Machine Learning for Power System Digital Twin Development

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- For **publications**: https://sites.google.com/a/ncsu.edu/ninglu/mypublicatons?authuser=0
- Related **projects**: https://sites.google.com/a/ncsu.edu/ninglu/gridwrx-lab/gridwrxprojects?authuser=0

Outline

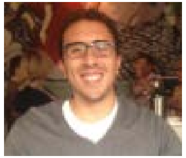
- Our Path Towards Developing Machine Learning Applications
- An Overview of Power System Digital Twin-based Approach
  - Configurations and design considerations of the PARS platform
  - Uniqueness of the digital-twin based approach
- Machine Learning Applications in Digital-twin Development
  - Synthetic Data and Scenarios generation
  - Parameterization
  - Co-simulation
  - Automated forecasting methods
  - Control and energy management systems modeling
  - Faster-than-real-time response option selection
  - Anomaly detection: natural or man-made errors and cyber attacks
- Conclusions

My focuses in each part

- Our Path Towards Developing Machine Learning Applications
- An Overview of Power System Digital Twin-based Approach
  - Configurations and **design considerations** of the PARS platform
  - **What is the digital-twin based approach?**
- Machine Learning Applications in Digital-twin Development
  - **Synthetic Data and** Topology **Generation (empirical and GAN-based Methods)**
  - Parameterization
  - Co-simulation
  - **Automated forecasting methods (Meta-learning, TCN)**
  - **Control and energy management systems modeling (Reinforcement Learning)**
  - Faster-than-real-time response option selection
  - Anomaly detection: natural or man-made errors and cyber attacks
- Conclusions

Our Path Towards Developing Machine Learning Applications

2017 — 2018 — 2019 — 2020 — 2021 — 2022 — 2023



Gonzague Henri

1. A **supervised machine learning** approach to control energy storage devices

2. A Multi-Agent **Shared Machine Learning** Approach for Real-time Battery Operation Mode Prediction and Control

Yao Meng

3. Time Series **Classification** for Locating Forced Oscillation Sources

4. FeederGAN: Synthetic Feeder Topology Generation via Deep Graph Adversarial Nets

Ming Liang

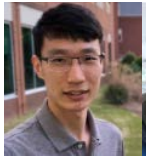
Yiyan Li

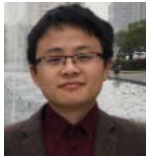
5. A **meta-learning** based distribution system load **forecasting** model selection framework

6. TCN-based Spatial-Temporal PV **Forecasting** Framework with Automated Detector Network Selection

7. ProfileSR-GAN: A GAN based Super-Resolution Method for Generating High-Resolution Load Profiles

Lidong Song





Si Zhang

7. A Two-stage Training Strategy for **Reinforcement Learning** based **Volt-Var Control**

8. **GAN-based** load profile generation method

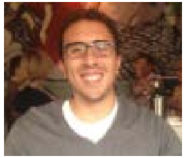
Yi Hu

9. **Other ongoing Activities:**

- Parameterization
- Baseline Quantification
- Anomaly Detection
- Load Disaggregation

Our Path Towards Developing Machine Learning Applications

2017



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2019

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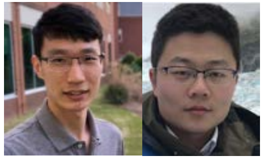
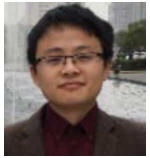


2021



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2022

8. **GAN-based** load profile generation method

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2023

9. **Other ongoing Activities:**

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- Baseline Quantification
- Anomaly Detection
- Load Disaggregation

An Overview of the Digital twin based co-simulation platform

1. Configurations and design considerations
2. What is a digital-twin based approach

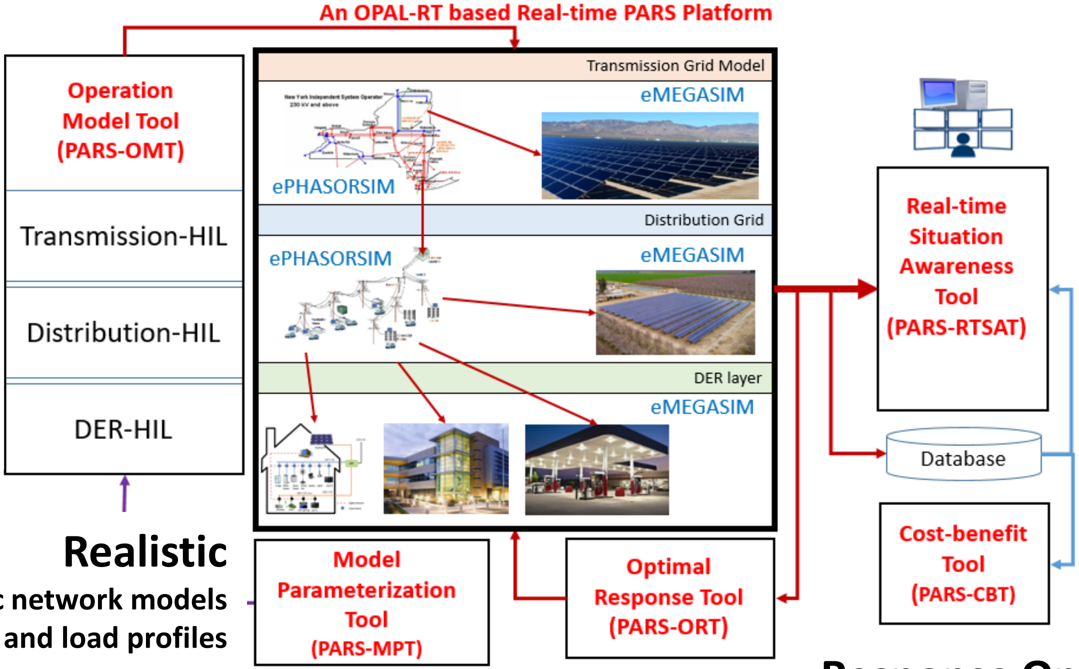
PARS: Key Design Considerations

Develop a ***Photovoltaic (PV) Analysis and Response Support (PARS) platform* as a** *power grid digital twin* that provides real-time situational awareness and optimal response plan selection.

Highly Scalable

High Fidelity

Grid-forming:
μs-level EMT domain
Grid-following:
Ms-level phasor domain
Power Management:
Intra 5-min quasi-steady-state
Energy Management:
5-Minute to 24-ahead



Realistic

Realistic network models
Realistic PV and load profiles

Visibility

Machine Learning enhanced forecasting

Secure by Design

Response Options

Faster-than Real-time

https://sites.google.com/a/ncsu.edu/ninglu/pars-platform?authuser=0

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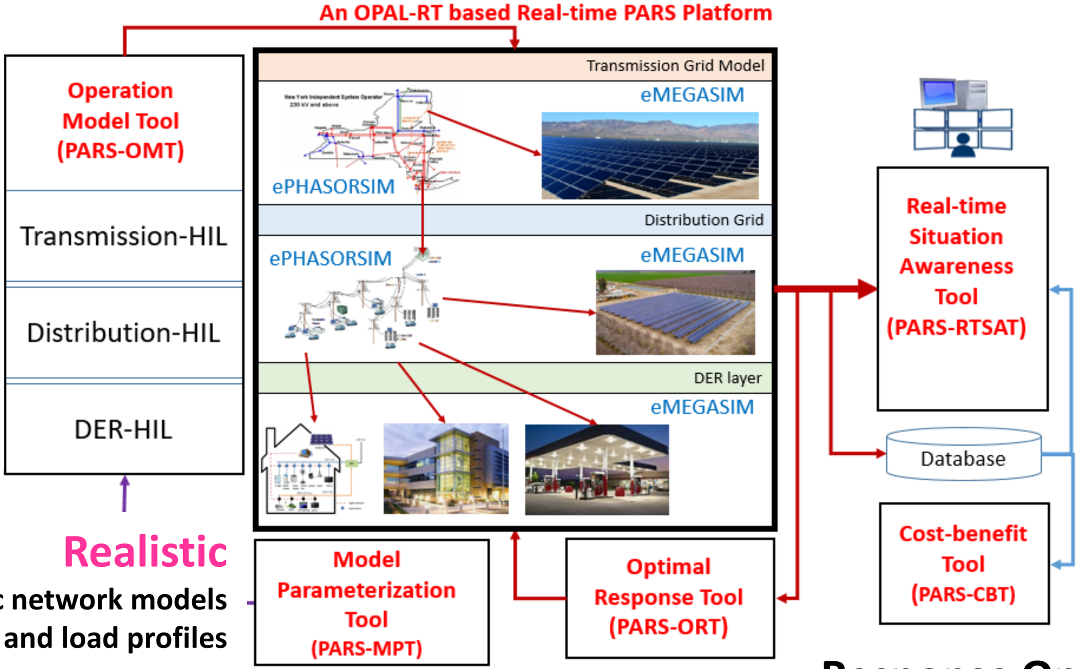

Realistic

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Realistic PV and load profiles

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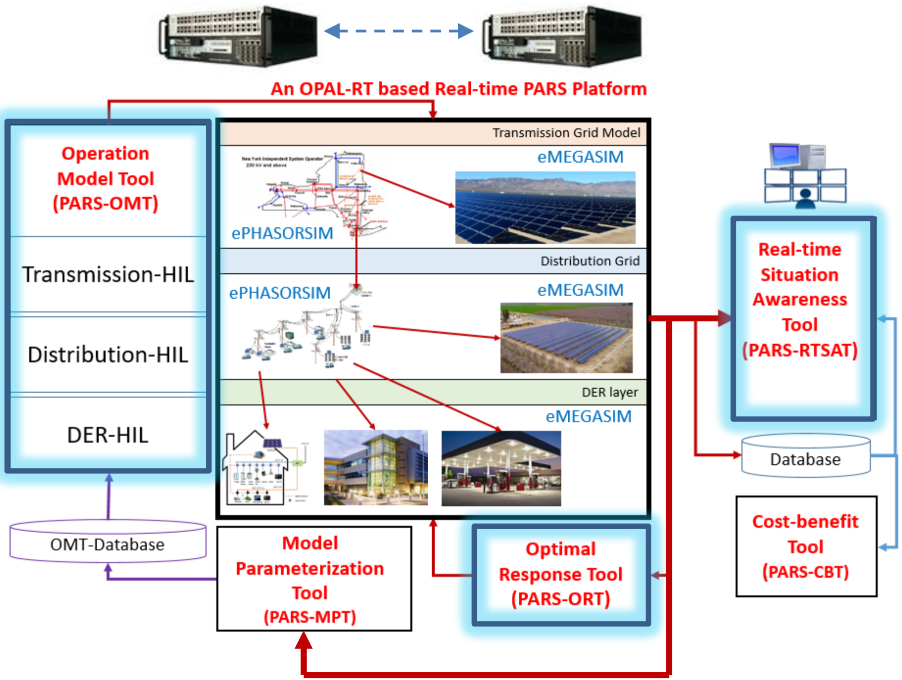
Response Options

Faster-than Real-time

PARS: three Main Platforms

HIL: Hardware-in-the-loop



1. PARS Real-time HIL simulation platform

Requirement: Modeling the operation of **interconnected** physical systems in high-fidelity

Approaches:

1. Populate the model with **synthetic data and topology**
2. Develop automated parameterization

2. Situation Awareness

Requirement: Monitor the current status, **forecast** the future, authenticate the data, detect anomalies.

