SOLAR ENERGY
TECHNOLOGIES OFFICE
U.S. Department Of Energy

PORTFOLIO REVIEW
2018

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2018 SETO Portfolio Review

VADER – Visualization and Analytics with High Penetration of Distributed Energy Resources

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Outline

Problem Statement

Project Overview and Goals

Major achievements

- Technical
- Industry Engagement
- Publications

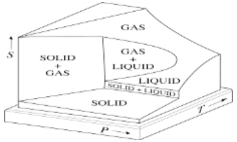
Problem Statement

Overall Challenges with PV adoption:

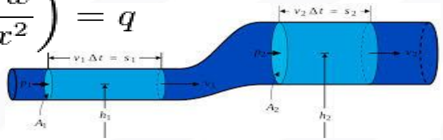
- More active devices that are not modeled or difficult to model.
- Utility unaware of small deployments that add up to a lot.
- Bi-directional power flow and over voltages.

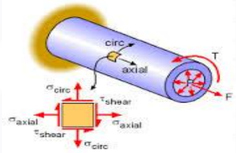
Data-Driven Modeling

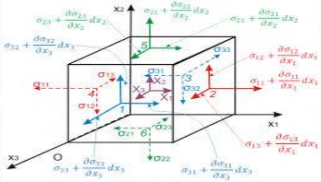
Physics-based models use basic equations of continuum mechanics, materials, heat transfer, power flow, …. that capture the phenomenon in a mathematical form



$$\frac{d^2}{dx^2}\left(EI\frac{d^2w}{dx^2}\right) = q$$







We don’t have ‘basic equations’ for social, medical, behavioral, economic and other complex phenomena.

Source: Guha Ramanathan

Data-Driven Modeling has been extremely successful.

Take lots of data and fit the curve …

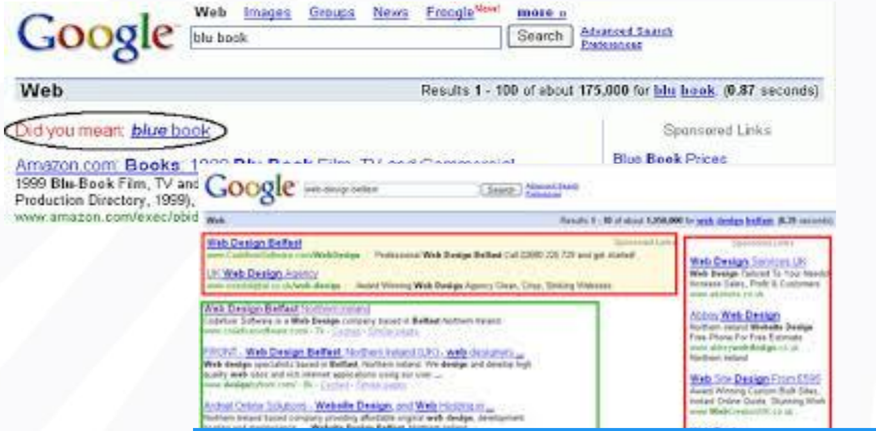
(No causal equations required)

Lots of data and compute power

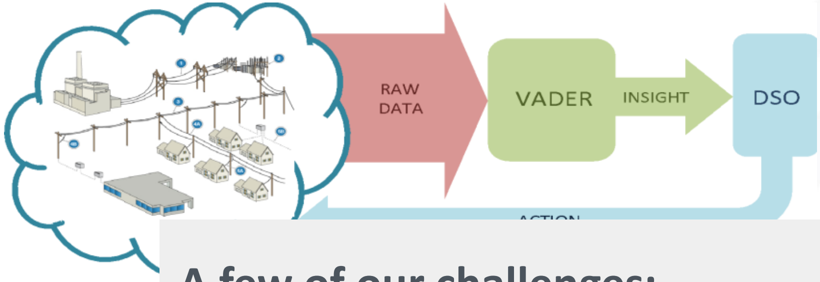
Extremely successful in the last 10 years

- Spell Correction
- Web search and advertising
- News feed
- Perception: Vision, speech

