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Analysis of Reactive Power Load Modeling Techniques for PV Impact Studies

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***Abstract*—The increasing availability of advanced metering infrastructure (AMI) data has led to significant improvements in load modeling accuracy. However, since many AMI devices were installed to facilitate billing practices, few utilities record or store reactive power demand measurements from their AMI. When reactive power measurements are unavailable, simplifying assumptions are often applied for load modeling purposes, such as applying constant power factors to the loads. The objective of this work is to quantify the impact that reactive power load modeling practices can have on distribution system analysis, with a particular focus on evaluating the behaviors of distributed photovoltaic (PV) systems with advanced inverter capabilities. Quasi-static time-series simulations were conducted after applying a variety of reactive power load modeling approaches, and the results were compared to a baseline scenario in which real and reactive power measurements were available at all customer locations on the circuit. Overall, it was observed that applying constant power factors to loads can lead to significant errors when evaluating customer voltage profiles, but that performing per-phase time-series reactive power allocation can be utilized to reduce these errors by about 6x, on average, resulting in more accurate evaluations of advanced inverter functions.**

***Keywords*—advanced metering infrastructure (AMI), autonomous Volt-VAR, high penetration photovoltaics (PV), load allocation, load modeling, reactive power allocation**

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Contents

Introduction

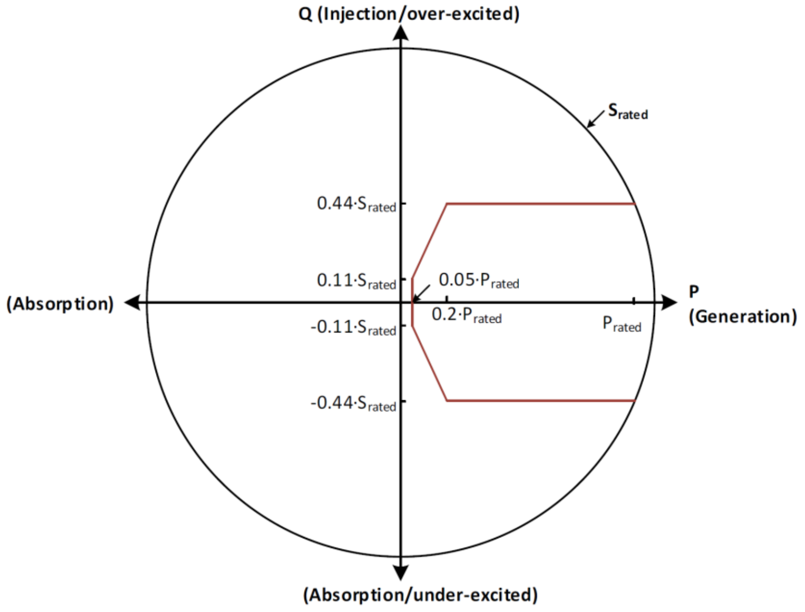
- Load modeling is one of the most critical components of distribution system analysis
- Recently, the widespread adoption [1,2] of advanced metering infrastructure (AMI) or "smart meters" has led to significant improvements in load modeling practices
  - AMI typically record measurements every 15-minutes (30- and 60-min. resolutions are also common)
  - Modeling loads with smart meter data represents a drastic improvement to spatial and temporal resolution of distribution system analyses
- However, while today's smart meters have a variety of features and measurement options, many utilities only record and store real power measurements
- When reactive power measurements are unavailable, assumptions have to be applied like assigning constant power factors (PFs) to the loads
  - Often, the PFs used for this are based on measurements from peak load conditions

Background

- Conventionally, load allocation was implemented, and a static analysis was performed to analyze the peak loading conditions modeling for static peak load analysis
  - In this case, the demand measured at the substation or feeder head is allocated to the downstream loads. The "allocation factors" for the loads were typically selected based on billing information (like peak energy usage) or based on the upstream service transformer rating
  - Next, the allocation algorithm would implement an iterative power flow analysis, adjusting the loads after each iteration until the simulation results matched the measured values, whereby the iterative process accounts for losses and other mismatches in the system model
- Today, many analysis and planning tasks require time-series power flow analyses, or quasi-static time-series (QSTS) simulations
- A recent EPRI report [3] highlighted the impacts of various load allocation approaches on the accuracy of QSTS simulations, specifically that accuracy improves with:
  - The frequency of allocation (e.g., every time step vs 1/year)
  - The proximity of the sensors to the customer
  - Reactive power measurements

Background

- Per the IEEE 1547 Standard [4], all new PV inverters must be able to operate in a variety of grid-support modes, including Volt-VAR (VV) mode
  - In VV mode, inverter will inject reactive power to boost low voltages and consume reactive power to reduce high voltages, **curtailing** real power if necessary (VAR-priority)
- In order to evaluate the performance of distributed PV systems with Volt-VAR enabled, an accurate feeder model is required as well as accurate time-series load models to ensure the voltages at the PV inverter terminals are accurate



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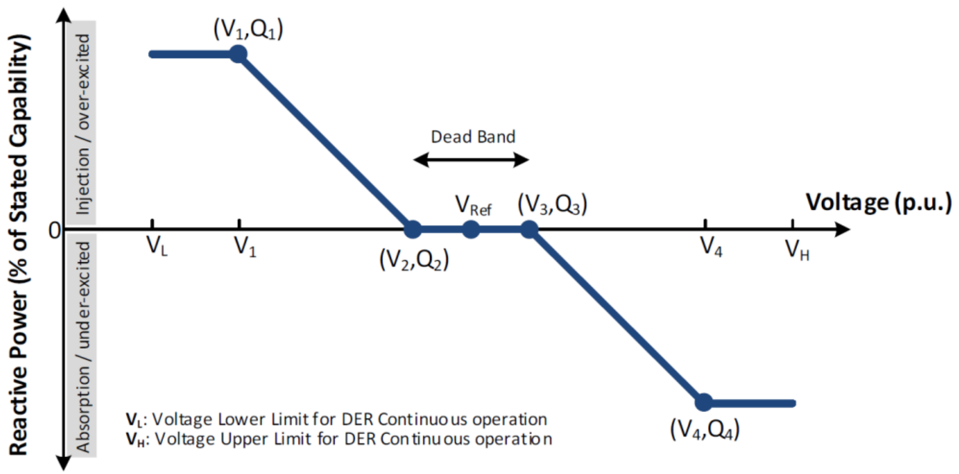
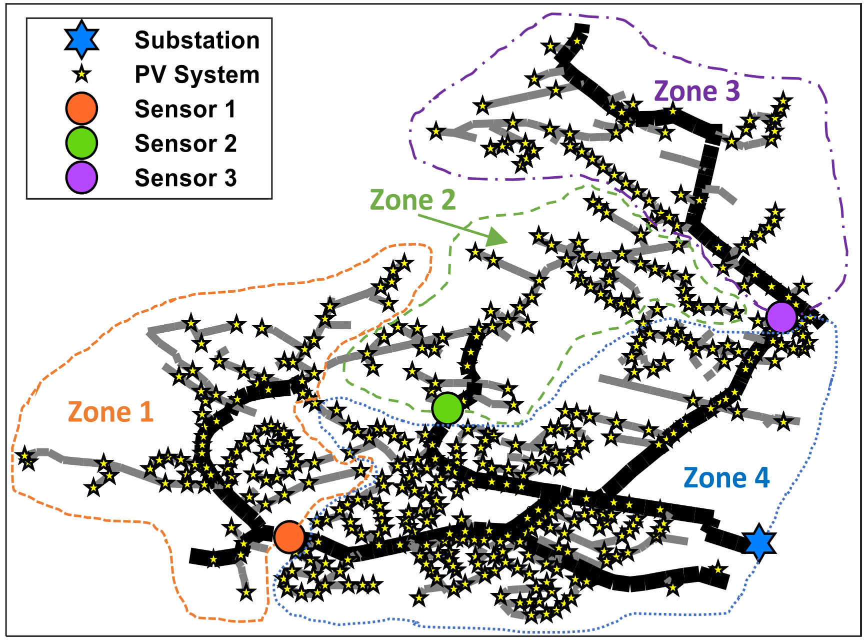