Approach:

1. **Meta-learning** for generalizable tool sets
2. **TCN** for capturing spatial and temporal correlation

3. Faster-than-real-time Optimal Response Tool (External to the HIL)

Requirement: energy and power management and response options (from 24-hour ahead to intra-hour to real-time)

Approaches: 1) Optimization, and 2) Machine learning based (reinforcement learning for adaptability)

Digital Twins versus Conventional Models

Reference	Modeling Considerations	Synchronization	Communication
[1]	Electromagnetic transients + phasor model	Yes	N/A
[2]	Electromagnetic transients + phasor model	Yes	N/A
[3]	Phasor model	Yes	Wireless communication simulator
[4]	Electromagnetic transients + hardware	Asynchronous	N/A
[5]	Phasor model + hardware	Asynchronous	JSON-link over Ethernet
Digital Twin based Approach [6-10]	Electromagnetic transients + phasor model + hardware **+ Parameter Updates** **+ Communication Links** **+ Forecast the Model Evolutions** **+ Energy/Power Management Systems**	Asynchronous	1. Modbus 2. File-shared over Ethernet 3. VPN connections required for implementation of multi-area networked digital twins

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7. F. Xie, C. McEntee, M. Zhang, B. Mather and N. Lu, "Development of an Encoding Method on a Co-Simulation Platform for Mitigating the Impact of Unreliable Communication," in IEEE Transactions on Smart Grid, vol. 12, no. 3, pp. 2496-2507, May 2021, doi: 10.1109/TSG.2020.3039949. Videos related with the paper: https://www.youtube.com/watch?v=SdibDKEpw60.
8. F. Xie et al., "Networked HIL Simulation System for Modeling Large-scale Power Systems," 2020 52nd North American Power Symposium (NAPS), 2021, pp. 1-6, doi: 10.1109/NAPS50074.2021.9449646.
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10. Victor Paduani, Bei Xu, David Lubkeman, Ning Lu, "Novel Real-Time EMT-TS Modeling Architecture for Feeder Blackstart Simulations," 22PESGM1449, submitted to 2022 IEEE PESGM. Available online at: https://arxiv.org/pdf/2111.10031.pdf

Reference – Development of the PARS platform

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Big-Data in Digital-twin Development

1. **Synthetic Data and Topology Generation (GAN-based Methods)**
2. Parameterization (Regression or Clustering)
3. Co-simulation
4. **Automated forecasting methods (Meta-learning, TCN)**
5. **Control and energy management systems modeling (Reinforcement Learning)**
6. Faster-than-real-time response option selection
7. Anomaly detection: natural or man-made errors and cyber attacks

Challenges in Data Acquisition

- Data are collected and stored in **different places** with **different format** and with **different data qualities**
  - Across a few departments
  - Dependent of applications
- **Proprietary Information** that are sensitive and it is difficult if not possible for utilities to share their data with the academia
  - Privacy
  - Security
- As a result, only **a small amount of data are sharable**
  - Insufficient for testing and validating the developed methodologies
  - Hard to transfer knowledge learnt from one case to another

Synthetic Data Generation

- Acquisition and sharing of actual data sets are extremely hard
  - Proprietary, Privacy, Security

- **Generate realistic synthetic data** for power system digital twins
  - **Topology** and **time series load and PV** profiles
  - Generate from actual data sets and network models
  - A transparent modeling process with customizable parameters
  - Can cover a large amount of operation conditions and network topology variations

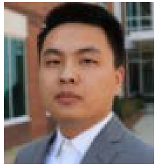
Part 1: Load Disaggregation Methods

1. **Feeder Load Disaggregation**

Wang, Jiyu, Xiangqi Zhu, Ming Liang, Yao Meng, Andrew Kling, David L. Lubkeman, and Ning Lu. "A Data-Driven Pivot-Point-Based Time-Series Feeder Load Disaggregation Method." *IEEE Transactions on Smart Grid* 11, no. 6 (2020): 5396-5406.

2. HVAC Load Disaggregation

Hyeonjin Kim, Kai Ye, Han Pyo Lee, Rongxing Hu, Di Wu, PJ Rehm, and Ning LU, "An ICA-Based HVAC Load Disaggregation Method Using Smart Meter Data" submitted to 2023 ISGT. Available online at: https://arxiv.org/abs/2209.09165



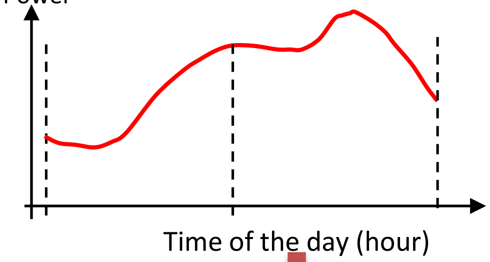
Ming Liang, Jiyu Wang, Yao Meng, Ning LU, David Lubkeman, and Andrew Kling. "A Sequential Energy Disaggregation Method using Low-resolution Smart Meter Data, " *Proc. of IEEE Innovative Smart Grid Technologies*, Washington DC, 2019.

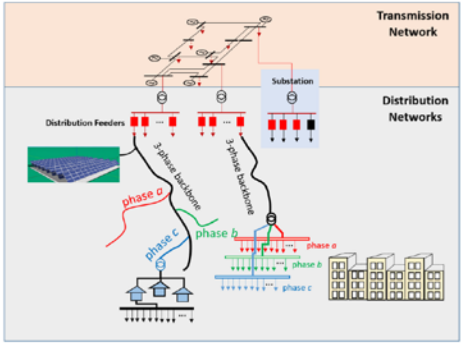
In the past – No diversity

In the past:

- Feeder head data is recorded at the substation
- Sub-nodes load profiles are not measured
- **Use the same load profile for all sub-nodes**

Feeder Head Load Profile





decompose

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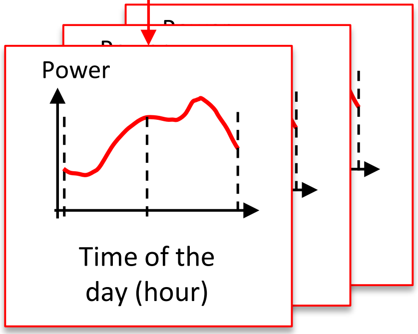
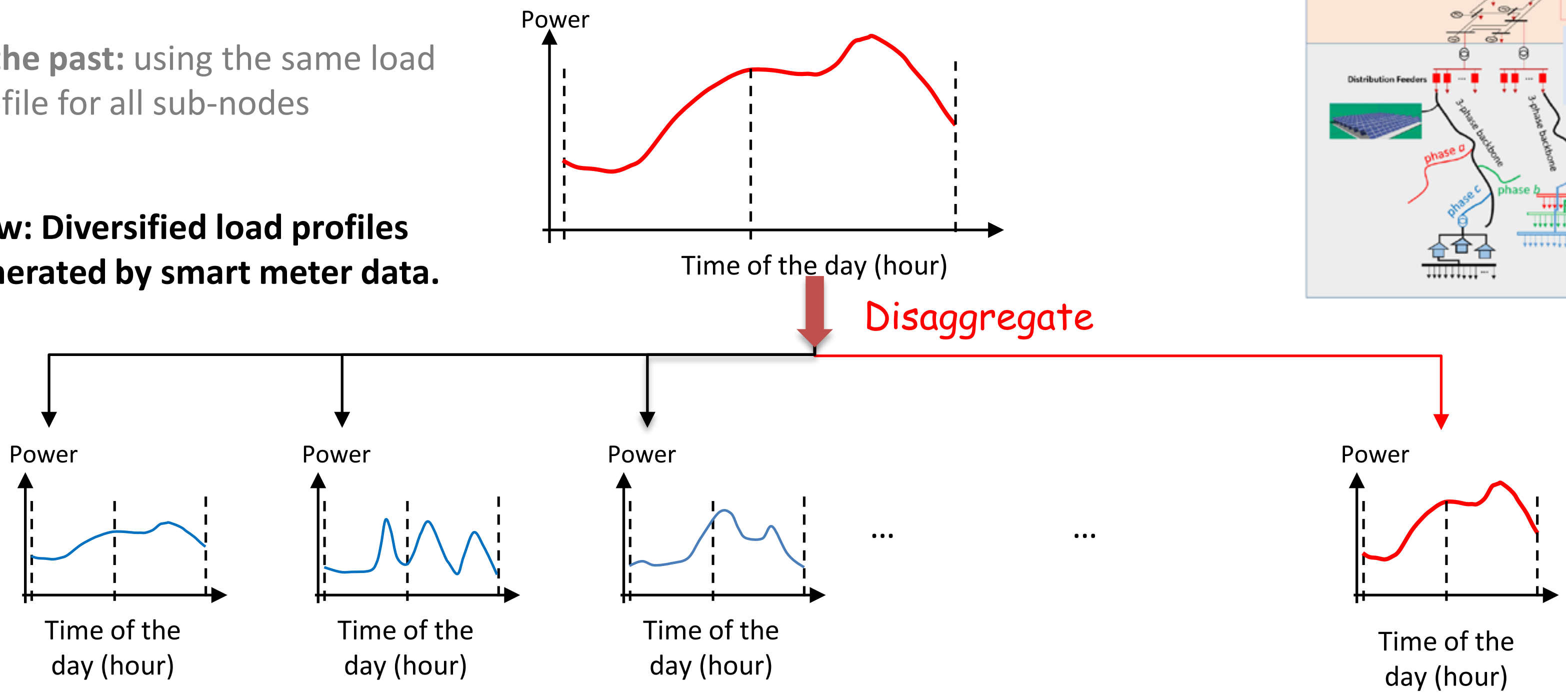


Digital Twin: diversified and realistic profiles

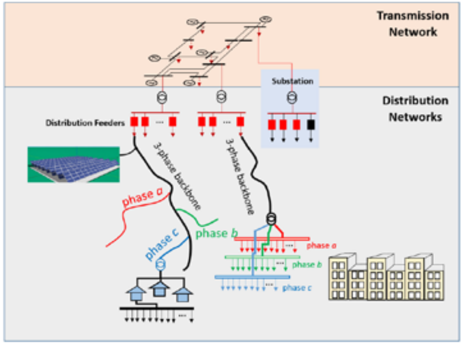
In the past: using the same load profile for all sub-nodes

Now: Diversified load profiles generated by smart meter data.

Known Feeder Head Load Profile



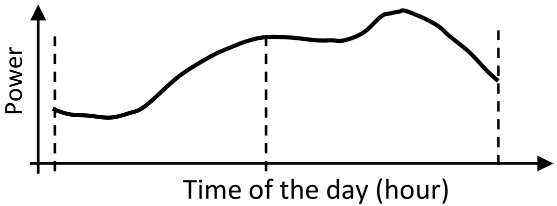
Nodal Load Profile

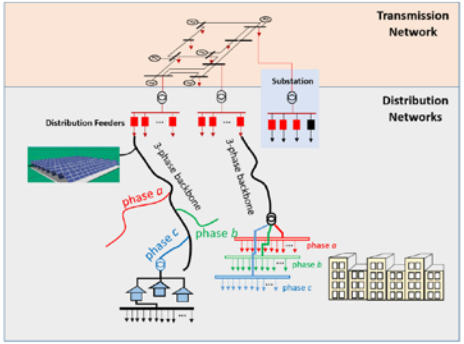


Improve the Realisticness of Load Models

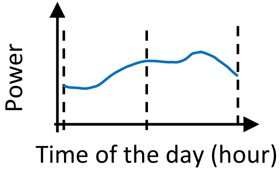
Goal: Generate diversified load profiles using smart meter data.

