VADER: Visualization and Analytics of Distributed Energy Resources

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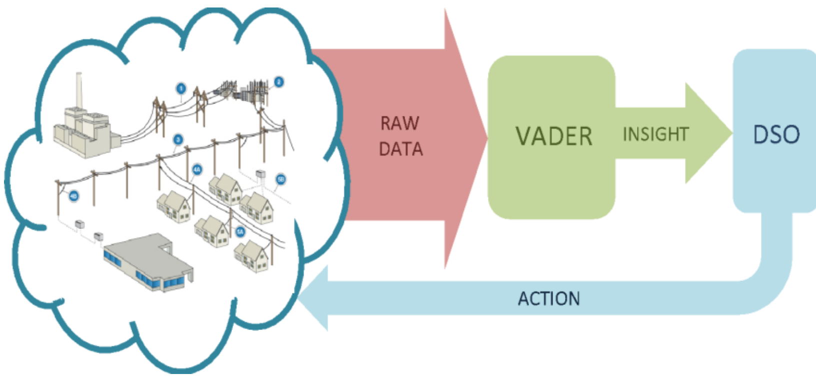
Outline

- Goals of the project
- Challenges due to high penetration of PV
- Major achievements and challenges
  - Solar Disaggregation
  - Switch Configuration Detection
  - Machine Learning-based Power Flow

VADER - Goals



Integrate large number of “high-resolution” and heterogeneous data sources

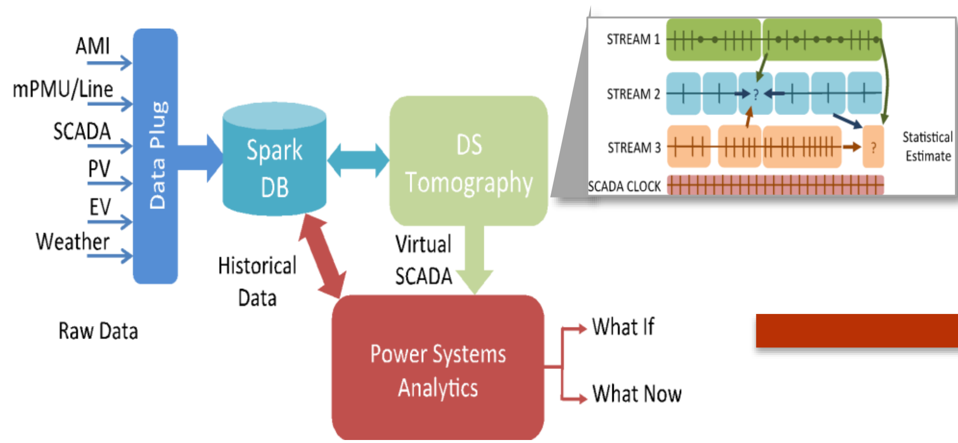
Define a broad set of industry, utility and research driven use cases