Methods

- In this work, the objective was to quantify the impact of various reactive power modeling practices on the ability to evaluate the performance of distributed PV systems with advanced inverter functions (i.e., autonomous Volt-VAR)
- **Test Circuit:** Modified EPRI Ckt 5
  - 1379 customers, each modeled with 15-minute P and Q profiles from an actual utility AMI dataset
  - 701 distributed PV systems, separately metered
    - PV penetration = 35% peak load
- **QSTS simulations:**
  - Yearlong simulation with 15-minute time steps in OpenDSS
  - 1st simulation, all PV set to output unity PF
  - 2nd simulation, all PV set to Volt-VAR mode
    - IEEE 1547 [4] Cat. B Default Volt-VAR settings, with max. VAR output at 0.95 and 1.05 Vpu
  - Total yearlong PV energy difference between the simulations represents the curtailed energy for each PV system



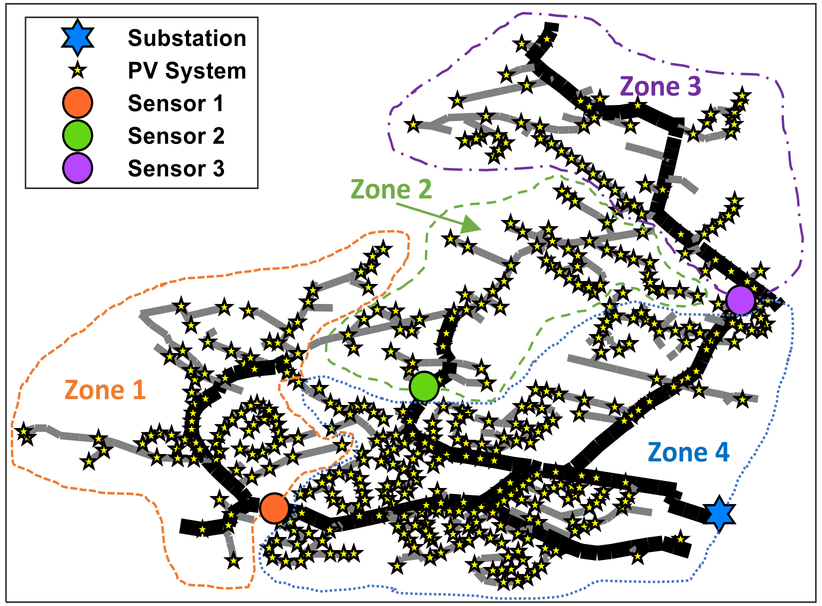
Zone	# of Loads	# of PVs
1	233	122
2	167	89
3	199	95
4	780	395
Total	**1379**	**701**

Methods

- 5 different reactive power modeling scenarios were explored
  - For all scenarios, real power consumption is based on 15-minute AMI data
- Each scenario represents a different spatial and/or temporal resolution of Q modeling

Scenario 1 (Baseline)

- P and Q both modeled with 15-minute AMI data for all 1379 loads
- Each load has a unique P, Q, and PF at each time point of the year (i.e., 1379 Q profiles)

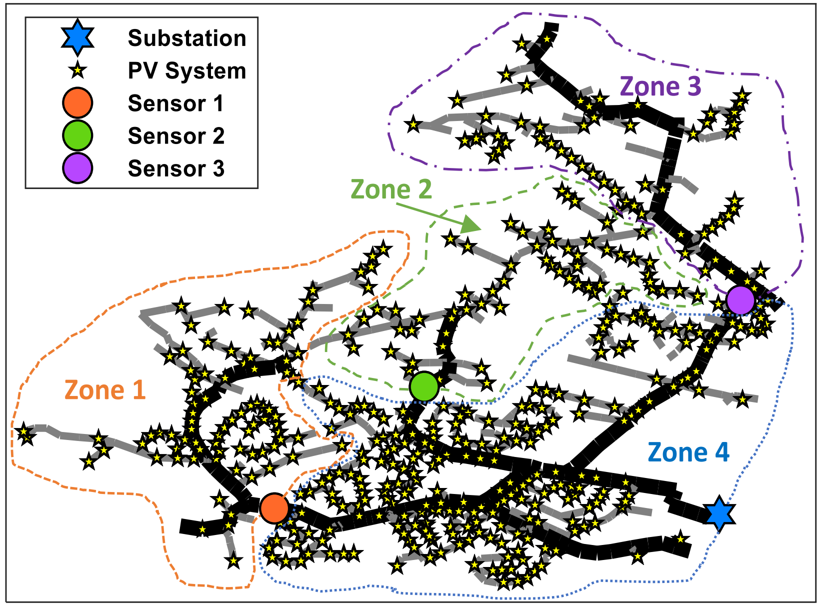


Scenario	# of Q Profiles	Q Methods
1	1379	AMI
2	12	Allocated Per-Phase, Per-Zone
3	3	Allocated Per-Phase
4	0	Constant PF, Per-Phase from peak load = [0.9540, 0.9539, 0.9568]
5	0	Constant PF, Avg. from peak load = [0.9549] applied to all customers

Methods

Scenario 2: Q-Allocation Per-Phase, Per-Zone

- Reactive power measurements from the *substation* **and** *3 grid sensors* are allocated to the loads in their respective zones **at each time step**
  - Q allocation applies an iterative power flow simulation that adjusts the magnitude of the load reactive power to account for circuit losses until the simulated value matches the measured value at the sensor
  - Additional details provided on next slide
- Ultimately, each load ends up with unique P and Q profiles, but always shares a PF with loads in the same *Zone* and *Phase*
  - 12 types of Q profiles (4 Zones x 3 Phases)