(Mostly web-ecosystem products)



VADER Overview



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 capabilities

Validate the platform utilizing a pilot Hardware-
ed
g data from industry and

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

A few of our challenges:

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

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

VADER Accomplishments

- Initial set of analytics developed and tested with IEEE-123 Bus Model (GridLab-D integration) and some validated with actual data
  - Machine Learning-based Power Flow
  - Switch Detection
  - Solar Disaggregation
  - Forecasting
  - Topology detection
  - Statistical Clear Sky
  - PV Power Intraday Forecasting
- Platform demonstration with historical data
- Platform transition to more scalable implementation
- Held VADER Workshops and Labs
- Started applying Southern California Edison's data and getting results
  - Solar Disaggregation
  - Switch Detection
- Expanded machine learning-based Power Flow to three-phase systems.
- Developed flexibility analytics.

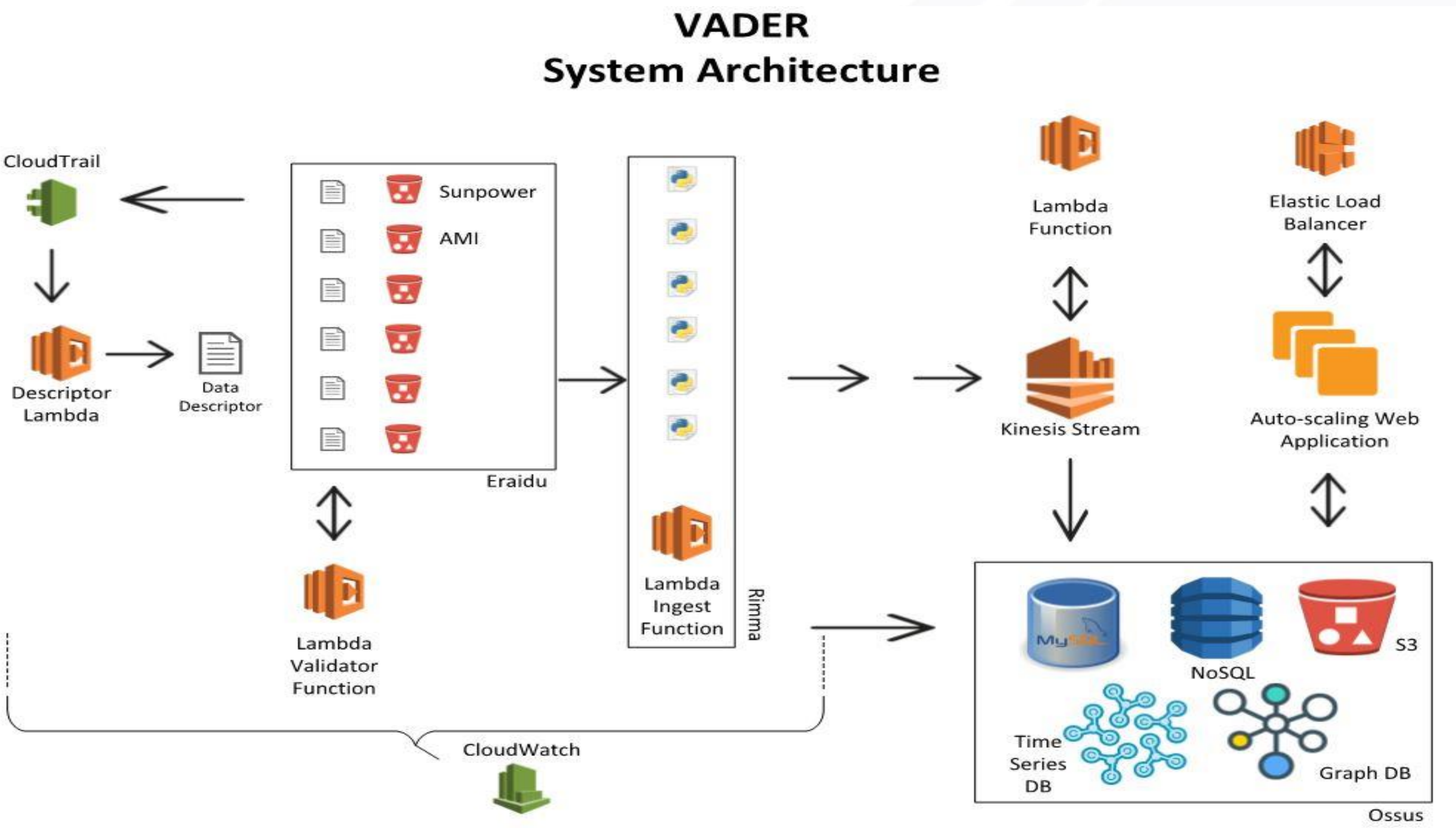
Utilization of Data for Power System Analytics Tools (1/2)