Embed existing tools and QSTS capabilities

Validate the platform utilizing a pilot Hardware-in-the-Loop (HIL) testbed

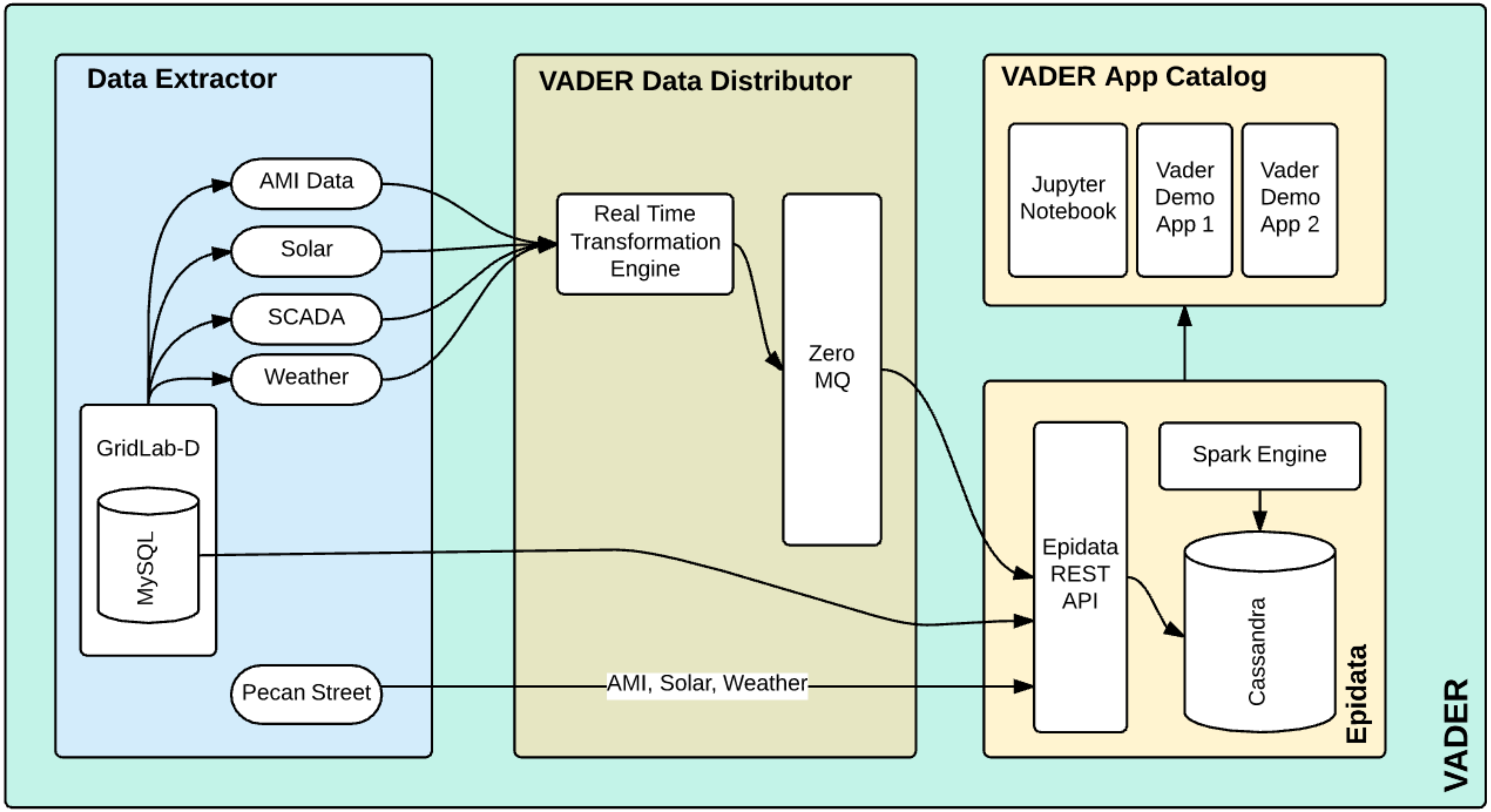
Demonstrate tools using data from industry and utility partners

How to plan and monitor distribution systems with high penetration of Distributed Energy Resources?



- Resource placement
- **PV shortage or over-generation management**
- Voltage issues
- Flexibility planning
- Performance evaluation of distribution systems.

VADER Infrastructure



Challenges

Overall Challenges with PV adoption:

- More active devices that are not modeled or difficult to model.
- Utility unaware of small deployments that add up to a lot.
- Bi-directional power flow and over voltages.

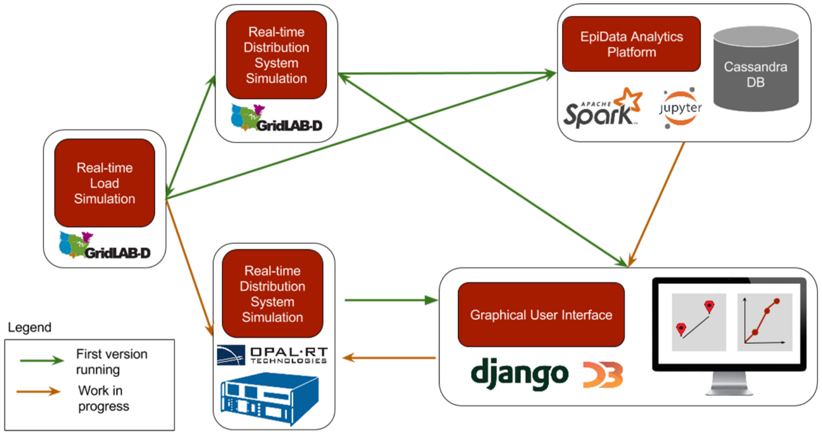
VADER Challenges:

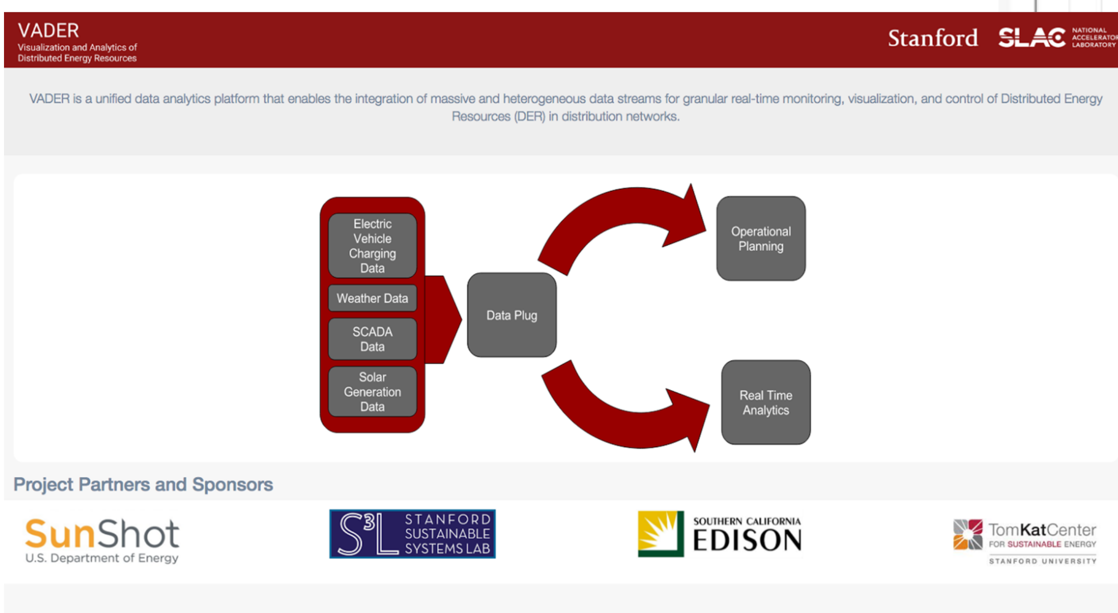
- Interoperability among models (GridLab-D, CYMEDist, Opal-RT)
- Messy data
- Developing schemas for data sets

VADER Accomplishments

- Initial set of analytics developed and tested with IEEE-123 Bus Model (GridLab-D integration)
  - Machine Learning-based Power Flow
  - Switch Detection
  - Solar Disaggregation
  - Forecasting
  - Topology detection
- Platform demonstration with historical data
- Held first VADER Lab in March 2017
- Started applying SCE's data and getting results
  - Solar Disaggregation
  - Switch Detection
- Expanded machine learning- based Power Flow to three-phase systems.
- Developed EV flexibility analytics.

Platform built and initial set of analytics tested





VADER Learning Lab

Two VADER Learning Labs hosted:

- End of March @ SLAC: industry participation
- End of May @ CEC: CEC staff participation

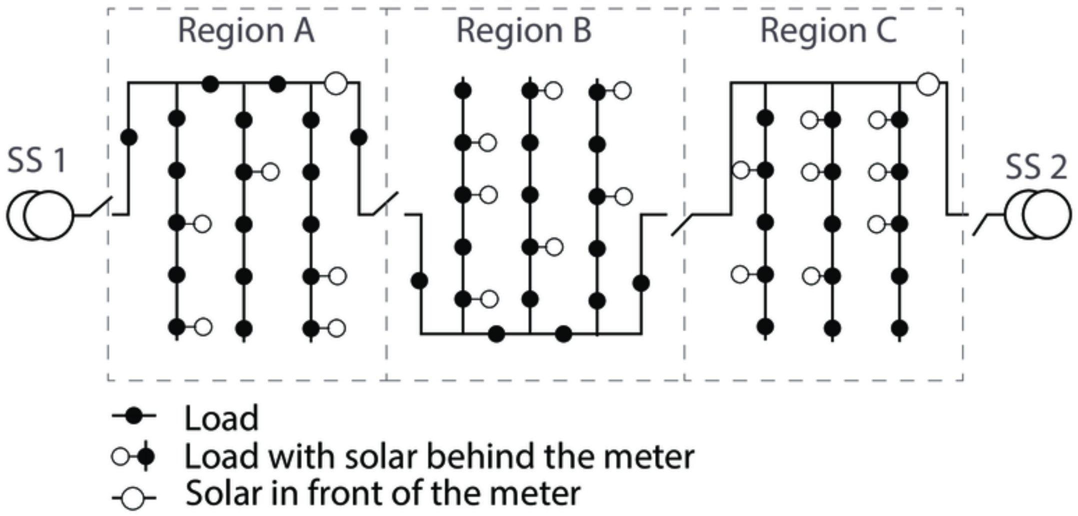
Goals: Critical review and increase awareness to drive adoption

