

Estimating the behind-the-meter solar generation with existing infrastructure

Emre Can Kara,
Michaelangelo Tabone, Sila Kiliccote

AI-at-SLAC

July 11, 2017

Our team

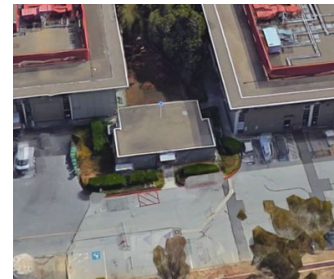
Science Directorate > Applied Energy Program:

- Materials for energy
- Subsurface Technology
- 21st Century Electric Grid



gismo.slac.stanford.edu

- Team of 15 researchers, scientists and engineers.
- Major funding:
 - DOE EERE
 - CEC EPIC
 - ARPA-e



What do we do @GISMo?



POWER GRID

- Distributed control
- Data-driven planning and operations with DERs
- Pricing mechanisms and market structures
- Business models
- Regulatory frameworks

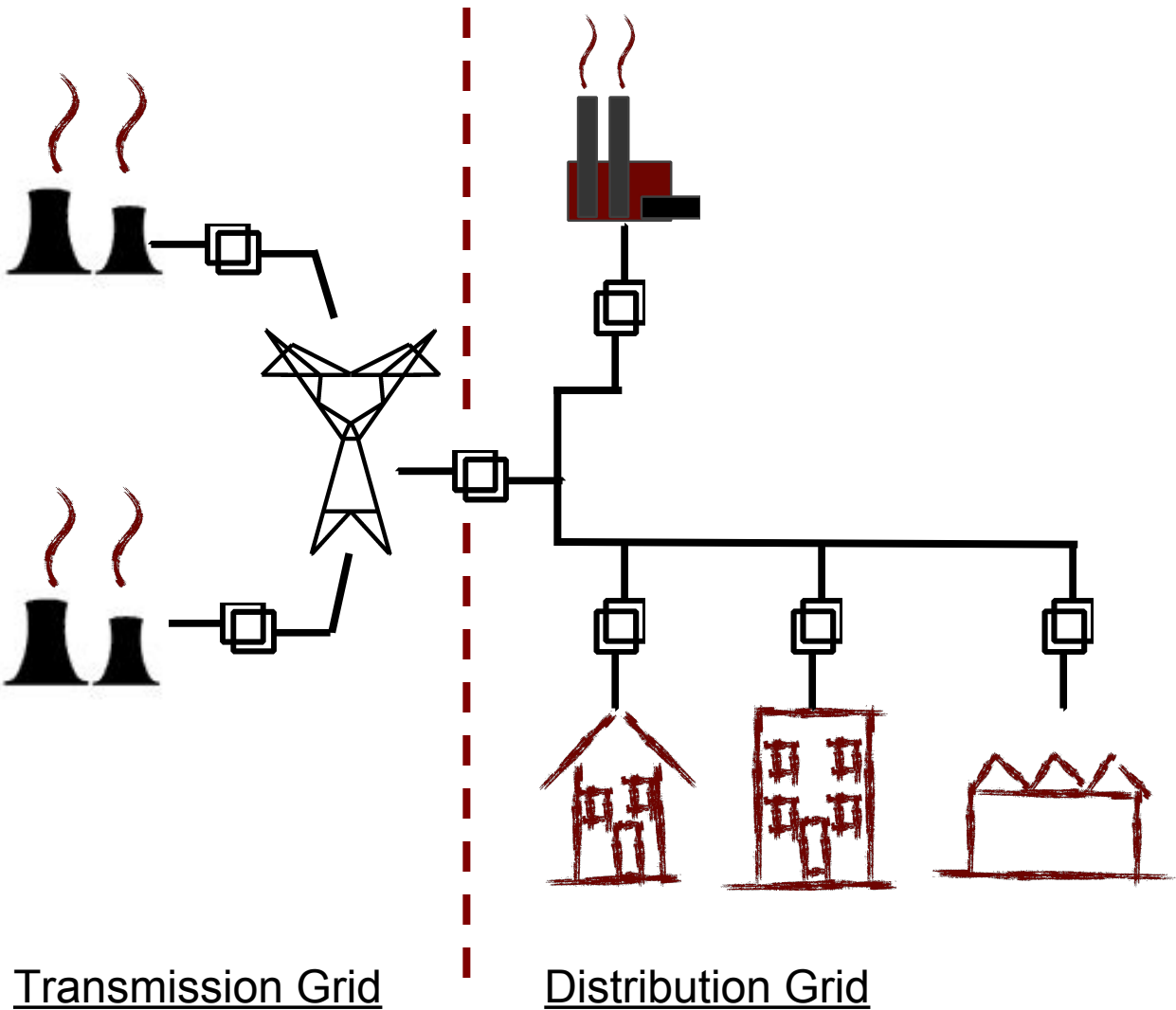
AMBIENT /BUILDING INTELLIGENCE

- Interaction design
- Seamless integration
- Embedded
- Context aware
- Personalized
- Adaptive
- Anticipatory

MOBILITY

- Mobility as a service
- Electrification of transportation
- Data-driven modeling and analysis
- Vehicle-to-building
- Vehicle-to-grid

