Machine Learning and Big Data Analytics in Power Distribution Systems

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  - Osten Anderson (B.S. UCLA), Yuanbin Cheng (M.S. USC)
  - Xianghao Kong (B.S. HDU)

Current and Past Projects and Sponsors

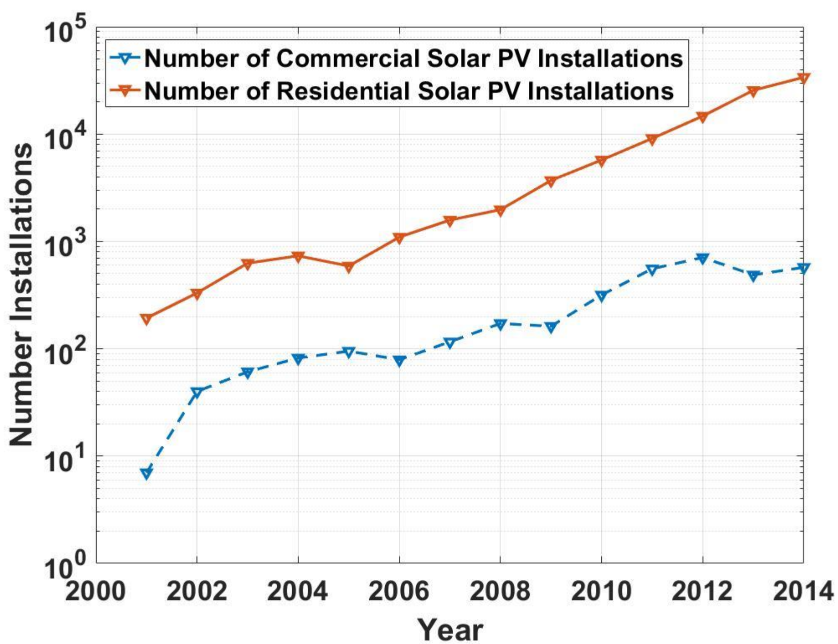
- Over 10 Million of Research and Development Projects as PI and Co-PI
  - DOE PMU Data Analytics (PI, DOE, $1 Million)
  - Distributed Energy Management System (PI, CEC, $1.2 Million)
  - Distribution System Operator Managed Electricity Market (PI, DOE, $0.45 Million)
  - Smart Cities (PI, NSF, $0.3 Million)
  - Water-Energy-Climate Nexus (PI, CEC, $0.45 Million)
  - Big Data Analytics and Machine Learning (PI, Electric Utilities, $0.3 Million)
  - Green Computing (PI, CEC, $1.8 Million)
  - DOE Education (Site-PI, DOE, $0.5 Million)

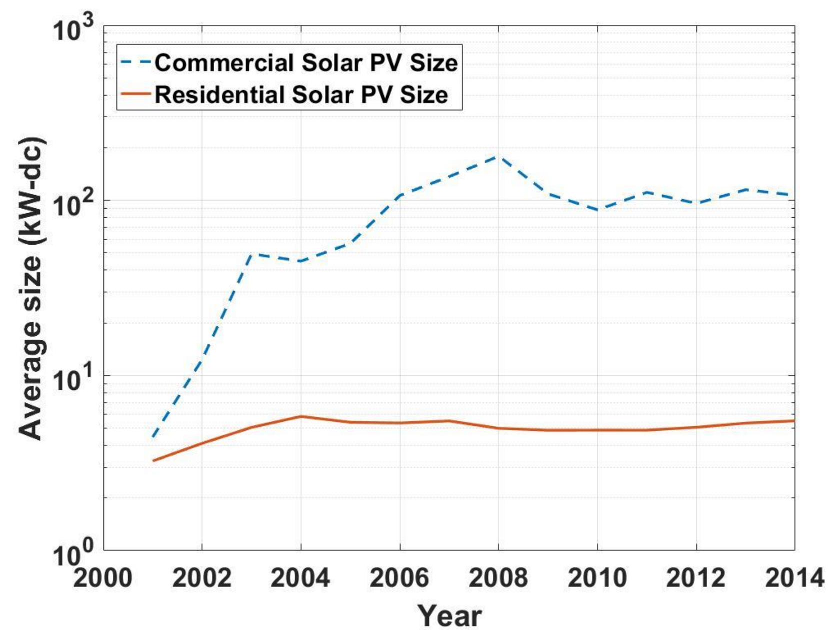
Outline

- Why do we focus on electric power distribution systems?
- Big Data in Power Distribution Systems
  - Volume, Variety, Velocity, and Value
- Applications of Machine Learning and Big Data Analytics in Power Distribution Systems
  - Topology Identification – Phase Connectivity Identification
  - Anomaly Detection – Electricity Theft Detection
  - Reinforcement Learning based Control – Volt-VAR Control
  - Predictive Maintenance – Distribution Transformers
  - Estimation of Behind-the-meter Solar Generation

Why distribution systems?

- Increasing penetrations of distributed energy resources (DERs) in electric power distribution systems
  - E.g. California's transition to local renewable energy, 12,000 MW by 2020 (peak load 50,000 MW)
- DERs
  - Rooftop solar PV systems (1.84 GW of installed capacity by June 2017)





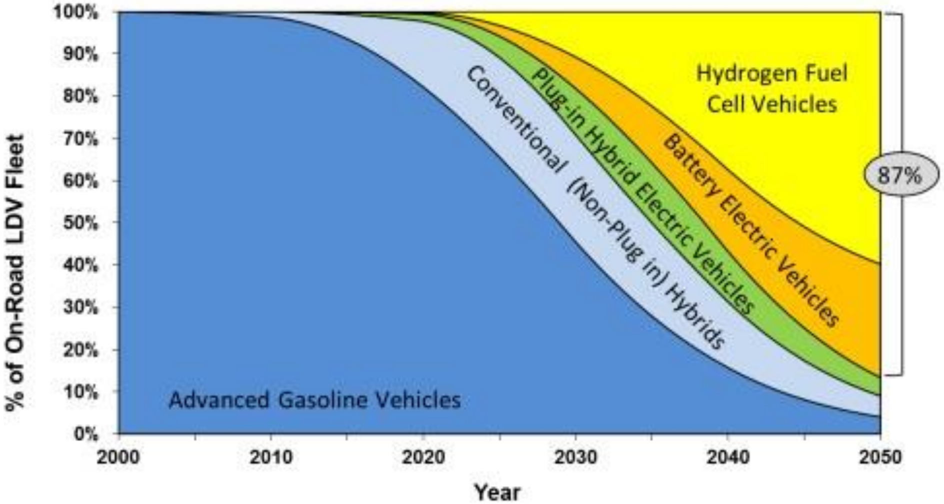
Why distribution systems?

- Increasing penetrations of distributed energy resources (DERs) in electric power distribution systems
  - E.g. California’s transition to local renewable energy, 12,000 MW by 2020 (peak load 50,000 MW)
- DERs
  - Energy storage systems
    - In California 1,325 MW of energy storage will be integrated into the power system by 2020.

System Level	Applications & Revenue Streams	Technical Requirements	
		Typical Cycles / Year	Typical Discharge Duration
Distribution	13. Distribution Peak Shaving	20 to 50	1 to 4 hours
	14. Distribution Voltage Support	50 to 100	1 to 4 hours
	15. Distribution Power Quality	50 to 100	1 to 4 hours
	16. Retail Energy Time-Shift	20 to 50	15 min to 1 hour
Microgrid / Consumer	17. Energy Cost Minimization	N/A	N/A
	18. Microgrid Voltage Support	50 to 100	1 to 4 hours
	19. Microgrid Power Quality	50 to 100	1 to 4 hours
	20. Demand Charge Management	50 to 100	1 to 4 hours

Why distribution systems?

- Increasing penetrations of distributed energy resources (DERs) in electric power distribution systems
  - E.g. California's transition to local renewable energy, 12,000 MW by 2020 (peak load 50,000 MW)
- DERs
  - Electric vehicle
    - In Nov 2016, the cumulative sales of battery electric and plug-in hybrid sales in California hits 250,000 which accounts for 20% of global cumulative sales.



The need for advanced modeling, monitoring, & control of distribution systems!

- The cold, hard facts about modern power distribution systems
  - Modeling
    - Incomplete topology information in the secondary systems (phase connection, transformer-to-customer mapping)
    - Even the three-phase load flow results are unreliable.
  - Monitoring
    - Most utilities do not have online three-phase state estimation for their entire distribution network
  - Control
    - Focus on system restoration
    - Limited predicative and preventive control
      - Volt-VAR control, network reconfiguration

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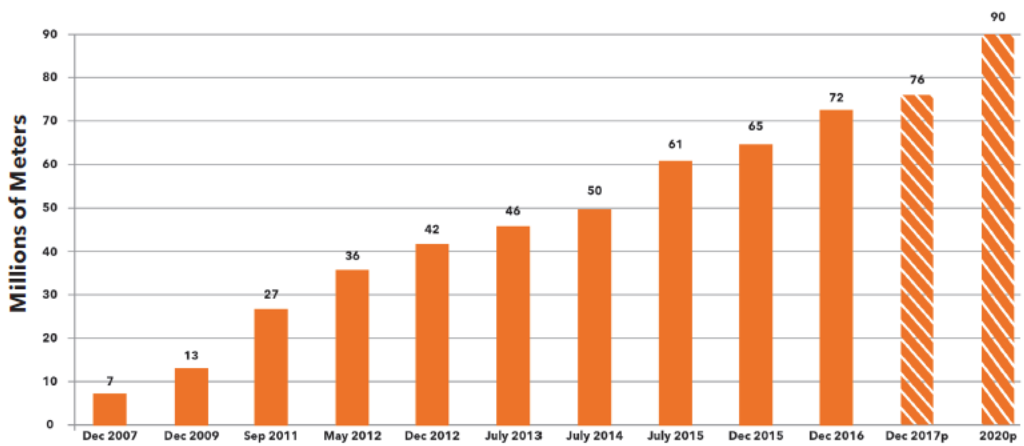
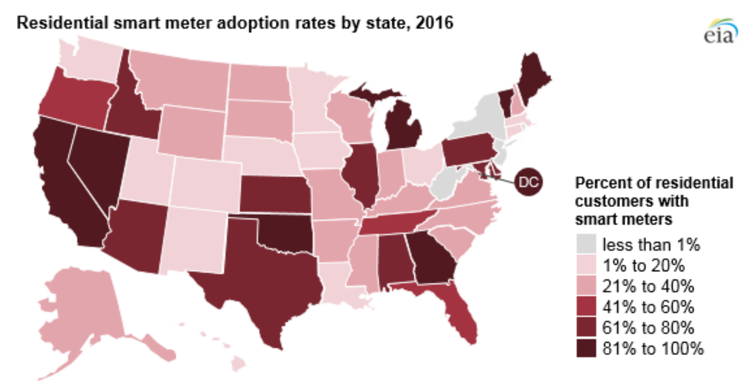
Big Data in Distribution Systems: Volume

- In 2017, the U.S. electric utilities had about 78.9 million AMI installations covering over 50% of 150 million electricity customers.
- The smart meter installation worldwide will surpass 1.1 billion by 2022.
- In 2012, the AMI data collected in the U.S. alone amounted to well above 100 terabytes.
- By 2022, the electric utility industry will be swamped by more than 2 petabytes of meter data alone.

U.S. Smart Meter Installations Projected to Reach 90 Million by 2020

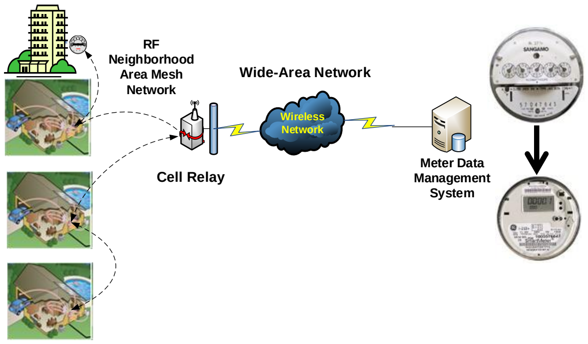


Source: Institute for Electric Innovation



Source: U.S. Energy Information Administration

Big Data in Distribution Systems: Variety



- Advanced Metering Infrastructure
  - Electricity usage (15-minute, hourly)
  - Voltage magnitude

- Weather Station
- Geographical Information System
- Census Data (block group level)
  - Household variables: ownership, appliance, # of rooms
  - Person variables: age, sex, race, income, education

- SCADA Information
- Micro-PMU
  - Time synchronized measurements with phase angles

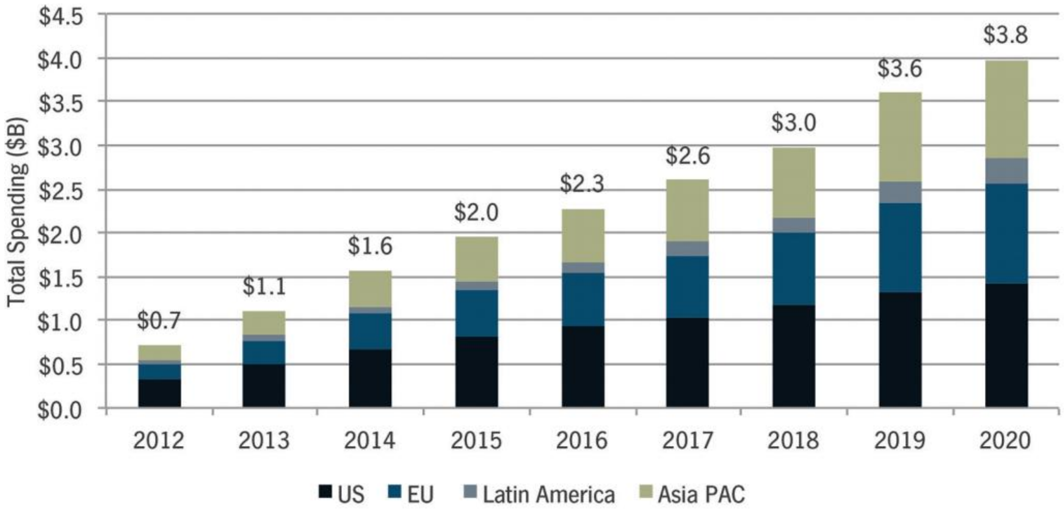
- Equipment Monitors

Big Data in Power Distribution Systems: Velocity

- Sampling Frequency
  - AMI's data recording frequency increases from **once a month** to one reading **every 15 minutes to one hour**.
  - Micro-PMU hundreds (512) of samples per cycle at 50/60 Hz
- Bottleneck in Communication Systems (Distribution Network)
  - Limited bandwidth for zigbee network
  - Most of the utilities in the US receives smart meter data with ~24 hour delay
- Edge Computing Trend
  - Itron and Landis+Gyr extend edge computing capability of smart meters
  - Increasing data transmission range and computing capabilities of smart meters
  - Centralized → distributed / decentralized

Big Data in Power Distribution Systems: Value

- The big data collected in the power distribution system had utterly swamped the traditional software tools used for processing them.
- Lack of innovative use cases and applications to unleash the full value of the big data sets in smart grid[1].
- Insufficient research on machine learning and big data analytics for power distribution systems.
- Electric utilities around the world will spend over $3.8 billion on data analytics solutions in 2020.



Source: GTM Research

1. Nanpeng Yu, Sunil Shah, Raymond Johnson, Robert Sherick, Mingguo Hong and Kenneth Loparo, “Big Data Analytics in Power Distribution Systems” *IEEE PES ISGT*, Washington DC, Feb. 2015.

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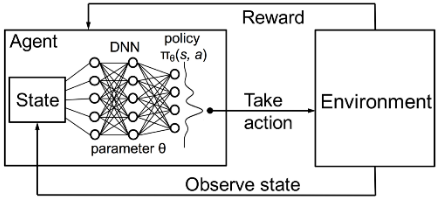
Applications of Big Data Analytics and Machine Learning in Power Distribution Systems

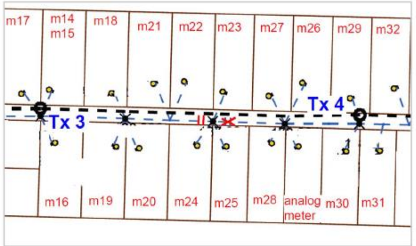
Spatio-temporal Forecasting
Electric Load / DERs – Short-Term / Long-Term

Anomaly Detection
Electricity Theft, Unauthorized Solar Interconnection

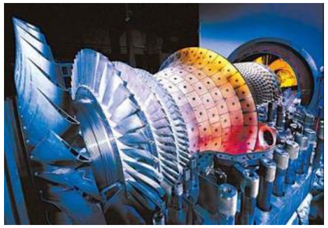
System Monitoring
State Estimation & Visualization

Distribution System Controls
Deep Reinforcement Learning





Network Topology and Parameter Identification
Transformer-to-customer, Phase connectivity, Impedance estimation



Equipment Monitoring
Predictive Maintenance
Online Diagnosis

Customer Behavior Analysis
Customer segmentation, nonintrusive load monitoring, demand response