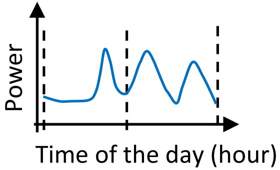
From the Known feeder-head load profile

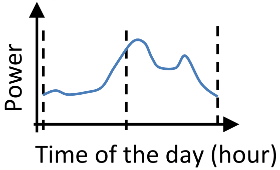




Step 1: Feeder Load Disaggregation to obtain diversified nodal loads







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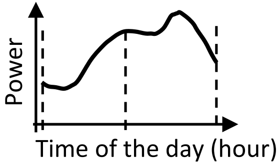
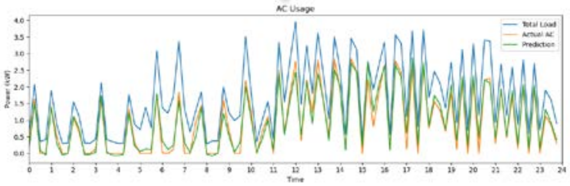
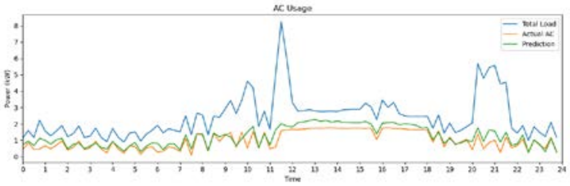
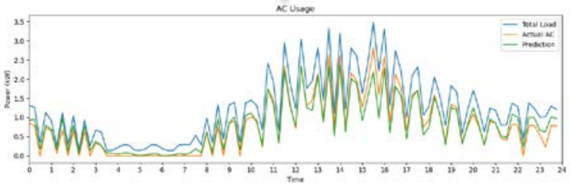


Step 2: Building Load Disaggregation to obtain the HVAC, PV, and charging loads







Feeder Load Disaggregation Algorithm (FLDA)

FLDA-LPS: Load profile selection

- Randomly select load profiles
- Select pivot-point
- Select reference load profiles

FLDA-LPA: Load profile allocation

- Distribution transformer rating
- Load type
- Square footage

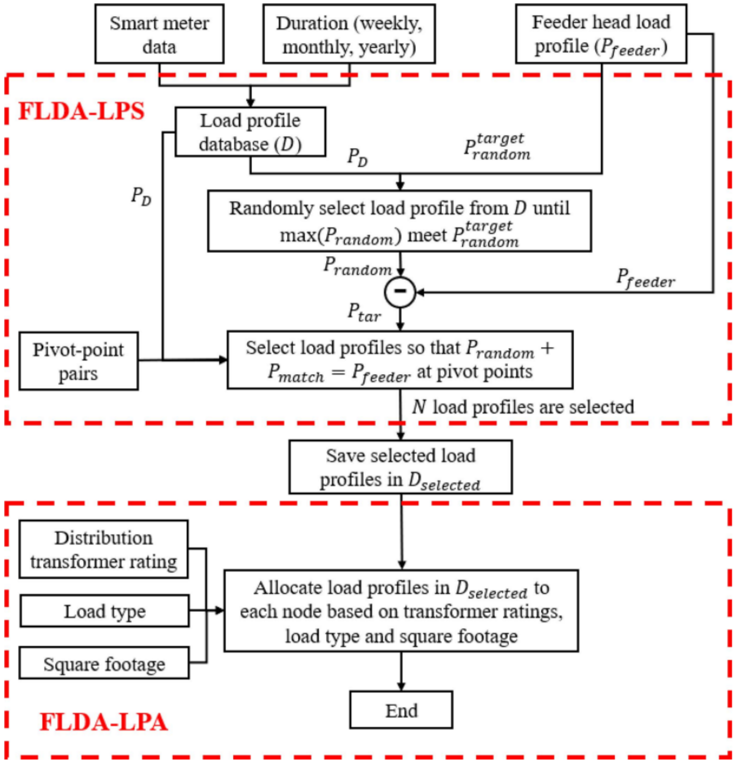


Fig. 1. Flowchart of the feeder load disaggregation algorithm.

Wang, Jiyu, Xiangqi Zhu, Ming Liang, Yao Meng, Andrew Kling, David L. Lubkeman, and Ning Lu. "A Data-Driven Pivot-Point-Based Time-Series Feeder Load Disaggregation Method." ***IEEE Transactions on Smart Grid*** **11, no. 6 (2020): 5396-5406.**

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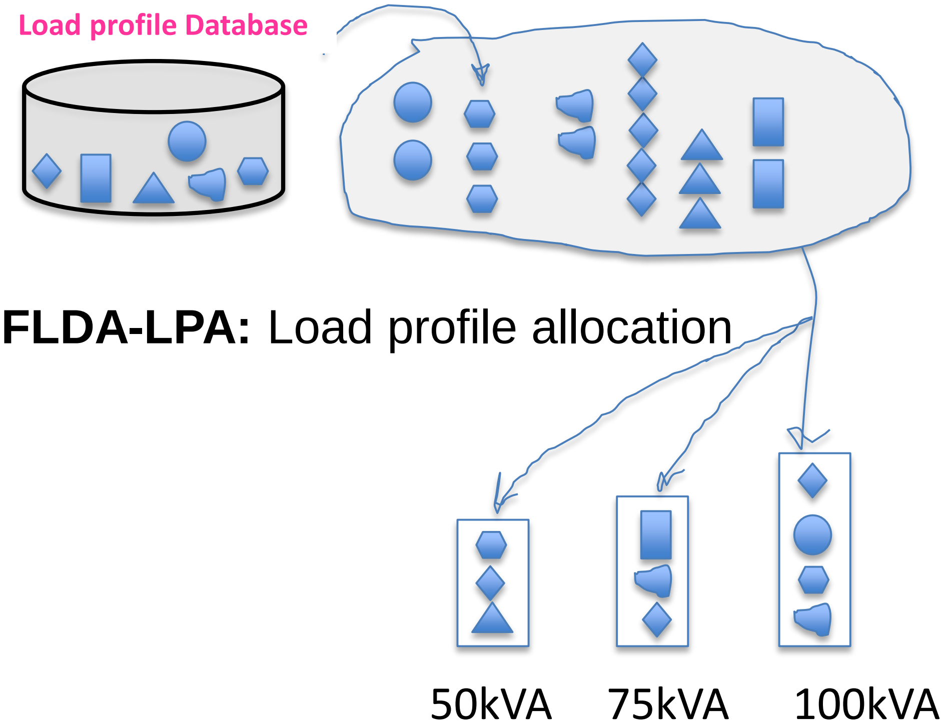

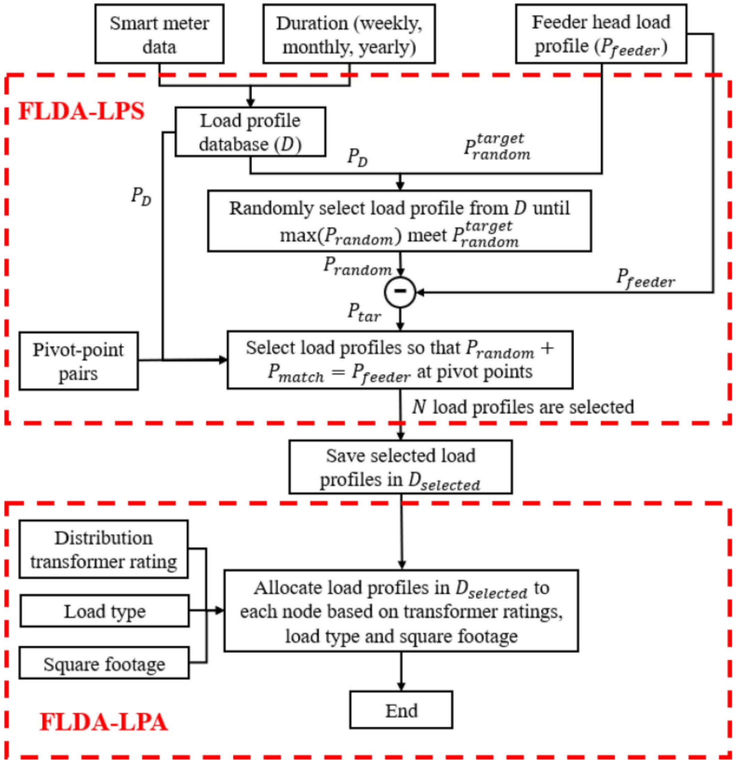

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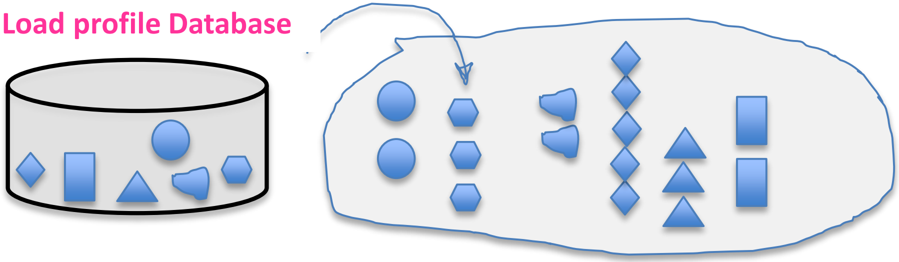
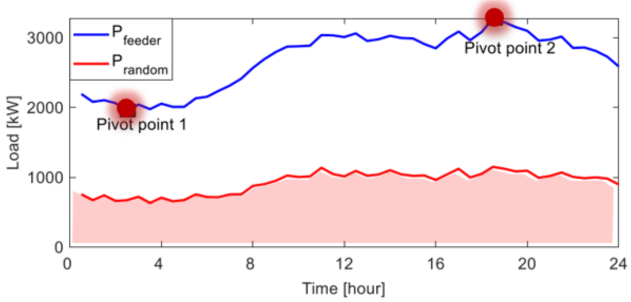
Load profile Database





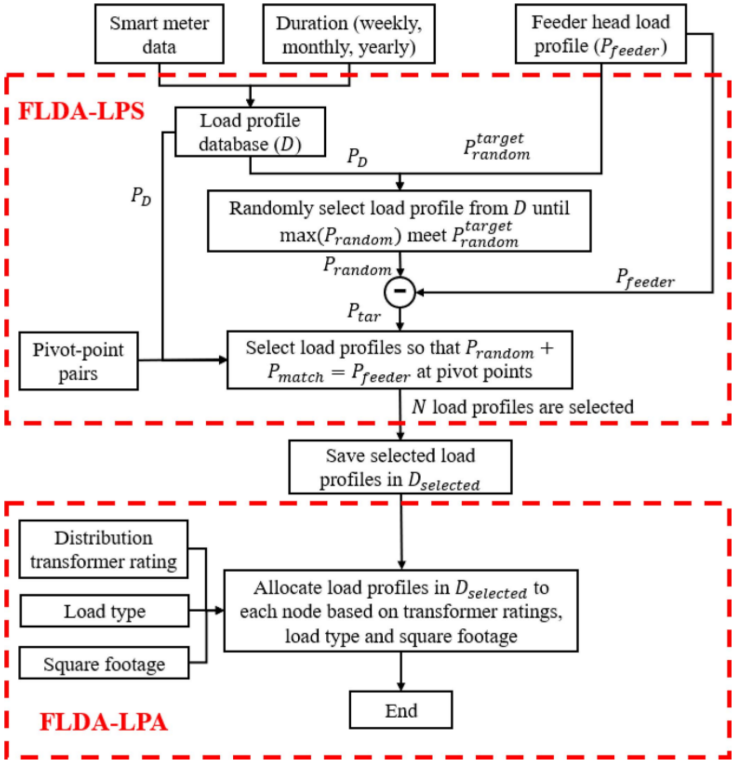


Fig. 1. Flowchart of the feeder load disaggregation algorithm.