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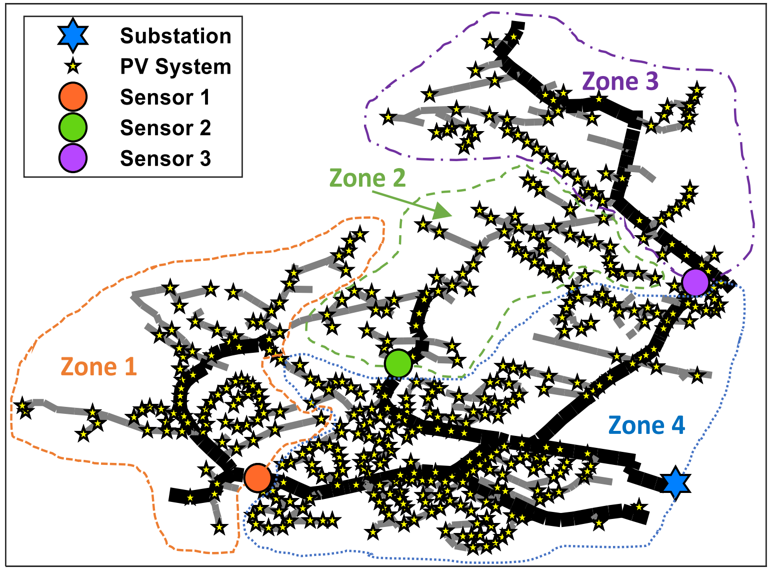


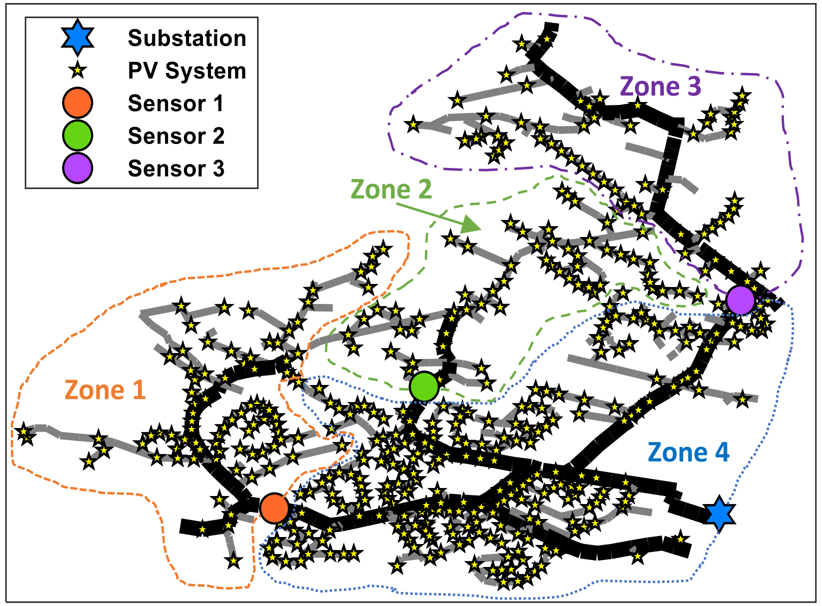
Q-Allocation Procedure Overview

1. Run a baseline QSTS simulation (Scenario 1), record Q measurements at each sensor and substation to represent the "measured" values
2. Reset the simulation and remove Q profiles from the loads
3. Set t=1, solve initial power flow
4. For Zone 1, take per-phase "measured" Q from Sensor 1 and subtract the "simulated" per-phase Q values from the power flow solution
5. Allocate that reactive power difference to any 3-phase loads based on their share of the total real power of all loads in that zone (sum of AMI P for all Zone 1 loads)
6. Allocate the remaining Phase 1 reactive power to the Phase 1 loads in that zone based on their share of the total Phase 1 real power (sum of AMI P for Phase 1 loads)
7. Solve the power flow again and compare "simulated" and "measured" values. Repeat Steps 4-6 adjusting allocated Q as needed until convergence (below some pre-defined error threshold)
8. Repeat Steps 4-7 until all Zones have converged, then repeat Steps 4-8 for all remaining time points

Methods

Scenario 3: Q-Allocation Per-Phase

- Reactive power measurements from the **substation only** are allocated to the loads **at each time step**
  - Same procedure as Scenario 2 but now all loads are essentially in the same zone
- Ultimately, each load ends up with unique P and Q profiles, but always shares a PF with loads in the same *Phase*
  - 3 types of Q profiles (1 Zone x 3 Phases)



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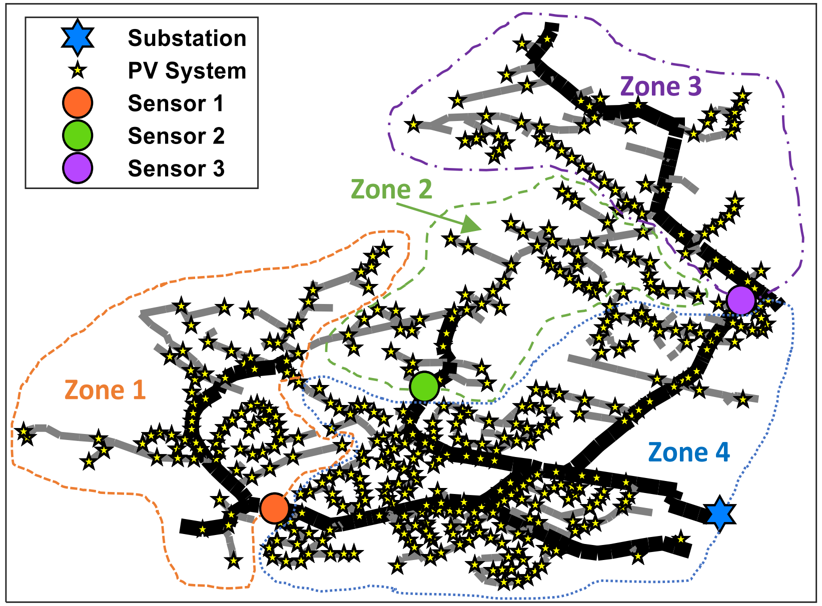
Methods

Scenario 4: Constant PF (Peak Load, Per-Phase)

- All loads on the same phase are assigned a constant PF as measured at the substation during peak load conditions
  - PF does not change, there no time-series Q profiles applied to the loads
- Utilities use peak load measurements for a variety of applications, so the input data for this scenario is very common
  - The measurements would first have to be adjusted for known reactive power injections (e.g., from capacitor banks) but no such sources were present in this case

Scenario 5: Constant PF (Peak Load, 3P avg.)