Power System Analytics	Types of Data
(1) Distribution grid topology reconstruction	(1.1) Hourly bus voltage magnitudes * Two weeks of data for training * Extensive testing & validation using one year of data
(2) Detection of distribution grid topology switching	(2.1) 1-minute resolution of voltage data * Data for several hours
(3) Distribution grid topology and line parameter estimation	(3.1) Phase angles from μ-PMU data in addition to data type (1.1) (3.2) Active (*P*) and reactive power (*Q*), if available
(4) Distribution grid outage detection	(4.1) Bus voltage magnitude and phase angle from μ-PMU
(5) Distribution grid machine learning power flow, state estimation	(5.1) Data synchronization between utility and third parties (e.g. PV data from SunPower), data plug module (5.2) *P* & *Q* at each bus (5.3) SunPower voltage magnitude and its *P* at solar locations will improve estimates

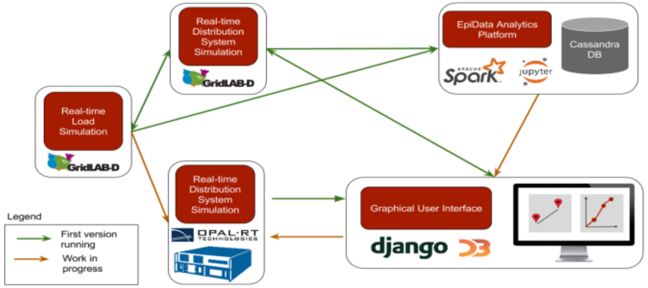
Utilization of Data for Power System Analytics Tools (2/2)

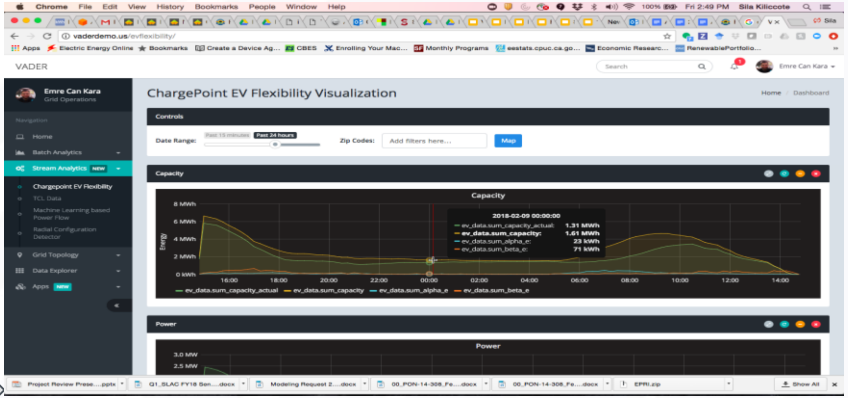
Power System Analytics	Types of Data
(6) Solar disaggregation	(6.1) Net load measurements at the point of disaggregation (three scenarios): At substation (SCADA ~4 sec sampling rate) / transformer (aggregated from AMI downstream) / AMI meters (15-minute or faster) (6.2) Outside temperature from the region of interest (6.3) solar proxy; data from irradiance sensors and/or active power measurements, typically 1-2 minute sampling rate (6.4) Reactive power, if available, at substation / transformer / AMI at same sampling rate as load
(7) Customer load forecasting	(7.1) Hourly smart meter active power * Two weeks of data for training
(8) Clear sky solar prediction	(8.1) measured output power of PV system