Wang, Jiyu, Xiangqi Zhu, Ming Liang, Yao Meng, Andrew Kling, David L. Lubkeman, and Ning Lu. "A Data-Driven Pivot-Point-Based Time-Series Feeder Load Disaggregation Method." *IEEE Transactions on Smart Grid* 11, no. 6 (2020): 5396-5406.

LPS-Step 1: Pivot point selection

- Critical points that can capture the key load characteristic of a load curve
- One day: a pivot pair (peak&valley)
- Monthly profile: may need multiple pivot pairs

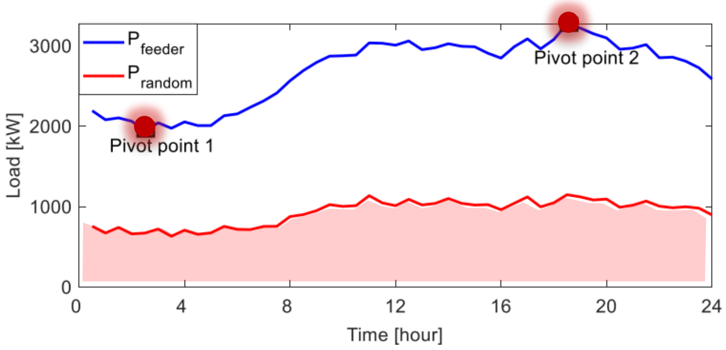


Fig. 2. Pivot points and random load selection.

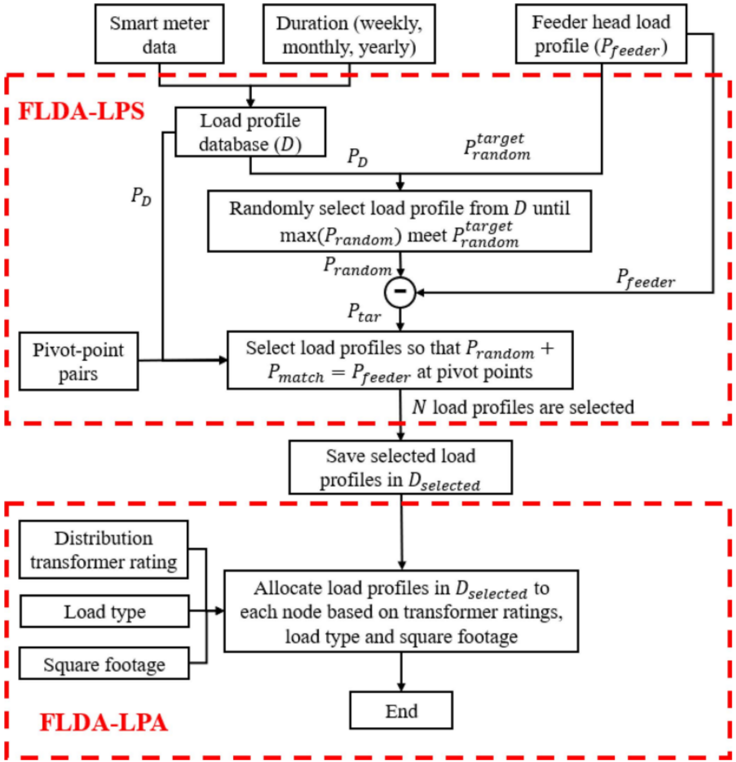


Fig. 1. Flowchart of the feeder load disaggregation algorithm.

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LPS-Step 2: Random Load Profiles Selection

Radom load ratio: R_{random}

$$(1-\varepsilon) \times P_{random}^{target} \leq \max(P_{random}) \leq P_{random}^{target}, \qquad (10)$$

$$P_{random}^{target} = R_{random} \times \min(P_{feeder}), \qquad (11)$$

where

$$0 \leq R_{random} \leq 1.$$

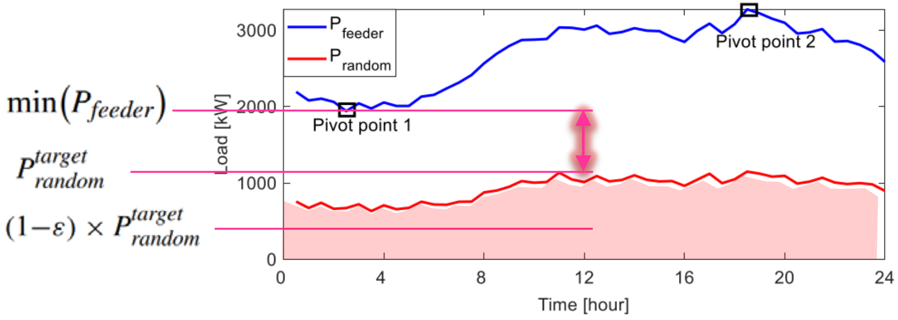
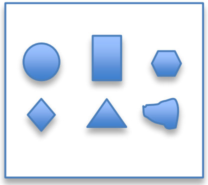


Fig. 2. Pivot points and random load selection.

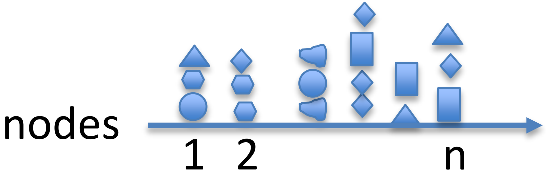
Smart Meter Database $\boldsymbol{D}$

4302 sets of smart meter data with 30-minute data points



Randomly select load profiles and put them into $D_{selected}$

$D_{selected}$



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LPS-Step 3: Reference load profile

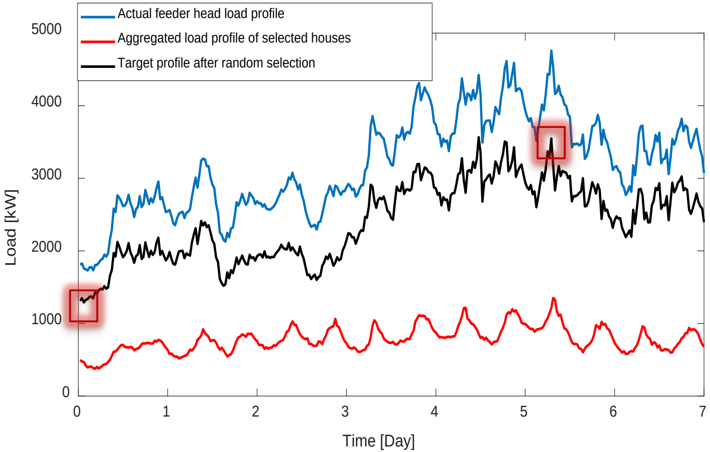
Way 1

$$P_{tar}^{(0)}(t_n) = P_{feeder}(t_n) - P_{random}(t_n) \quad (12)$$

$$P_{tar}^{(u+1)}(t_n) = P_{tar}^{(u)}(t_n) - P_{m}^{(u)}(t_n). \quad (13)$$

$$P_{tar}^{(u)}\left(t_{peak}^{pp}\right) = \max\left(P_{tar}^{(u)}(t_n)\right), \quad (14)$$

$$P_{tar}^{(u)}\left(t_{valley}^{pp}\right) = \min\left(P_{tar}^{(u)}(t_n)\right). \quad (15)$$



Way 2

$$P_{ref}^{(u)}(t_n) = \frac{P_{tar}^{(u)}(t_n)/\max\left(P_{tar}^{(u)}(t_n)\right)}{P_D(t_n)/\max(P_D(t_n))}, \quad (16)$$

$$P_{ref}^{(u)}\left(t_{peak}^{pp}\right) = \max\left(P_{ref}^{(u)}(t_n)\right), \quad (18)$$

$$P_{ref}^{(u)}\left(t_{valley}^{pp}\right) = \min\left(P_{ref}^{(u)}(t_n)\right). \quad (19)$$

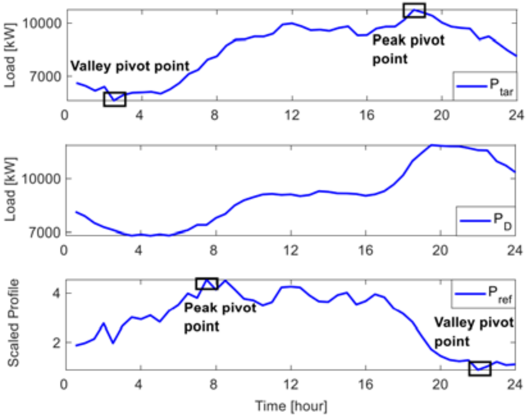


Fig. 3. Pivot points selected using the Target and Reference load profiles.

$$P_{feeder}^{tar} = P_{feeder} - P_{feeder}^{random}$$

$$P_D = \sum_{m=1}^{N_D} P_m.$$

Wang, Jiyu, Xiangqi Zhu, Ming Liang, Yao Meng, Andrew Kling, David L. Lubkeman, and Ning Lu. "A Data-Driven Pivot-Point-Based Time-Series Feeder Load Disaggregation Method." *IEEE Transactions on Smart Grid* 11, no. 6 (2020): 5396-5406.