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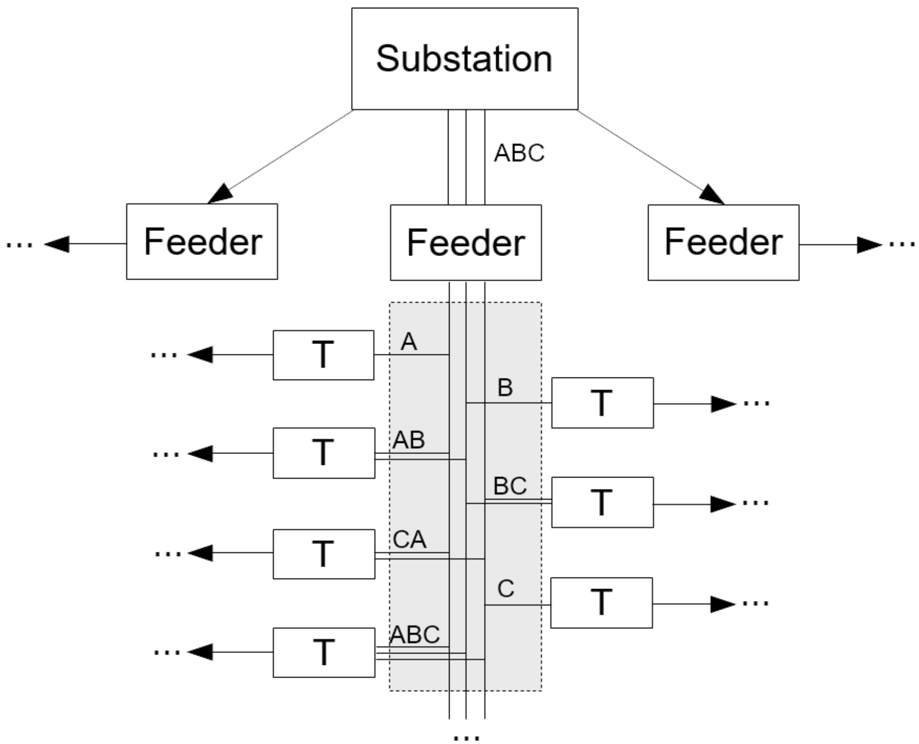
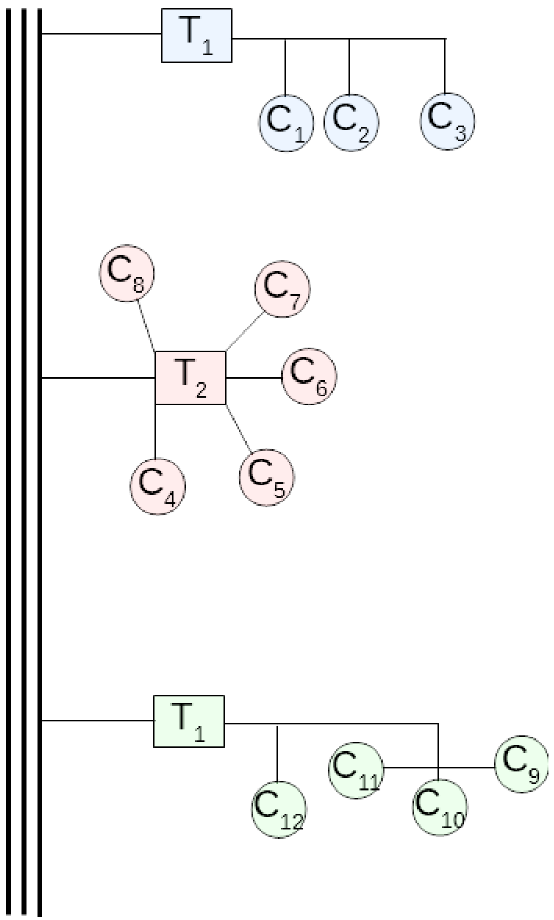
Phase Identification

- Phase Connectivity Identification
  - Unsupervised Machine Learning
    - Linear dimension reduction and centroid-based clustering
    - Nonlinear dimension reduction and density-based clustering
  - Supervised Machine Learning
    - A comprehensive evaluation of supervised machine learning algorithms
    - Improvement with the theory of information losses

Distribution System Topology Identification

- The distribution system topology identification problem can be broken down into two sub-problems
  - The phase connectivity identification problem
  - The customer to transformer association problem



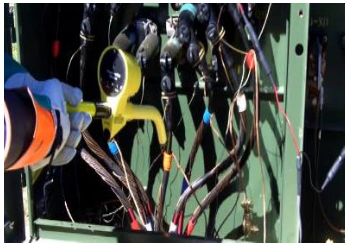


Phase Connectivity Identification

- Problem Definition
  - Identify the phase connectivity of each customer & structure in the power distribution network.
  - Very few electric utility companies have completely accurate phase connectivity information in GIS!
- Why is it important? (Business Value)
  - Phase connectivity is crucial to an array of distribution system analysis & operation tools including
    - 3-phase Power flow
    - Load balancing
    - Distribution network state estimation
    - 3-phase optimal power flow
    - Volt-VAR control
    - Distribution network reconfiguration and restoration

Phase Connectivity Identification

- Primary Data Set
  - Advanced Metering Infrastructure, SCADA, GIS, OMS
  - Training data (field validated phase connectivity)
- Solution Methods
  - Physical approach with Special Sensors
    - Micro-synchrophasors, Phase Meters
    - Drawback: expensive equipment, labor intensive ($2,000 per feeder), 3,000 feeders for a regional electric utility company ($6 million)

Phase Connectivity Identification

- Solution Methods
  - Integer Optimization, Regression and Correlation based Approach
    - 0-1 integer linear programming (IBM)
    - Correlation/Regression based methods (EPRI)
    - Drawback: cannot handle delta connected Secondaries, low tolerance for erroneous or missing data, low accuracy and high computational cost
  - Data-driven phase identification technology
    - Synergistically combine machine learning techniques and physical understanding of electric power distribution networks.
    - Unsupervised and supervised machine learning algorithms
    - High accuracy on all types of distribution circuits. (overhead, underground, phase-to-neutral, phase-to-phase, pilot demonstration on over 100 distribution feeders)

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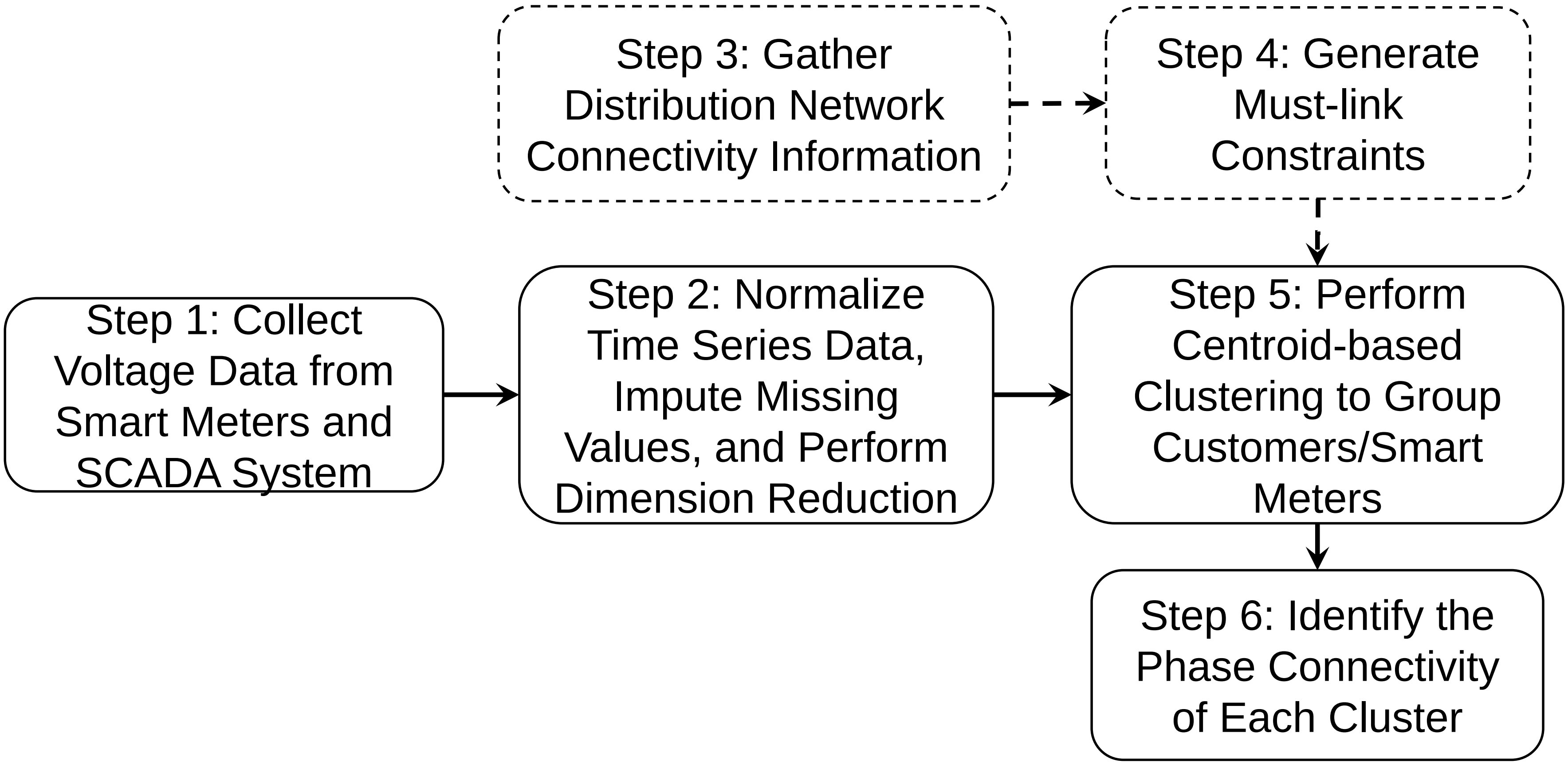
Unsupervised Machine Learning Algorithm[1]

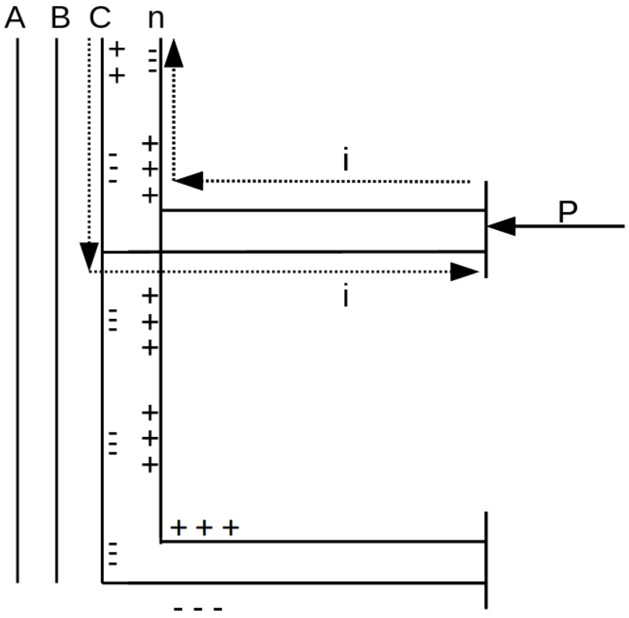
General Framework



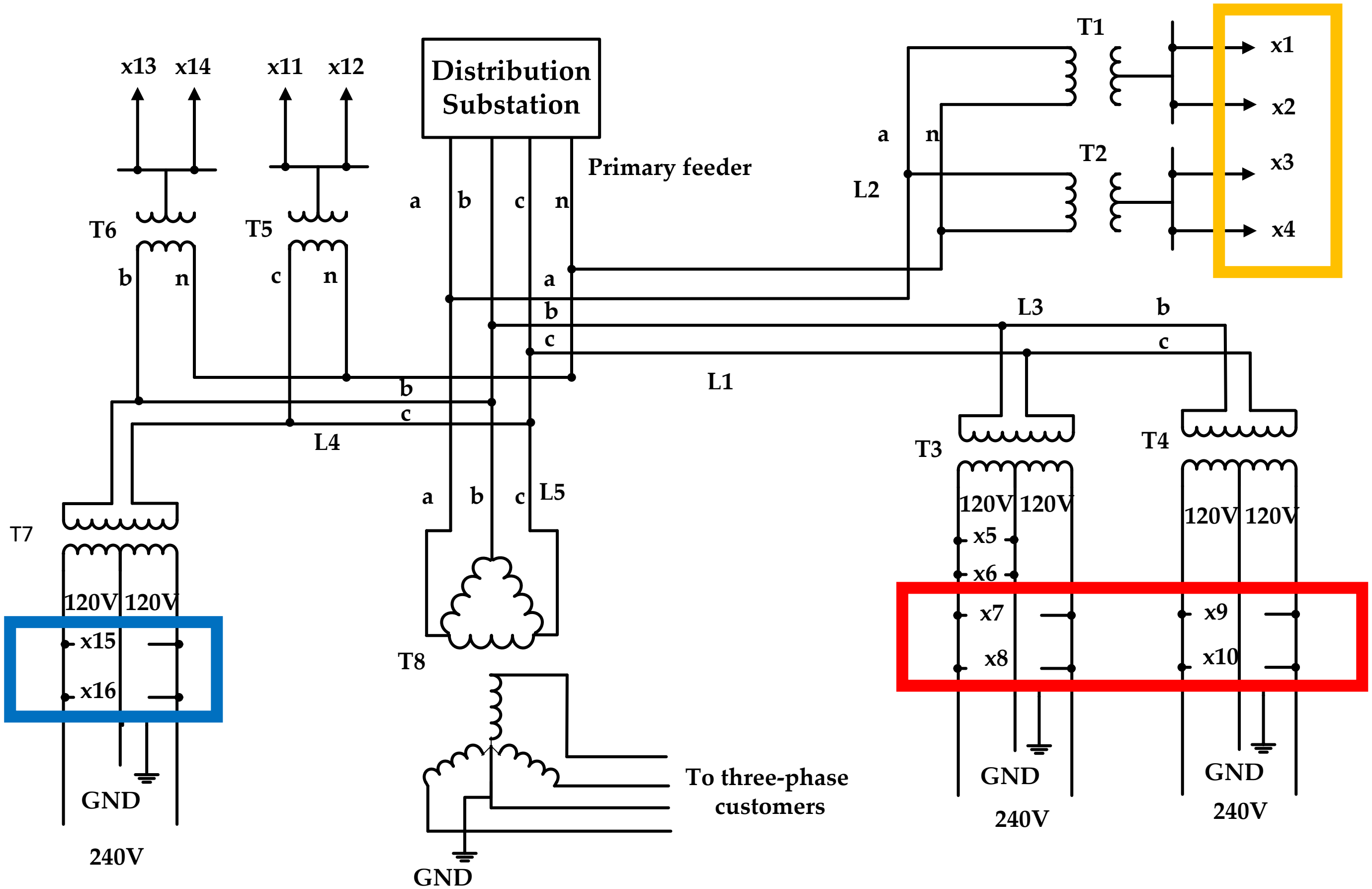
1. W. Wang, N. Yu, B. Foggo, and J. Davis, "Phase identification in electric power distribution systems by clustering of smart meter data" *15th IEEE International Conference on Machine Learning and Applications* (ICMLA), pp. 1-7, Anaheim, CA, 2016.

Why Voltage Data Is Predictive of Phase?

- Voltage data is fairly informative of phase type
  - Consider a power injection at bus k whose phase type is AB.
  - This induces a current along the lines A and B.
  - Any customer also feeding from either of those lines will notice a change.
  - Due to the capacitive and inductive effects of the primary feeder, both lines will also induce a voltage change along the lines C and n.
  - However, the off-diagonal elements of the phase impedance and shunt admittance matrices are much smaller than the diagonal ones.
  - Hence, the power injection at bus k will have much less effect on phase C than phase A and B.



Must-link Constraints



Customers connected to the same secondary must have the same phase connections

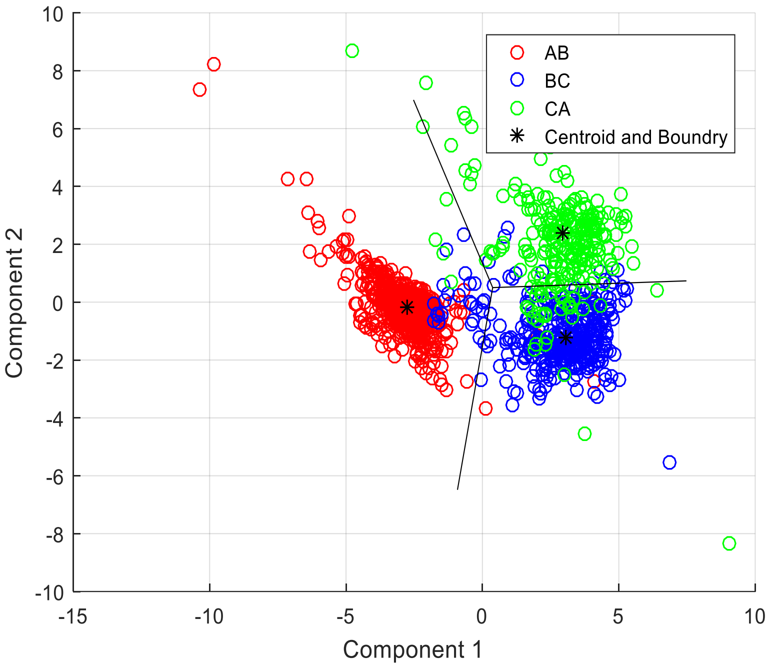
Case Study: Southern California Edison Distribution Circuit

Voltage Level	12.47 kV
Peak load	~5 MW
Number of Customers	~1500
Customer type	95% residential

- Most of the customers served by a three-wire single-phase system through center-tapped transformers (120/240 V).
- Highly unbalanced in terms of phase currents.
- 6 month of hourly smart meter data and SCADA data.
- Engineers gather actual phase connectivity of each building and structure through field validation.

Unsupervised Learning: Unconstrained Clustering

Phase Identification Accuracy: **92.89%**

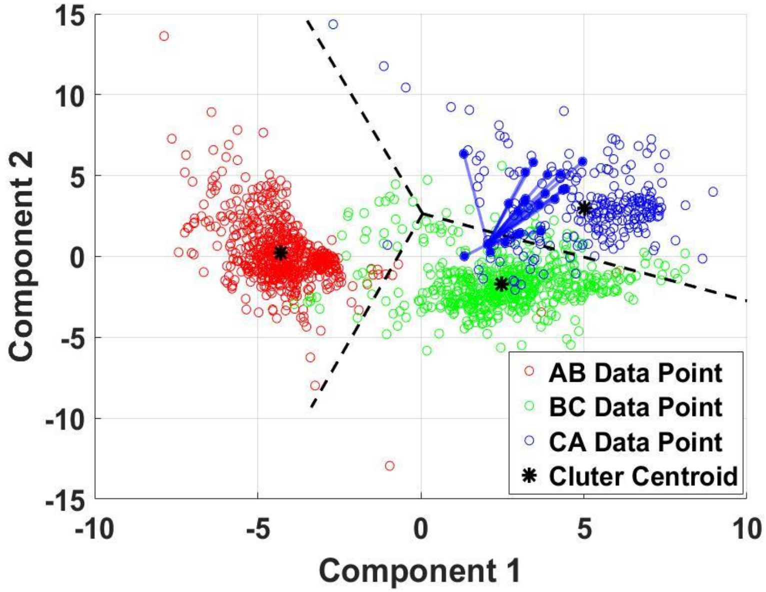


Cluster number	Number of customers	Accuracy (%)	Phase
1	226	94.25	CA
2	647	95.21	AB
3	364	87.91	BC

- The circuit is highly unbalanced and has 3 possible phase connections.
- Even linear dimension reduction technique results in reasonable separation among customers with different phase connections.