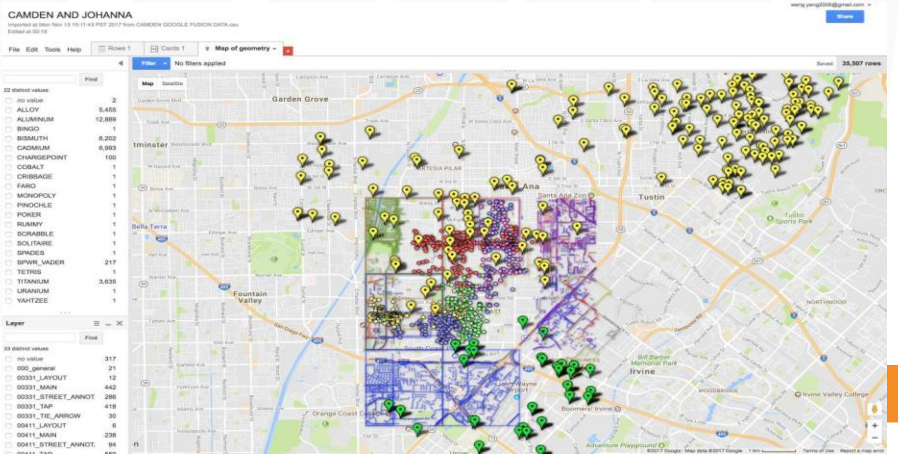
VADER Infrastructure



Platform Built and Analytics Tested







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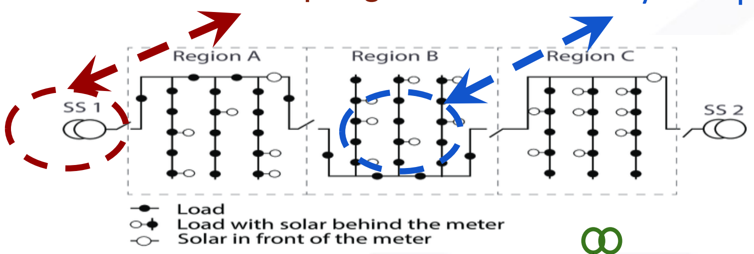
Solar Disaggregation: gain visibility into behind-the-meter solar (Emre Kara, Michaelangelo Tabone)

Disaggregate solar generation from meter readings of net load

2 measurements of net load in distribution systems

Real-time SCADA measurements
Typical 4 seconds sampling

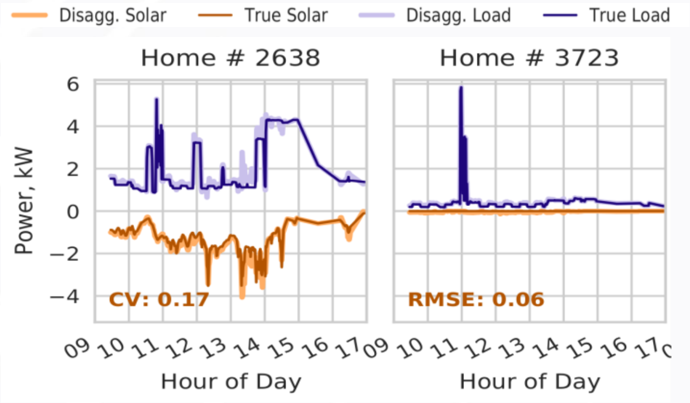
AMI: overnight updates
1-min to hourly sampling rate



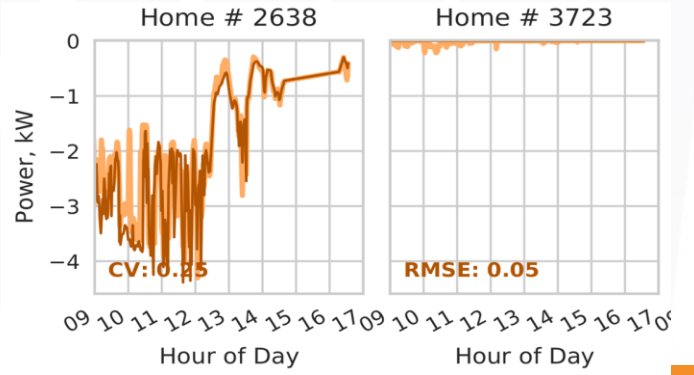
Initial work at LBNL doing feeder level solar-disaggregation has received an R&D 100 award.