LPS-Step 4: Select Profiles with the Similarity Index

At each matching step, for each load profile in D, form a sorting matrix X as follows:

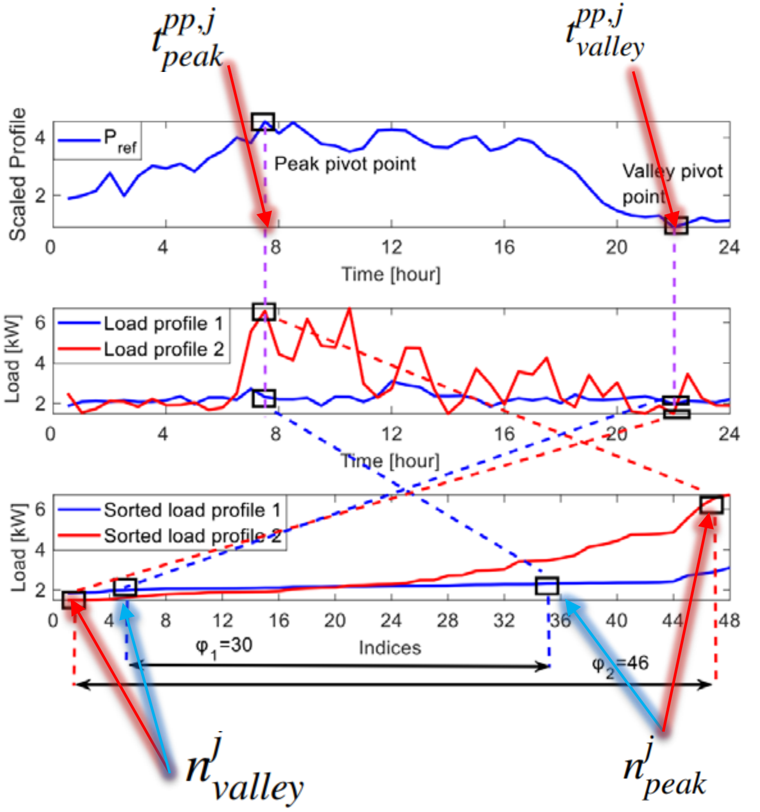
$$\mathbf{X}_m = \begin{pmatrix} P_m(t_1) & P_m(t_2) & \dots & P_m(t_{N_T}) \\ t_1 & t_2 & \dots & t_{N_T} \end{pmatrix}. \qquad (20)$$

$$\mathbf{X}_m\ (2, n_{peak}^j) = t_{peak}^{pp,j}$$

$$\mathbf{X}_m(2, n_{valley}^j) = t_{valley}^{pp,j}$$

$$\varphi_m = \sum_{j=1}^{J} \left(n_{peak}^j - n_{valley}^j\right). \qquad (21)$$

Note that a load profile with a larger similarity index tends to have a higher load at $t_{peak}^{pp,j}$ or a lower load $t_{load}^{pp,j}$.



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LPS-Step 5: Tolerance of the Matching Error

- Define the tolerance of the matching error

$$e = \sum_{t=1}^{N_T} \left| \frac{P_{feeder}(t_n) - \tilde{P}_{feeder}(t_n)}{P_{feeder}(t_n)} \right|. \qquad (22)$$

In the recursive process, after a load profile is selected, e should decrease. Thus, if a selected load profile causes e to increase, the load profile will be unselected and will be taken out of D.

Wang, Jiyu, Xiangqi Zhu, Ming Liang, Yao Meng, Andrew Kling, David L. Lubkeman, and Ning Lu. "A Data-Driven Pivot-Point-Based Time-Series Feeder Load Disaggregation Method." *IEEE Transactions on Smart Grid* 11, no. 6 (2020): 5396-5406.

LPS-Step 6: Considerations on Load Types

- To consider different load types, D can be divided into different load groups: residential load profiles and commercial load profiles.
- Then, instead of selecting load profiles from D, load profiles can be selected from different load groups.

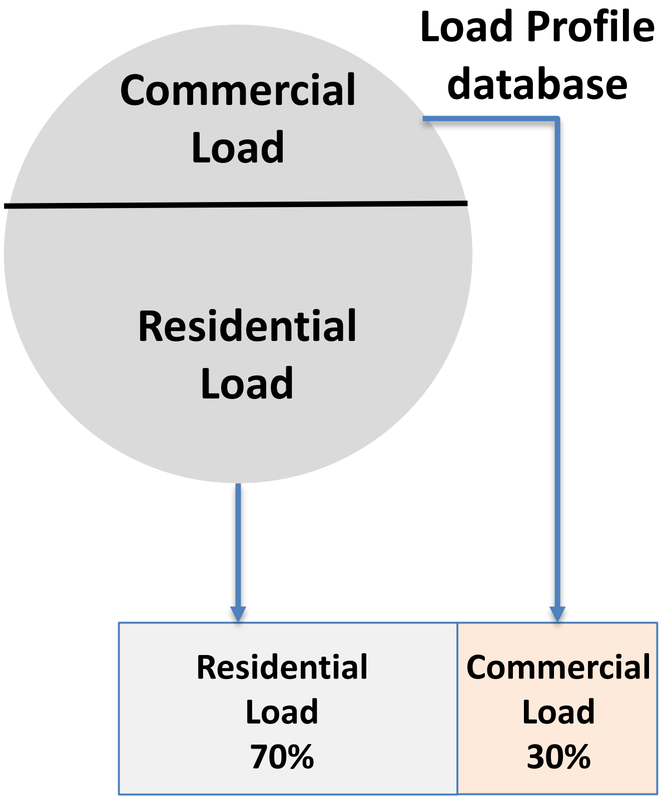
70%

$$\frac{\sum_{t=1}^{N_T} \tilde{P}_{LT}(t_n)}{\sum_{t=1}^{N_T} \tilde{P}_{feeder}(t_n)} < R_{LT}, \tag{23}$$

$$\tilde{P}_{LT} = \tilde{P}_{LT} + P_m, \tag{24}$$

$$\frac{\sum_{t=1}^{N_T} \tilde{P}_{LT}(t_n)}{\sum_{t=1}^{N_T} P_{feeder}(t_n)} < R_{LT} * (1+\varepsilon). \tag{25}$$

error margin



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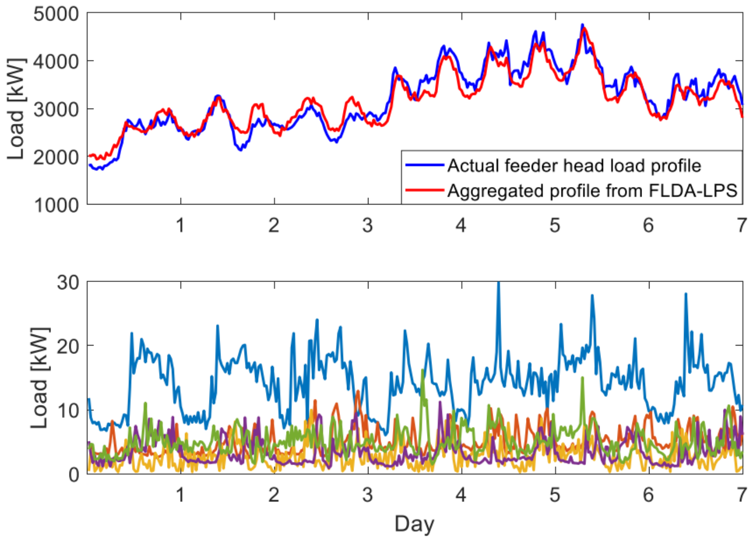
Example Results

- *for weekly matching:* select 4-5 pairs of pivot points (i.e., the peak/valley load of 4/5 days);
- *for monthly matching:* select 16-24 pairs of pivot points (i.e., the peak/valley loads of 4/5 days in each week);
- for yearly matching, select 36 pairs of pivot points (i.e., the peak/valley load of 3 weeks in each month).

$$ME = \frac{\sum_{t=1}^{T_D} \left| \frac{P_{feeder}(\mathrm{t}) - \tilde{P}_{feeder}(\mathrm{t})}{P_{feeder}(\mathrm{t})} \right|}{T_D}, \tag{26}$$

$$NE = \left| \frac{N_{feeder} - \tilde{N}_{feeder}}{N_{feeder}} \right|, \tag{27}$$

$$LCE = \left| \frac{\sum_{t=1}^{T_D} \tilde{P}_{LT}(t)}{\sum_{t=1}^{T_D} \tilde{P}_{feeder}(t)} - R_{LT} \right|. \tag{28}$$



WEEKLY MATCHING RESULTS

	Number of Pivot-Pairs						
	1	2	3	4	5	6	7
ME (%)	1.70	1.43	1.42	1.21	1.16	1.64	3.00
NE (%)	4.97	2.54	2.55	1.40	0.31	2.05	3.65
LCE (%)	0.59	0.51	0.66	0.56	0.53	0.69	0.71
Run-time (s)	9.2	9.0	9.2	9.4	9.3	9.6	9.5

Wang, Jiyu, Xiangqi Zhu, Ming Liang, Yao Meng, Andrew Kling, David L. Lubkeman, and Ning Lu. "A Data-Driven Pivot-Point-Based Time-Series Feeder Load Disaggregation Method." ***IEEE Transactions on Smart Grid*** **11, no. 6 (2020): 5396-5406.**

Part 2-1: GAN-based Methods

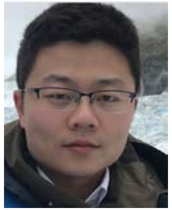
1. Synthetic Data Generation
2. Synthetic Topology Generation
3. Super Resolution: from Low-Resolution to High Resolution

Part 2-1: GAN-based Methods

1. Synthetic Data Generation

Yi Hu

Yiyan Li



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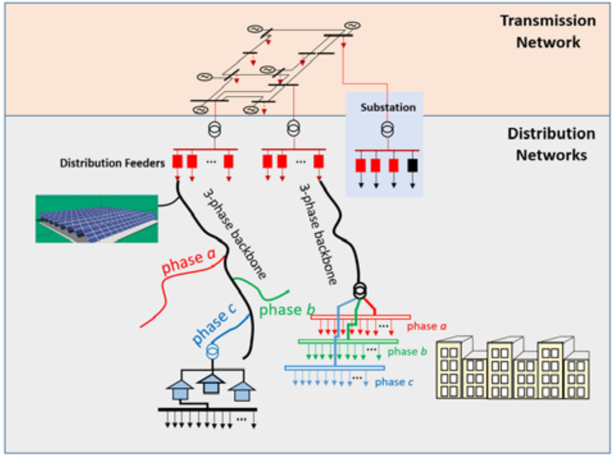
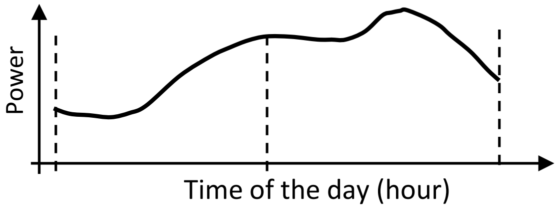
Improve the Realisticness of Load Models

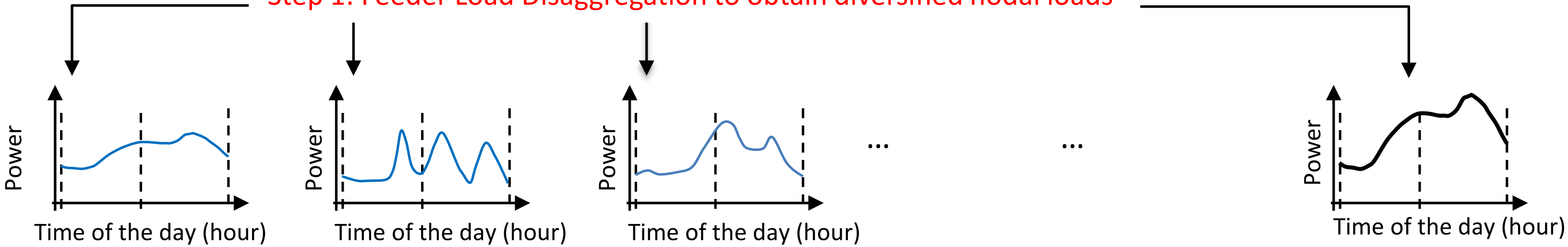
Goal: Generate **a group of diversified load profiles** using smart meter data.