Integrating Renewable Energy

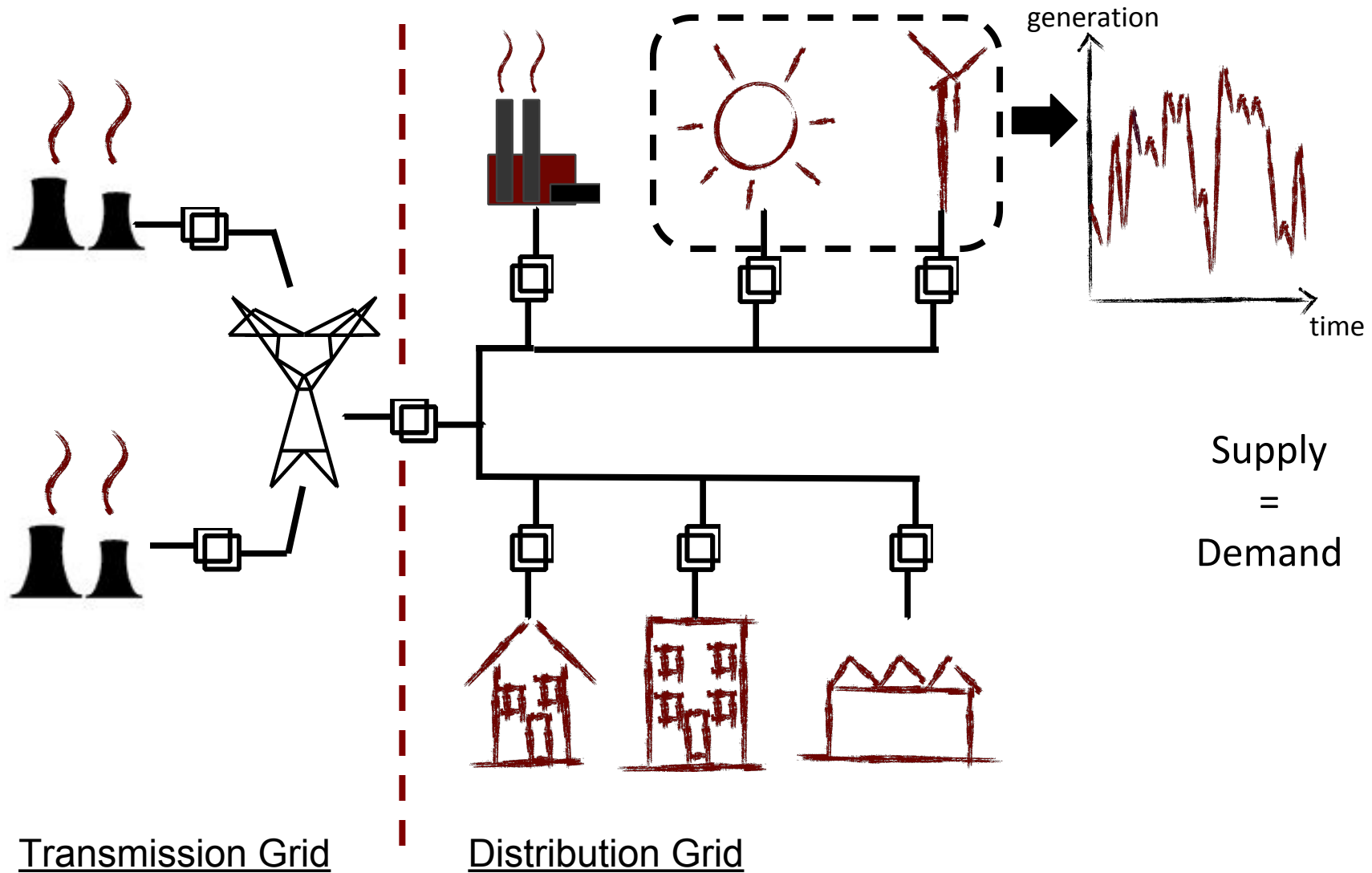


Supply
=
Demand

Transmission Grid

Distribution Grid

Integrating Renewable Energy



Transmission Grid

Distribution Grid

VADER: Visualization and Analytics for Distributed Energy Resources

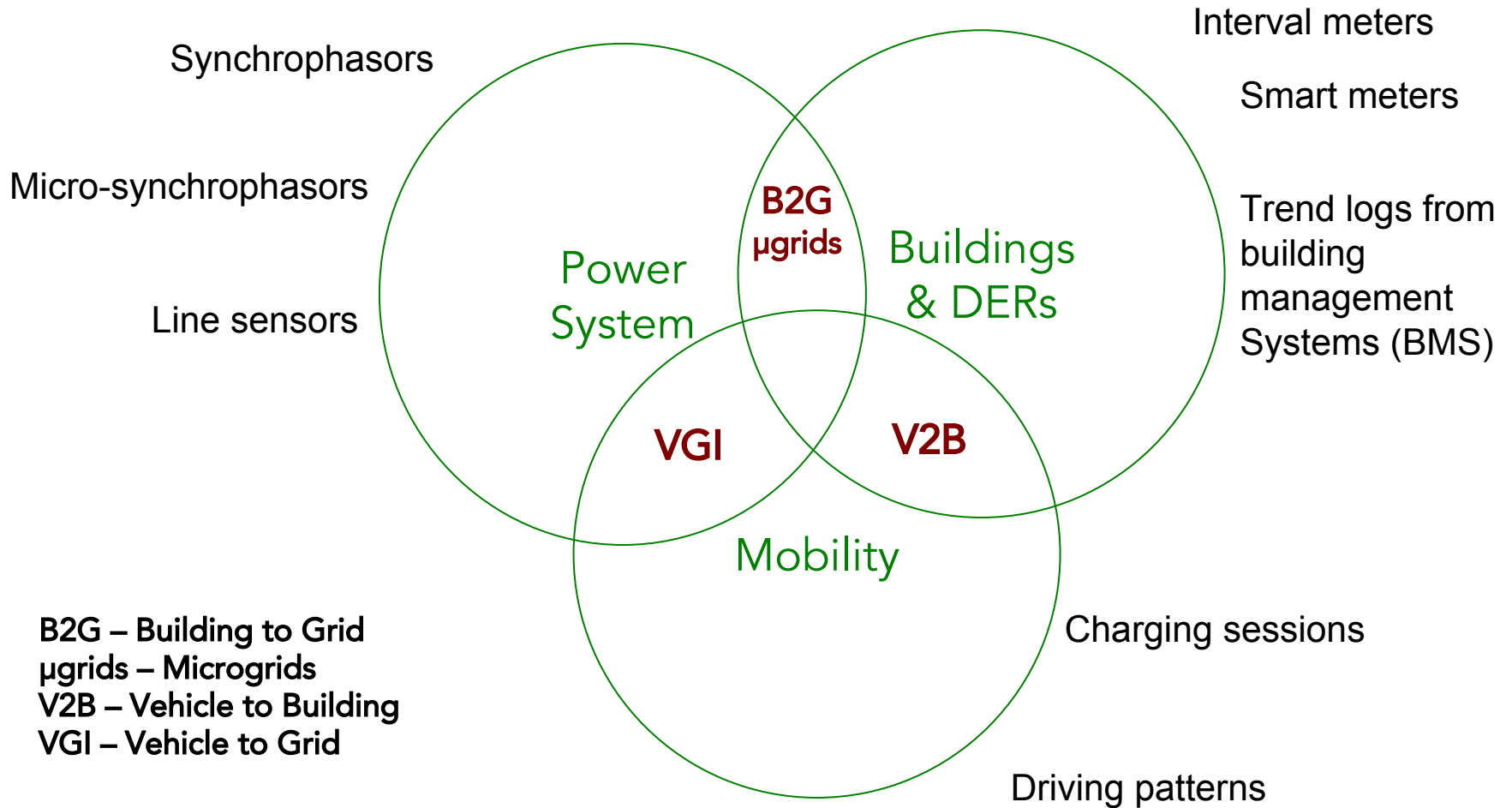
Enabling high penetration of renewables requires:

- More comprehensive and dynamic situational awareness; and
- Active control of the distribution network.

Traditional approach/technology is inadequate:

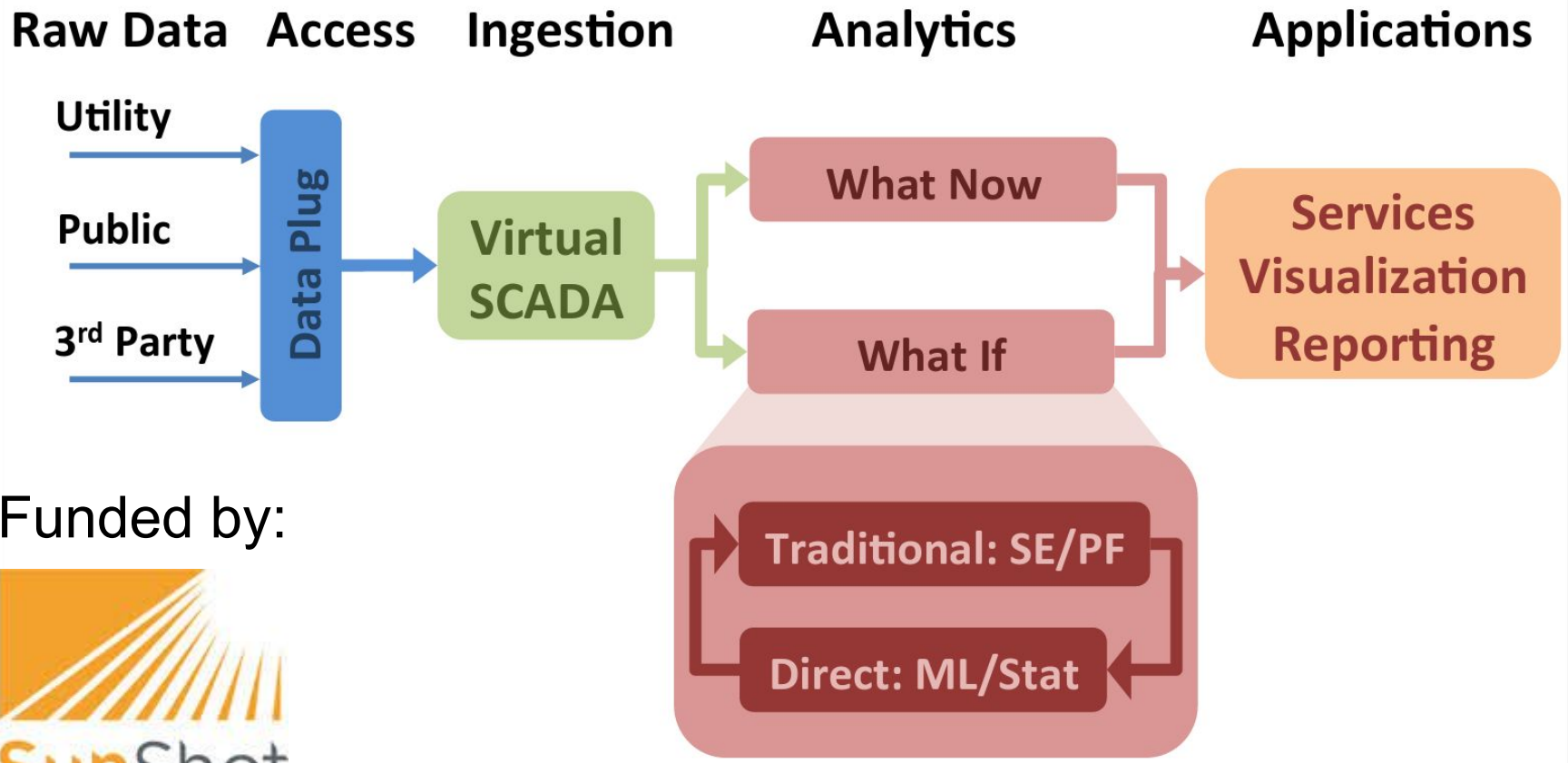
- Partial observability
- New devices and models
- Heterogenous data sources and data streams

Plenty of data that is not being used!



VADER Introduction

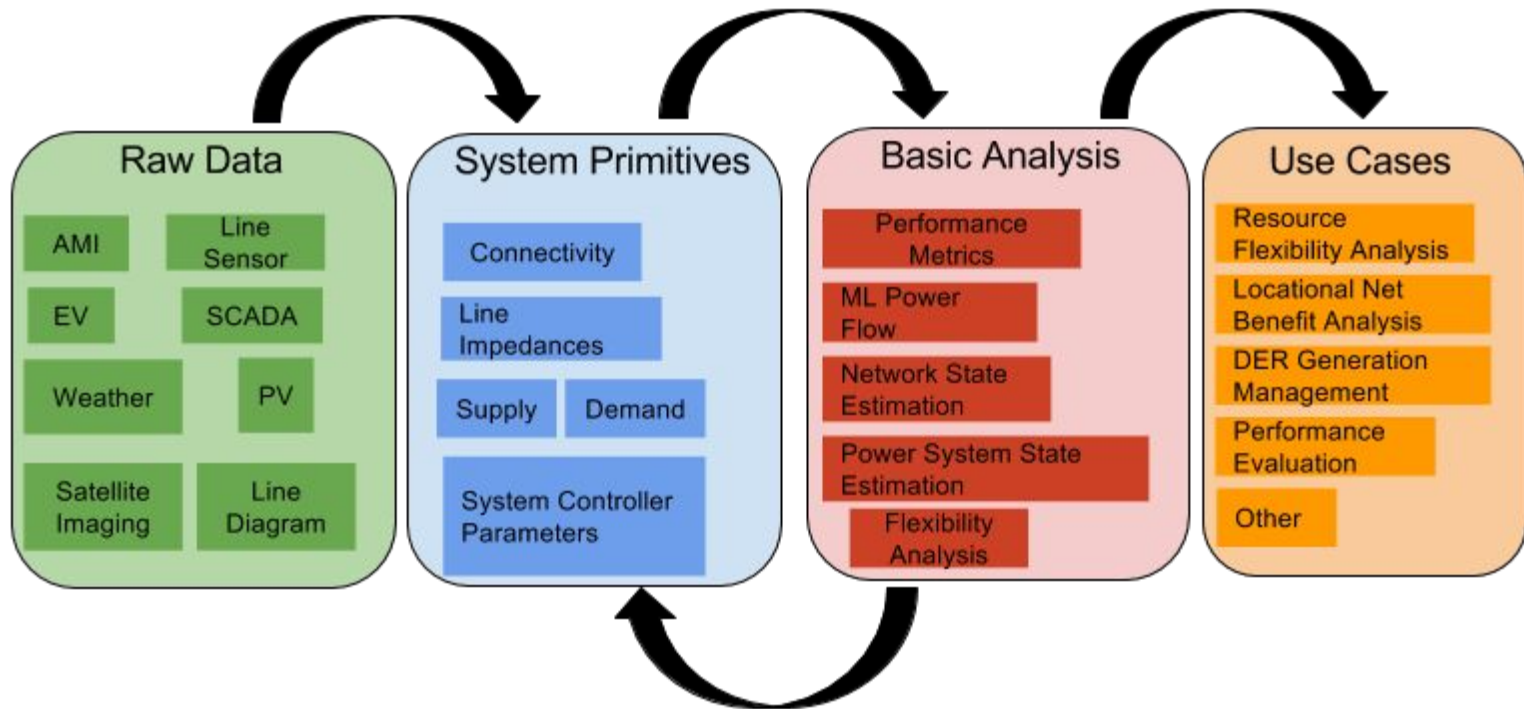
Visualization and Analytics of Distributed Energy Resources



Funded by:



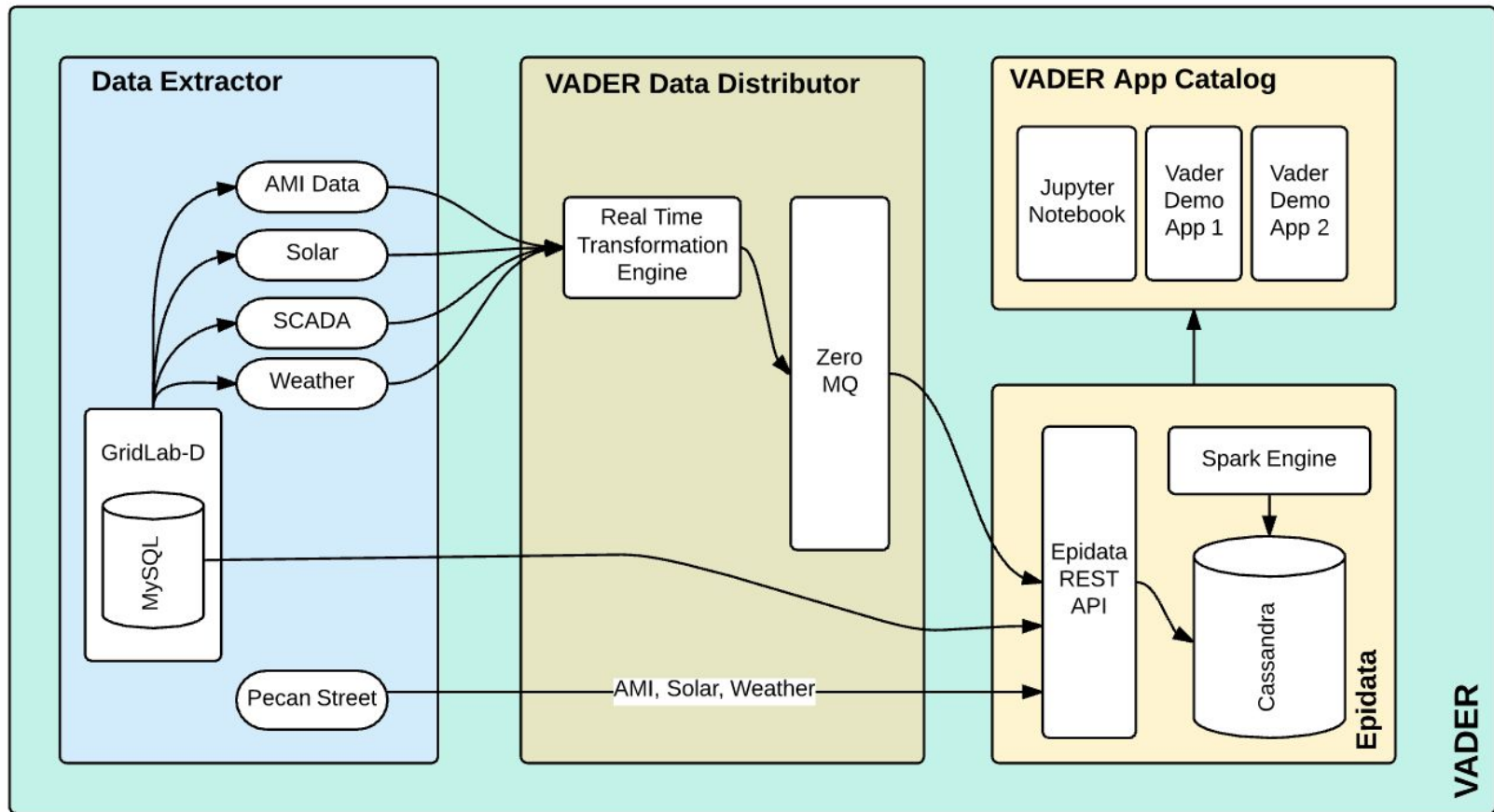
VADER Analytics



VADER key analytics pieces:

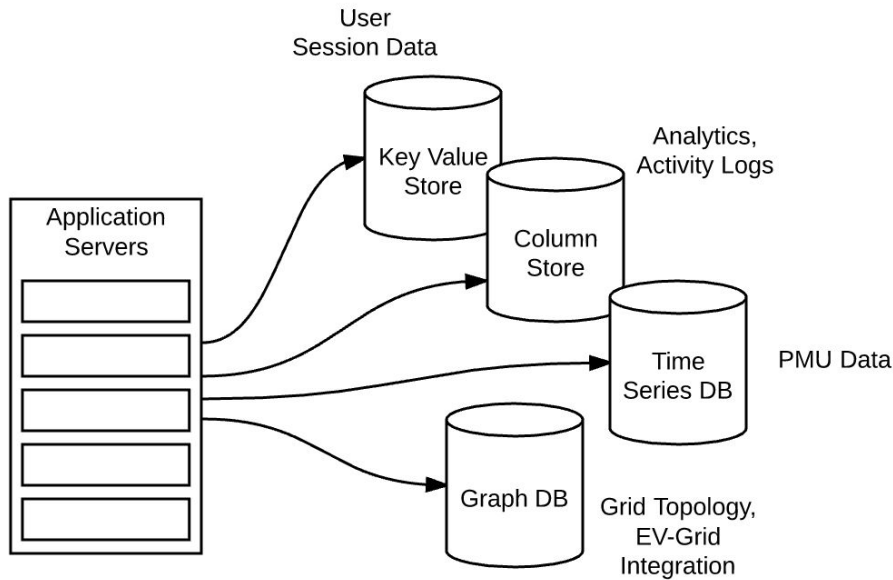
- Solar disaggregation
- Switch configuration
- ML-based power flow analysis
- Network topology detection
- Load forecasting

VADER Infrastructure

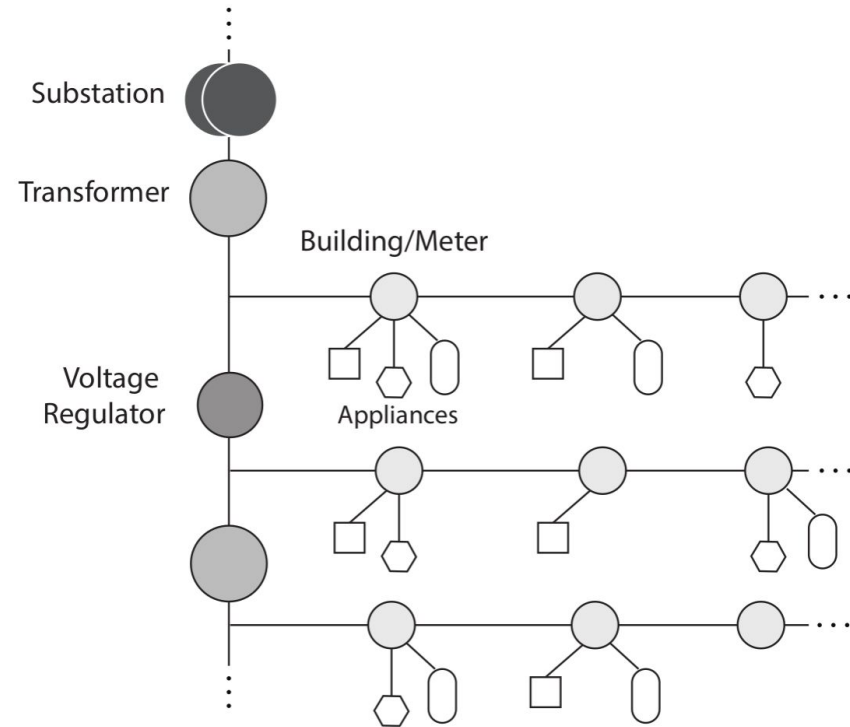


VADER Infrastructure

- Polyglot persistence:
 - Why?

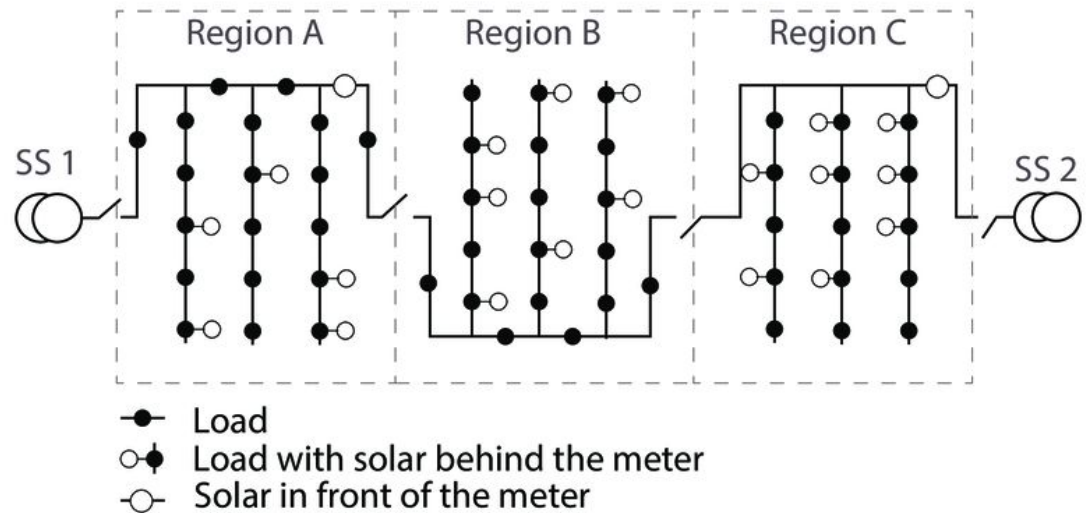


Polyglot Persistence Architecture



Introduction

- 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?