Supervised Learning: Constrained Clustering

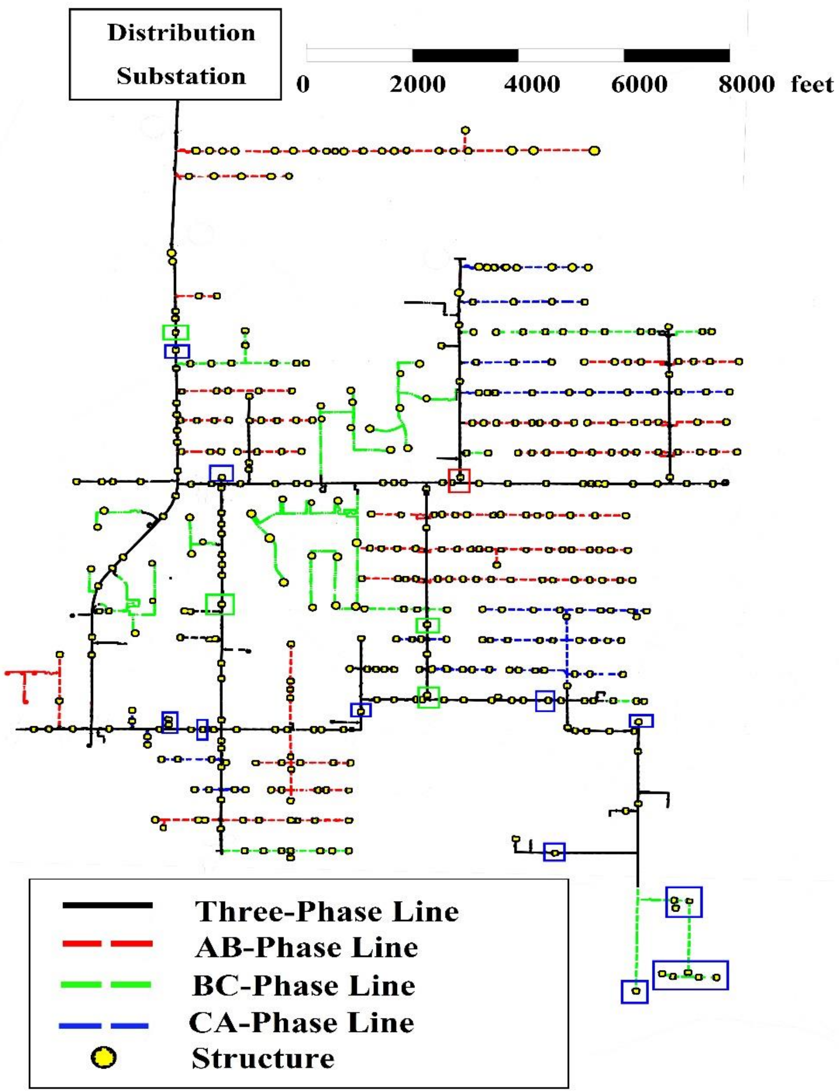
Phase Identification Accuracy: **96.69%**



Cluster number	Number of customers	Accuracy (%)	Phase
1	618	99.84	AB
2	384	91.41	BC
3	235	97.02	CA

- The must-link constraints pulled some of the blue points (customers with phase connections of CA) in the green region back to the blue area.
- The must-link constraints improve the phase identification accuracy.

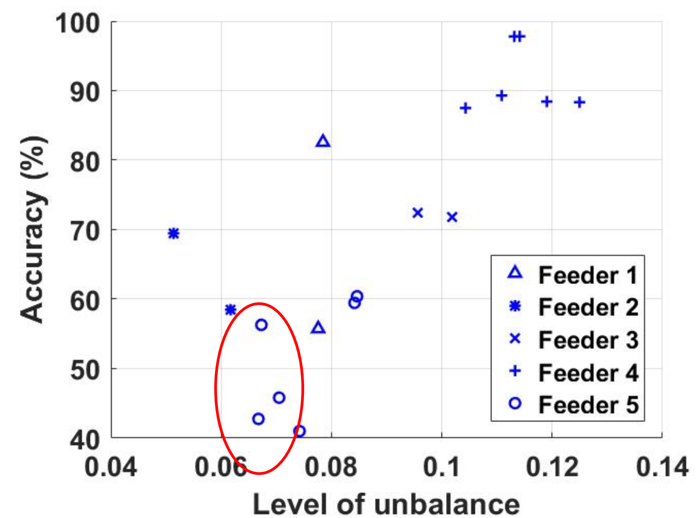
Visualization of Phase Identification Results



- With GIS inputs, visualization of distribution circuit with phase connection information can be generated automatically
  - Each line is colored according to its actual phase
  - Each structure is represented by a small dot
  - A colored rectangle is overlaid on top of a structure if it is assigned to the wrong cluster.

Drawbacks of Constrained K-means Clustering Algorithm (CK-Means)

- First, all of the prior proposed methods assume that the number of phase connections are known.
  - E.g., in the CK-Means algorithm, the number of phase connections/clusters needs to be know as prior knowledge
- Second, the existing methods can not provide accurate phase identification results when there is a mix of phase-to-neutral and phase-to-phase connected smart meters and structures.
  - The phase identification accuracy decreases as the number of possible phase connection increases.
- Third, the existing methods are quite sensitive to the level of unbalance in a distribution feeder.
  - The phase identification accuracy decrease as the level of unbalance decreases.



Phase Identification

- Phase Connectivity Identification
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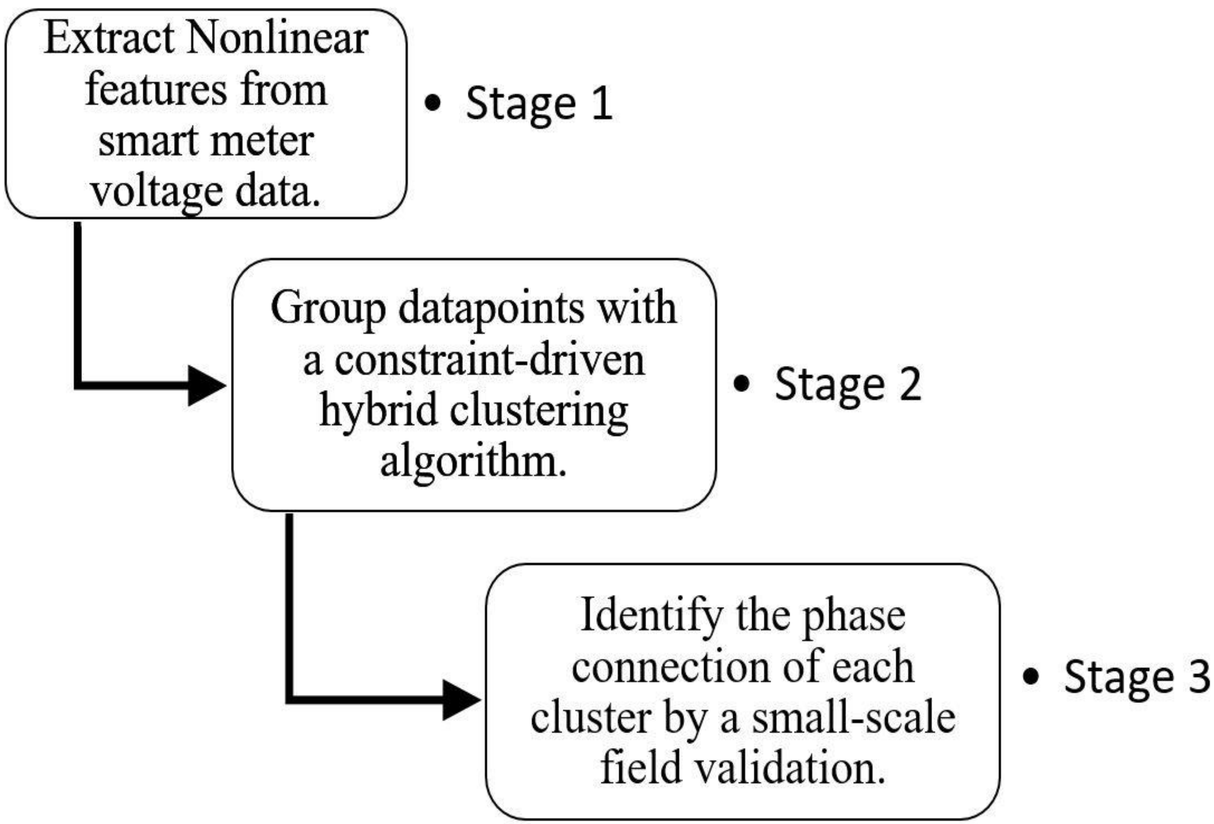
Nonlinear Dimension Reduction & Density-based Clustering[2]

General Framework



2. W. Wang and N. Yu, "AMI Data Driven Phase Identification in Smart Grid," *the Second International Conference on Green Communications, Computing and Technologies*, pp. 1-8, Rome, Italy, Sep. 2017.

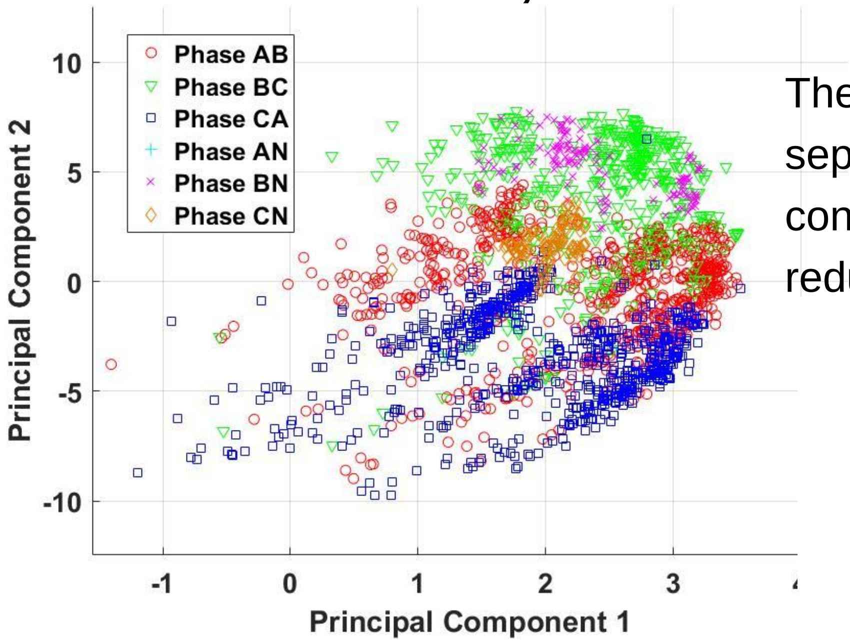
Stage 1 Feature Extraction from Voltage Time Series

- Dimension reduction techniques
  - Linear dimension reduction techniques (E.g., PCA)
    - Drawbacks
      1. Restricted to learning only linear manifolds. High-dimensional data lies on or near a low-dimensional, non-linear manifold.
      2. Difficult for linear mappings to keep the low-dimensional representations of very similar points close together.
    - Explains the lower accuracy of phase identification algorithm using linear features for less unbalanced feeders.
  - Nonlinear dimensionality reduction techniques
    - Sammon mapping, curvilinear components analysis (CCA), Isomap, and t-distributed stochastic neighbor embedding (t-SNE).
    - We adopt t-SNE, because it has been shown to work well with a wide range of data sets and captures both local and global data structures.
    - t-SNE improves upon SNE by

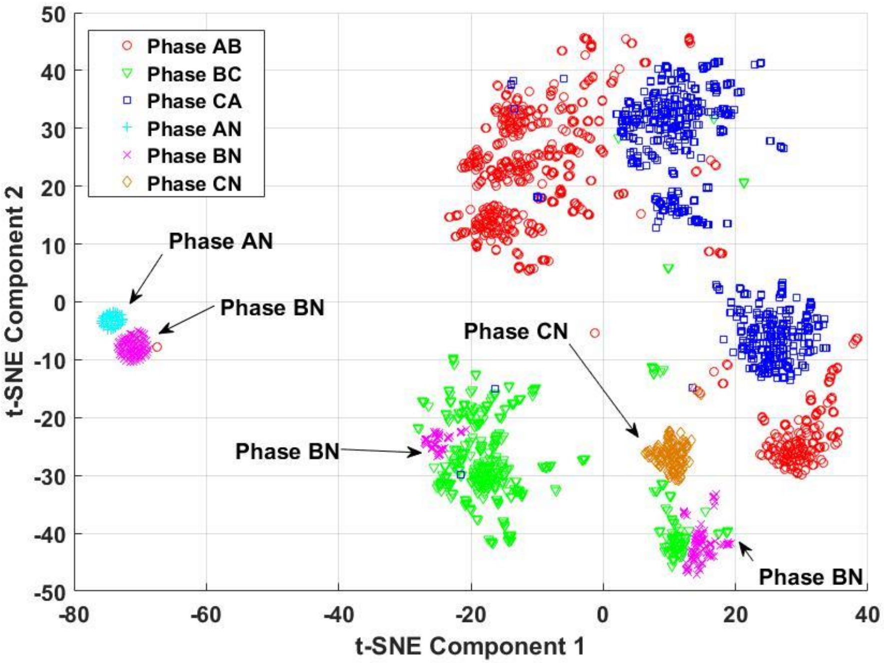
    1. Simplifying the gradient calculation with a symmetrized version of the SNE cost function
    2. Adopting a Student-t distribution rather than a Gaussian to compute the similarity between two points in the low-dimensional space

Comparison between PCA & t-SNE

Feeder 5, data set 18 with a low level of unbalance

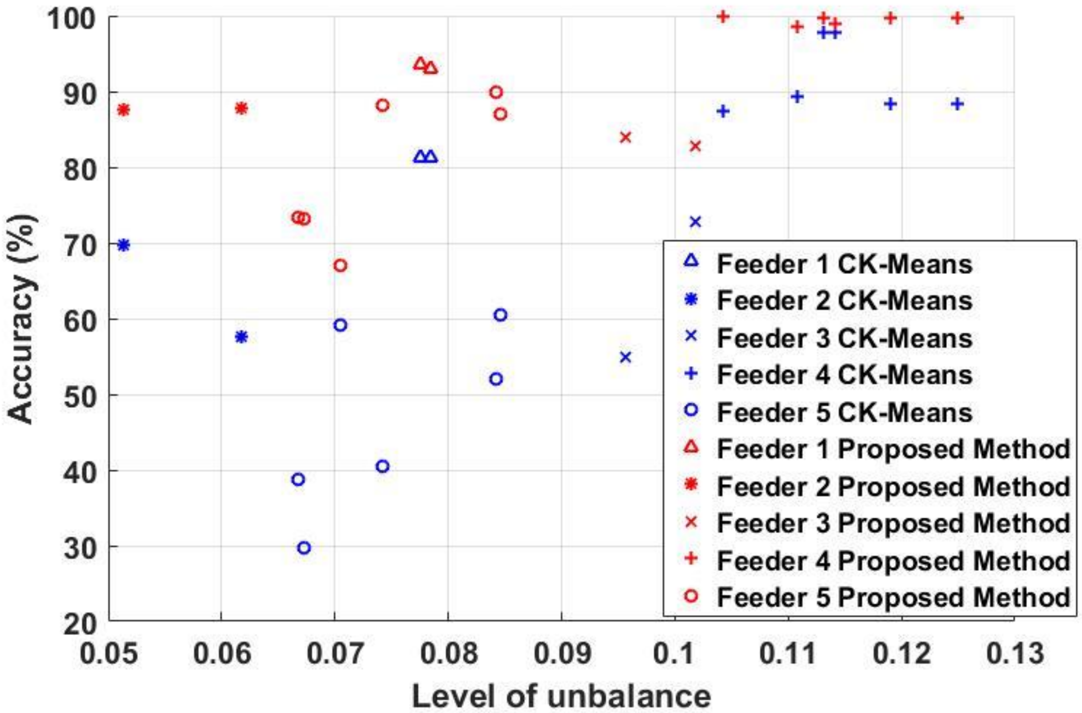


The data points are not well separated according to phase connection with linear dimension reduction.



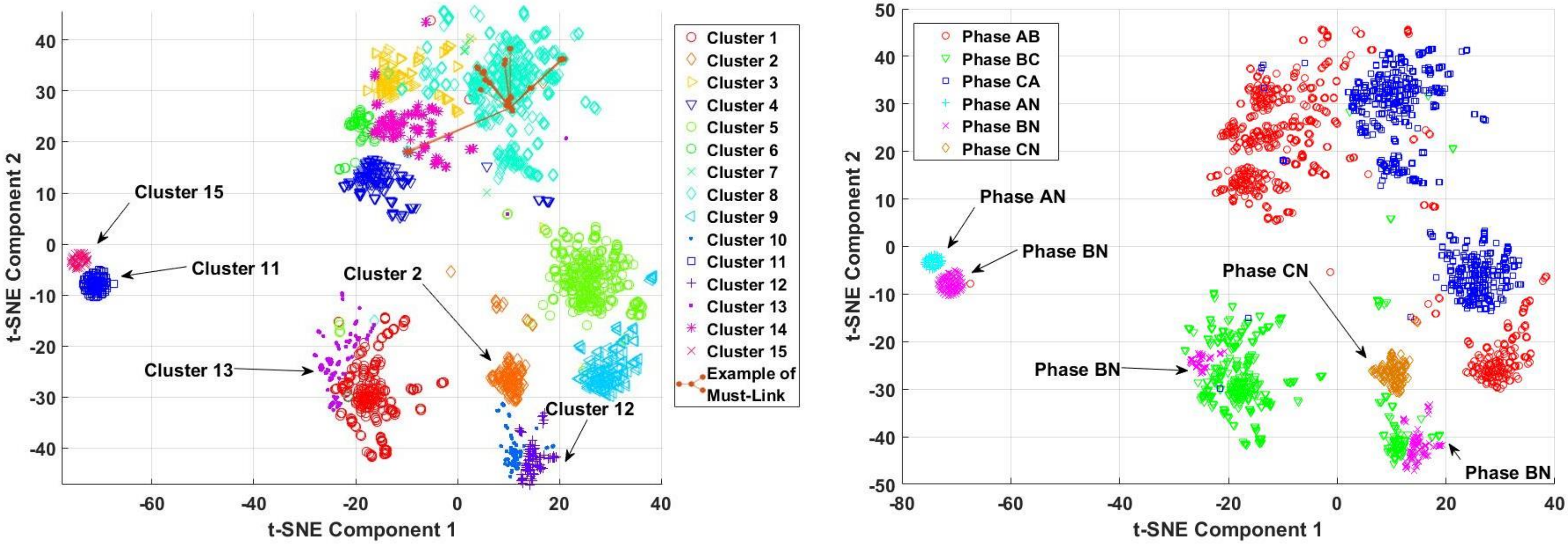
The non-linear dimensionality reduction technique does a much better job in extracting hidden features from the voltage time series during a less unbalanced period for the feeders.