Agenda:

- Overview of VADER
- Intro to infrastructure and UI
- ML-based power flow and Solar disaggregation tutorials followed by tasks for participants
- Wrap up and feedback

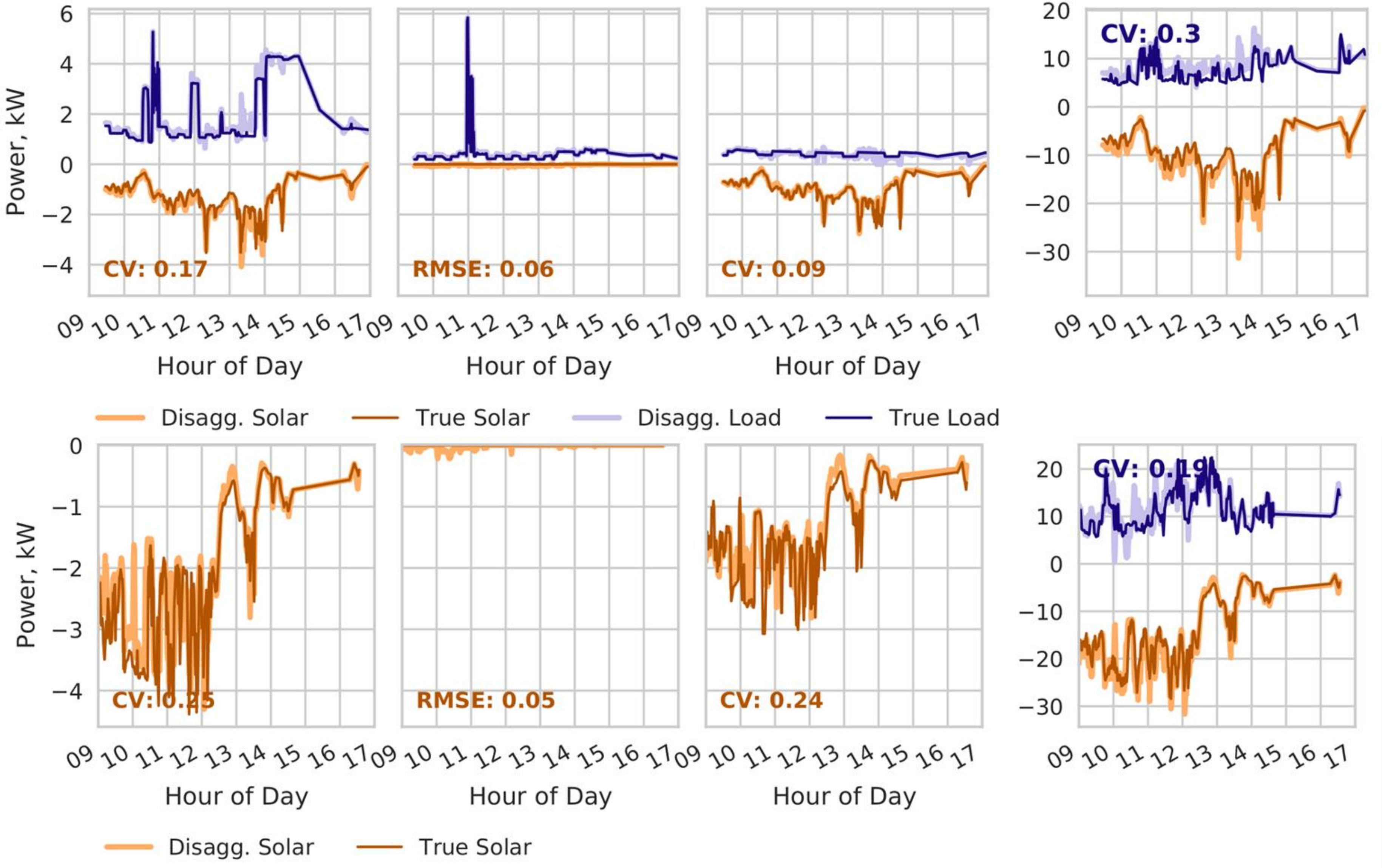
Solar Disaggregation

- Increasing solar penetration
  - –Behind-the-meter
  - –Distribution-level
- Switches maintain a radial structure
- Load is masked
- Visibility into behind-the-meter solar generation is limited



How do we gain more visibility into the load and solar generation?