Introduction

- Traditional approaches include:
 - Physics-based models:
 - Geometry of the array
 - Nameplate capacity
 - Site-specific irradiance measurements (diffuse horizontal, direct normal, and global horizontal irradiance)
 - Costly to obtain DHI and DNI often only GHI is available

**Can we use existing measurements that are collected by the utilities to estimate behind-the-meter solar in real-time?
If so, how accurate these estimates would be?**

- Could be costly to do in real-time.

Problem formulation

- Contextually supervised source separation* :
 - Observing an aggregate measurement of signals of interest
 - Each signal can be represented as a linear model
 - Contextual knowledge about signal characteristics
 - Used in Non-intrusive Load Monitoring

*Wytock, Matt, and J. Zico Kolter. "Contextually Supervised Source Separation with Application to Energy Disaggregation." AAAI. 2014.

Error between the estimates of the signal and what the linear model would do

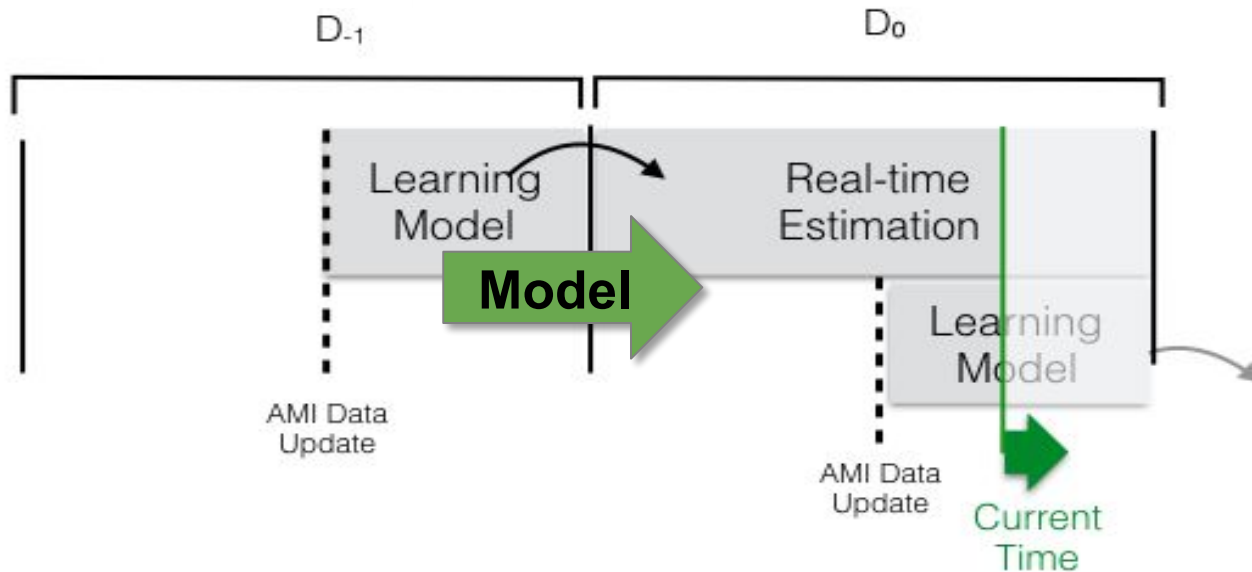
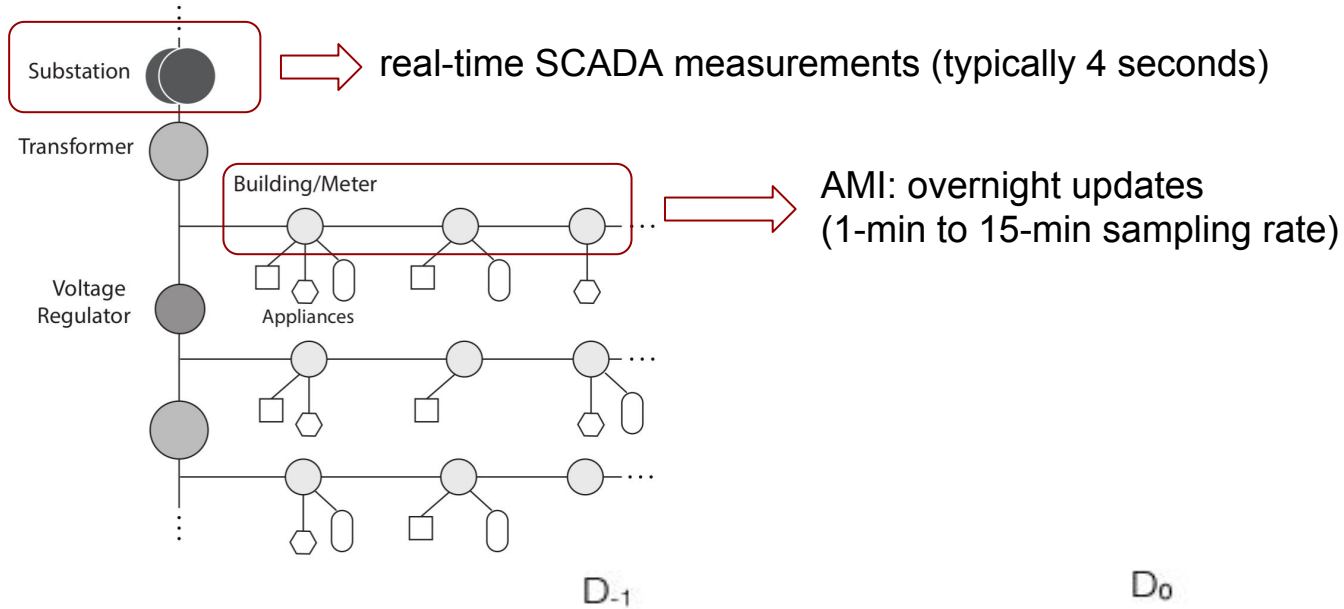
Regularization

$$\text{minimize}_{Y_i, \Theta_i} \{ \alpha_i l_i((Y_i - X_i \Theta_i)) + \eta_i g_i(Y_i) + \gamma_i h_i(\Theta_i) \}$$

$$\text{subject to } Y_{agg} = \sum_{i=0}^L Y_i$$

Contextual knowledge on the shape of individual signals

Problem formulation



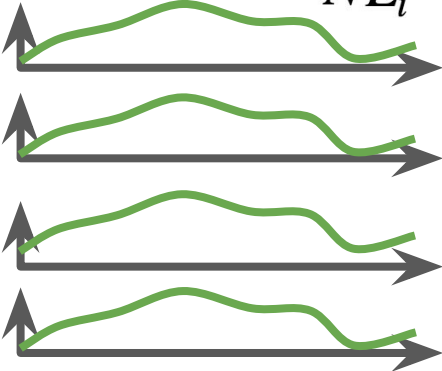
Problem formulation

Day-ahead training problem (learning the model):

Inputs

AMI data

NL_i



Sparse # of solar sensors

X_i

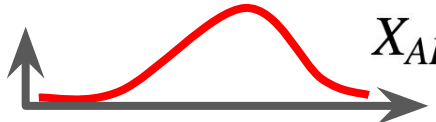


+

Outdoor Temp.