Generate a group of load profiles for a transformer, a feeder and an area



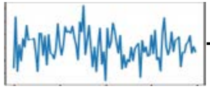
Step 1: Feeder Load Disaggregation to obtain diversified nodal loads



Motivation: State-of-the-art

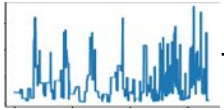
Step 1: Generate one load profile at a time

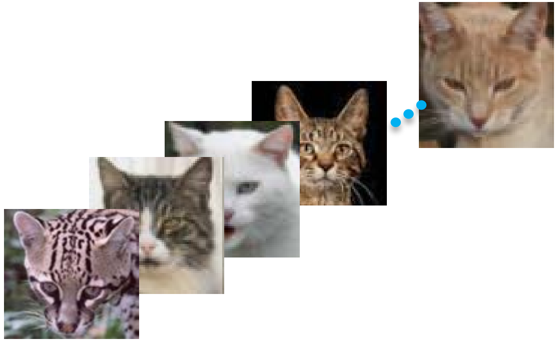
Noise



SingleLoad-GAN

A load profile

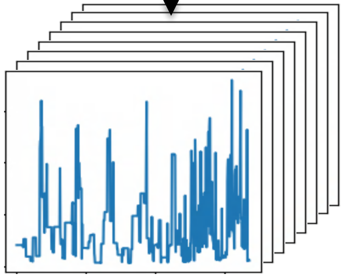




Step 2: Run step 1 for many times to obtain a database of load profiles

Load profile Database

Step 3: Randomly sample N load profiles to form a group of loads



A group of load profiles

Drawbacks:

Cannot account for group-level characteristics

Yi Hu, Yiyan Li, Lidong Song, Han Pyo Lee, PJ Rehm, Matthew Makdad, Edmond Miller, and Ning Lu, "MultiLoad-GAN: A GAN-Based Synthetic Load Group Generation Method Considering Spatial-Temporal Correlations," submitted to IEEE Transactions on Smart Grid (2022). Available online at: https://arxiv.org/abs/2210.01167

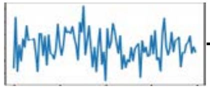
Preserve the Group-level Characteristics

Step 1: Generate one load profile at a time

Step 2: Run step 1 for many times to obtain a database of load profiles

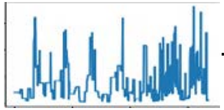
Step 3: Randomly sample N load profiles

Noise



SingleLoad-GAN

A load profile

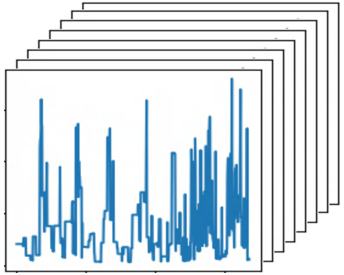


Load profile Database

Noise

MultiLoad-GAN

Generate N load profiles in one shot



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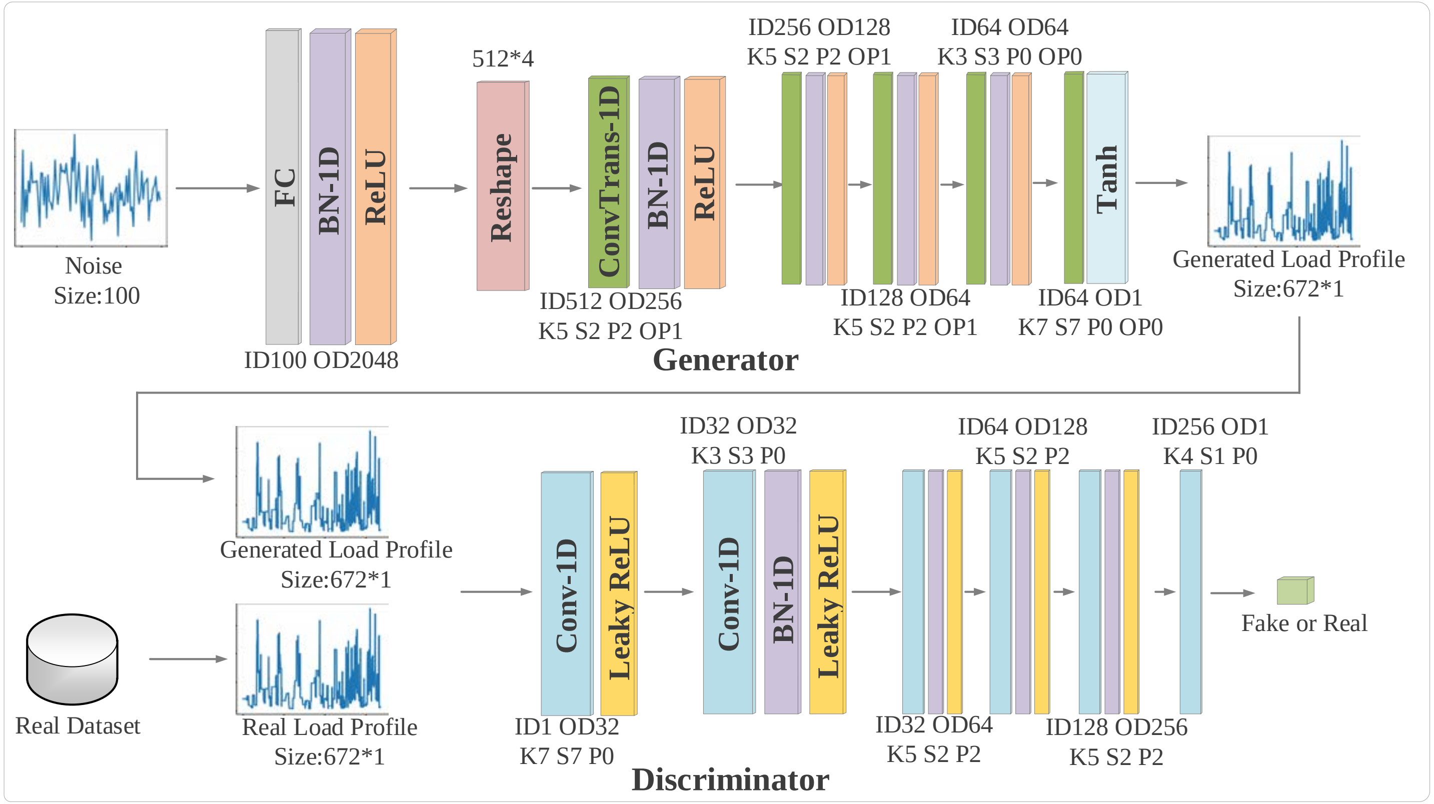
Configuration of SingleLoad-GAN



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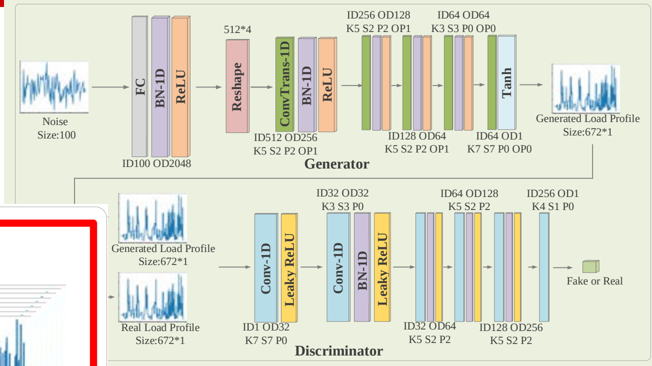
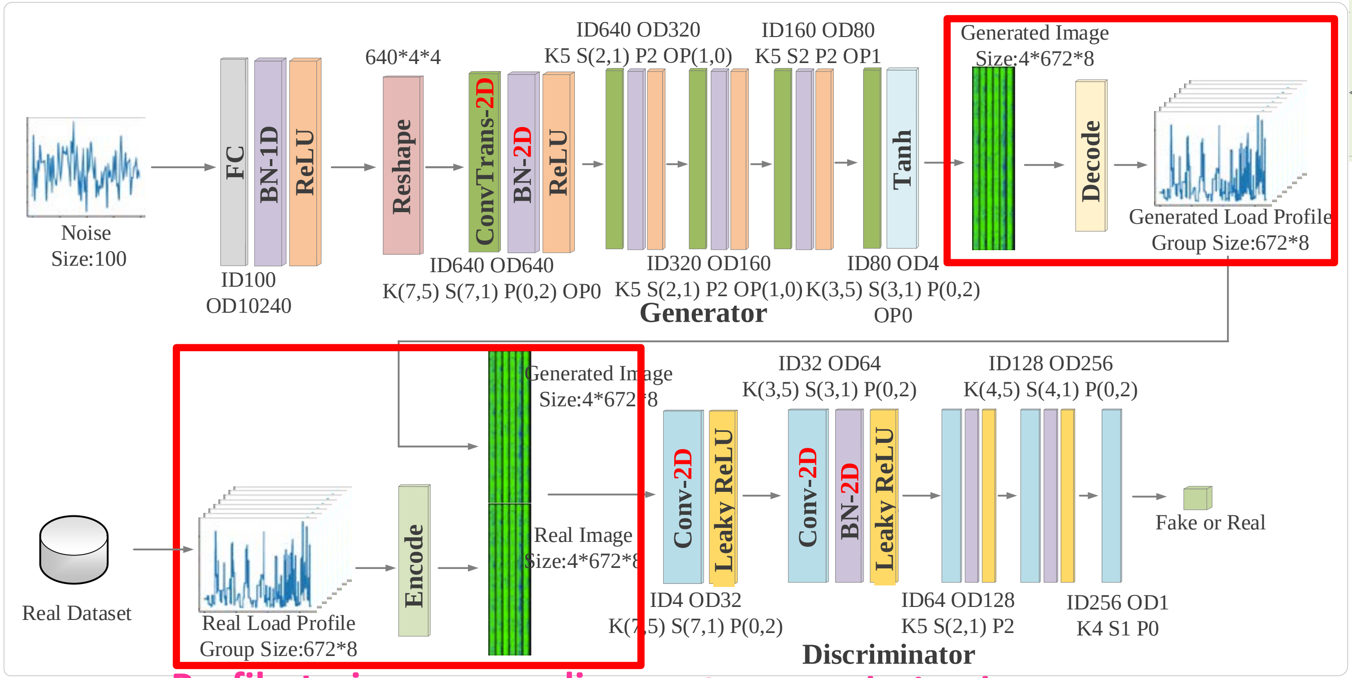
Configuration of MultiLoad-GAN