Results (Training vs. Real-time)

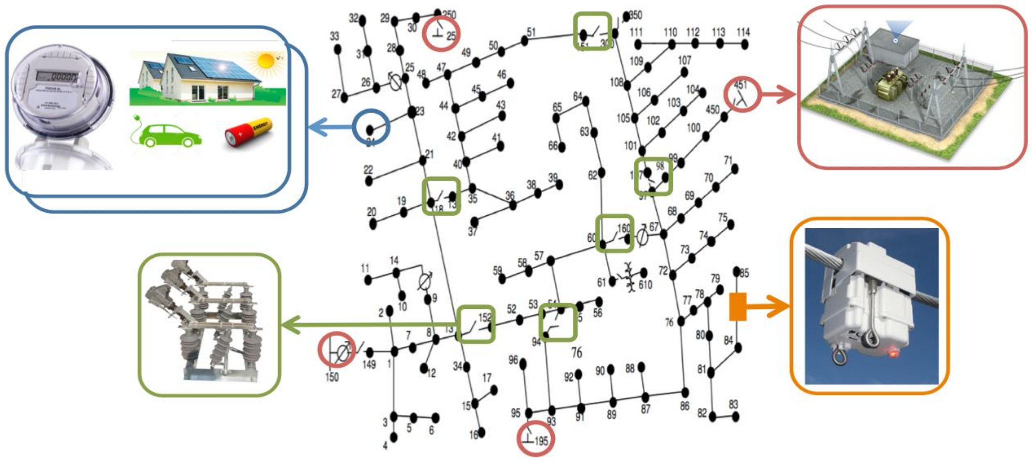


SCE Radial Configuration Detection

Overview:

Detect Switch Status

Sensing: AMI, Line Sensing, Substation



Traditional Approach:

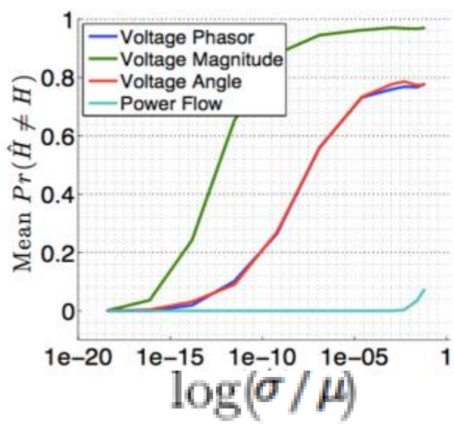
General State Estimation; Voltage, Current

Flow Based Detection

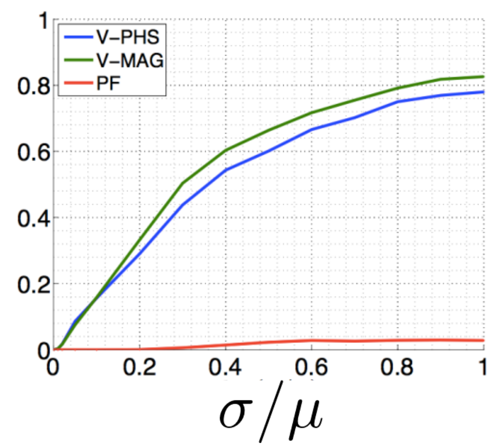
Simple assumptions, detection guarantees