=

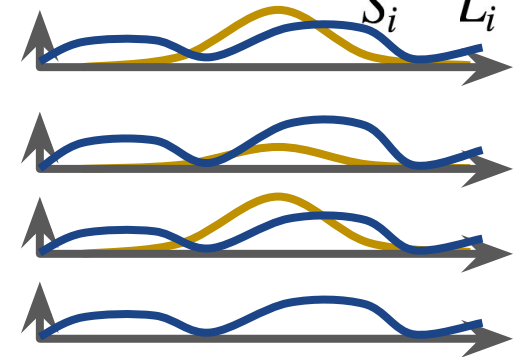
X_{AL}



Outputs

Load and solar at each meter

S_i L_i



Problem formulation

Need to be tuned

$$\text{minimize}_{L, S, \theta} \alpha_{AL} \|AL - \theta_{AL} X_{AL}\|_2 + \sum_{i=1}^N \alpha_i \|S_i - \theta_i X_i\|_2$$

$$\text{subject to } L_i + S_i = NL_i, \quad \forall i$$

$$S_i \leq 0 \quad \forall i,$$

$$L_i \geq 0 \quad \forall i,$$

$$\sum_{i=1}^N L_i = AL$$

$$\theta_i \geq 0.$$

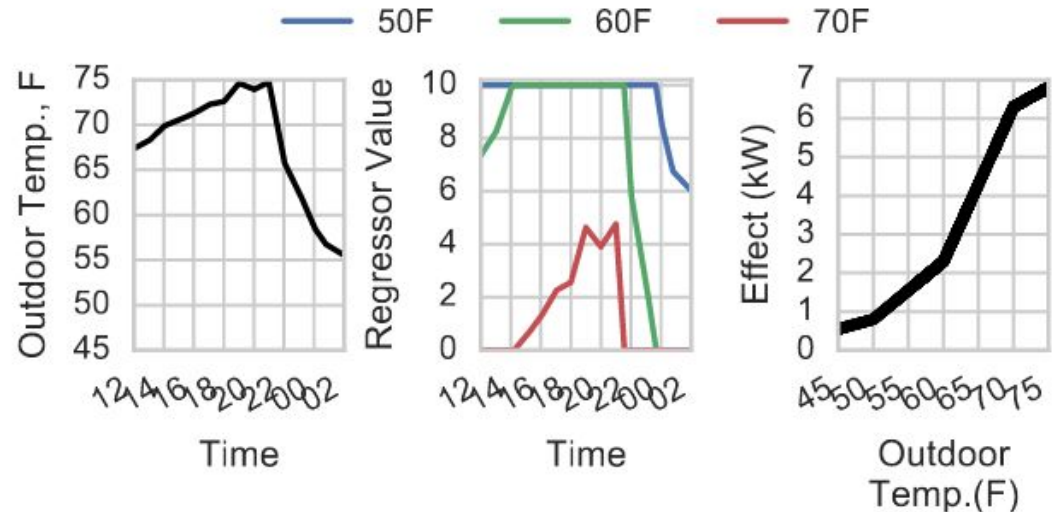
Aggregate load
is much more
predictable

Problem formulation

Creation of aggregate load regressors:

$$T_t^{(LB)} = \begin{cases} 0 & T_t < LB \\ 10 & T_t > LB + 10 \\ T_t - LB & LB \leq T_t \leq LB + 10 \end{cases}$$

$Temp_t$	Int	Regressors, X_{AL}		
		$T_t^{(60)}$	$T_t^{(70)}$	$T_t^{(80)}$
66	1	6	0	0
68	1	8	0	0
70	1	10	0	0
72	1	10	2	0
74	1	10	4	0
80	1	10	10	0
82	1	10	10	2
84	1	10	10	4



Tuning alphas

- Intuitive choice: the inverse of the expected variance of model's errors
- During nighttime there is no solar generation
 - Net load = Aggregate Load
 - Estimate the error for the AL model
- During day time we can estimate the total error.
- Assuming the all errors are independent:

$$Var(\epsilon_{AL}) = Var(\epsilon_{Total}) - \sum_{i=1}^N Var(\epsilon_i)$$

Problem formulation

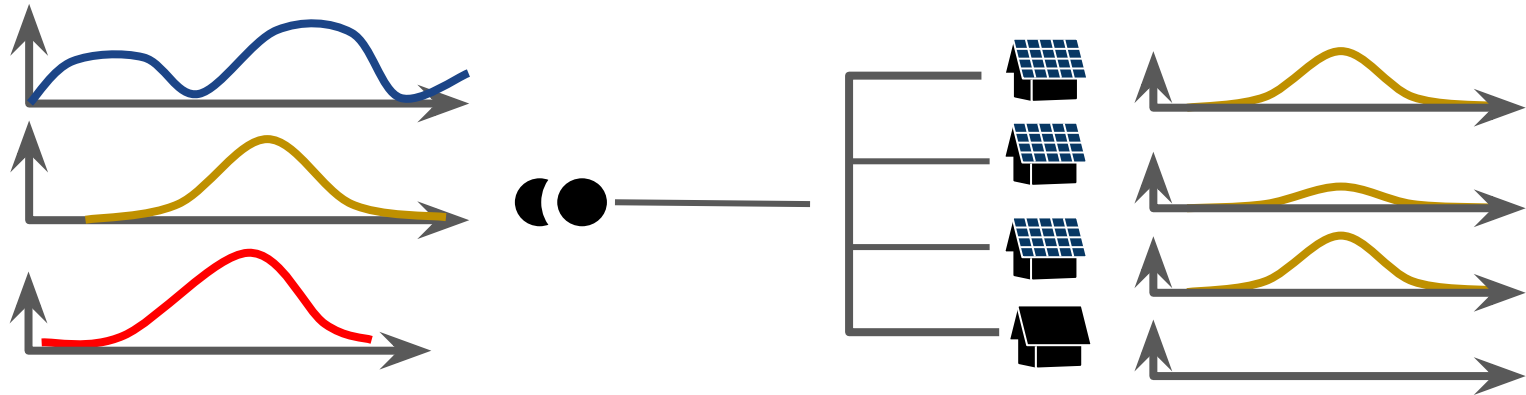
Real-time estimation problem:

Input

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

Outputs

Solar at each meter



Problem formulation

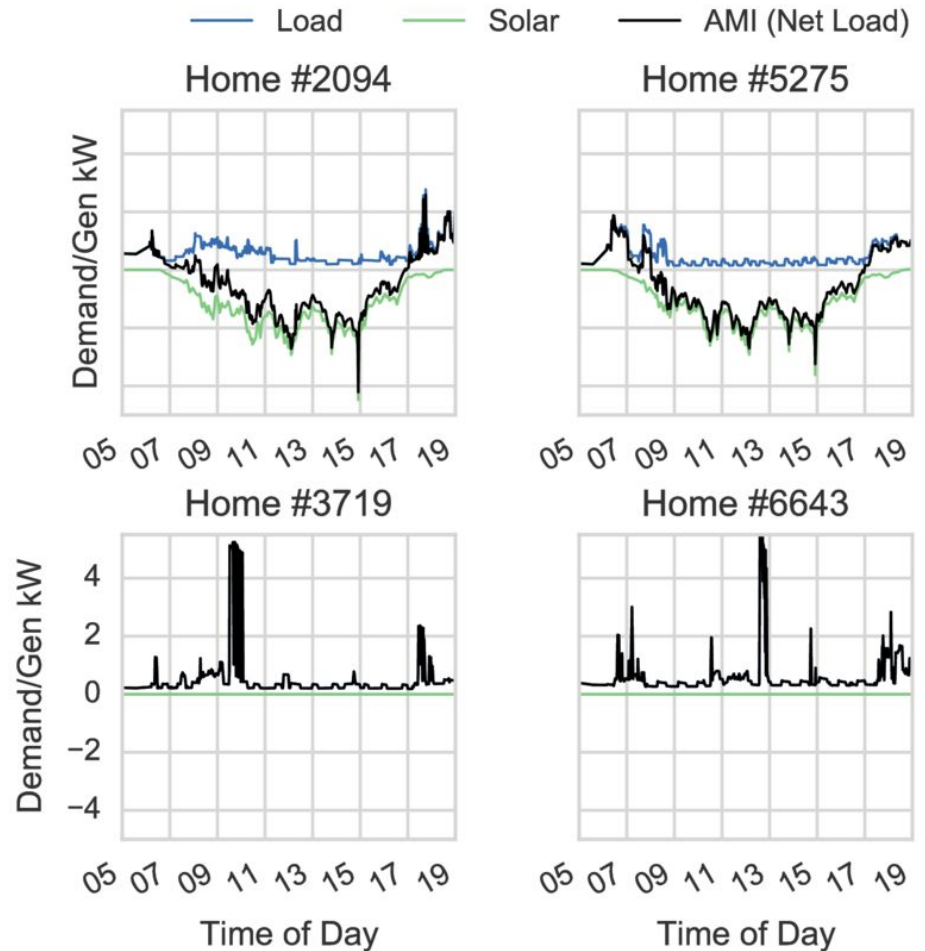
$$\underset{AL, S_i}{\text{minimize}} \quad \alpha_{AL} \|AL - \theta_{AL} X_{AL}\|_2 + \sum_{i=1}^N \alpha_i \|S_i - \theta_i X_i\|_2$$

$$\text{subject to} \quad AL + \sum_{i=1}^N S_i = \sum_{i=1}^N NL_i, \quad \text{Observed through SCADA}$$
$$S_i \leq 0 \quad \forall i.$$

Dataset

Subset of Pecan Street dataset:

- Load and solar sub-metered at 1-minute resolution
- 110 households in TX
- Total duration 7-days
- Divided into:
 - 55 homes with solar
 - 55 homes without solar
 - Varying number of distribution-level solar (used as proxy)