- Same as Scenario 4, but assumes only 3-phase total measurements are available, meaning the peak load PF represents the average across all 3 phases



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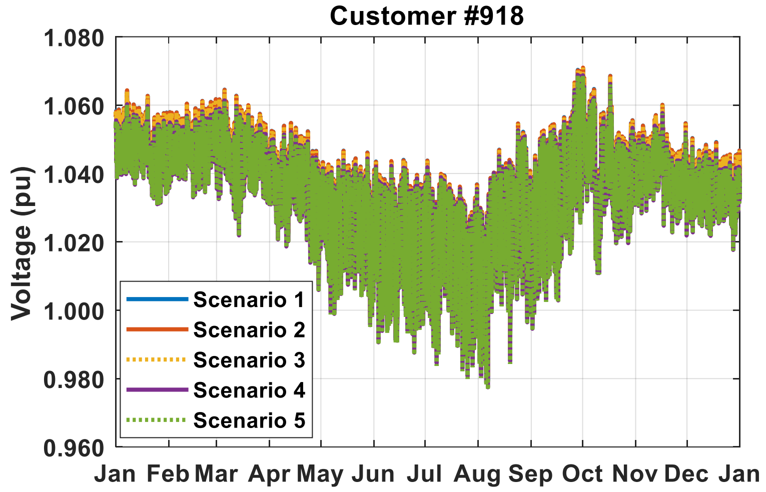
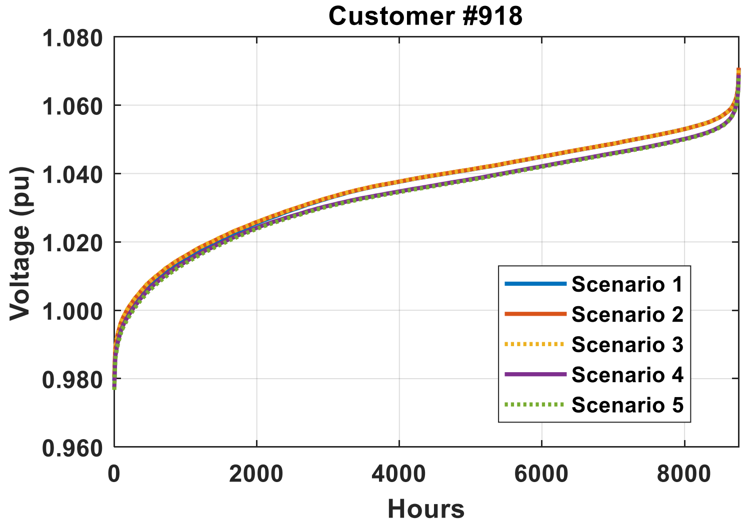
Results – Customer Voltage Accuracy

All PV at PF=1: Voltage Comparison to Baseline Scenario 1 for a Single Customer (#918)





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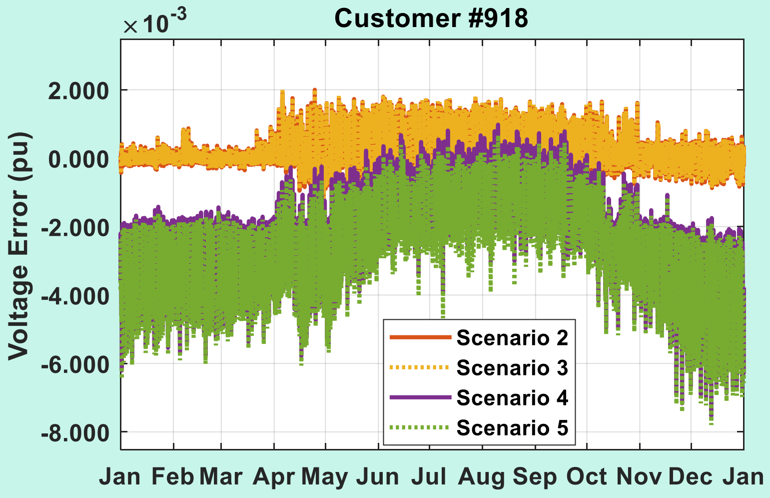
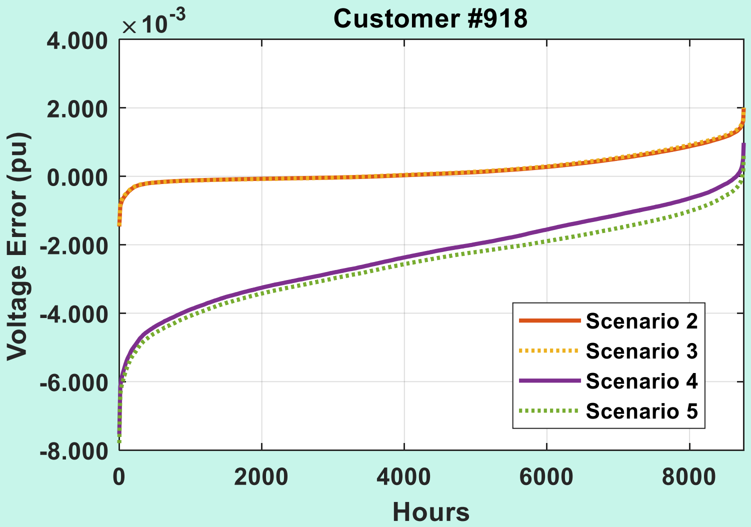




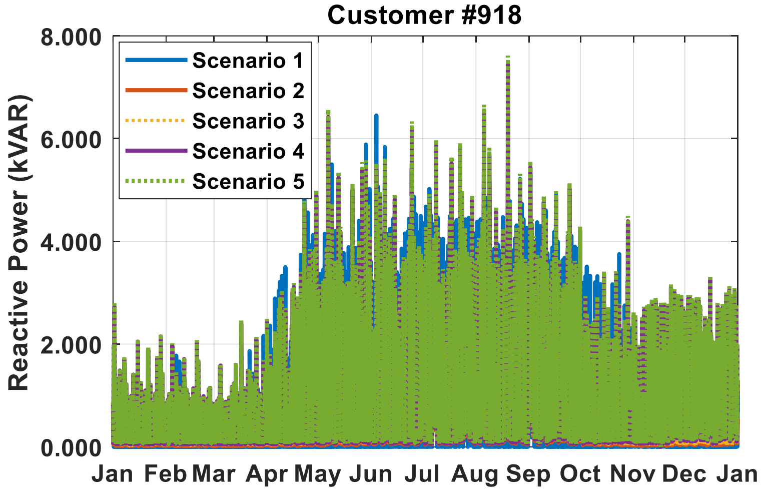
To compare the results of all customers, we will calculate the **mean absolute error** (MAE) by taking the average of these yearly time-series V error plots for every customer