Phase Identification Accuracy with CK-Means and the Proposed Method



- The proposed phase identification algorithm significantly outperforms the CK-Means method with all data sets in terms of accuracy.
- On average, the proposed phase identification algorithm improves the identification accuracy by 19.81% over the CK-Means algorithm.

Clustering Results of the Proposed Method



- Nonconvex clusters are identified.
- The proposed phase identification algorithm not only groups phase-to-phase meters for phase AB, BC, and CA accurately, but also groups single-phase meters with high accuracy

Impact of Data Granularity on Accuracy

Feeder	Data Set	Granularity of Meter Readings		
		1 hour	15-minute	5-minute
1	s1	93.06%	93.93%	93.88%
	s2	93.62%	94.32%	94.40%
2	s3	87.55%	88.86%	92.03%
	s4	87.79%	90.47%	89.93%
3	s5	83.94%	90.02%	91.56%
	s6	82.83%	84.51%	87.16%

- As the granularity of meter readings increases from hourly to every 15 minutes and then 5 minutes, the phase identification accuracy increases.
- The average increase in phase identification accuracy over the 3 distribution circuits is 3.36% when the meter reading granularity increases from hourly to 5 minutes.
- More granular voltage readings allows extraction of features/patterns that may not be present in coarse data sets

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A Comprehensive Evaluation of Supervised Machine Learning Algorithms

Simple Circuit Example

Train%	5%	10%	20%	30%
1-NN	95.4%	95.7%	96.6%	96.7%
5-NN	93.1%	94.2%	95.7%	96.0%
DT	88.9%	92.0%	92.5%	94.4%
RF	92.4%	94.6%	96.0%	96.4%
Ada	89.5%	92.5%	94.1%	95.0%
LR	97.8%	98.0%	98.3%	98.2%
ANN	96.8%	98.3%	**99.0%**	**99.0%**
MCD	**97.2%**	**98.7%**	**99.0%**	**99.0%**

NN – Nearest Neighbor

DT – Decision Tree

RF – Random Forest

Ada – Adaboost

LR – Logistic Regression

ANN – Neural Network

MCD – Monte Carlo Dropout

A Comprehensive Evaluation of Supervised Machine Learning Algorithms

Complex Circuit Example

Train%	5%	10%	20%	30%
1-NN	80.3%	84.1%	89.0%	92.0%
5-NN	78.0%	80.7%	83.5%	85.9%
DT	78.7%	81.5%	84.7%	87.1%
RF	83.2%	85.9%	88.6%	90.5%
Ada	78.6%	81.2%	84.1%	85.8%
LR	88.8%	90.3%	91.6%	91.9%
ANN	90.9%	93.2%	95.0%	**96.7%**
MCD	**91.74%**	**93.6%**	**95.47%**	96.5%

NN – Nearest Neighbor

DT – Decision Tree

RF – Random Forest

Ada – Adaboost

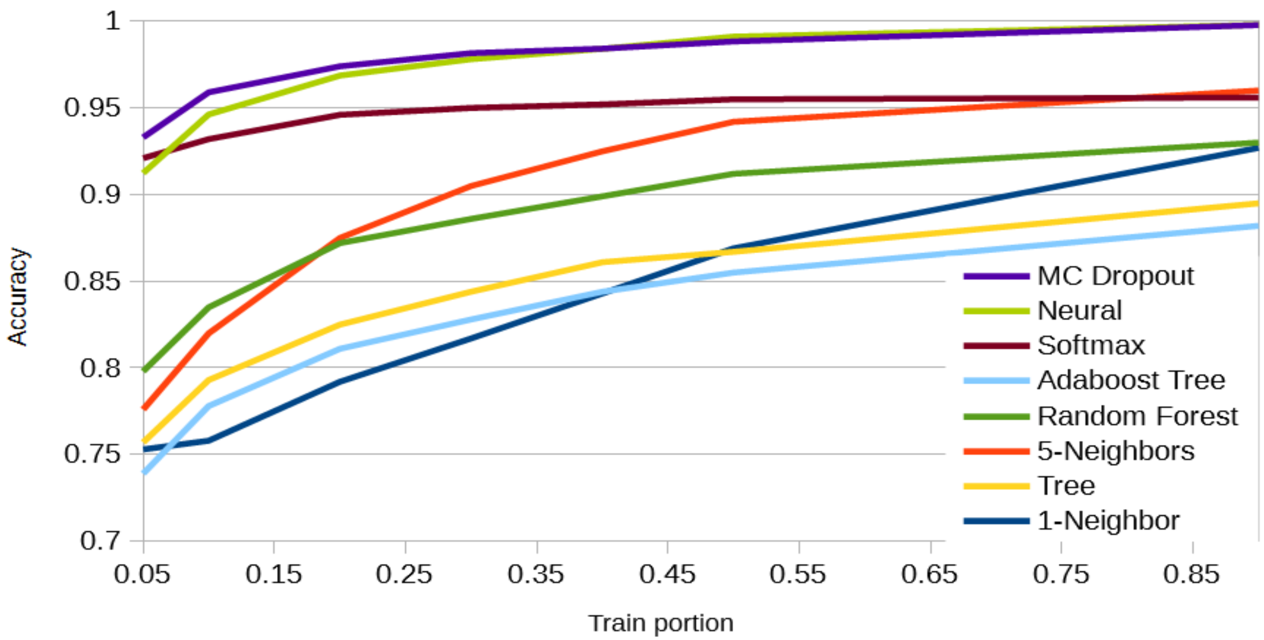
LR – Logistic Regression

ANN – Neural Network

MCD – Monte Carlo Dropout

Supervised Machine Learning Algorithm

- Physically inspired supervised machine learning algorithm achieves over 95% accuracy with less than 5% of training data.
- Neural network with dropout layers which is equivalent to a sample of a Gaussian process approximated through a variational distribution performed the best with a small amount of training data.



Brandon Foggo, Nanpeng Yu, and Wenyu Wang, "A Comprehensive Evaluation of Supervised Machine Learning for the Phase Identification Problem," in the 20th International Conference on Machine Learning and Applications, pp.1-9, Copenhagen, Denmark, 2018.

Training Data Selection

- Not all data is equally useful.
- Facility location optimization:

$$\underbrace{z^*}_{\text{facility location}} = \max_{S \subseteq \mathcal{D}} \sum_{i=1}^{N} \max_{j \in S} \underbrace{w_{ij}}_{\text{similarity}}$$

Feeder	5% random	5% selected
1	93.4%	97.9%
2	91.0%	95.3%
3	95.2%	96.7%
4	93.3%	97.2%
5	98.8%	99.6%
6	88.0%	91.9%
7	97.2%	98.6%

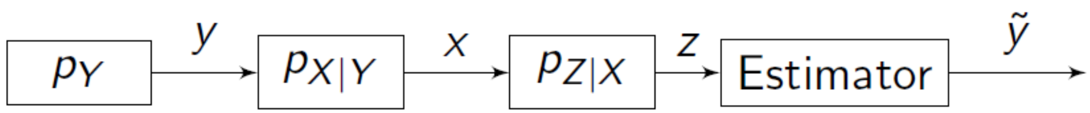
Training data selection improves accuracies by 3% on average.

Phase Identification

- Phase Connectivity Identification
  - Unsupervised Machine Learning
    - Linear dimension reduction and centroid-based clustering
    - Nonlinear dimension reduction and density-based clustering
  - Supervised Machine Learning
    - A comprehensive evaluation of supervised machine learning algorithms
    - Improvement with the theory of information losses

A Generic Classification Model with Deep Neural Network

- Assuming that all probability distributions can be written as density functions, a generic classification model can be viewed through the following figure:



- A discrete random variable is drawn from a distribution.
- This is then mapped to a feature vector x.
- The feature generates a representation z, which is used to determine the value of y that was drawn.
- Inputs to the neural network: x, the last hidden layer of neural network: z, the output layer: y.

Why is the Representation Important?

- We could have just said that we have an estimator $\tilde{y}$ generated from the feature vector x without explicit reference to the ‘inner’ variable z.
- But z itself is an important variable to study.
- ‘Complicated’ representations tend to make the final estimation step harder.
  - e.g., if $\dim(Z) \to \infty$, we will need infinite training data to ‘cover’ the space.
- But too simple a representation will lose its ability to estimate at all
  - e.g., if $\mathrm{z} = 0\ \forall y$, then we can do better than random guessing.

Mutual Information

- Some recent work has attempted to quantify the above trade-off.
- First, however, we need to define an important probabilistic quantity called Mutual Information.
- Definition of Mutual Information
  - If A, B are random variables with joint distribution P_{AB}, then the mutual information between A and B is given by.

$$I(A;B) = \mathbb{E}_{p_{AB}}[log_2(\frac{p_{AB}(a,b)}{p_A(a)\cdot p_B(b)})]$$

where $p_A(a) = \mathbb{E}_{p_{AB}}\left[1_{\{a'=a\}}p_{AB}(a',b')\right]$

$$p_B(b) = \mathbb{E}_{p_{AB}}[1_{\{b'=b\}}p_{AB}(a',b')]$$

Quantifying a Good Representation

- What does it mean for a representation to be 'good'?

- To answer this, we look at Fano's inequality:

$$h_2(P_e) + P_e log_2(|\mathcal{Y}| - 1) \geq H(Y|Z) = H(Y) - I(Y;Z)$$

- This bounds the probability of estimation error below by a monotonically decreasing function of $I(Y;Z)$

- Thus a good representation should have high mutual information with Y – ideally $H(Y)$.

Finite Data Information Losses

- But the representation can only retain as much information as it has seen from the samples training it.
- Thus full information of a random variable cannot be transfer to a representation by finite samples – some information is lost.
- We thus need to study these information losses.

Existing Studies

- Existing literature has made some progress on such losses.

- Letting $\hat{I}(Y;Z)$ refer to the information between Y and Z in a model parameterized as $p(x)\hat{p}(y|x)p(z|x)$, we have:

$$\left|I(Y;Z)-\hat{I}(Y;Z)\right| \leq \mathcal{O}\left(\sqrt{\frac{|\mathcal{Y}|}{2m}}\,2^{I(X;Z)}\right)$$

- This bound[1,2] leads to the idea of using $I(X;Z)$ as a measure of complexity of Z as, according to this bound, increasing $I(X;Z)$ leads to gigantic losses!

- But recent experimental work has shown that deep neural network models have small losses even with high $I(X;Z)$ - this bound is extremely lax.

1. Ravid Shwartz-Ziv and Naftali Tishby, Opening the black box of deep neural networks via information, arXiv preprint arXiv:1703.00810 (2017).
2. Naftali Tishby and Noga Zaslavsky, Deep learning and the information bottleneck principle, Information Theory Workshop (ITW), 2015 IEEE.

Estimated Information Bound

- Theorem (Estimated Information Bound)[1]

$$\left|I(Y;Z) - \hat{I}(Y;Z)\right| \leq \bar{\delta}_{TV}\left(\mathbb{P}, \widehat{\mathbb{P}}\right) I(X;Z) + h_2\left(\bar{\delta}_{TV}\left(\mathbb{P}, \widehat{\mathbb{P}}\right)\right)$$

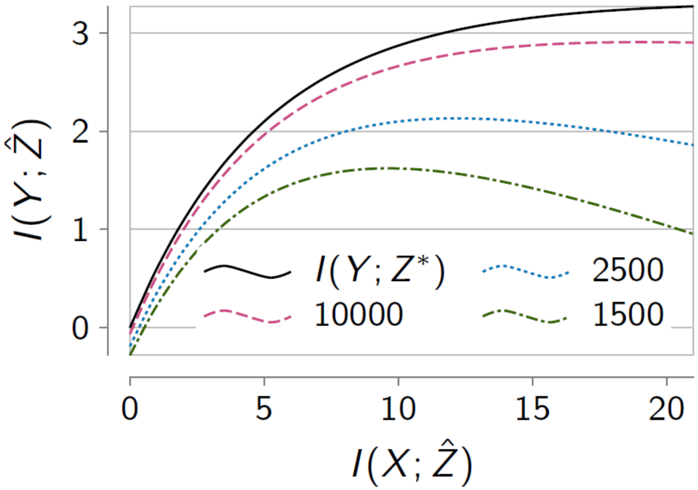
Where $\bar{\delta}_{TV}\left(\mathbb{P}, \widehat{\mathbb{P}}\right)$ is defined as the coupling total variation. This notation emphasizes its role as an average total variation distance.

$$\bar{\delta}_{TV}\left(\mathbb{P}, \widehat{\mathbb{P}}\right) = \mathbb{E}_{\mathbb{P}_X}\left[\frac{1}{2}\sum_{y} |p(y|x) - \hat{p}(y|x)|\right]$$

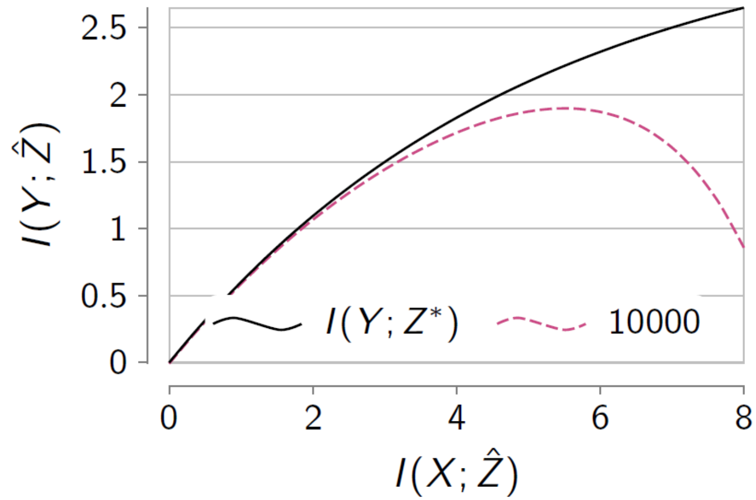
- These bounds explain experimental discrepancy.
- It is not optimal to always compress a neural network's input.
- We will visualize this on the next slide.

1. Foggo, Brandon, Nanpeng Yu, Jie Shi, and Yuanqi Gao. "Asymptotic Finite Sample Information Losses in Neural Classifiers." *arXiv preprint arXiv:1902.05991* (2019).

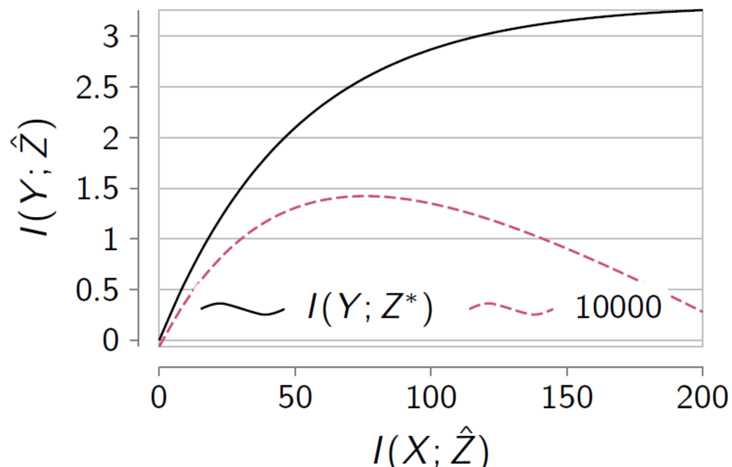
Visualization



Low Entropy / New



Low Entropy / Old



High Entropy / New

Information Loading

- The entropy of the feature space for phase identification problem is very low[1].
- An information 'anti-regularization' term should be added to the loss function of supervised machine learning algorithm to penalize compression.

$$\mathcal{L} - \beta I(X;Z),\ \beta > 0$$

Circuit	Neural Network	Information Load & Training Data Selection
I	80.7%	91.0%
II	64.7%	96.3%
III	74.1%	93.1%
IV	75.0%	98.8%
V	51.7%	97.3%

1. Brandon Foggo and Nanpeng Yu, "Improving Supervised Phase Identification Through the Theory of Information Losses, under review," 2019.

Outline

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- Big Data in Power Distribution Systems
  - Volume, Variety, Velocity, and Value
- Applications of Machine Learning and Big Data Analytics in Power Distribution Systems
  - Topology Identification – Phase Connectivity Identification
  - Anomaly Detection – Electricity Theft Detection
  - Reinforcement Learning based Control – Volt-VAR Control
  - Predictive Maintenance – Distribution Transformers
  - Estimation of Behind-the-meter Solar Generation

Anomaly Detection - Electricity Theft

- Problem Definition
  - Energy Theft: The activity of reducing electricity bill by altering the electricity consumption (physical / cyber)
    - Physical: Bypassing the smart meter, tamper electricity meters
    - Cyber: Hack into meters, communication network to change kWh readings
- Why is it important? (Business Value)
  - According to Northeast Group, LLC, the world loses $89.3 billion annually to electricity theft in 2015 (India $16.2 billion).
  - In the North America energy theft costs between 0.5% and 3.5% of annual gross revenue.
  - B.C. Hydro estimates up to 3% of energy theft with 1500 ‘electrical diversions’ caught in 3 years. Center Point estimates energy theft is 1% to 2%.
  - Traditional detection methods rely on labor intensive inspections.

