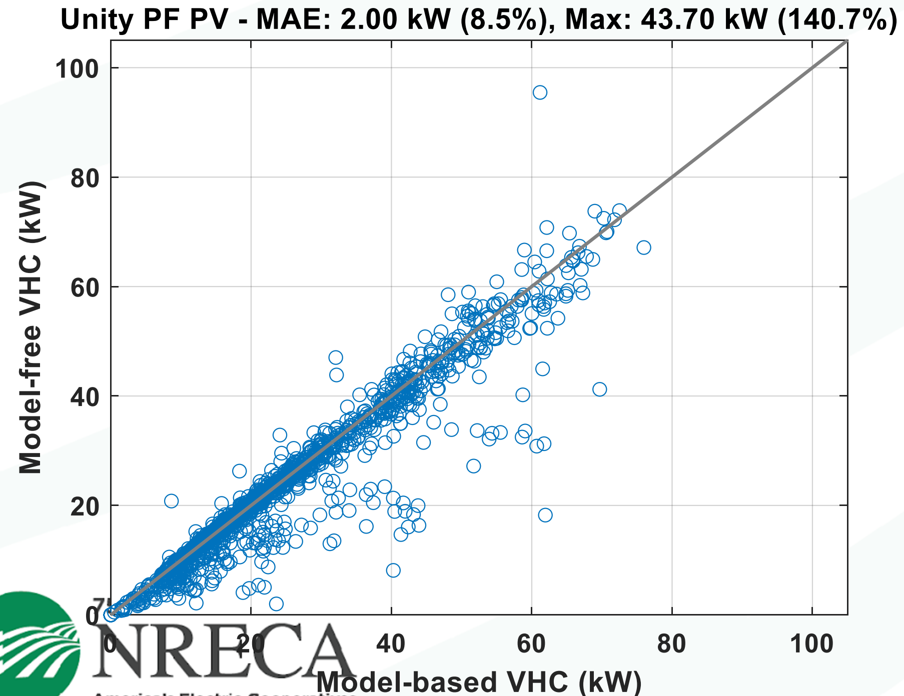
75 Years of Service NRECA America's Electric Cooperatives