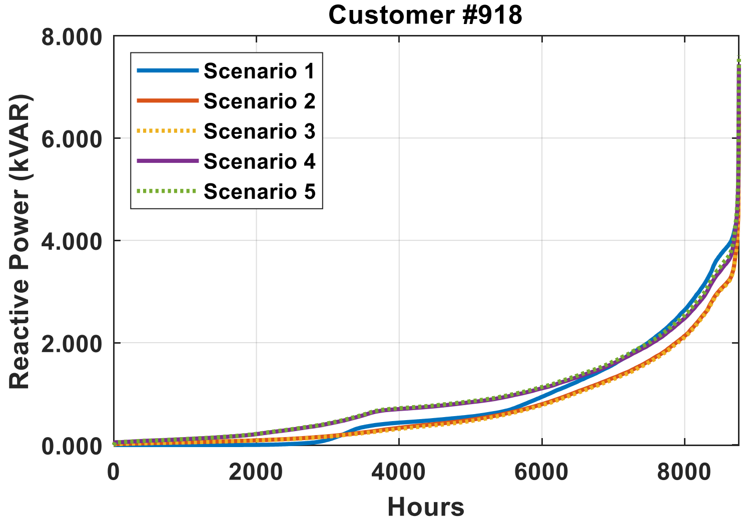
Cust. #918

Scen.	MAE (Vpu)
2	0.298 e-3
3	0.312 e-3
4	2.304 e-3
5	2.556 e-3

Results – Customer Reactive Power Accuracy

All PV at PF=1: Reactive Power Comparison to Baseline Scenario 1 for a Single Customer (#918)





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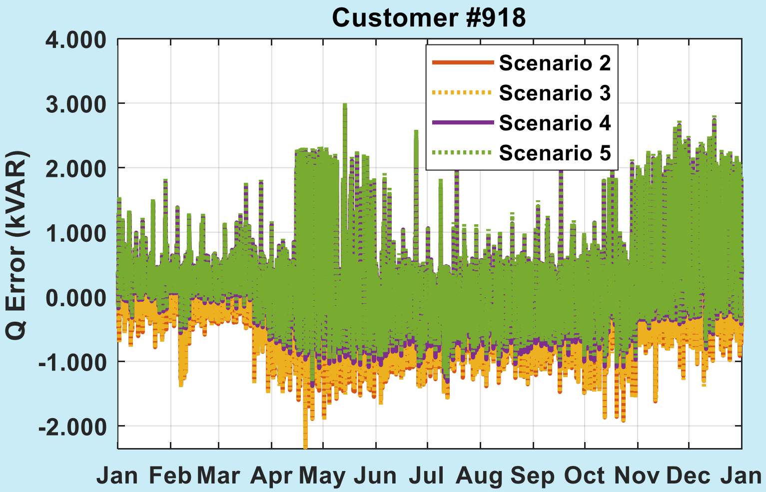
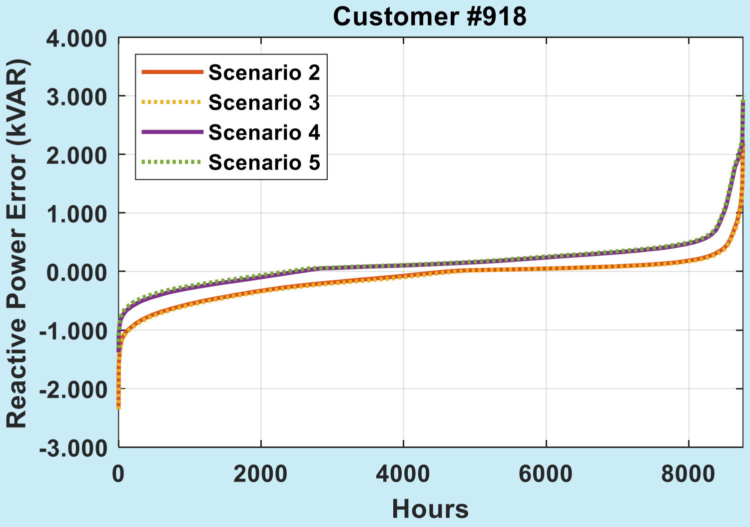




To compare the results of all customers, we will calculate the **mean absolute error** (MAE) by taking the average of these yearly time-series Q error plots for every customer

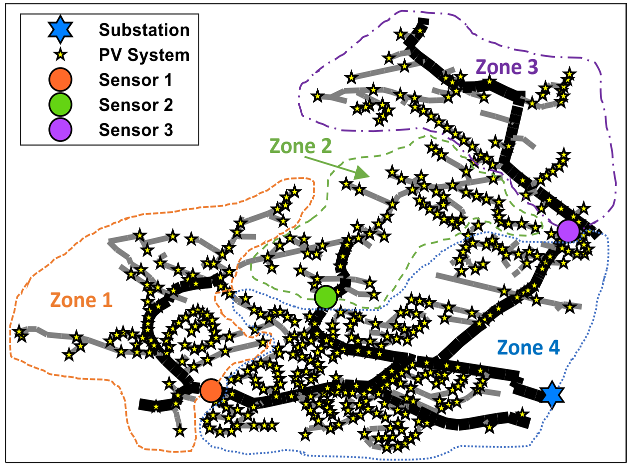
Cust. #918

Scen.	MAE (kVAR)
2	0.2495
3	0.2551
4	0.2876
5	0.2885

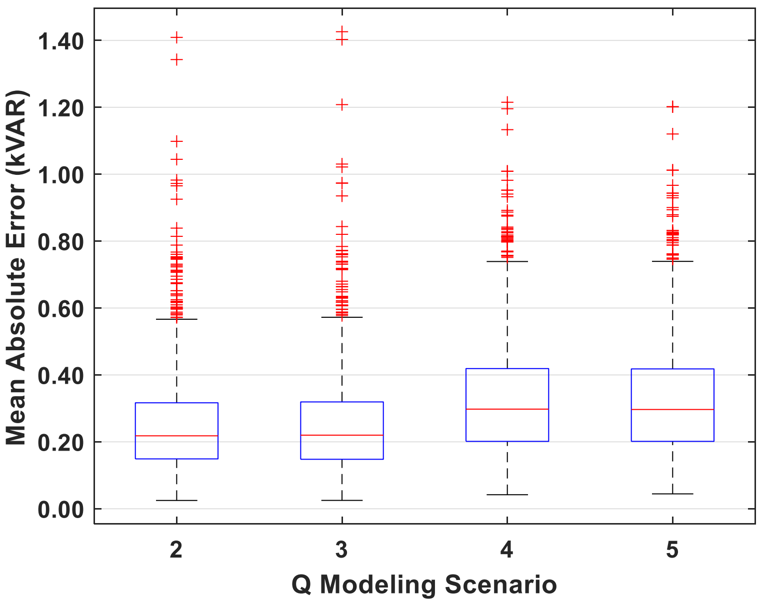
Results – Customer Voltage and Reactive Power Accuracy