Validation set: submetered solar and load from Pecan Street

Day Ahead Model Training AMI + SCADA



Streaming Analytics SCADA



SCE Radial Configuration Detection (Raffi Sevlian)

Overview:

Detect Switch Status

Sensing: AMI, Line Sensing, Substation

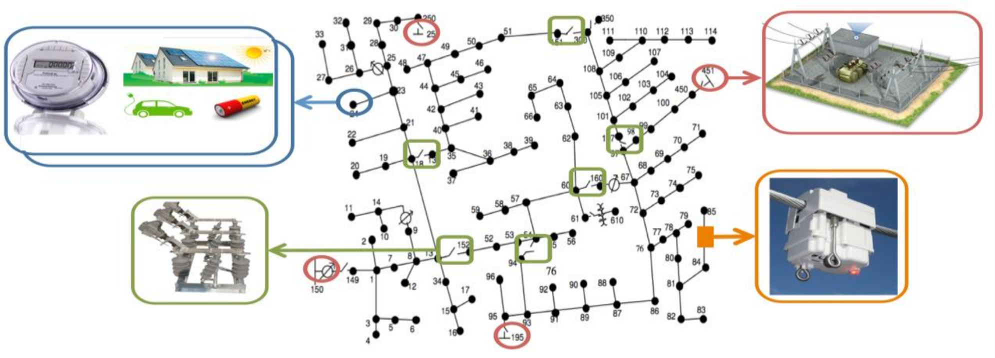
Traditional Approach:

General State Estimation; Voltage, Current

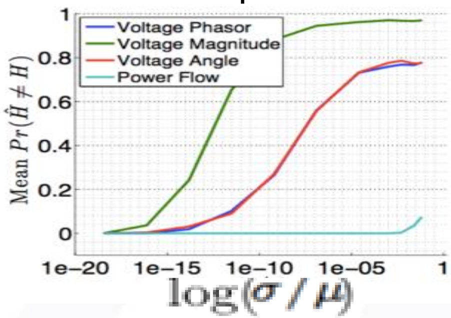
Flow Based Detection

Simple assumptions, detection guarantees

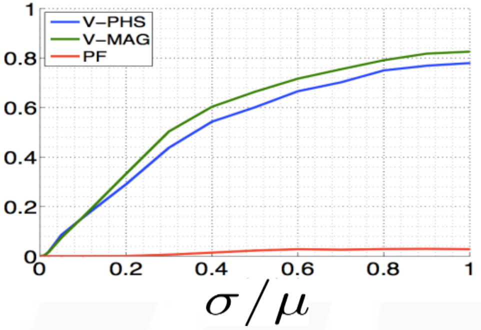
Robust to noise, unknown impedance



Error in Impedances

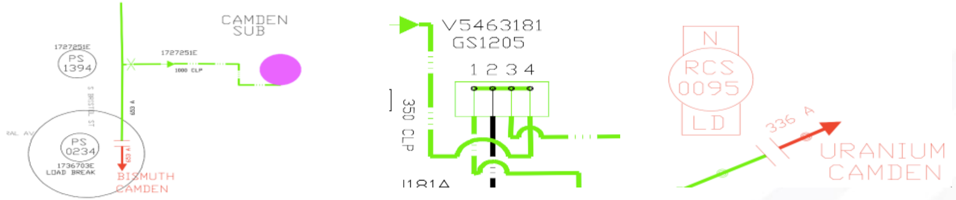


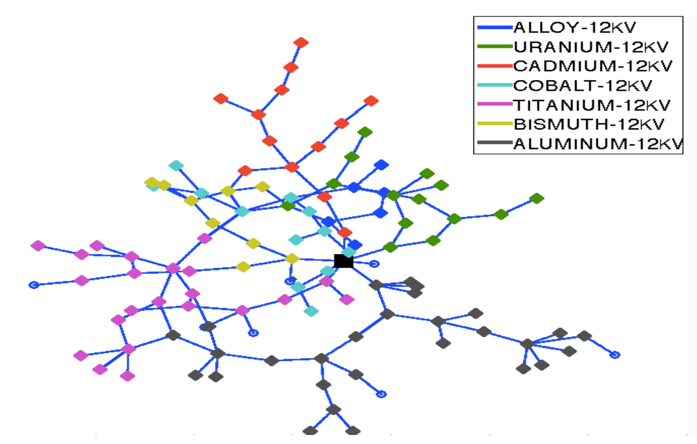
Error in Voltage Meas.



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 (Ram Rajagopal)

Availability of topology line parameters

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

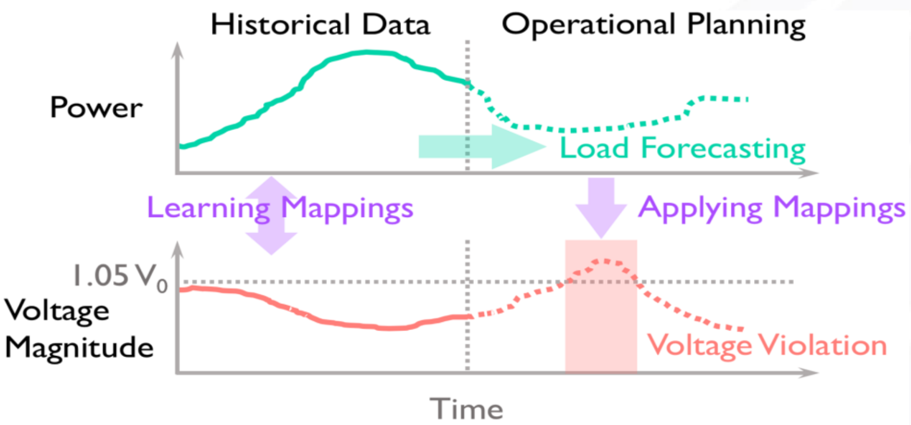
Ability to handle missing measurements

- 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.*

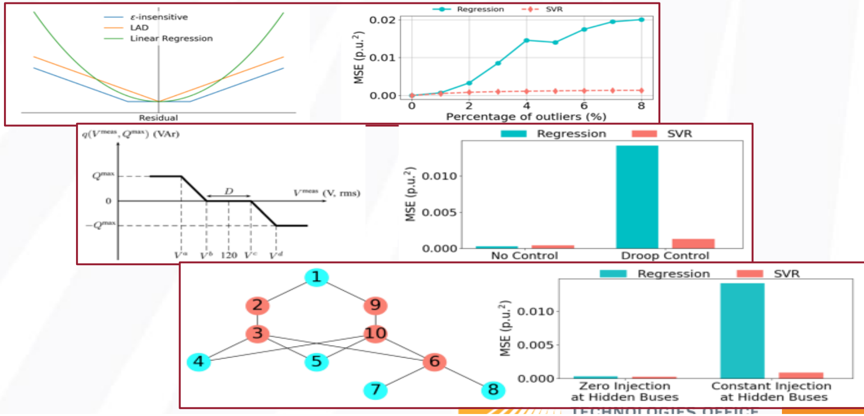
Ability to conduct voltage forecasting / power flow

- 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).

Industry Engagement - Workshops and Learning Lab

Two workshops hosted at SLAC

Goal: to receive critical review

Two VADER Learning Labs hosted:

- End of March 2017 @ SLAC: industry participation
- End of May 2017 @ California Energy Commission: CEC staff participation

Goal: Increase awareness to drive adoption

Publications

[1] Yizheng Liao, Yang Weng, and Ram Rajagopal, "Urban Distribution Grid Topology Reconstruction via Lasso", *Proceedings of IEEE Power and Energy Society General Meeting*, 17-21 July, 2016.