Existing Approaches

- The existing data-driven methods can be categorized into three groups based on the type of data available
  - Group 1: Smart Meter Data Not Available
    - Leverage ancillary information: Biannual electricity consumption and credit scores.
    - Machine Learning Model: SVM [Nagi 2010], Random Forest [Ramos 2011], Fuzzy Clustering [Angelos 2011].
  - Group 2: Smart Meter Data & Theft Cases
    - Supervised Machine Learning Model: Extreme learning machine [Nizar 2008].
    - If transformer consumption data is also available, then nontechnical loss can be detected in an area with multiclass SVM [Jokar 2016].
  - Group 3: Smart Meter Data, Network Topology & Topology Info
    - State-estimation based approaches [Huang 2013].
    - Formulate anomaly detection as an optimization problem [Drzajic 2015].

Drawbacks of the Existing Approaches

- Most electric utilities cannot obtain the data necessary to use them
  - Transformer data, reliable topology documentation, and network parameter information are not readily available.
- Many existing methods analyze electricity consumption data alone
  - These methods cannot distinguish electricity theft from non-malicious customer activities. (Installation of a new electric device).
- Supervised approaches for electricity theft detection need theft samples.
  - Confirmed electricity theft cases are very rare.

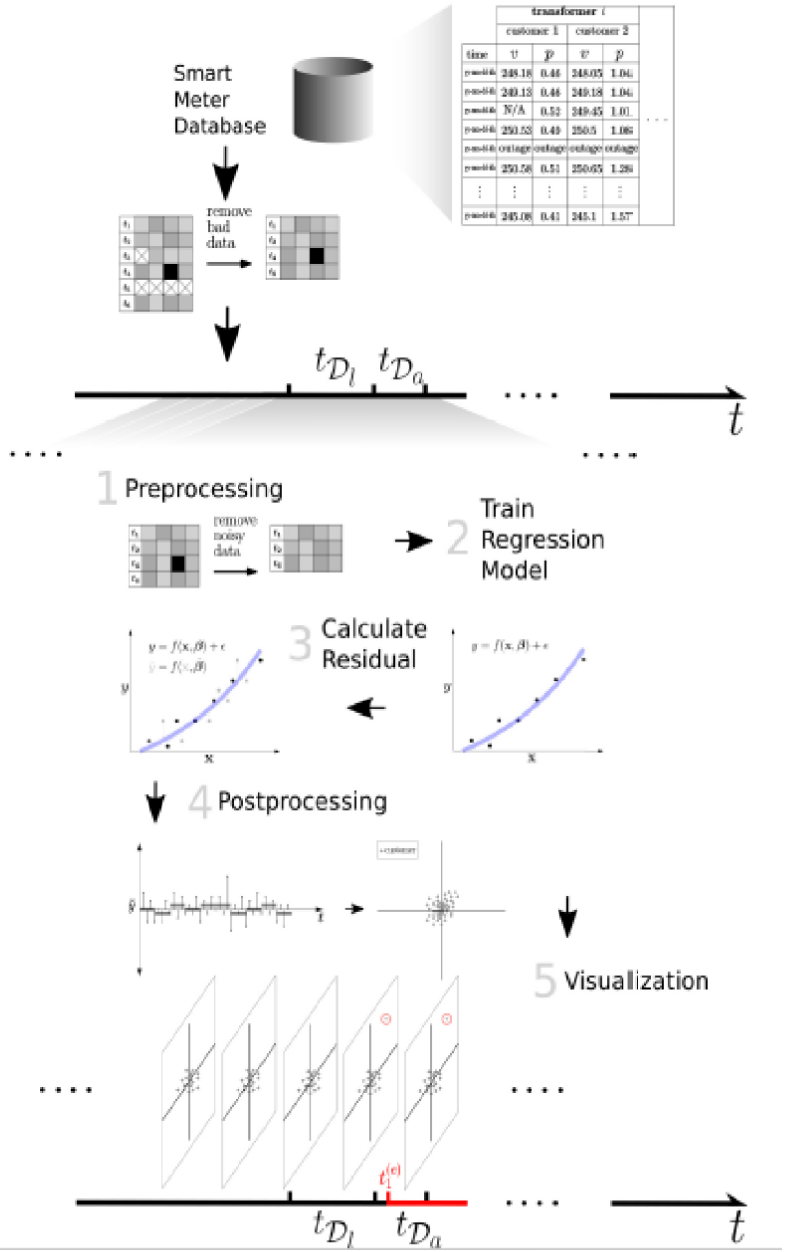
Physically Inspired Data-Driven Model[1]

- There exists linear models between power and voltage magnitudes to distribution secondaries.
  - Find a tangent plane to power flow manifold centered at a suitable point.
- Establishes an exploitable relationship between theft data and honest data.
  - Theft data has large negative residuals and the summation of all customers’ residuals on the same secondary is zero.
- The proposed algorithm does not depend on training samples for theft cases nor a complete network topology documentation.

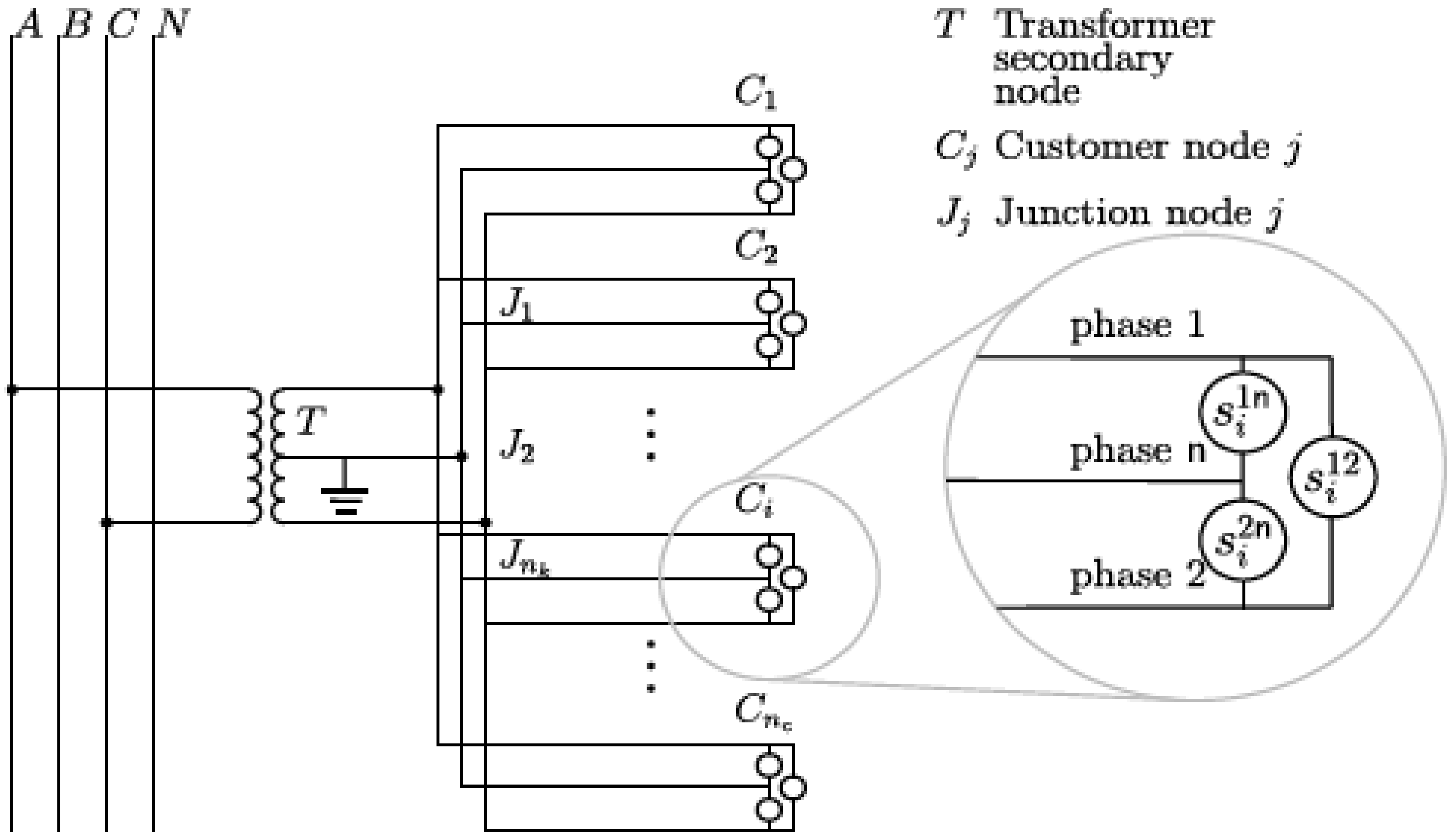
1. Yuanqi Gao, Brandon Foggo, and Nanpeng Yu, "A Physically Inspired Data-driven Model for Electricity Theft Detection with Smart Meter Data," in *IEEE Transactions on Industrial Informatics,* vol. 15, no. 9, pp. 5076-5088, Sept. 2019.

Overall Framework

- 1. Preprocessing
- 2. Train Regression Model
- 3. Calculate Residual
- 4. Post processing
- 5. Calculate Anomaly Scores



Electricity Theft Detection by Secondary Circuit/Transformer



Linearized Power Flow Equations for Unbalanced Secondary

- Approximate the nonlinear power flow equation as a linear one

$$\mathcal{F}(\boldsymbol{v},\boldsymbol{\theta},\boldsymbol{p},\boldsymbol{q}) = \mathbf{0} \quad \rightarrow \quad \mathrm{F}_{\overline{\mathbb{X}}}[\boldsymbol{v}^{\boldsymbol{T}},\boldsymbol{\theta}^{\boldsymbol{T}},\boldsymbol{p}^{\boldsymbol{T}},\boldsymbol{q}^{\boldsymbol{T}}]^{\boldsymbol{T}} = \mathbf{0}$$

Where $\mathrm{F}_{\overline{\mathbb{X}}}$ is the Jacobian matrix of $\mathcal{F}$ evaluated at some operating point $\overline{\mathbb{X}} = [\bar{v}\ \bar{\theta}\ \bar{p}\ \bar{q}]^T$. This point must be itself be a solution to the power flow equation $\mathcal{F}(\overline{\mathbb{X}}) = 0$.

$$\begin{bmatrix} G^{11} & -G^{12} & -B^{11} & B^{12} \\ -G^{12} & G^{22} & B^{21} & -B^{22} \\ -B^{11} & B^{12} & -G^{11} & G^{12} \\ B^{21} & B^{22} & G^{21} & -G^{22} \end{bmatrix} \begin{bmatrix} v^1 \\ v^2 \\ \theta^1 \\ \theta^2 \end{bmatrix} = \begin{bmatrix} p^1 \\ p^2 \\ q^1 \\ q^2 \end{bmatrix}$$

p^1, p^2, q^1, q^2: Real and Reactive Power injections for phase 1 and 2

v^1, v^2, θ^1, θ^2: Voltage magnitude and angles for phase 1 and 2

$$\boldsymbol{y}^{\boldsymbol{r}} = \begin{bmatrix} \boldsymbol{p}^{\boldsymbol{r}} \\ \boldsymbol{q}^{\boldsymbol{r}} \end{bmatrix} = \begin{bmatrix} \boldsymbol{L}_{\mathbf{11}}^{\boldsymbol{r}} & \boldsymbol{L}_{\mathbf{12}}^{\boldsymbol{r}} \\ \boldsymbol{L}_{\mathbf{21}}^{\boldsymbol{r}} & \boldsymbol{L}_{\mathbf{22}}^{\boldsymbol{r}} \end{bmatrix} \begin{bmatrix} \boldsymbol{v}^{\boldsymbol{r}} \\ \boldsymbol{\theta}^{\boldsymbol{r}} \end{bmatrix} = \boldsymbol{L}^{\boldsymbol{r}} \boldsymbol{x}^{\boldsymbol{r}}$$

Modified Linear Model

- Conversion to Smart Meter Measurement: Many smart meters read line-line voltage magnitudes and sum of single-phase powers.

$$\boldsymbol{y}^s = \begin{bmatrix} \boldsymbol{p}^s \\ \boldsymbol{q}^s \end{bmatrix} = \begin{bmatrix} \boldsymbol{L}_{11}^s & \boldsymbol{L}_{12}^s \\ \boldsymbol{L}_{21}^s & \boldsymbol{L}_{22}^s \end{bmatrix} \begin{bmatrix} \boldsymbol{v}^s \\ \boldsymbol{\theta}^s \end{bmatrix} = \boldsymbol{L}^s \boldsymbol{x}^s$$

- Remove dependency on voltage angles.

$$\boldsymbol{p}^s = \left(\boldsymbol{L}_{11}^s - \boldsymbol{L}_{12}^s \boldsymbol{L}_{22}^{s\dagger} \boldsymbol{L}_{21}^s\right)\boldsymbol{v}^s + \boldsymbol{L}_{12}^s \boldsymbol{L}_{22}^{s\dagger} \boldsymbol{q}^S$$

- Assume constant power factor

$$\boldsymbol{p} = \boldsymbol{L}_{pv}\boldsymbol{v} + \boldsymbol{\epsilon}$$

- A remedy for not having transformer data

$$\begin{bmatrix} p_T \\ \boldsymbol{p}_C \end{bmatrix} = \begin{bmatrix} l_{TT} & \boldsymbol{l}_{TC} \\ \boldsymbol{l}_{CT} & \boldsymbol{L}_{CC} \end{bmatrix} \begin{bmatrix} v_T \\ \boldsymbol{v}_C \end{bmatrix} + \begin{bmatrix} \epsilon_T \\ \boldsymbol{\epsilon}_C \end{bmatrix}$$

$$\boldsymbol{p}_C = -\boldsymbol{l}_{CT} l_{TT}^{-1}(1^T \boldsymbol{p}_C) + (\boldsymbol{L}_{CC} - \boldsymbol{l}_{CT} l_{TT}^{-1} \boldsymbol{l}_{TC})\boldsymbol{v}_C + \boldsymbol{\epsilon}_C'$$

- Final linearized model

$$y_i(t) = \begin{bmatrix} \boldsymbol{x}(\boldsymbol{t})^T & \sum_{j=1}^{n_c} y_j(t) \end{bmatrix} \begin{bmatrix} \boldsymbol{\beta}_i^{\chi} \\ \beta_i^{y} \end{bmatrix} + \epsilon_i'(t)$$

Where $\boldsymbol{x}(\boldsymbol{t}) = [1, v_1(t), v_2(t), \cdots, v_{n_c}(t)]^T$, $y_i(t) = p_i(t)$

Properties of Residuals Under Theft

- Suppose without loss of generality that customer i is the thief, then

$$y_i^{(e)} = y_i - y_i^s \qquad y_j^{(e)} = y_j \quad \forall j \neq i$$

- Let $\tilde{y}_i^{(e)}$ and $\tilde{y}_i$ denote the out-of-sample residual time series for the energy thief

- Then the following results hold

Lemma 1. $$\tilde{y}_i^{(e)} - \tilde{y}_i = -\sum_{j \neq i} \beta_j^y y_i^s$$

Lemma 2. $$\sum_j \tilde{y}_j^{(e)} = \sum_j \tilde{y}_j = 0$$

Lemma 3. For any $\delta > 0$, there exists a training data window length $T > 0$ such that for each j

$$\mathbb{P}\left(\beta_j^y \geq -\delta\right) > 1 - \delta$$

- Lemma 1 and Lemma 3 combine to show that a thief's residuals will become negative once he or she begins to steal power.

- Lemma 2 shows that the residuals of the other customers will raise to balance their sum.

Anomaly Score & Energy Theft Detection

- We define an anomaly score in terms of the residuals $\tilde{y}_i$ for each customer i and each rolling window f.
- Customer and rolling window with higher anomaly scores are more likely to be thieves or have malfunctioning smart meters.
- Anomaly score $d_i(f) = \omega_i(f)\|\tilde{y}_i'\|_2$ where $\omega_i(f) = \sqrt{|t^D(f)|}/\left\|\tilde{y}_i^D(f)\right\|_2$ is a weighting coefficient.
- Energy thefts are identified by ranking $d_i(f)$ for all i and all f.
- The higher $d_i(f)$ is the higher priority of investigation customer i should have.
- This ranking method can be simplified to ranking $max_f d_i(f)$ for all i when theft time is unimportant.

Experimental Results

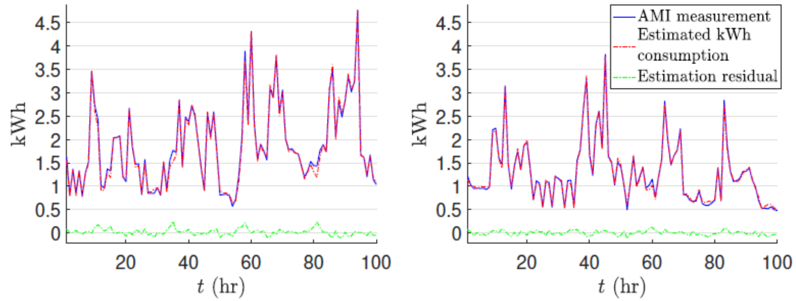
- Perform tests on a real dataset with synthetic electricity theft cases.
- Real-world smart meter data comes from a 12 KV distribution feeder in SCE's service territory.
- Study period: August 1, 2015 to February 1, 2016.
- Number of transformers 190.
- Number of residential customers 980.
- The amount of electricity theft from the kth customer during hour t, $p_k^s(t)$, is defined as

$$p_k^s(t) = p_k(t) - p_k^{(e)}(t) \quad \text{where} \quad 0 \leq p_k^s(t)$$

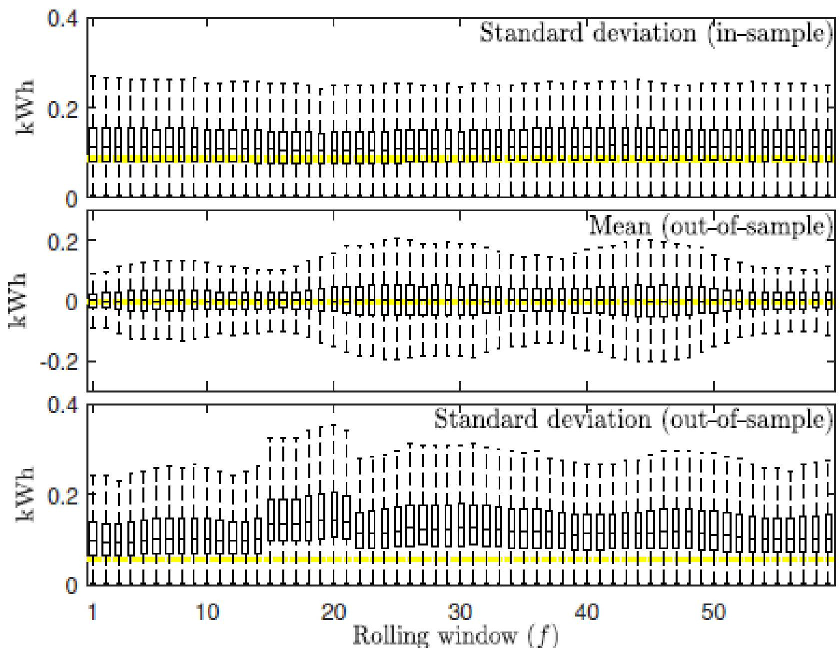
- Four electricity theft cases are simulated
  - Case 1: 100% of electricity theft for n hours: $p_k^s(t) = p_k(t)$
  - Case 2: A constant amount of electricity theft: $p_k^s(t) = \alpha_{c2}$
  - Case 3: A uniformly distributed electricity theft: $p_k^s(t) \sim \mathcal{U}(0, \alpha_{c3})$
  - Case 4: A constant percentage of electricity theft: $p_k^s(t) = \alpha_{c4} p_k(t)$

Performance of the MLM

- Consider a distribution secondary consisting of 4 residential customers. The training and testing data sets include 60 and 7 days of data.