All PV at PF=1: Comparison to Baseline Scenario 1 for **All Customers**

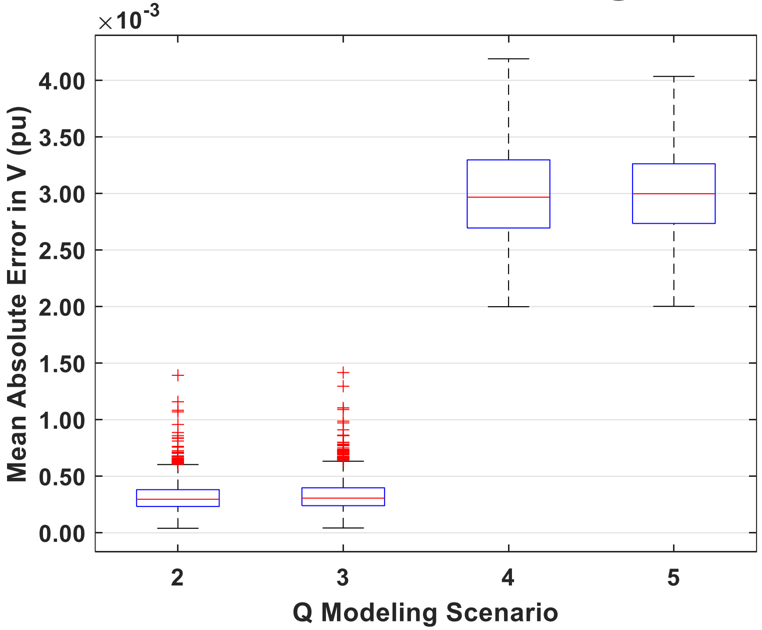
- Impacts were more pronounced on customer voltages
- Using estimated reactive power profiles was better than using constant power factors, median error was 6x lower
- Q estimation algorithm could provide more accurate synthetic voltages when AMI Q data is unavailable



Each Customer Q Error Through the Year



Each Customer V Error Through the Year



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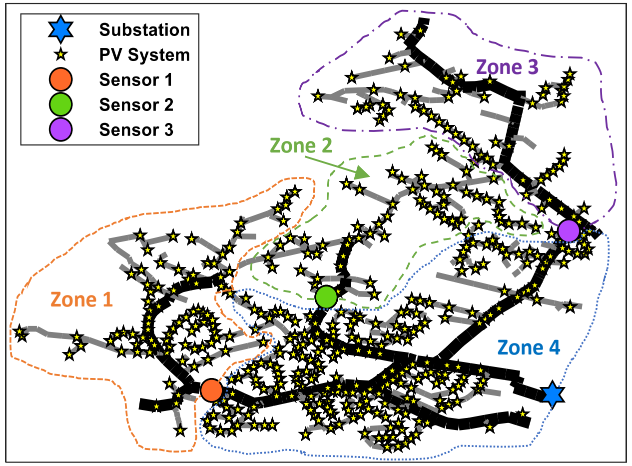
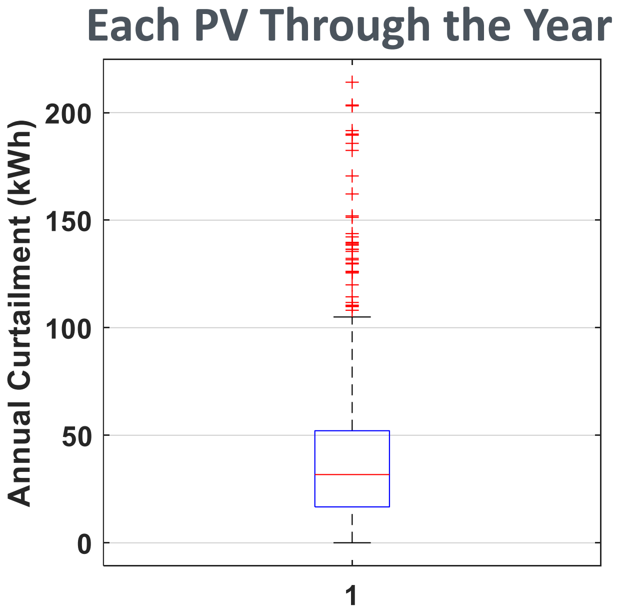
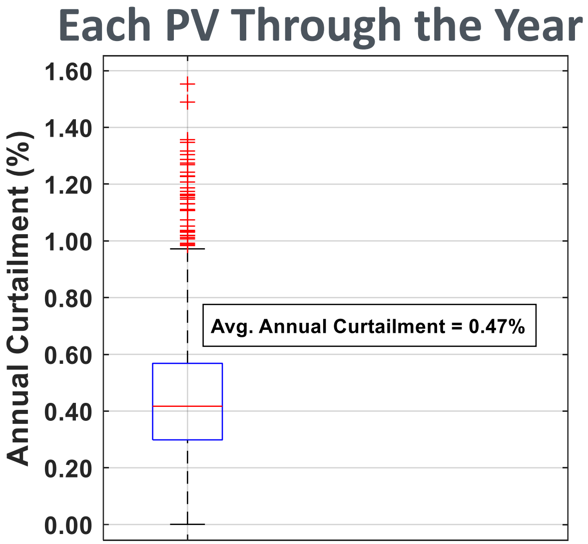
Results – Volt-VAR Curtailment Accuracy

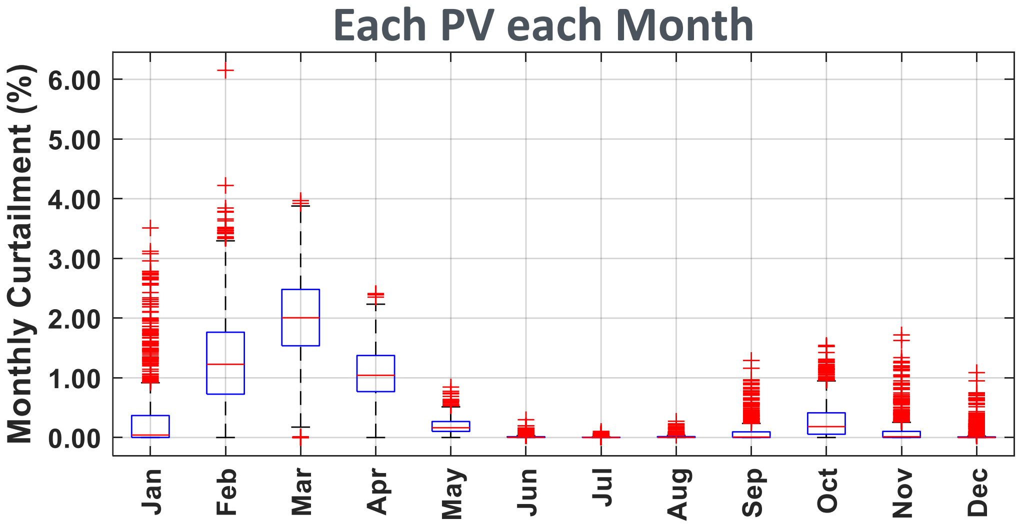
Baseline Curtailment Evaluation

- The curtailment evaluation results are shown below for the baseline Scenario 1, representing the real energy difference when Volt-VAR was enabled
- Since load reactive power modeling impacts customer voltages, it will also impact the performance of the PV inverters when Volt-VAR is enabled