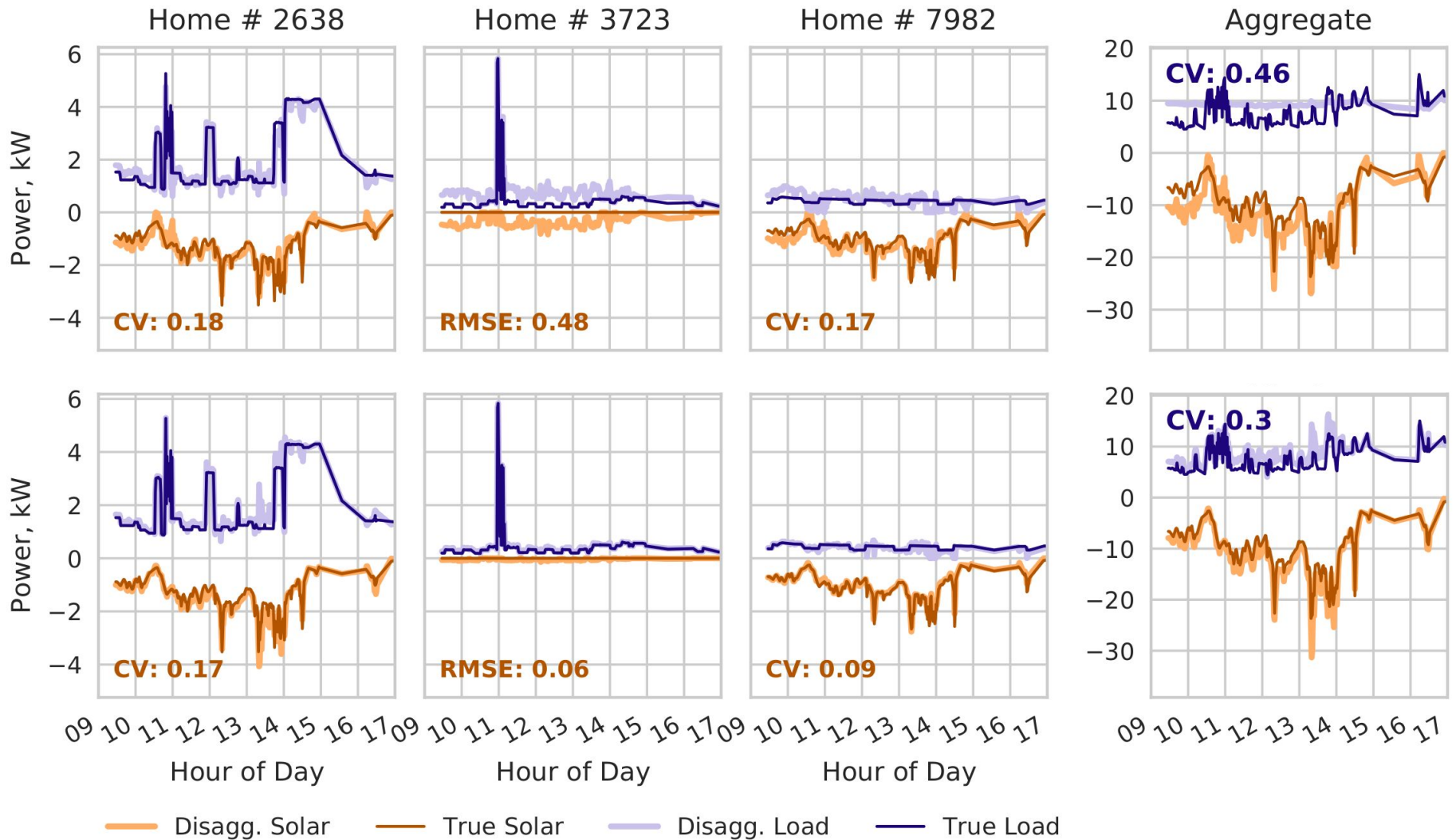


Results

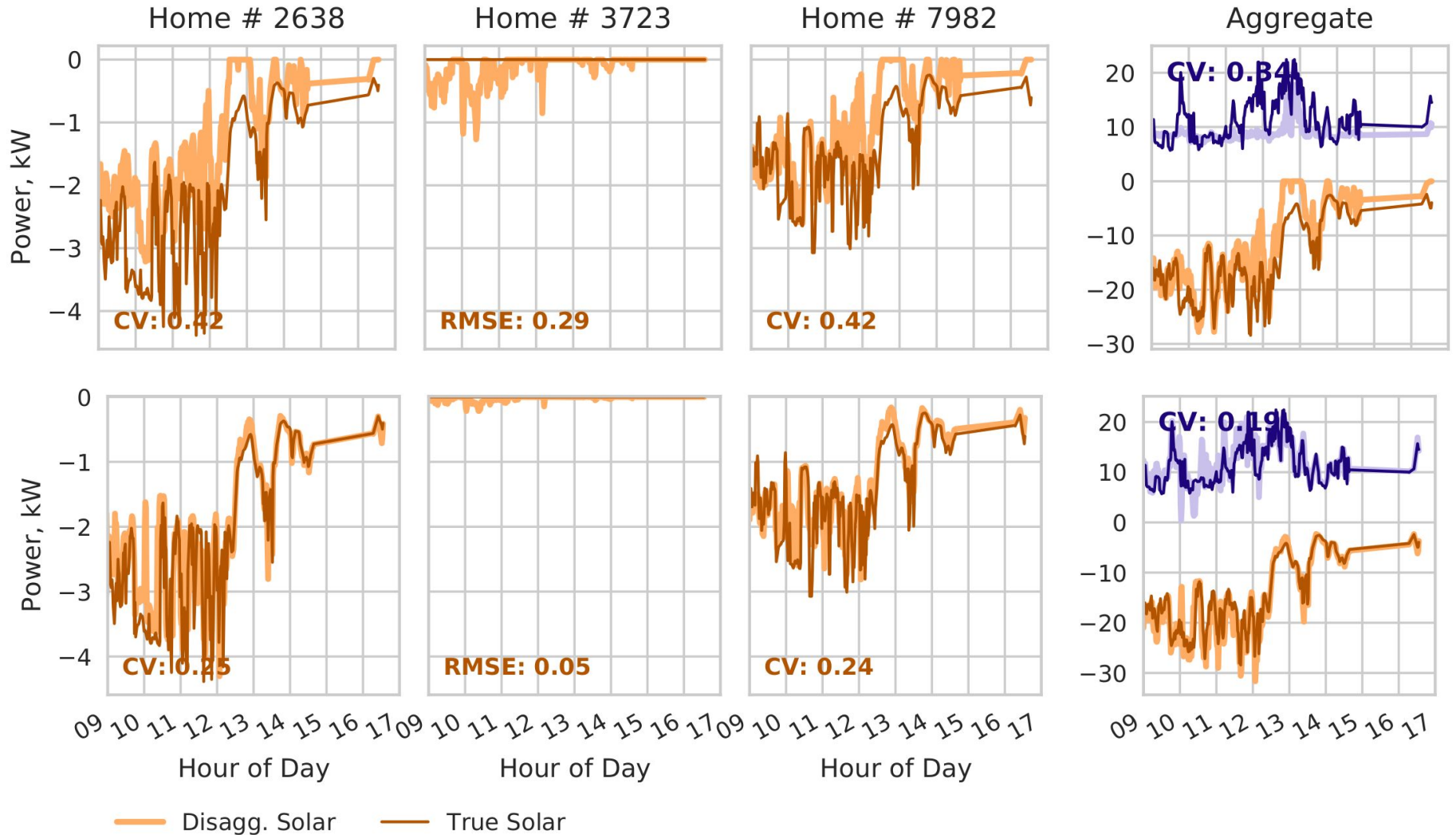
- We use coefficient of variation for homes with solar.
- We report only RMSE for homes without solar.

$$CV = \frac{\sqrt{\sum_{i=1}^T (truth_t - estimate_t)^2}}{\frac{1}{T} \sum_{i=1}^T truth_t}$$
$$= \frac{RMSE}{Mean\ truth}$$

Training Results (Untuned vs. Tuned)



Real-time Results (Untuned vs. Tuned)



Conclusions & Future Work

- Useful tool to estimate behind-the-meter solar in real-time.
 - Can also be used to select the optimal number of proxies and their locations for a guaranteed performance of estimation.
- Incorporate losses in the network
- Expanding the disaggregation strategy to incorporate storage
- Running the model on a larger network in SCE's territory through our partnership in VADER.

Thank you!



Michaelangelo Tabone
Post-doctoral Fellow
Stanford University,
SLAC National Accelerator
Laboratory
mtabone@stanford.edu



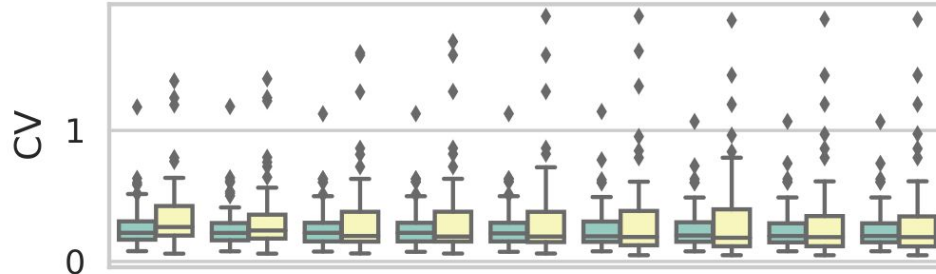
Emre Can Kara
Associate Staff
Scientist
SLAC National
Accelerator Laboratory
ekara@stanford.edu



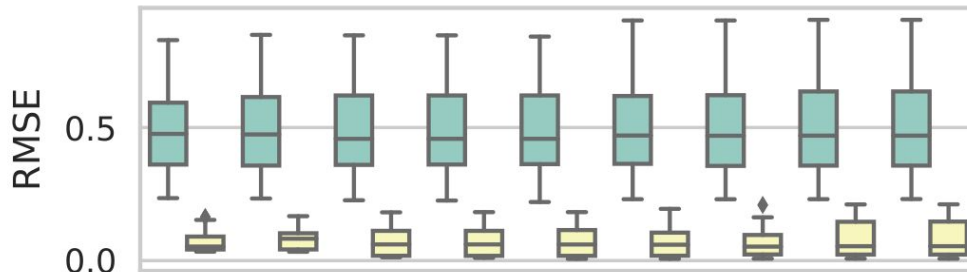
Sila Kiliccote
Staff Scientist
SLAC National
Accelerator Laboratory
silak@stanford.edu

Additional Slides

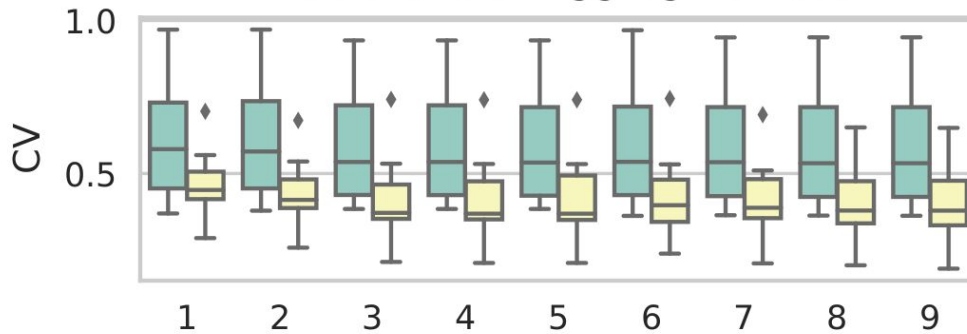
Predictions of BTM Solar (homes with solar)



Predictions of BTM Solar (homes without solar)



Predictions of Aggregate Load



Number of Proxies
flat tuned