Robust to noise, unknown impedance

Error in Impedances

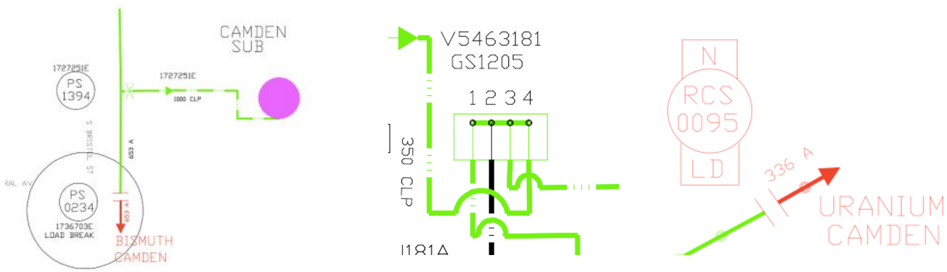


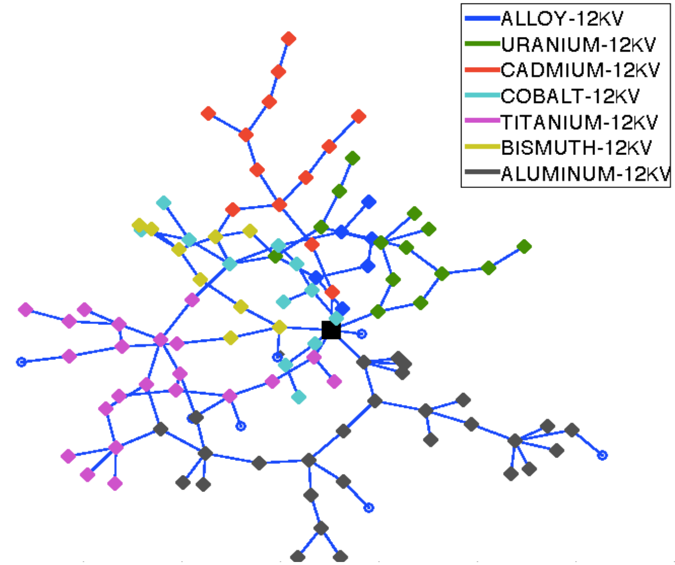
Error in Voltage Meas.



SCE Radial Configuration Detection

Camden Substation





Inter/Intra Feeder:

Underground, Pole Top, Remote Controlled

Network Summary

112 Aggregated Loads with 1, 2, 3 phase loads.

123 Switches to Monitor

5.76057e+09 Possible Radial Configurations

Theory Predicts:

AMI + 12 Line Measurements vs. 123 SCADA Sensors

Current Work:

Extending Algorithms for lossy/3-phase networks.

Machine Learning-based Power Flow

Availability of topology line parameters

- Traditional state estimation method: require line connectivity and parameters information
- ML method: *no need for line Information*

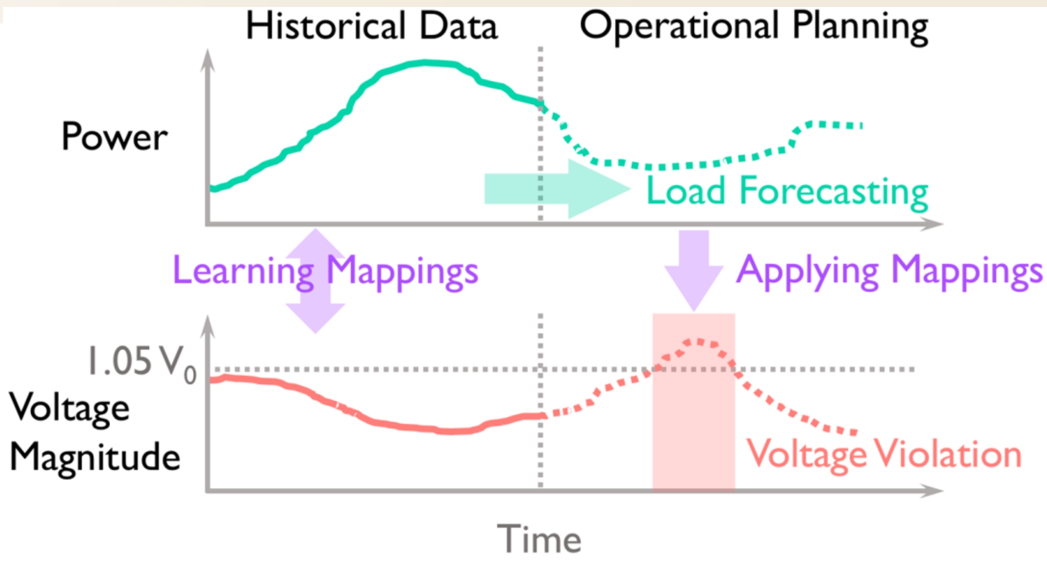
Ability to handle missing measurements

- Traditional Method: No. It needs the whole system to be observable.
- ML Method: Yes. It only *builds correlation between available data at available time slots.*