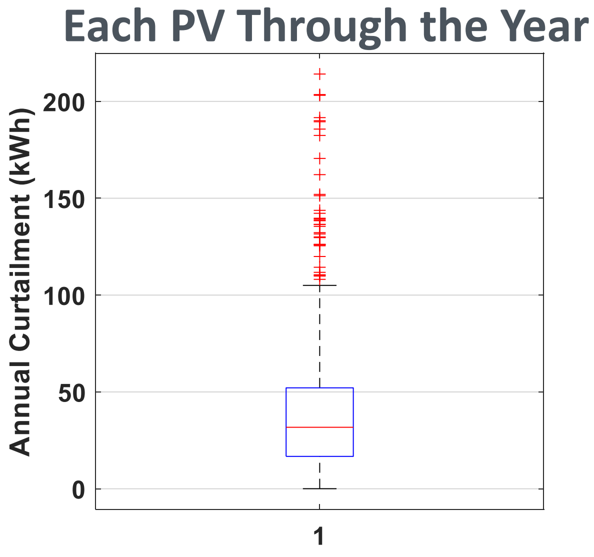


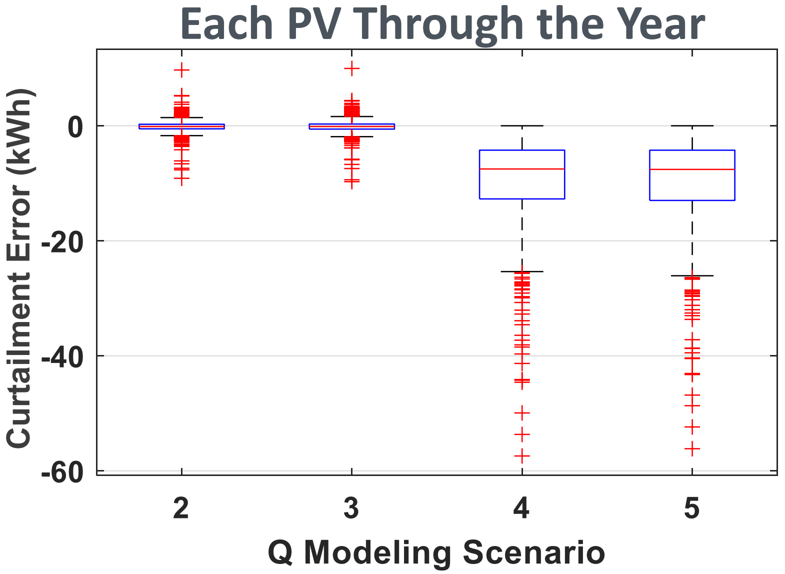


Scenario	# of Q Profiles	Q Methods
1	1379	AMI

Results – Volt-VAR Curtailment Accuracy

- Compared to Scenario 1, Scenarios 2 and 3 were the most accurate while Scenarios 4 and 5 were both significantly less accurate
- For Scenarios 2 and 3, curtailment errors were normally distributed around 0
- For Scenarios 4 and 5, curtailment errors were always negative

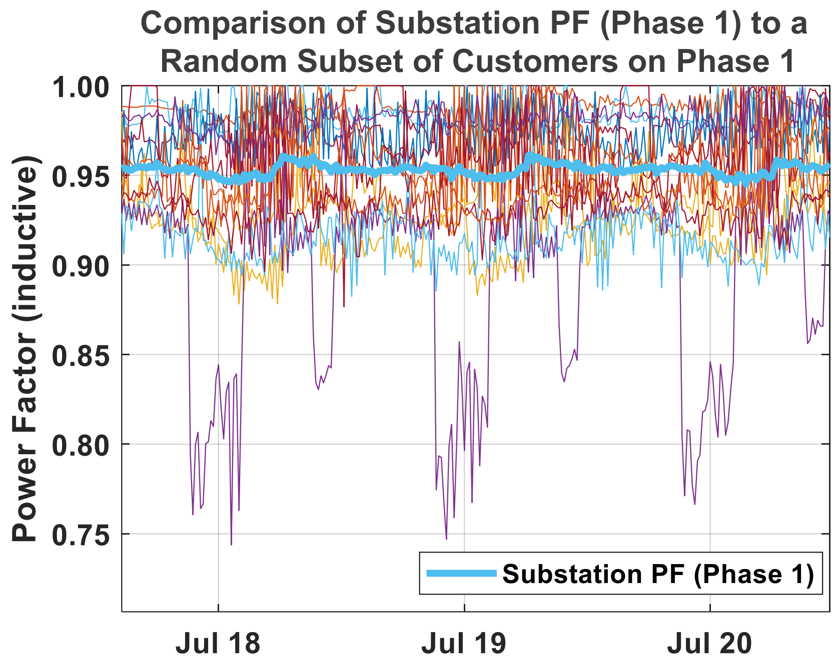


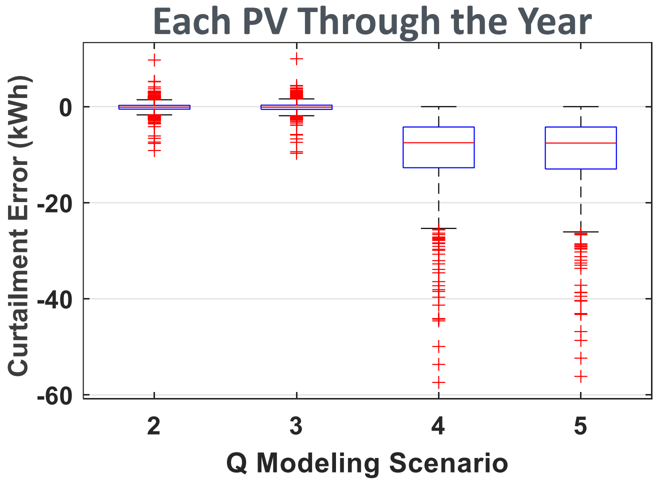


	Curtailment Error Percentiles (kWh)				
Scenario	5th	25th	50th	75th	95th
2	-1.75	-0.52	-0.13	0.26	1.77
3	-1.70	-0.57	-0.12	0.31	1.84
4	-24.02	-12.71	-7.51	-4.24	-2.33
5	-24.92	-12.98	-7.58	-4.24	-2.36