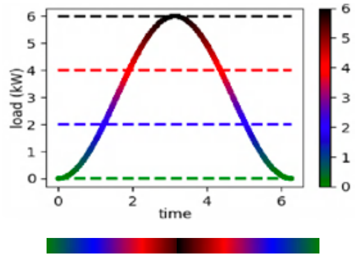


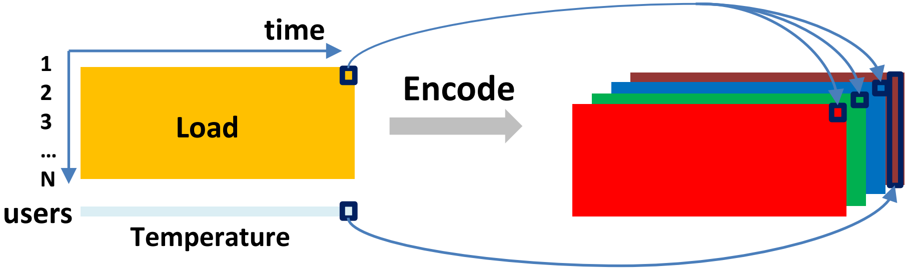
Profile-to-image encoding **2D-convolution layers**

Yi Hu, Yiyan Li, Lidong Song, Han Pyo Lee, PJ Rehm, Matthew Makdad, Edmond Miller, and Ning Lu, "MultiLoad-GAN: A GAN-Based Synthetic Load Group Generation Method Considering Spatial-Temporal Correlations," submitted to IEEE Transactions on Smart Grid (2022). Available online at: https://arxiv.org/abs/2210.01167

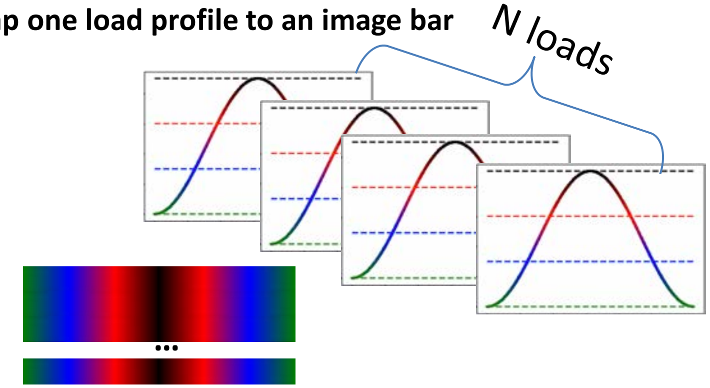
Profile-to-image Mapping

Profile-to-image Encoding: time-series plots to 4-channel ([r, g, b, t]) image





(a) Map one load profile to an image bar

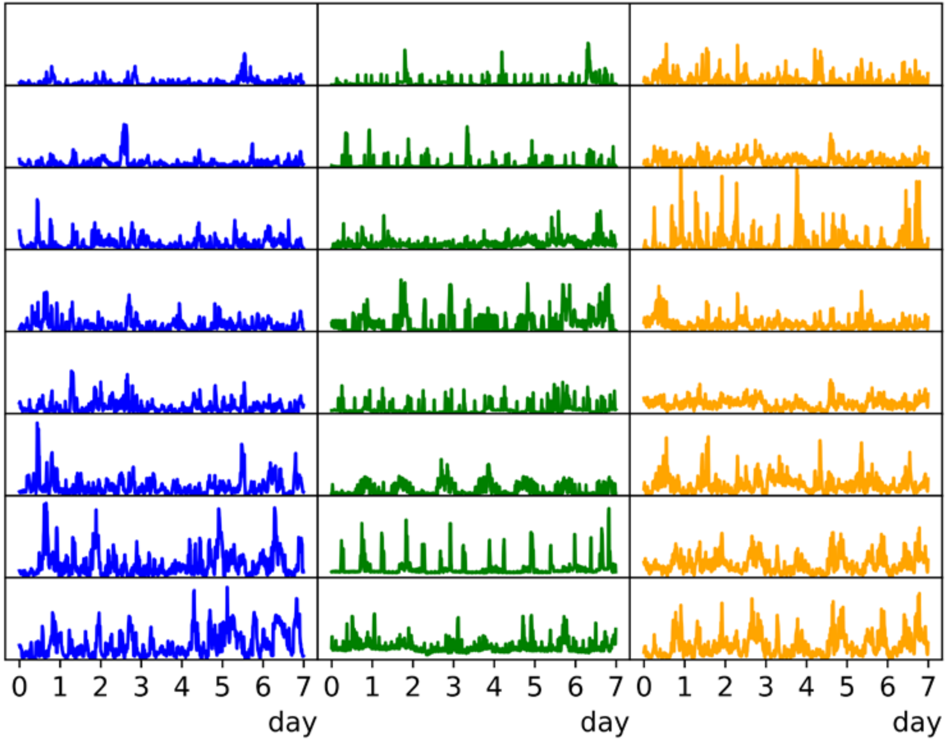


(b) Map a group of loads to an image with N bars

Load (kW)	[r, g, b]	Temperature(°F)	Vector [t]
0	[0, 1, 0]	0	[0]
(0, 2)	g↓, b↑	(0,120)	t↑
2	[0, 0, 1]		
(2, 4)	b↓, r↑		
4	[1, 0, 0]		
(4, 6)	r↓		
[6, +∞)	[0, 0, 0]	120	[1]

MultiLoad-GAN: Unique Challenges

It's hard to decide which one is more realistic by visual inspection.



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Realisticness Evaluation Metrics

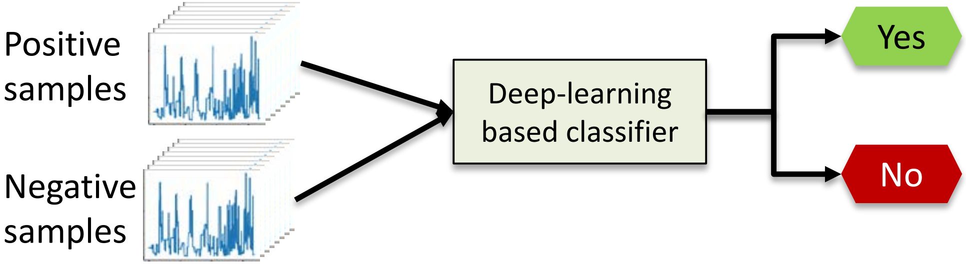
Statistical Evaluation

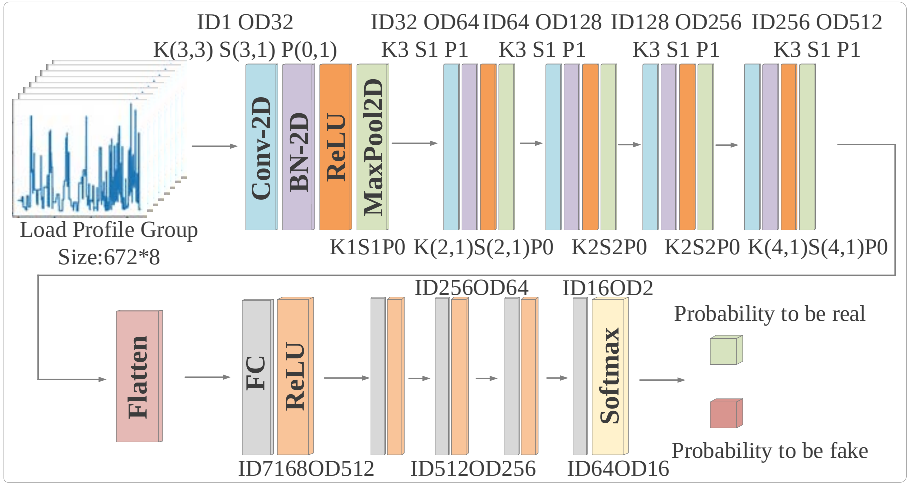
Whether or not group-level correlations are preserved?

Level	Indices
Household	Peak load distribution
	Mean power consumption distribution
	Load ramps distribution
	Hourly energy consumption distribution
	Daily energy consumption distribution
Transformer Level	Peak load distribution
	Mean power consumption distribution
	Load ramps distribution
	Hourly energy consumption distribution
	Daily energy consumption distribution

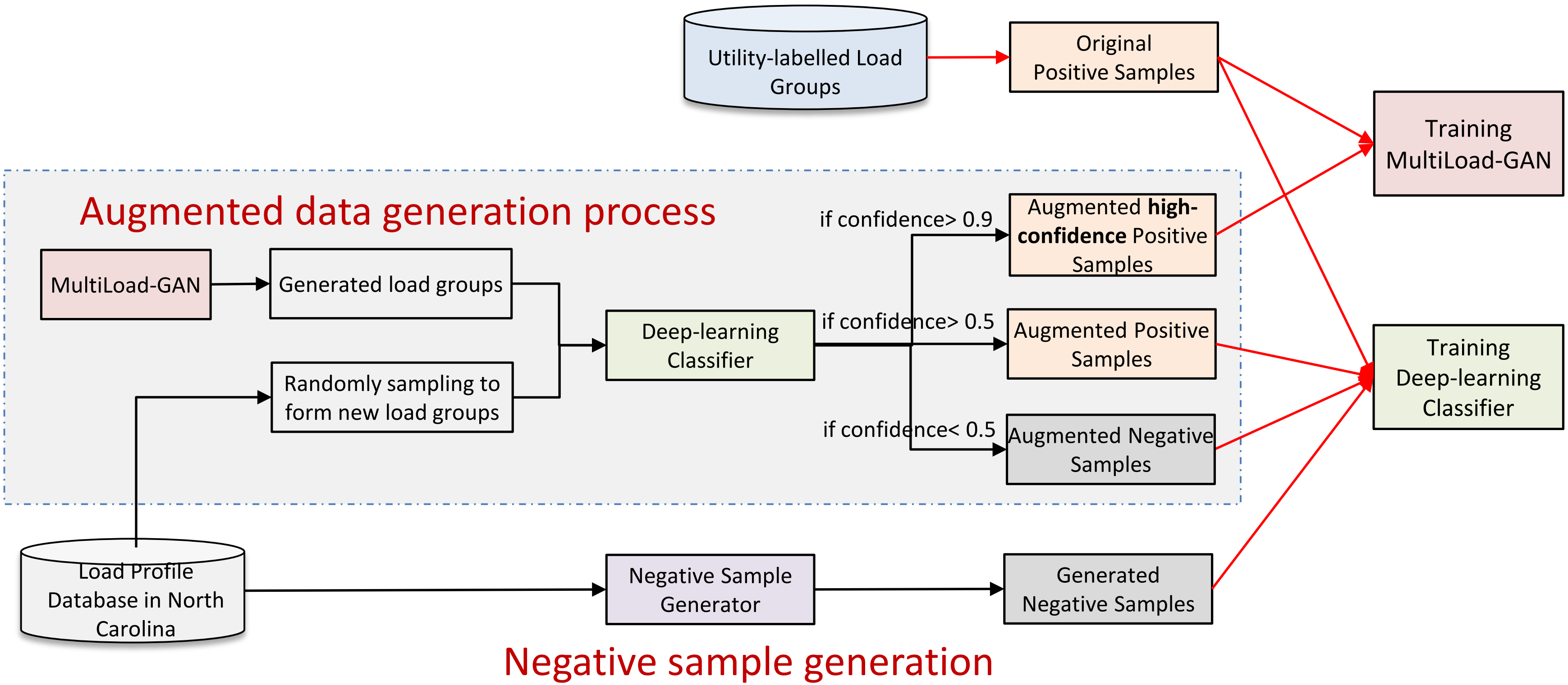
Deep-learning based Specialized Classifier

Whether or not high-level hidden features are similar?