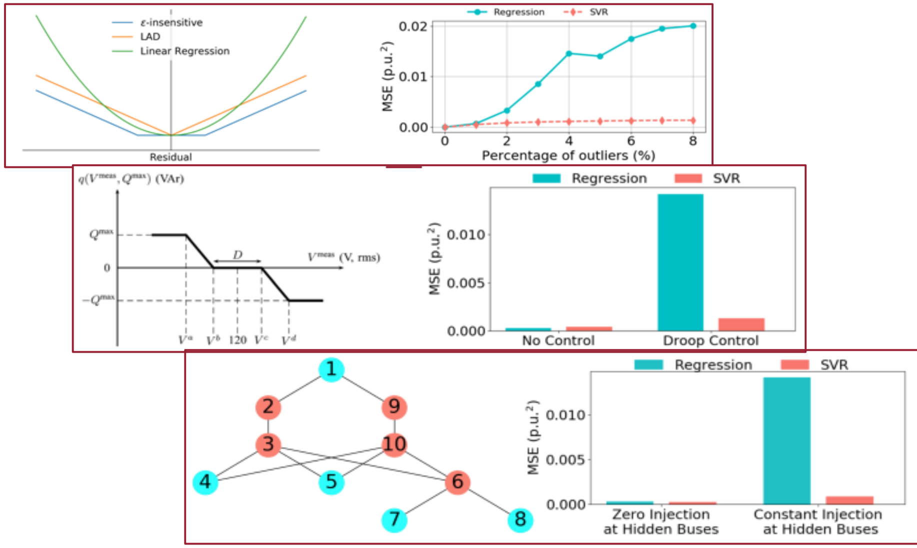
Ability to conduct voltage forecasting / power flow

- Traditional Method: No. It is static state estimation.
- ML Method: Yes. It only *builds correlation between voltages and power*, forecast power, and recover voltage based on the relationship.

Machine Learning Based Power Flow - How does it work and how does it compare

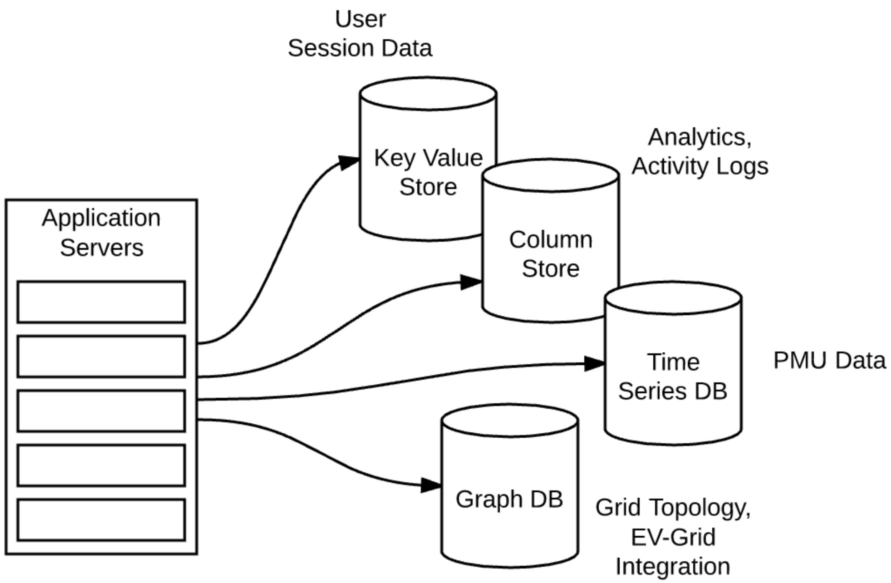


- Practical Advantages of Machine learning based Power Flow
  - Equivalence to physical model
  - Robustness against outliers
  - Capability of modeling 3rd party controllers
  - Flexibility for partially observed systems model construction
  - Capability of inverse mapping: P, Q to voltage mapping