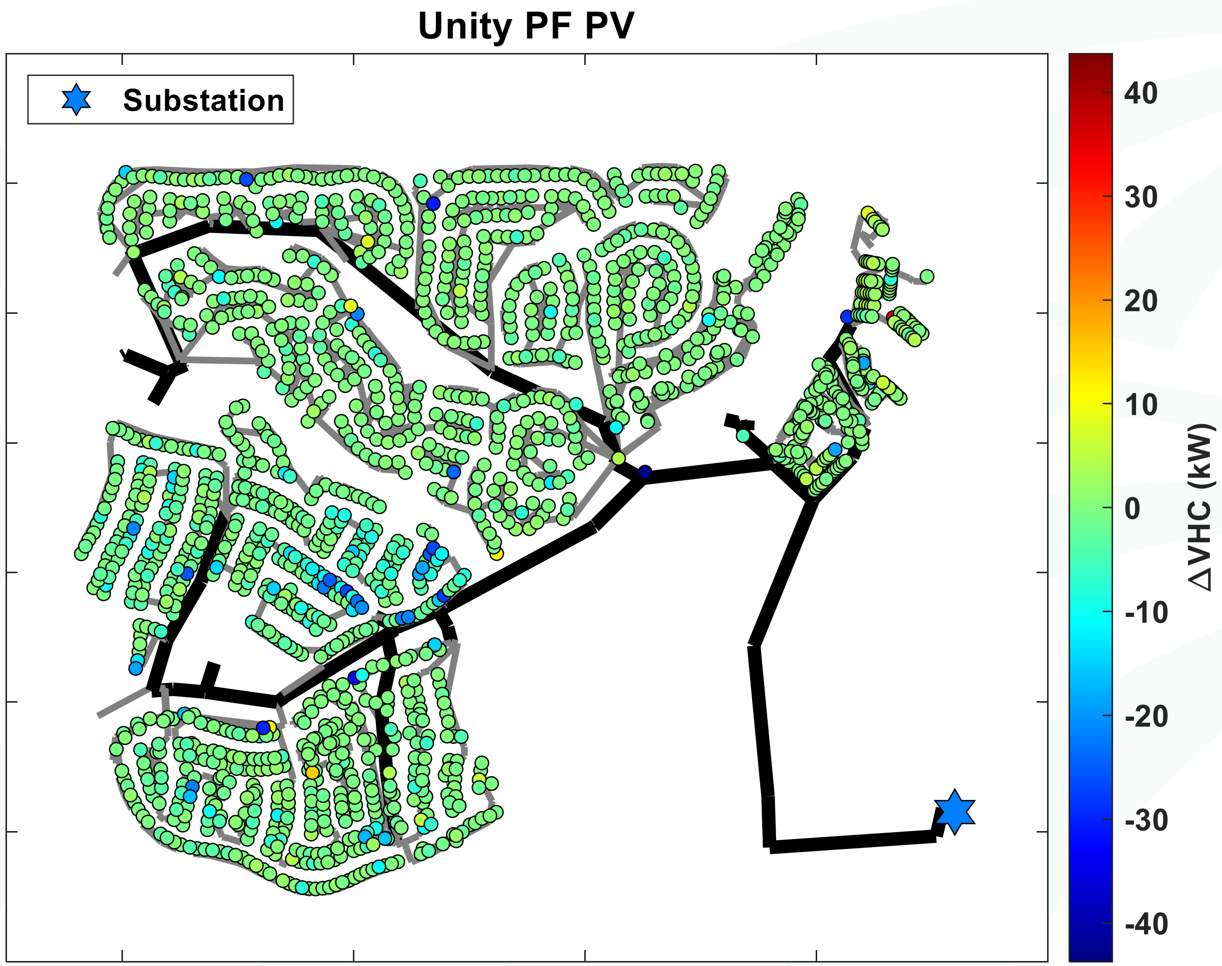
HCA Results– MoHCA vs Model-based

Voltage-Constrained HC (VCHC)

1232/1563 locations (78.82%) were accurate within 10% of model-based results

Map on the right shows the **difference** between MoHCA and model-based HCA results