(a) In-sample ($t^{\mathcal{D}}$) (b) Out-of-sample ($t^{\mathcal{D}_a}$)

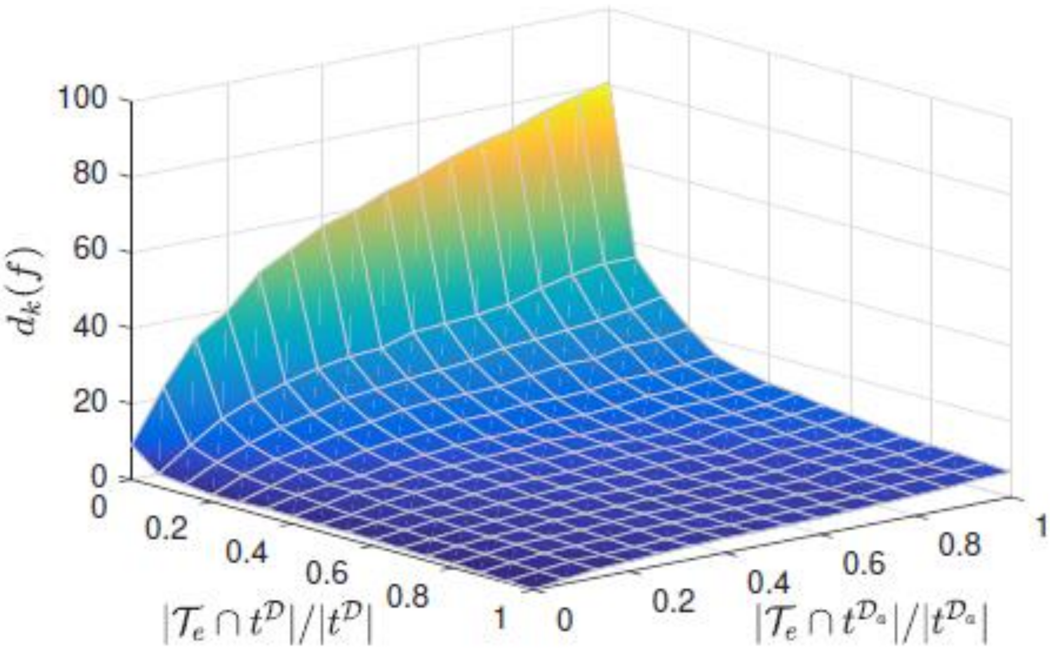


- The average electric load consumed by the customer is 1.6 kWh.
- The mean of the estimation residual is -0.01 kWh and its standard deviation is 0.1 kWh.

- Apply analysis to every customer on the feeder over 59 rolling windows.
- Most customers have a small residual mean and standard deviation.
- The proposed MLM is accurate in estimation the consumption of most customers on the feeder.

Properties of the Anomaly Score

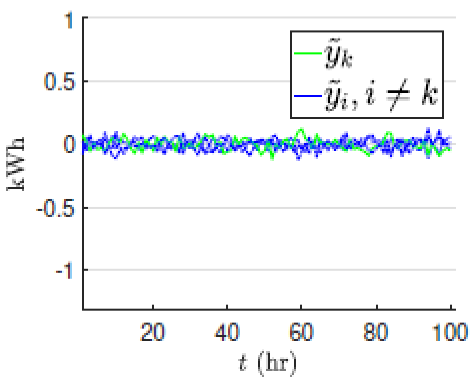
- We increase the percentage of theft hours in the in-sample $|\mathcal{T}_e \cap t^D|/|t^D|$and out-of-sample data $|\mathcal{T}_e \cap t^{D_a}|/|t^{D_a}|$.



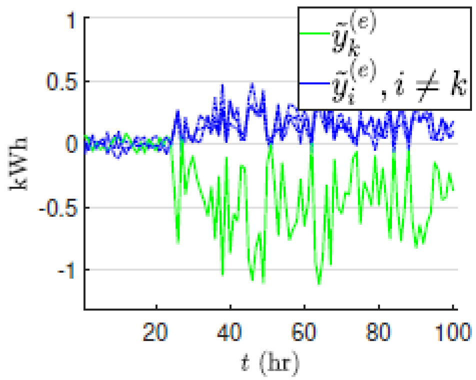
- The anomaly score increases with the amount of theft hours $\mathcal{T}_e$ contained in the testing dataset.
- The anomaly score decreases with the amount of theft hours $\mathcal{T}_e$ contained in the training dataset.

The Impact of Energy Theft on Out-of-Sample Residuals

- Synthesize smart meter data for customer k under theft case 3.
- We assume that the electricity theft activities occur from hour $t_1^e = 25$ to hour $t_2^e = 168$ in the out-of-sample period.
- The amount of electricity theft follows a uniform distribution with $p_k^s(t) \sim \mathcal{U}(0{,}1.8)$ kWh



(a) original data



(b) synthesized data

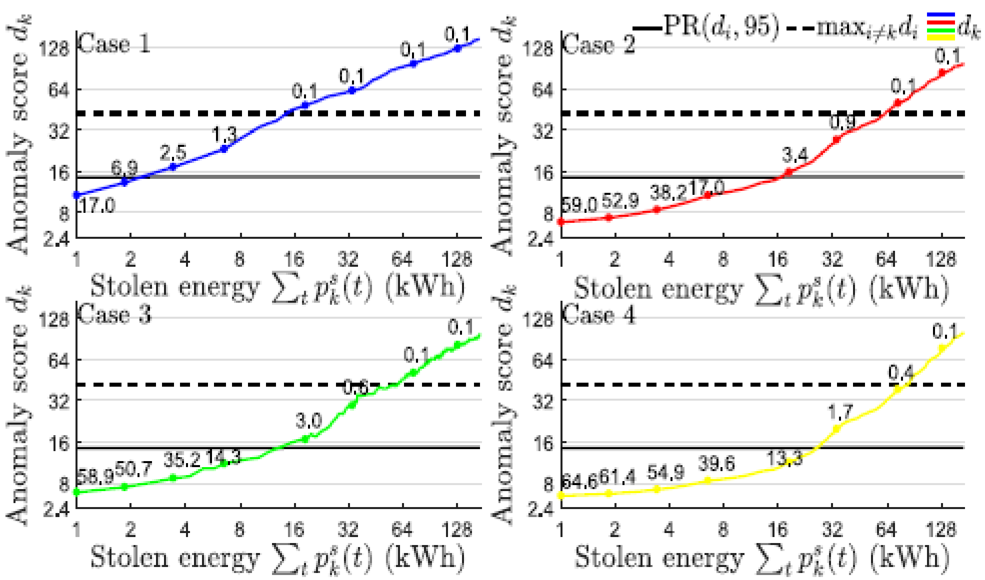
- Customer k has negative residuals while the honest customers have positive residuals.
- The sum of the residuals at any given hour is zero.

The Impact of Energy Theft on Anomaly Scores

› Anomaly score for customer k is much higher than that of all other customers in the feeder

d_k	Ranking	$\sum_i d_i/N$	PR(d_i,95)	$\max_{i \neq k} d_i$
79.4	1 (0.1%)	8.1	14.6	42.2

› Anomaly scores increase with the amount of stolen electricity.



› Anomaly score of customer k increases monotonically with the amount of stolen electricity.

› In all cases, customer k's anomaly score will surpass the 95th percentile of all customers if it steals more than 32 kWh in two weeks or 0.19 kWh per hour.

› In cases 1-3, if customer k steals more than 0.38 kWh of power per hour, then its anomaly score will the largest of all customers.

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Motivation

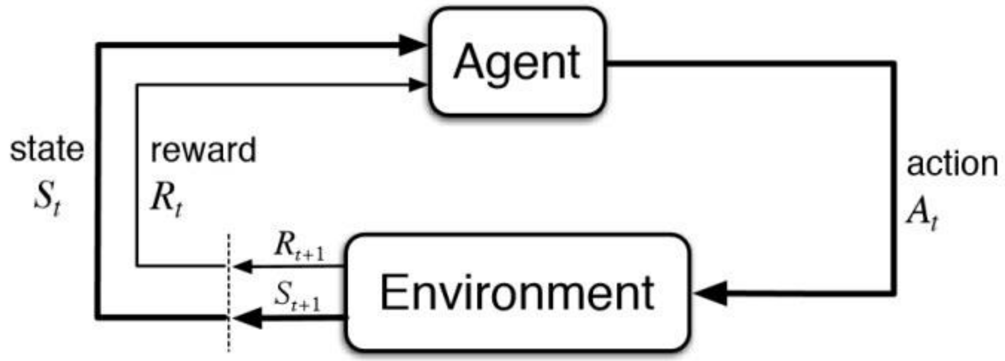
- Physical Model-based Control in Power Distribution Systems
  - Advantages: theoretical guarantees in some cases.
  - Rely heavily on accurate knowledge of grid topology and parameters.
  - Unsatisfactory performance (e.g., VVC)
- Practical Challenges
  - Difficult for regional utilities to maintain reliable network models oftentimes involving millions of buses.
  - Secondary feeder (transfer-to-customer association, phase connectivity)
- Reinforcement Learning-based (Model-free) Approach
  - Do not need reliable and complete distribution network model
  - Use operational data (real-time and/or historical)
  - Learn control policies by interacting with the distribution network.
  - Challenges: safe, optimality, sample efficient, robust.

Background of Volt-VAR Control (VVC)

- As penetration level of DERs continues to rise, it is increasingly difficult to keep the nodal voltages within the desired range.
- The voltage profile highly impacts the electricity service quality for end users.
- Over- and under-voltage reduce energy efficiency, cause equipment malfunction, and damage customers’ electrical appliance.
- Control objectives of VVC
  - Maintain voltages within allowable range
  - Manage power factor
  - Reduce network losses and equipment wear and tear.
- Coordinate the operations of various voltage regulating devices
  - Voltage regulators, on-load tap changers
  - Switchable capacitor banks and smart inverters

Reinforcement Learning based Control

- Main Idea
  - A computational approach to understanding and automating goal-directed learning and decision making.
  - Key Difference (compare to other computational approaches)
    - Learning by an agent from direct interaction with its environment
    - Without requiring exemplary supervision or complete models of the environment.
  - Reinforcement learning (RL) uses the formal framework of Markov decision processes to define the interaction between a learning agent and its environment.
  - Key Concepts
    - States, actions, and rewards.



Markov Decision Process (MDP)

- MDPs: Formalization of sequential decision making, where actions influence not just immediate rewards, but also subsequent states and future rewards.
- MDPs are a mathematically idealized form of the reinforcement learning problem for which precise theoretical statements can be made.
- Specifically, the agent and environment interact at each of a sequence of discrete time steps, $t = 0, 1, 2, 3, \ldots$.
- At each time step t, the agent receives some representation of the environment's state, $S_t \in \mathcal{S}$, and on that basis selects an action, $A_t \in \mathcal{A}(s)$.
- One time step later, in part as a consequence of its action, the agent receives a numerical reward, $R_{t+1} \in \mathcal{R} \subset \mathbb{R}$, and finds itself in a new state, S_{t+1}.
- The MDP and agent together thereby give rise to a sequence or trajectory that begins like this: $S_0, A_0, R_1, S_1, A_1, R_2, S_2, A_2, R_3, \ldots$

Discounted Return, Policy, Value Functions

- The goal of an agent is to choose action A_t to maximize the expected *discounted return* $G_t \doteq R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \cdots = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1}$.
- *Value functions* – functions of states (or of state-action pairs) that estimate *how good* it is for the agent to be in a given state (or how good it is to perform a given action in a given state).
- Value functions are defined wrt to particular ways of acting, called policies.
- Formally, a *policy* π is a mapping from states to probabilities of selecting each possible action $\pi(a|s)$.
- The value function of a state s under a policy π, denoted $v_\pi(s)$, is the expected return when starting in s and following π thereafter.

$$v_\pi(s) \doteq \mathbb{E}_\pi[G_t | S_t = s] = \mathbb{E}_\pi[\sum_{k=0}^{\infty} \gamma^k R_{t+k+1} | S_t = s], \text{ for all } s \in \mathcal{S}$$

- The value of taking action a in state s under a policy π, denoted $q_\pi(s,a)$, as the expected return staring from s, taking the action a, and thereafter following policy π:

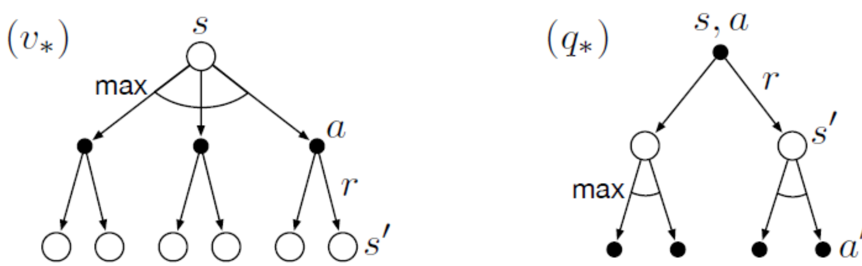
$$q_\pi(s,a) \doteq \mathbb{E}_\pi[G_t | S_t = s, A_t = a] = \mathbb{E}_\pi[\sum_{k=0}^{\infty} \gamma^k R_{t+k+1} | S_t = s, A_t = a]$$

Optimal Policies and Value Functions

- Optimal policies π_* are the ones that have expected returns greater than or equal to any other policy for all states.
- π_* share the same state-value function, called the *optimal state-value function*, denoted by $v_*(s) \doteq \max_{\pi} v_\pi(s)$, for all $s \in \mathcal{S}$.
- π_* also share the same optimal action-value function, denoted q_* defined as: $q_*(s,a) \doteq \max_{\pi} q_\pi(s,a)$, for all $s \in \mathcal{S}$ and $a \in \mathcal{A}(s)$.
- Optimal value functions must satisfy the self-consistency condition given by the Bellman equations.

$$v_*(s) = \max_a \sum_{s',r} p(s',r|s,a)\,[r + \gamma v_*(s')]$$

$$q_*(s,a) = \sum_{s',r} p(s',r|s,a)\,[r + \gamma \max_{a'} q_*(s',a')]$$



Constrained MDP (CMDP)

- A constrained MDP (CMDP) is an MDP augmented with constraints that restrict the set of allowable policies for that MDP.
- We augment the MDP with an auxiliary cost functions, C and limits $\bar{J}$.
- Let $J(\pi)$ denote discounted total return:
- $J(\pi) = E_{\tau \sim \pi}[\sum_{t=0}^{T} \gamma^t R(s_t, a_t, s_{t+1})]$
- Let $J_C(\pi)$ denote the expected discounted return of policy π with respect to cost function C.
- $J_C(\pi) = E_{\tau \sim \pi}[\sum_{t=0}^{T} \gamma^t R_C(s_t, a_t, s_{t+1})]$.
- The CMDP is then

$$\max_{\pi} J(\pi)$$

$$\text{s.t. } J_C(\pi) \leq \bar{J}$$

Formulate VVC as a CMDP

- Agent & Environment
  - The grid operator/controller & power distribution grid
- State
  - A tuple of real and reactive power injections, the current tap positions, and the global time. $s = [\boldsymbol{P}, \boldsymbol{Q}, \mathcal{T}, t]$.
- Action
  - Control the tap positions of controllable devices $\mathcal{T}'$.
  - The size of the action space is $\prod_{i=1}^{N_s} n_i$.
- Reward
  - Negative of the system operational costs include the cost associated with real power losses and equipment operations.
- Constraints
  - To enforce the voltage constraints, we augment the MDP with a set of cost functions $R_C(s_t, a_t, s_{t+1})$.
  - $R_C(s_t, a_t, s_{t+1}) = \sum_{i=1}^{N} [1(|v_i^{t+1}| > \bar{v}) + 1(|v_i^{t+1}| < \underline{v})]$

Policy Gradient Method

- Action-value Methods
  - Approximate the action-value functions through learning and then selects actions based on estimated action-value functions.
- Policy Gradient Methods (PGM)
  - Learn a parameterized control policy that directly selects actions without consulting a value function.
- Advantages of PGM
  - The policy function could be easier to approximate than the action-value functions.
  - The parameterized policy could be more smooth and flexible than the ϵ-greedy choice.
- Policy Gradient Theorem

$$\nabla J(\pi_\theta) = E_{\tau\sim\pi_\theta}\left[\sum_{t=0}^{T} \nabla_\theta ln\, \pi_\theta(a_t|s_t)\big(G_t - b(s_t)\big)\right] = E_{\tau\sim\pi_\theta}\,[\sum_{t=0}^{T} \nabla_\theta ln\, \pi_\theta(a_t|s_t)(Q^{\pi_\theta}(s_t,a_t) - b(s_t))]$$

G_t: discounted return. $b(s_t)$: baseline function, which helps reduce variance.