[2] Yizheng Liao, Yang Weng, Chin-Woo Tan, and Ram Rajagopal, "Urban Distribution Grid Line Outage Detection",*Proceedings of IEEE Conference on Probabilistic Methods Applied to Power Systems*, Beijing, China, 16-20 October, 2016. (<u>Best Conference Paper Award</u>)

[3] Emre C. Kara, et al., "Estimating Behind-the-meter Solar Generation with Existing Measurement Infrastructure",*Buildsys'16 ACM International Conference on Systems for Energy-Efficient Built Environments*, November 2016.

[4] Emre C Kara, et al., "Towards real-time estimation of solar generation from micro-synchrophasor measurements",*arXiv preprint arXiv:1607.02919* (2016).

[5] Junjie Qin, Insoon Young, and Ram Rajagopal, "Submodularity of Energy Storage Placement in Power Network", *Proceedings of IEEE Conference on Control and Decision*, 12-14 December, 2016.

[6] Souhaib Ben Taieb, Jiafan Yu, Mateus Neves Barreto, and Ram Rajagopal, "Regularization in Hierarchical Time Series Forecasting with Application to Electricity Smart Meter Data", *Proceedings of AAAI conference on Artificial Intelligence*, 4-9 February, 2017.

[7] Jiafan Yu, Junjie Qin, and Ram Rajagopal, “On Certainty Equivalence of Demand Charge Reduction Using Storage”, *Proceedings of American Control Conference*, Seattle, WA, 24-26 May, 2017.

[8] Bennet Meyers and Mark Mikofski, “Accurate Modeling of Partially Shaded PV Arrays”, *Proceedings of Photovoltaic Specialists Conference* (PVSC-44), Washington, DC, 25-30 June, 2017.

Publications cont.

[9] Jiafan Yu, Yang Weng, and Ram Rajagopal, “Data-Driven Joint Topology and Line Parameter Estimation for Renewable Integration”, *Proceedings of IEEE Power and Energy Society General Meeting,* Chicago, IL, 16-20 July, 2017.

[10] Jiafan Yu, Yang Weng, and Ram Rajagopal, “Robust Mapping Rule Estimation for Power Flow Analysis in Distribution Grids”, North American Power Symposium, Morgantown, WV, 17-19 September, 2017.

M. Malik et al. “A Common Data Architecture for Energy Data Analytics”, IEEE SmartGridComm

[11] Nikolay Laptev, Jiafan Yu, and Ram Rajagopal, “Deepcast: Universal Time Series Forecaster”, *International Conference on Learning Representations*, 2017.

[12] Raffi Sevlian and Ram Rajagopal, "Distribution System Topology Detection Using Consumer Load and Line Flow Measurements." *arXiv preprint arXiv:1503.07224* (2017).

[13] Yizheng Liao, Yang Weng, and Ram Rajagopal, “Distributed Energy Resources Topology Identification via Graphical modeling”, *IEEE Transactions on Power Systems,* 2017 (accepted for publication).

[14] Yizheng Liao, Yang Weng, Guangyi Liu, and Ram Rajagopal, “Urban MV and LV Distribution Grid Topology via Group Lasso”, *IEEE Transactions on Power Systems,* 2017 (under review).http://web.stanford.edu/~yzliao/pub/TPS_info.pdf.

[15] Jiafan Yu, Yang Weng, and Ram Rajagopal, “PaToPa: A Data-Driven Parameter and Topology Joint Estimation Framework in Distribution Grids”, *IEEE Transactions on Power Systems* (under review).

Thank you

VADER Team:

Emre Kara, David Chassin, Mayank Malik, Raffi Sevlian, Supriya Premkumar, Alyona Ivanova, Bennet Meyers, Berk Serbetcioglu

Ram Rajagopal, Chin-Woo Tan, Michaelangelo Tabone, Mark Chen, Yizheng Liao, Jiafan Yu, Yang Weng, Siobhan Powell

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