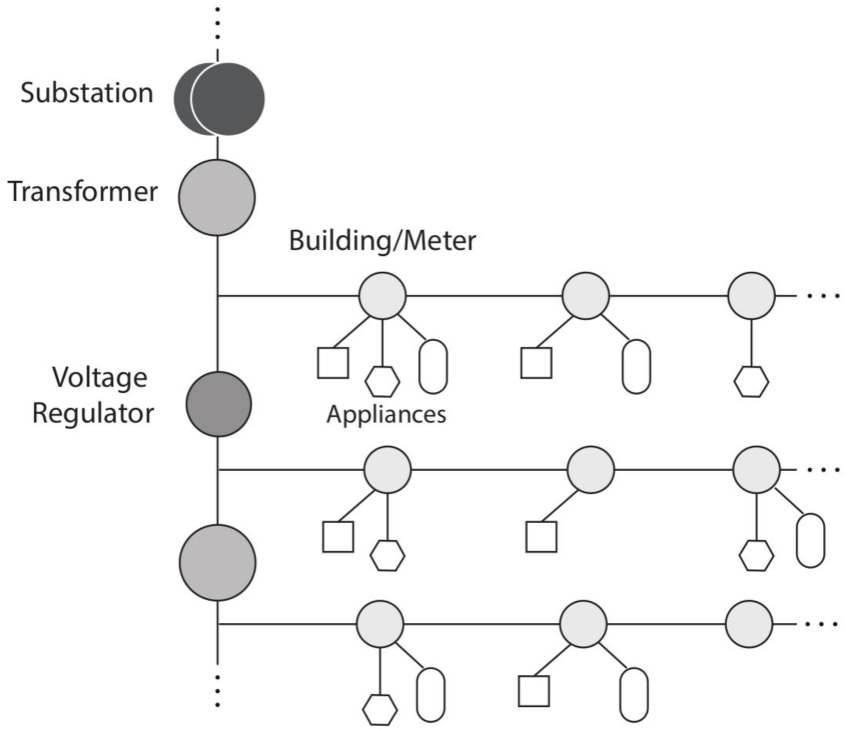


Yu, Jiafan, Yang Weng, and Ram Rajagopal. "Mapping Rule Estimation for Power Flow Analysis in Distribution Grids." *arXiv preprint arXiv:1702.07948*(2017).

VADER Infrastructure - growing new work



Polyglot Persistence Architecture



Discussion and follow on research considered at Data Commons Workshop, Stanford University, July 25, 2017

References

- M. Tabone et al. “Disaggregating solar generation from net load measurements”, IEEE Transactions on Smart Grid (to be submitted)
- Kara et al. “Estimating Behind-the-meter Solar Generation with Existing Measurement Infrastructure (Short Paper)” , Buildsys’16 ACM International Conference on Systems for Energy-Efficient Built Environments (2016)
- Raffi Sevlian and Ram Rajagopal, "Distribution System Topology Detection Using Consumer Load and Line Flow Measurements", IEEE Transactions on Control of Network (to be submitted)
- M. Malik et al. “A Common Data Architecture for Energy Data Analytics”, IEEE SmartGridComm (under review)
- Yu, Jiafan, Yang Weng, and Ram Rajagopal. "Mapping Rule Estimation for Power Flow Analysis in Distribution Grids." *arXiv preprint arXiv:1702.07948*(2017).

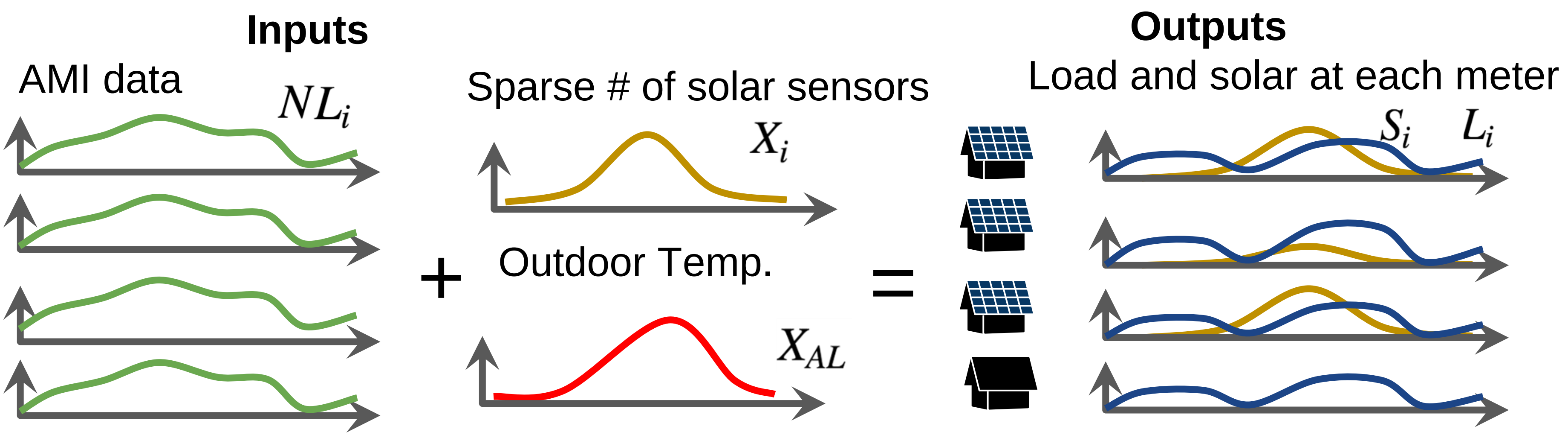
Thank you

Questions?

Back-up Slides

Problem formulation

Day-ahead training problem (learning the model):



Problem formulation

Real-time estimation problem:

Input
Data from load aggregation point (substation)
Solar from sparse # of sensors
Outdoor Temp.

Outputs
Solar at each meter