Trust Region Policy Optimization

- Trust region policy optimization (TRPO) algorithm provides a theoretical guarantee of monotonic improvement of the control policy at each policy iteration step.

- The algorithm design is based on the lower bound of performance improvement of policy $\pi_{\theta'}$ over π_{θ}.

$$J(\pi_{\theta'}) - J(\pi_{\theta}) \geq \frac{1}{1-\gamma} E_{s\sim\eta^{\pi_\theta}, a\sim\pi'_\theta} [A^{\pi_\theta}(s,a)] - E_{s\sim\eta^{\pi_\theta}, a\sim\pi'_\theta} [\frac{\gamma\xi^{\pi_\theta'}}{(1-\gamma)^2} \sqrt{2KL(\pi_{\theta'}||\pi_\theta)[s]}]$$

- Where $\xi^{\pi_\theta'} = \max_s \left| E_{a\sim\pi_{\theta'}}[A^{\pi_\theta'}(s,a)] \right|, \eta^{\pi_\theta} = (1-\gamma)\sum_{t=0}^{T} \gamma^t P(s_t = s|\pi_\theta)$, KL denotes the KL-divergence

- Policy update

$$\pi_{\theta_{k+1}} = \arg\max_{\pi_\theta} E_{s\sim\eta^{\pi_{\theta_k}}, a\sim\pi_\theta} [A^{\pi_{\theta_k}}(s,a)]$$

$$\text{s.t. } KL(\pi_\theta||\pi_{\theta_k}) \leq \delta$$

Constrained Policy Optimization

- Upper bound of performance improvement

$$J_C(\pi_{\theta'}) - J_C(\pi_\theta) \le \frac{1}{1-\gamma} E_{s\sim\eta^{\pi_\theta}, a\sim\pi'_\theta}\left[A^{\pi_\theta}(s,a) + \frac{\gamma\xi^{\pi_\theta'}}{1-\gamma}\sqrt{2KL(\pi_{\theta'}||\pi_\theta)[s]}\right]$$

- Policy update

$$\pi_{\theta_{k+1}} = \arg\max_{\pi_\theta} E_{s\sim\eta^{\pi_{\theta_k}}, a\sim\pi_\theta}\left[A^{\pi_{\theta_k}}(s,a)\right]$$

$$s.t.\ KL(\pi_\theta||\pi_{\theta_k}) \le \delta$$

$$J_C(\pi_\theta) + \frac{1}{1-\gamma} E_{s\sim\eta^{\pi_{\theta_k}}, a\sim\pi_\theta}\left[A^{\pi_\theta}(s,a)\right] \le \bar{J}$$

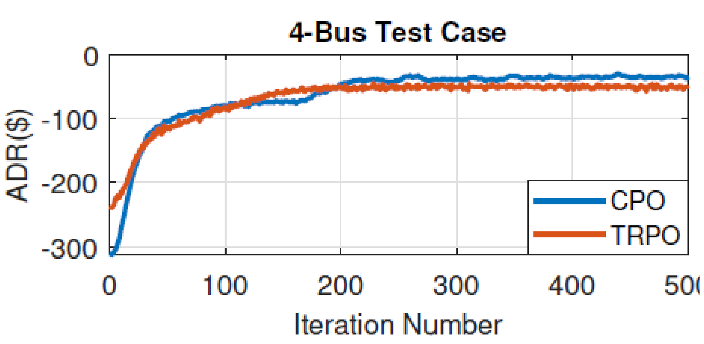
- Constraint satisfaction is almost guaranteed after a feasible solution is recovered.

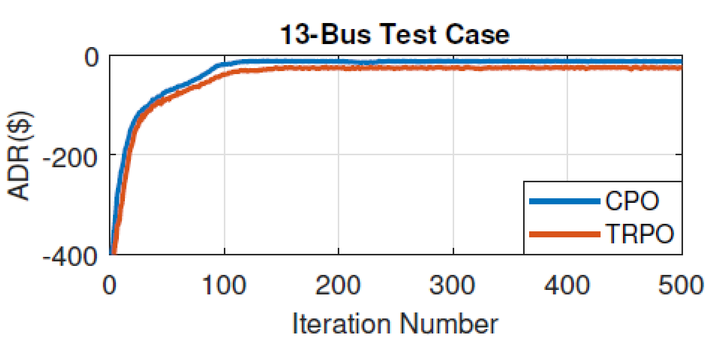
Numerical Study

- Test Systems
  - IEEE 4-bus and 13-bus distribution test feeders.
- Nodal Load and Voltage Measurements
  - Aggregated real-world smart meter data. Nodal voltages calculated via power flow simulations.
  - Length of training data: 6 months. Length of test data: 1 week.
- Switching Devices
  - Each test feeder has three switching devices: a voltage regulator, an on-load tap changer, and a capacitor bank.
  - Both the voltage regulator and on-load tap changer have 11 tap positions with turns ratios between 0.95 and 1.05.
  - The number of tap positions of the capacitor bank is treated to be 2.
  - The size of the action space for each test case is 242.
  - Electricity price: $40/MWh. Switching costs: $0.1 per tap change.

Benchmarking & Performance Comparison

- The MPC-based optimization algorithm is chosen as the first benchmark.
  - Control horizon: 24 hours.
  - The ARIMA model is used to forecast the load during the control horizon.
  - The mixed integer conic programming problem (MICP) is solved on a rolling basis.
  - MOSEK and GUROBI are used to solve the MICP problem.
- The second benchmark is set up by replacing the load forecast with actual load data in the MPC framework.
- The last benchmark represents the baseline where all switching devices are kept at their initial positions.





CPO algorithm outperform the TRPO algorithm by achieving a higher average discounted return.

Performance Comparison

	Algorithms	OC($)	# of TC	# of VV	AMV (per unit)
4-Bus Test Case	Baseline	150.13	0	91	2.748
	MPC(Actual)	111.44	18	0	0
	MPC (Forecast)	111.89	20	0	0
	CPO	115.01	9	5	0.044
	TRPO	120.05	3	16	0.286
13-Bus Test Case	Baseline	77.88	0	268	2.673
	MPC(Actual)	58.05	6	0	0
	MPC (Forecast)	58.44	6	0	0
	CPO	58.92	6	0	0
	TRPO	61.29	3	2	0.0004

	Algorithms	Average Time（s）	Maximum Time（s）
4-Bus	MPC(GUROBI)	10.4	90.3
	MPC (MOSEK)	346.8	3904.2
	TRPO/CPO	$<10^{-3}$	$<10^{-3}$
13-Bus	MPC(GUROBI)	4.69	8.57
	MPC (MOSEK)	53.83	328.98
	TRPO/CPO	$<10^{-3}$	$<10^{-3}$

OC: operation cost
VV: voltage violation
TC: tap changes
AMV: accumulated magnitude of VV

- CPO algorithm achieves near-optimal solutions with negligible voltage violations[1].
- Advantages of RL-based Method (fast execution speed, do not require complete and accurate distribution system model).

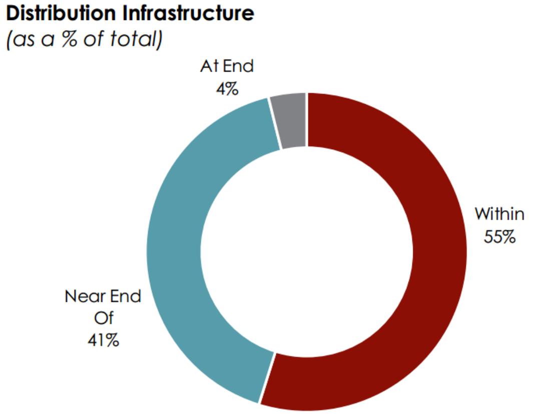
1. Wei Wang, Nanpeng Yu, Jie Shi, and Yuanqi Gao, "Volt-VAR control in power distribution systems with deep reinforcement learning." to appear in *2019 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, pp. 1-7. IEEE, 2019.

Outline

- Why do we focus on electric power distribution systems?
- Big Data in Power Distribution Systems
  - Volume, Variety, Velocity, and Value
- Applications of Machine Learning and Big Data Analytics in Power Distribution Systems
  - Topology Identification – Phase Connectivity Identification
  - Anomaly Detection – Electricity Theft Detection
  - Reinforcement Learning based Control – Volt-VAR Control
  - Predictive Maintenance – Distribution Transformers
  - Estimation of Behind-the-meter Solar Generation

Aging Infrastructure & Current Practice

- Aging Infrastructure
  - 70% of power transformers are 25+ years old (useful life- 20 years)[1]
  - 60% distribution poles surpassed useful life of 50 years[1]



Current Infrastructure Age Relative to Useful Life, Source: EEI

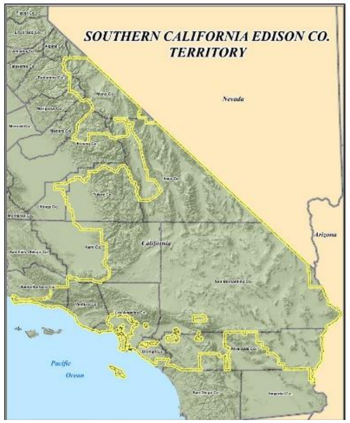
- Maintenance Practice for distribution Transformers
  - Run-to-failure (Current industry practice). Sudden failure leads to sudden interruption of power supply.
  - Preventive maintenance
    - Scheduled based on time regardless of health status.
    - Pros: Usually able to prevent failures. Cons: Early replacement leads to increased operational costs.
  - Predictive/Condition-based maintenance.
    - Pros: Minimize downtime. Avoid unnecessary corrective action and achieve lower operating costs.

[1]Failure to act: The economic impact of current investment trends in electricity infrastructure," American Society of Civil Engineers, Tech. Rep., 2011

Challenge, Solution, and Goal

- Challenge
  - Predictive maintenance for large power transformers: a combination of dissolved gas analysis (DGA) and data-driven machine learning techniques.
  - Requires semiconductor gas sensors for each transformer.
  - Suitable for transmission system. Not economically feasible for distribution system.
- Solution: Use low cost and readily available data
  - Environmental condition, Transformer specification, Historical Failure
  - Transformer location information (GIS), Loading information (AMI)
- Goal of the Study
  - Predict which transformers will fail in a given time horizon
  - Supervised binary classification task
  - Keep number of false positives low. Unexploited lifetime, increase in operating cost.
  - False negative has low cost
  - 'Match in top N' (MITN) metric suitable

Case Study



- Collaborating utility: Sothern California Edison
- Number of distribution transformers: Over 700,000
- 35% approaching useful life
- Data spans 2012-2016
  - Training and Validation: 2012-2014 Transformers failure data. 70% – 30% division.
  - Prediction horizon: 2 years. Test dataset: 2015-2016 transformer failure data.
- Input features: 42 categorical and 20 continuous

Variable Type	Variables
Transformer specification related	Age, KVA rating, KVA group, Line and phase voltages, Manufacturer group, Model group, Overhead/Underground indicator, Subtype, Primary rating categories, Used/New condition indicator
Loading related	Average loading, Peak loading, Percent time overloaded
Location related	Longitude, Latitude, District, Region, Fire zone indicator, Corrosion zone indicator, Flood zone indicator
Weather related	Temperature, Humidity, Wind speed, Rain, Solar radiation Statistics: Average, Min, Max, Standard deviation

Methodology

- Missing Value Replacement
  - 5% - 20% of weather, transformer location, loading, and specification data missing
  - MissForest method (non-parametric mixed-type imputation method)
- Feature Selection
  - Wrapper Models: Forward/Backward search
  - Filter Models: Mutual information, Pearson correlation coefficient
- Dealing with Imbalanced Dataset
  - RUSBoost integrates two algorithms
  - Random under-sampling of majority class
  - Boosting Tree
    - Ensemble of models
    - Assign higher weights to misclassified instances
    - AdaBoost M.2 algorithm

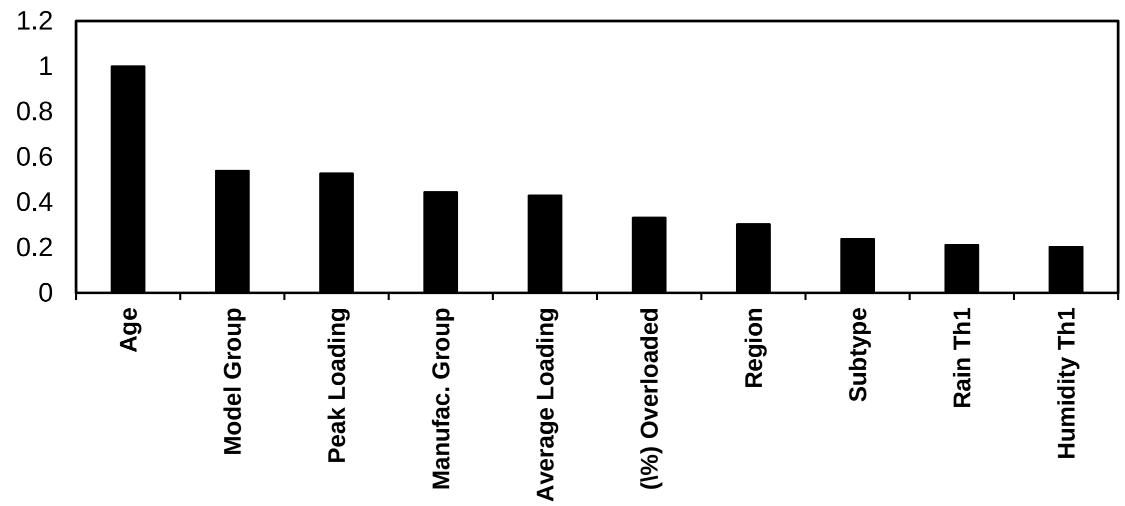
Results and Summary

- Data-driven algorithms outperform traditional age-based rule[1]
- Number of match acceptable for distribution transformer

Data Set	Age-based	Random Forest	RUSBoost
Validation	50	462	471
Test	50	312	359

Table: Comparison of age-based, random forest and RUSBoost model in ‘Match in top 1000’ metric

- Most Important factors for distribution transformer health level.
  - Transformer age
  - Model/Manufacturer group
  - Peaking/Average loading
  - % overleaded



1. Farzana Kabir, Brandon Foggo, and Nanpeng Yu, "Data Driven Predictive Maintenance of Distribution Transformers," in *the 8th China International Conference on Electricity Distribution*, pp. 1-5 2018.

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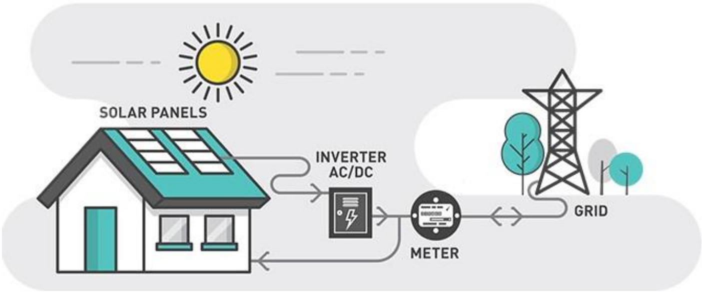
  - Estimation of Behind-the-meter Solar Generation

Motivation

- Residential solar PV adoptions are increasing rapidly around the world.
- Most residential solar PV systems are deployed behind the smart meters installed by the electric utilities.
- Utilities often only collect the net load data.
- Lack of visibility brings many operational and planning challenges.



Net Metering

$$net\ load = load - solar\ generation$$

- An accurate estimation of solar PV generation is crucial to an array of distribution system planning and operation activities.
  - Hosting capacity analysis
  - Feeder/substation net load forecasting
  - Volt-VAR control

Objective and Problem Set Up

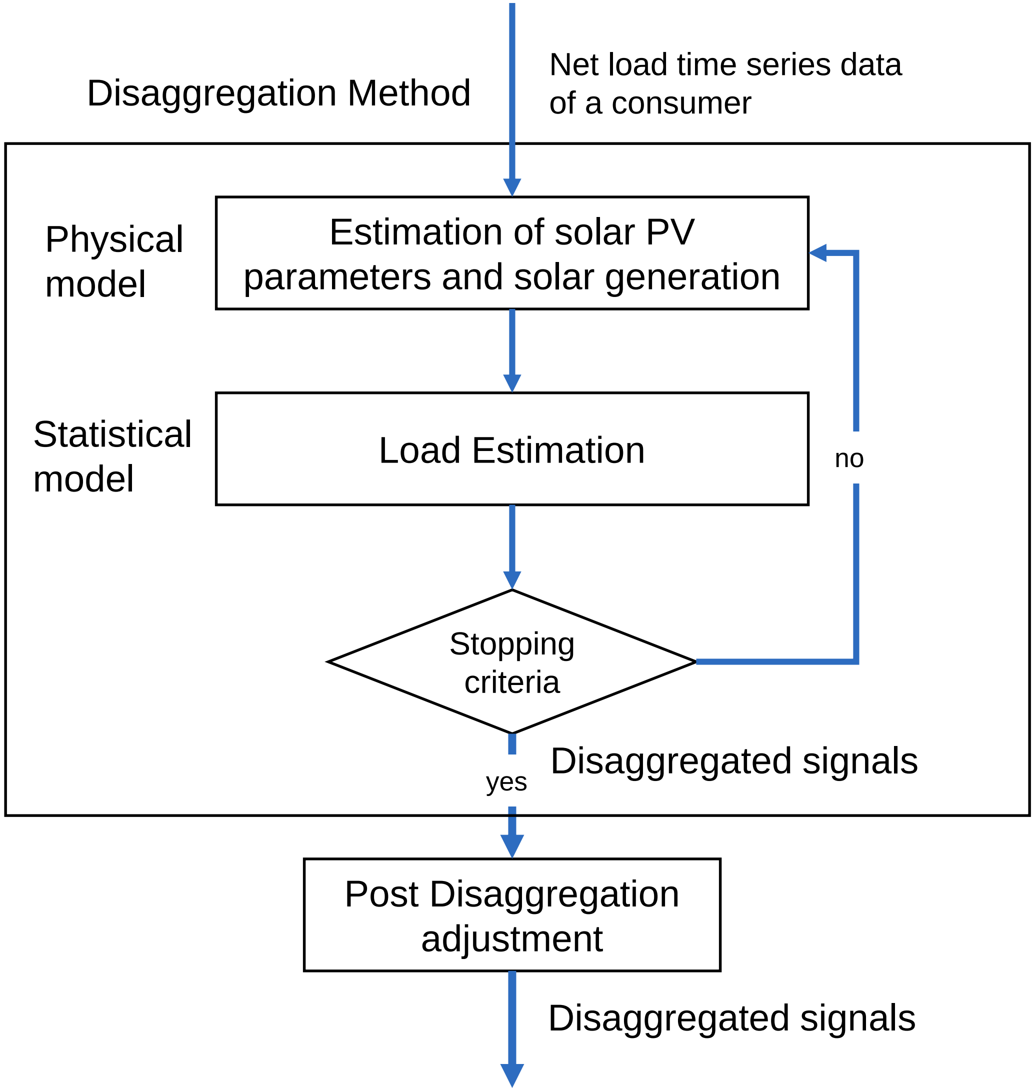
- Objective
  - For each residential customer with solar PV installation, disaggregate net load measurement (NL_t) at each time t into load (L_t) and solar generation (S_t).
  - where $NL_t = L_t - S_t; \quad L_t \geq 0, \ S_t \geq 0, \forall t$
  - Estimate key technical parameters of solar PV systems
- Problem Set Up
  - Smart meter data is available (hourly or more granular data).
  - Historical load and solar generation data is not available.
  - Some or all of the solar panel configuration and parameters are not available
    - DC Size, tilt, azimuth angle, loss of the PV array, and nominal efficiency of the inverter.
  - Knowing the exact location of each customer could increase accuracy.
    - However, the information is not necessary. The city's approximate longitude and latitude could be used as a proxy.
  - A nearby weather station's data are needed.
- Main Idea
  - Synergistically combine a *physical* PV system performance model and a *statistical* load estimation model.