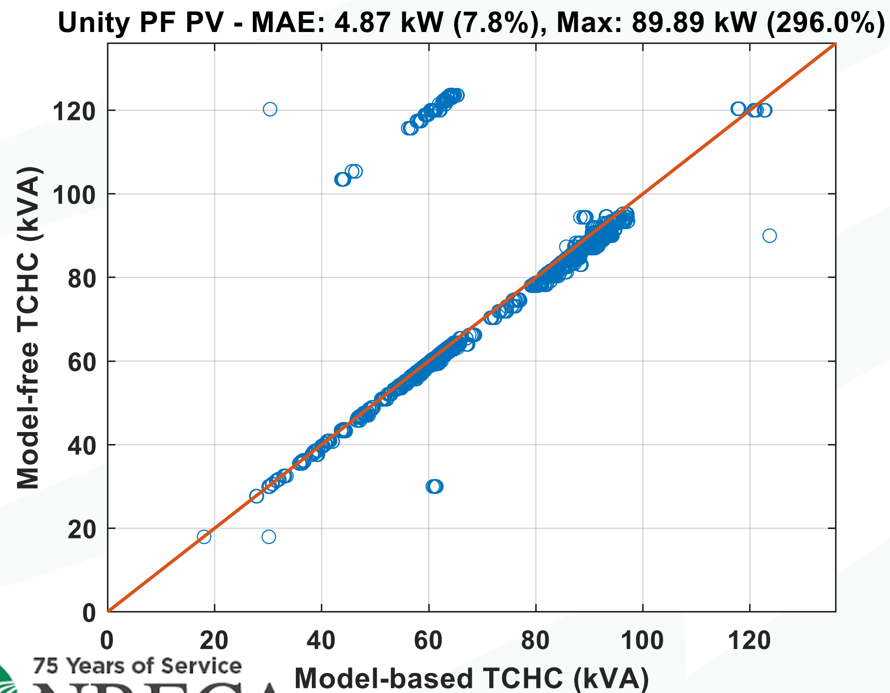


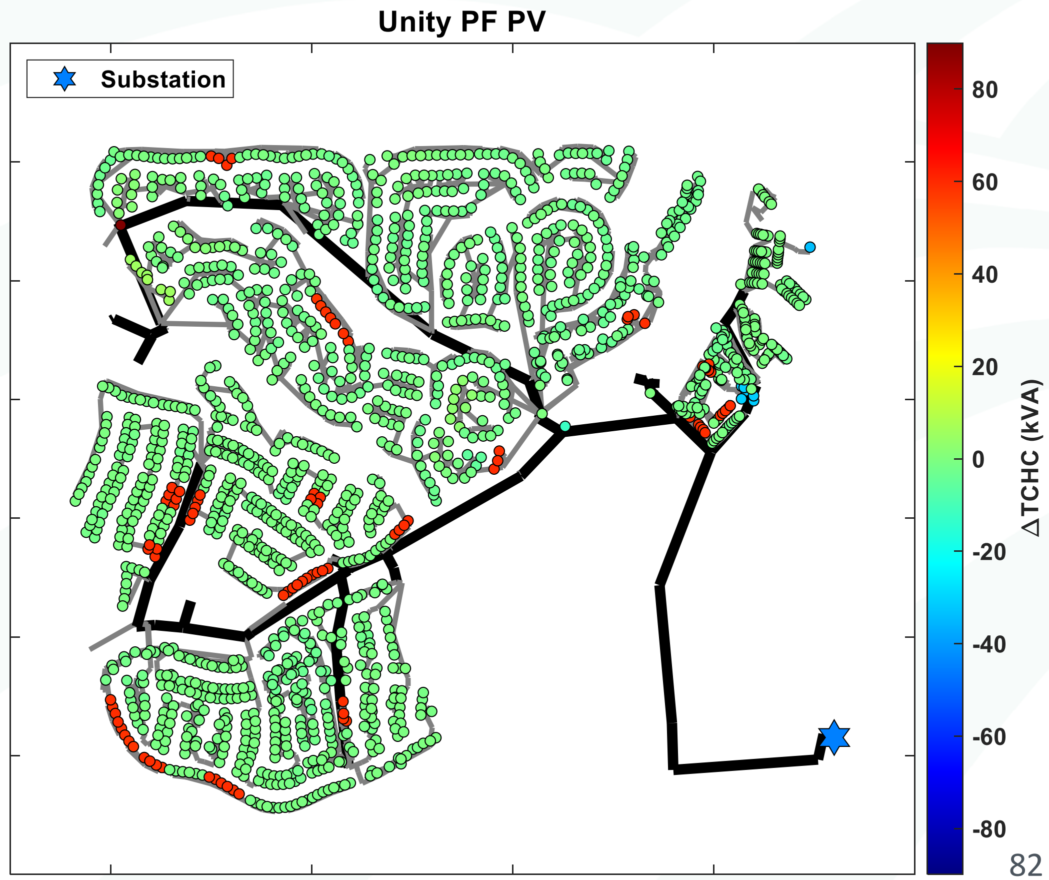
NRECA
America's Electric Cooperatives

HCA Results– MoHCA vs Model-based

TCHC if Service Transformer Sizes are known:

Assuming customer-transformer groupings are accurate, just take the difference between total existing load on the transformer (i.e., sum smart meter data) and max capacity





75 Years of Service NRECA America's Electric Cooperatives

Impact and Innovation

- High Impact - Leveraging >$1 billion U.S. investment in smart meters provides a very high value/cost tradeoff for multiple stakeholders (utility, solar developer, customers, etc.)
- Since the proposed approach directly incorporates data analytics and does not require any power flow analyses to be performed, it has a variety of advantages over existing methods:
  - **Reduced complexity**. The proposed approach does not require any detailed (often error-prone) grid models and can be independently applied to any location with a smart meter.
  - **Improved speed and scalability**. Taking a data-driven approach to calculate solar HC avoids thousands of power flow solutions, dramatically reducing computation times. Faster speed results in hosting capacity maps updating more often with less stale data for stakeholders
  - **Added functionality**. Machine learning and data analytics techniques can offer additional insights into the locational impacts and benefits of advanced PV inverters.
  - **Enhanced accuracy**. Using field data provides better visibility into potential PV systems and timeseries hosting capacity analysis provides insight into operations during the entire year instead of just extreme points
- Provide actionable intelligence for developers to size and site PV

75 Years of Service
NRECA
America's Electric Cooperatives

Next Steps

- Next Steps
  - Improving the equipment constraint modeling for cases where no information is available about transformer connections
- What do you wish you could do with more funding?
  - Build on this work to facilitate interconnection screening and queue management
  - We get some variation of this question a lot: “Can this tool be used for interconnections?”
  - In theory, we can use info from interconnection requests to model the DER output, and leverage the PINN-based methods to determine the impact of that system on neighboring customer locations
- Biggest Challenge and Achievement of the project so far?
  - Biggest challenge was receiving utility models/datasets, then converting/cleaning them to be able to test our algorithms on them
  - Biggest achievement has been meeting all the accuracy metrics and project milestone on schedule

Call for Data, Hosting Capacity Analysis

- Algorithms are ready, and we'd like to calculate hosting capacity for your systems!
- We would need, for one circuit on your system:
  - Historical AMI data, ideally about a year's worth but more is fine, including the meter IDs, times of the readings (hourly or 15 minute), voltage values, kW values and (if you have them) kVAR values.
  - The Windmil model for that circuit (so we can benchmark the results against more traditional methods). If you can send the OpenDSS version that would be ideal (File > Export… and then choose the OpenDSS option), but you can also send us the native
    - .wm + eqdb files and we can extract the OpenDSS model.
- Sandia and NRECA have NDAs we can execute to keep your data secure.
- Interested? Please email david.pinney@nreca.coop.

Contacts

- **Sandia National Laboratory**
  - Dr. Matthew Reno, principal investigator, mjreno@sandia.gov
  - Dr. Joseph Azzolini, research lead, jazzoli@sandia.gov
  - Dr. Jubair Yusuf, researcher, jyusuf@sandia.gov
- **NRECA**
  - David Pinney, project coordinator, david.pinney@nreca.coop
  - Jennifer Thakkar, software engineer, jennifer-thakkar@nreca.coop
- **Iowa State**
  - Professor Zhaoyu Wang, wzy@iastate.edu