Results – Volt-VAR Curtailment Accuracy

- For Scenarios 4 and 5, the substation PFs are significantly lower during peak load conditions than they are the rest of the year
  - With low inductive PFs at all the loads, the Volt-VAR controllers did not need to absorb as much reactive power, meaning these scenarios consistently underrepresented the conditions for curtailment
- The substation per-phase PFs provide a fairly reasonable approximation for avg. customer PFs
  - The Q-allocation in Scenarios 2 and 3 uses these measurements as the starting point then estimates individual customer contributions
  - On average, those estimates are accurate and capture individual variability but the prediction for any specific customer may be noisy





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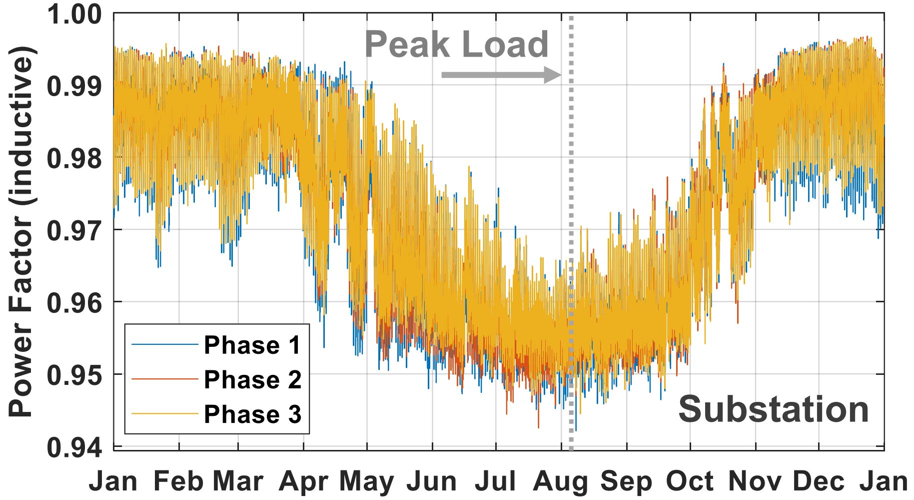


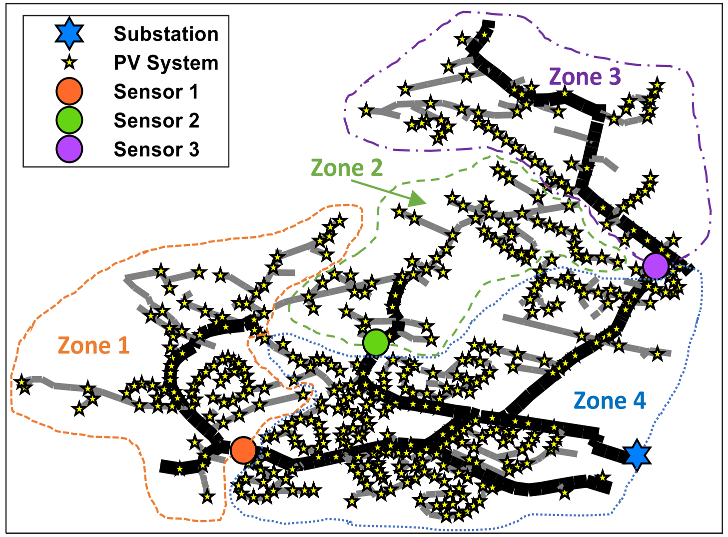
Conclusion

Estimating Customer Voltages:

- The estimated reactive power load profiles provided ~6x more accurate customer voltages than the constant PF methods
  - Slight advantage when additional feeder sensors are included in the estimation algorithm (Scenario 2 vs 3), but not very noticeable
  - The constant PFs used in Scenarios 4 and 5 led to an underestimation of voltages throughout the feeder

Analyzing PV System Performance:

- PV inverters perform grid-support functions (like Volt-VAR) and change their output based on grid conditions
- Estimating Q profiles for load modeling at each time step (Scenarios 2, 3) enabled the PV system performance to be accurately captured
  - Modeling loads with constant PFs does not capture enough temporal or spatial variability at the customer locations where the PV systems are installed



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Acknowledgements

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SOLAR ENERGY TECHNOLOGIES OFFICE U.S. Department Of Energy

References

[1] “Annual Electric Power Industry Report, Form EIA-861,” Oct. 2021. [Online]. Available: https://www.eia.gov/electricity/data/eia861/

[2] “Nearly half of all U.S. electricity customers have smart meters,” 2017. [Online]. Available: https://www.eia.gov/todayinenergy/detail.php?id=34012

[3] EPRI, "Enhanced Load Modeling: Leveraging Expanded Monitoring and Metering," Palo Alto, CA, 3002015283, 2019.

[4] *IEEE 1547 Standard for Interconnection and Interoperability of Distributed Energy Resources with Associated Electric Power Systems Interfaces*, IEEE, 2018.

[5] J. A. Azzolini, M. J. Reno, and K. A. W. Horowitz, “Evaluating Distributed PV Curtailment Using Quasi-Static Time-Series Simulations,” IEEE Open Access Journal of Power and Energy, 2021.

[6] J. A. Azzolini and M. J. Reno, “The Effects of Inverter Clipping and Curtailment-Inducing Grid Support Functions on PV Planning Decisions”, IEEE Photovoltaic Specialists Conference (PVSC), 2021.

[7] J. A. Azzolini, M. J. Reno, and K. A. W. Horowitz, “Evaluation of Curtailment Associated with PV System Design Considerations,” IEEE PES General Meeting, 2020.

[8] J. A. Azzolini and M. J. Reno, "Impact of Load Allocation and High Penetration PV Modeling on QSTS-Based Curtailment Studies," in IEEE PES General Meeting, 2021.

[9] Enhanced Load Modeling: Improved Reactive Power Load Modeling, EPRI, 2021. [Online]. Available: https://www.epri.com/research/products/000000003002022354

[10] J. Peppanen, M. Hernandez, J. Deboever, M. Rylander, M. J. Reno, “Distribution Load Modeling – Survey of the Industry State, Current Practices and Future Needs”, IEEE North American Power Symposium (NAPS), 2021.

[11] P. Siratarnsophon, M. Hernandez, J. Peppanen, J. Deboever, and M. J. Reno, “Improved Load Modelling for Emerging Distribution System Assessments,” CIRED Berlin 2020 Workshop, 2020.

[12] J. Deboever, M. Hernandez, J. Peppanen, P. Siratarnsophon, and M. J. Reno, “Impact of AMI Data Time Granularity on Quasi-Static Time-Series Load Flow Simulation,” IEEE Transmission & Distribution Conference & Exposition, 2020.