Literature Review

- Existing Approaches
  - Supervised Machine Learning
    - Assume historical load and solar generation data are available
  - Unsupervised Machine Learning (Preferred Solution)
- Unsupervised Methods
  - [Tabone 2018][1]
    - Estimate solar generation of individual homes located on the same distribution feeder
    - Has potential for real-time net load disaggregation
    - Cons: 1) Does not estimate solar panel parameters and 2) A large number of hyperparameters need to be jointly estimated.
  - Consumer Mixture Model [Cheung 2018][2]
    - Formulated as a convex optimization problem
    - Load modeled by a mixture of representative customers without solar PV systems
    - Cons: 1) Highly simplified solar generation model and 2) Does not estimate solar panel parameters.
  - SunDance Technique [Chen 2017][3]
    - Two modules: 1) Estimate a location's maximum clear sky solar generation potential & 2) Model universal weather-solar effect
    - Does estimate solar deployment geometry
    - Cons: Relies heavily on net load data of a house with load close to zero on sunny days.

[1]Tabone, M., Kiliccote, S., & Kara, E. C. (2018, November). Disaggregating solar generation behind individual meters in real time. In *Proceedings of the 5th Conference on Systems for Built Environments* (pp. 43-52). ACM.
[2]Cheung, C. M., Zhong, W., Xiong, C., Srivastava, A., Kannan, R., & Prasanna, V. K. (2018, October). Behind-the-Meter Solar Generation Disaggregation using Consumer Mixture Models. In 2018 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm) (pp. 1-6). IEEE.
[3]Chen, D., & Irwin, D. (2017, May). Sundance: Black-box behind-the-meter solar disaggregation. In *Proceedings of the Eighth International Conference on Future Energy Systems* (pp. 45-55). ACM.

Overall Framework[1]



- The net load includes two components
  - The electric load and solar generation
- Estimate one of the two components at a time while fixing the other component.
- Solar generation is estimated by a physical model with technical parameters of solar PV systems.
- The electric load is estimated based on a statistical model.
- Post-disaggregation adjustment needed to ensure electric load minus solar generation equals net load measurement at all times.

[1]Farzana Kabir, Nanpeng Yu, Weixin Yao, Rui Yang and Yingchen Zhang, "Estimation of Behind-the-Meter Solar Generation by Integrating Physical with Statistical Models" to appear in IEEE SmartGridComm, pp. 1-5, Beijing, China, 2019.

Technical Methods: Estimation of Solar Generation

- If an initial estimate of the solar PV generation of a customer is available
  1. First, estimate the technical parameters of the solar PV system.
     1) By minimizing the sum of squared error between the input solar generation estimates and the calculated solar generation from the PV system performance model.
  2. Second, calculate the updated solar PV generation based on the PV system performance model and the estimated technical parameters of the solar PV system
- The parameters of solar PV system $\boldsymbol{\theta}_S = [P_{dc0}, \theta_t, \theta_{az}, \eta_{nom}, l]$ can be estimated by the following constrained optimization:

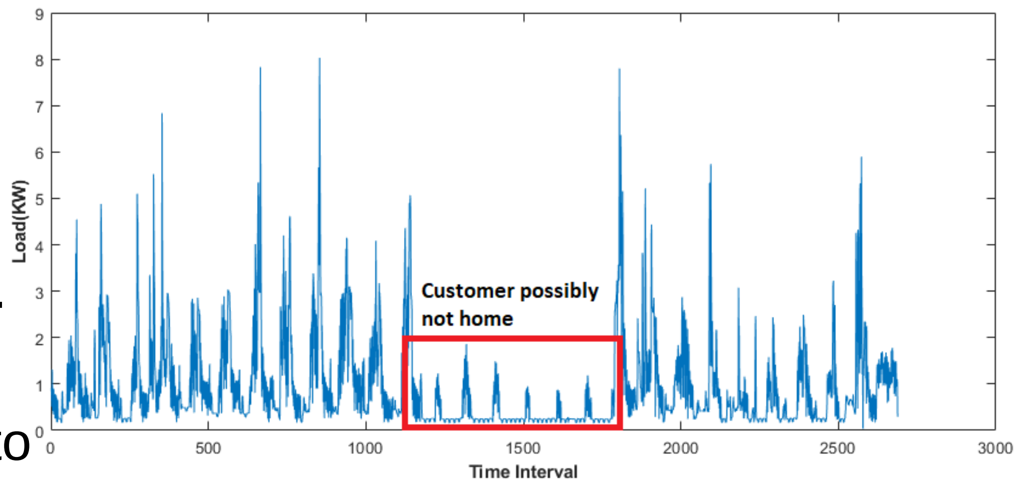
$$\underset{\boldsymbol{\theta}_S}{\operatorname{argmin}} \sum_{t=1}^{T} \left(S_t - g_t(\boldsymbol{\theta}_S)\right)^2$$

$$\text{subject to } \boldsymbol{\theta}_{S,min} \leq \boldsymbol{\theta}_S \leq \boldsymbol{\theta}_{S,max}$$

- Where S_t denotes the latest solar PV generation estimates of a customer at time t.
- $g_t(\boldsymbol{\theta}_S)$ denote the estimate for solar PV generation at time t based on the PV system performance model g_t with the technical parameters $\boldsymbol{\theta}_S$.
- DC rating P_{dc0}, array tilt angle θ_t, array azimuth angle θ_{az}, nominal inverter efficiency η_{nom}, and loss of the PV array l. $\boldsymbol{\theta}_{S,min}$ and $\boldsymbol{\theta}_{S,max}$ are lower and upper limits of the parameters.
- T is the length of the net load time series.

Load Modeling and Estimation

- Load modeling and estimation is very different from the typical task of load forecasting.
- For load modeling, no historical data is available. Supervised machine learning models or time series models (e.g. neural networks, ARIMA) are not applicable.
- Load modeling for individual customers is very challenging.
- Load data can exhibit quite different patterns depending on whether a customer is at home or not.
- This latent state is not observable.
- Thus, Hidden Markov Model regression analysis is well suited to model and estimate the electric load of individual customers.



Load time series of a sample customer

Hidden Markov Model and Parameter Estimation

- The electricity consumption behavior can be modeled by a hidden Markov model (HMM) regression given state z_t at time t

$$y_t = a_{z_t} + \boldsymbol{x}_t^T \boldsymbol{c}_{z_t} + \varepsilon_t, \qquad \varepsilon_t \sim N\left(0, \sigma_{z_t}^2\right), \qquad y_t \sim N\left(a_{z_t} + \boldsymbol{x}_t^T \boldsymbol{c}_{z_t}, \sigma_{z_t}^2\right)$$

- y_t: load of a customer at time t. $\boldsymbol{x}_t$: vector of explanatory variables (temperature, time). z_t: latent state at time t.
- a: intercept. $\boldsymbol{c}$: Regression coefficients. ε: error term. σ^2: variance of error.
- Estimation of HMM parameters
  - Expectation Maximization (EM) algorithm.
  - Iterative method for performing maximum likelihood estimation when some of the data (sequence of the states occupied by the Markov-chain) are missing.
  - E step: Compute the conditional expectations of the missing states in Complete Data Log Likelihood (CDLL) given the observations and the current estimate of $\boldsymbol{\theta}$
  - M step: Maximize, with respect to $\boldsymbol{\theta}$, the complete-data log-likelihood with the functions of the missing data replaced in it by their conditional expectations.
  - Repeat until convergence

Post-Disaggregation Adjustment

- To enforce that load minus generation is equal to net load at any time, we do the following post-disaggregation adjustment

$$\arg\min_{L_t, S_t} \sum_{t=0}^{T} \alpha' \left(L_t - \hat{L}_t \right)^2 + \beta' \left(S_t - \hat{S}_t \right)^2$$

$$\text{subject to } L_t \geq 0, S_t \geq 0, \quad L_t - S_t = NL_t$$

- Calculate hyperparameters

$$\alpha' = \frac{1}{Var\left(\varepsilon_{Load}\right)}, \quad \beta' = \frac{1}{Var\left(\varepsilon_{PV}\right)}$$

- Two variations
  - Known error variance: ground truth load and solar generation known for 10% of consumers
  - Unknown error variance: Assume that ground truth load and solar generation are the estimates from steps 4 and 7 of Algorithm 1

Numerical Study

- Data set
  - 15-minute interval data from Pecan Street Dataset
  - Net load, load, and solar PV generation, DC size data
- Location of customers: Austin Texas
- Study period: Oct 3, 2015 – Oct 30, 2015 (28 days)
- Number of customers with PV installations: 197
- Solar irradiance and temperature data: National Solar Radiation Database
- Feasible ranges of solar PV system parameters θ_S specified
  - $\theta_T \in [5^\circ, 50^\circ]$, $\theta_{AZ} \in [0^\circ, 360^\circ]$, $P_{dc0} \in [1KW, 15KW]$, $\eta_{nom} \in [9\%, 38\%]$
- Initial values for solar PV system's technical parameters
  - $[\theta_T, \theta_{AZ}, \eta_{nom}, l]$ set at their most common values
  - Gradually increase P_{dc0} from 1KW to 8 KW
- Compared the estimation results with consumer mixture model and SunDance model

Error Metrics

- Mean Squared Error

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{T}\sum_{t=1}^{T}\left(y_{i,t} - \hat{y}_{i,t}\right)^2$$

- Mean Absolute Scaled Error

$$MASE = \frac{1}{N}\sum_{i=1}^{N}\frac{T-1}{T}\frac{\sum_{t=1}^{T}|y_{i,t} - \hat{y}_{i,t}|}{\sum_{t=2}^{T}|y_{i,t} - y_{i,t-1}|}$$

- Coefficient of Variation

$$\mathrm{CV} = \frac{1}{N}\sum_{i=1}^{N}\left(\sqrt{\sum_{t=1}^{T}\left(y_{i,t} - \hat{y}_{i,t}\right)^2} \Big/ \frac{1}{T}\sum_{i=1}^{T} y_{i,t}\right)$$

$y_{i,t}$: Actual Value

$\hat{y}_{i,t}$: Estimated Value

Testing Results

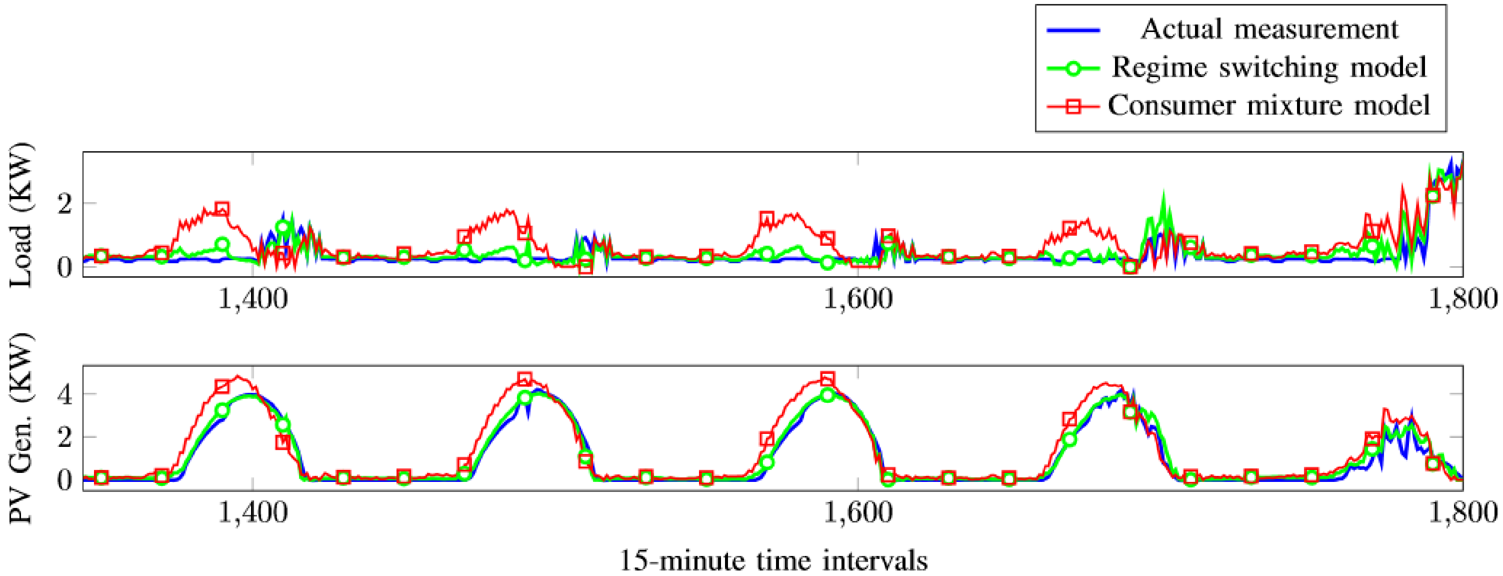
Table 1: Comparison of various disaggregation methods

Error Metric	Variable	HMM reg. model (known error variance)	HMM reg. model (unknown error variance)	Consumer Mixture Model	SunDance Model
MSE	Load	0.2114	0.2173	0.3786	0.4866
	Solar	0.2328	0.2356	0.4269	0.5409
MASE	Load	0.5357	0.5051	0.7374	0.8089
	Solar	2.9447	2.7440	3.9133	3.7409
CV	Load	0.3407	0.3475	0.4631	0.5707
	Solar	0.6057	0.6103	0.7874	0.8460

- Both of the HMM regression models outperform consumer mixture model and SunDance model
- Reduces the MSE by 45% compared to the consumer mixture model.

Testing Results

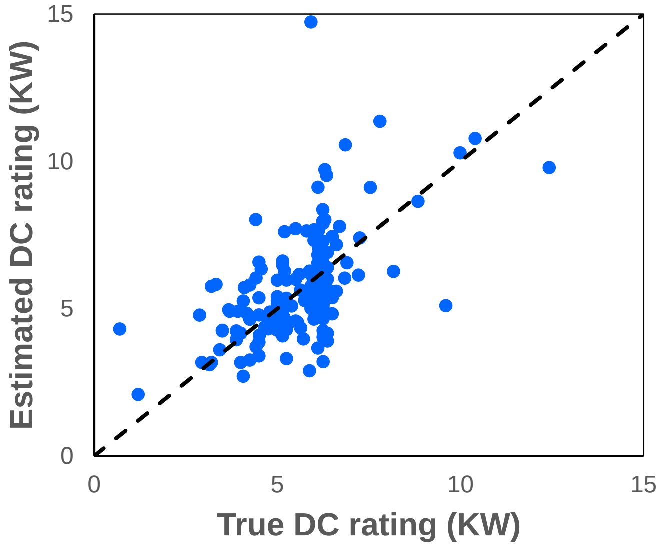
- Performance Improvement is significant for customers who are absent from home for an extended period
- There are 25 such customers out of 197 customers with PV installation.



Comparison of disaggregated load and solar PV generation with actual values for a customer from Oct 14 to Oct 19, 2015.

- Reduction of MSE is 52% for these customers
- HMM regression model is well suited to capture load behavior in different regimes.

Additional Results and Future Work



Comparison of true and estimated DC rating of PV array.

DC rating data is available for 90% customers.

- The proposed algorithm yields relatively accurate estimates for DC ratings of solar panels.
- Further improvement possible using more granular solar irradiance data.
- Real-time net load disaggregation will need live solar irradiance measurements or short-term forecasts.
- Estimate load of a group of customers together with a mixed effect model.

Thank You

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Publications: Big Data Analytics & Machine Learning in Smart Grid

1. N. Yu, S. Shah, R. Johnson, R. Sherick, Mingguo Hong and Kenneth Loparo, "Big Data Analytics in Power Distribution Systems", *IEEE PES Conference on Intelligent Smart Grid Technology*, Washington DC, Feb. 2015.

2. Xiaoyang Zhou, Nanpeng Yu, Weixin Yao and Raymond Johnson, "Forecast load impact from demand response resources" *Power and Energy Society General Meeting*, pp. 1-5, Boston, USA, 2016.

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https://intra.ece.ucr.edu/~nyu/

Computing Facilities

- Deep Learning Workstation
  - 4 x NVIDIA RTX 2080
  - 4 x 16 GB Memory
  - 512 GB SSD (OS)
  - 2 x 2TB HDD (Data)

- Oracle Big Data Appliance
  - Number of Nodes: 6
  - Number of Core: 216
  - Hard Drive: 288 TB of 7,200 rpm High Capacity SAS Disks
  - Memory: 768 GB DDR4
  - Hadoop Platform: CDH Enterprise Edition
  - Tools: Hive, Pig, Impala, PySpark, Scala, TensorFlow