Data Scarcity: A Novel Augmentation Process



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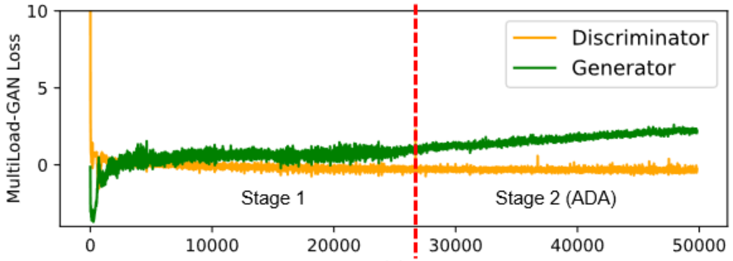
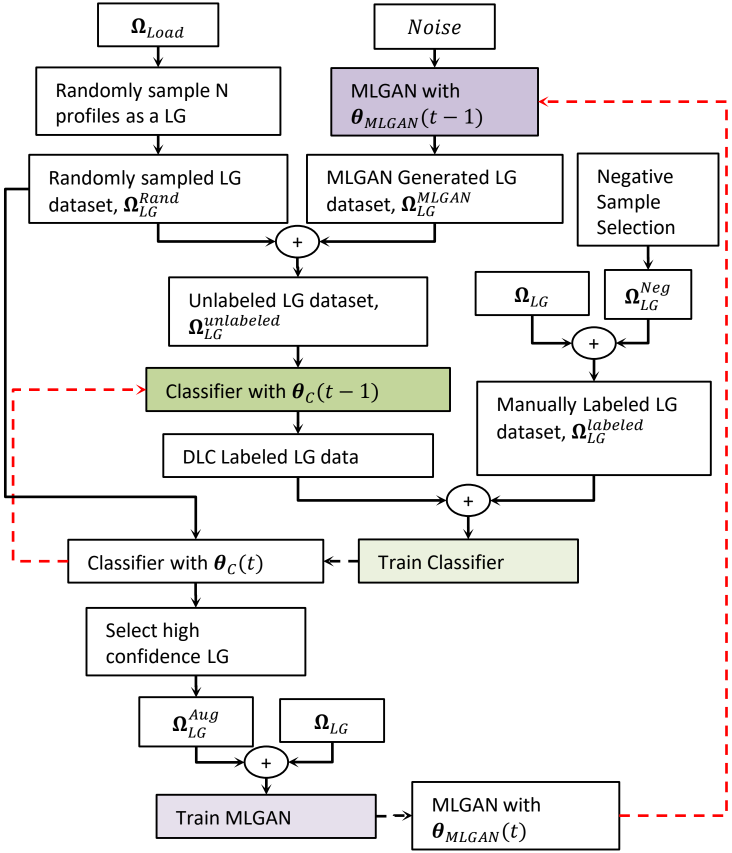
Iteratively Co-train MultiLoad-GAN and Classifier

- We train the Classifier and MultiLoad-GAN iteratively.
- Then, let the partially trained classifier and MultiLoad-GAN generate augmented training data to enrich the training data set.
- This will improve the performance of both.



(a)



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Performance

1. Percentage of True

$$POR = \frac{Q_{real}}{Q} \times 100\%$$

2. Mean Confidence Level

$$MCL = \frac{1}{Q}\sum_{i=1}^{Q} P_{true}(i)$$

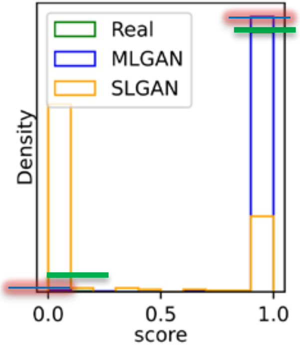
3. Confidence distribution

$$\tau\big(C(\boldsymbol{\Omega}_{LG})\big) = \tau([P_{true}(1), P_{true}(2), \dots, P_{true}(Q)])$$

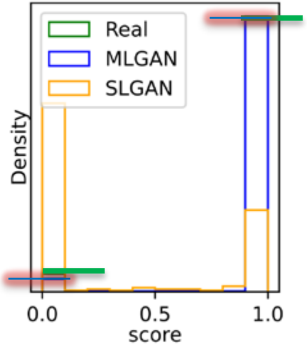
4. Fréchet inception distance

$$Similarity = FID(\tau(\boldsymbol{\Omega}_{\mathbf{LG}}), \tau(\boldsymbol{\Omega}_{\mathbf{LG}}^{\mathbf{ML}\boldsymbol{\mathcal{L}}\mathbf{GAN}}))$$

Dataset	Indices	Original	ADA Boosted
$\boldsymbol{\Omega}_{\mathbf{LG}}$	**POR**	94.38%	
	MCL	0.9371	
$\boldsymbol{\Omega}_{\mathbf{LG}}^{\boldsymbol{S\mathcal{L}}\mathbf{GAN}}$	**POR**	19.69%	
	MCL	0.1913	
	FID with $\boldsymbol{\Omega}_{\mathbf{LG}}$	0.5173	
$\boldsymbol{\Omega}_{\mathbf{LG}}^{\mathbf{M}\boldsymbol{\mathcal{L}}\mathbf{GAN}}$	**POR**	99.06%	94.99%
	MCL	0.9899	0.9491
	FID with $\boldsymbol{\Omega}_{\mathbf{LG}}$	0.01106	**0.000055**



W/O ADA



With ADA

Yi Hu, Yiyan Li, Lidong Song, Han Pyo Lee, PJ Rehm, Matthew Makdad, Edmond Miller, and Ning Lu, "MultiLoad-GAN: A GAN-Based Synthetic Load Group Generation Method Considering Spatial-Temporal Correlations," submitted to IEEE Transactions on Smart Grid (2022). Available online at: https://arxiv.org/abs/2210.01167

Part 2-1: GAN-based Methods

1. Synthetic Data Generation
2. **Synthetic Topology Generation**

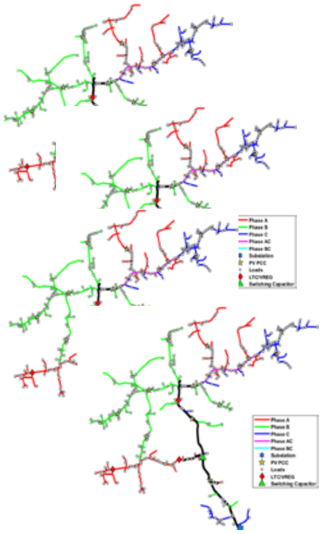
Ming Liang, Yao Meng, J. Wang, D. L. Lubkeman and Ning Lu, "FeederGAN: Synthetic Feeder Generation via Deep Graph Adversarial Nets," in *IEEE Transactions on Smart Grid*, vol. 12, no. 2, pp. 1163-1173, March 2021, doi: 10.1109/TSG.2020.3025259. A brief introduction of the paper can be found in Youtube at: https://youtu.be/r8cmSDyxlJ8

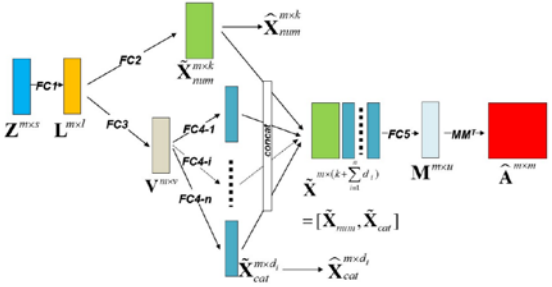
3. Super Resolution: from Low-Resolution to High Resolution

GAN-base Method 2: FeederGAN

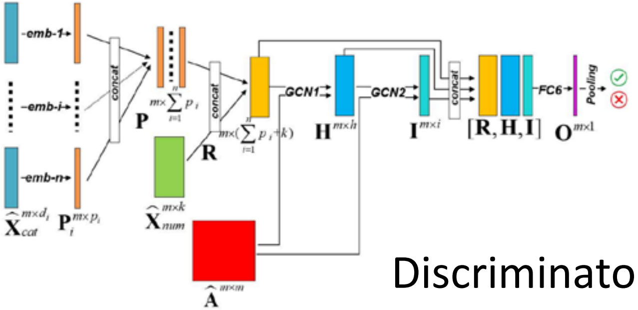
Goal: generate "DeepFake" feeder topologies

Real Feeder Topologies





Generator



Discriminator

Generated Feeder Topologies

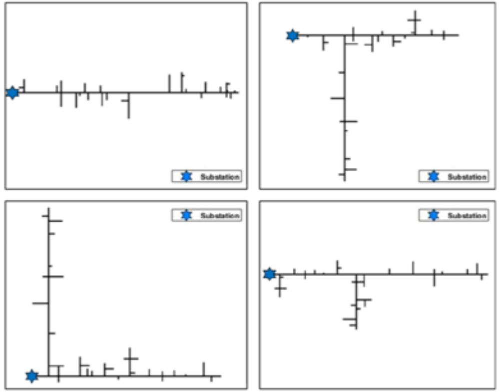
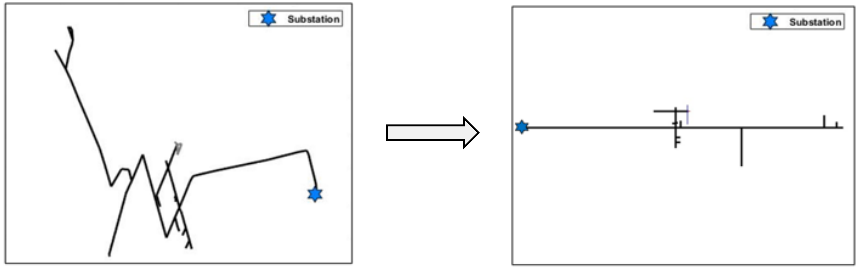


Fig.2.12 Generated feeders

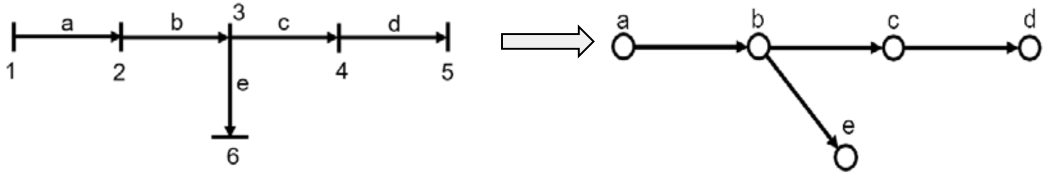
Ming Liang, Yao Meng, J. Wang, D. L. Lubkeman and Ning Lu, "FeederGAN: Synthetic Feeder Generation via Deep Graph Adversarial Nets," in *IEEE Transactions on Smart Grid*, vol. 12, no. 2, pp. 1163-1173, March 2021, doi: 10.1109/TSG.2020.3025259. A brief introduction of the paper can be found in Youtube at: https://youtu.be/r8cmSDyxIJ8

Uniqueness 1: Topology → Graph Representations

Mask the geographical coordinates of real feeders and make it stretch as straight as possible. Only keep the "**length**" of each device (e.g. cable or overhead line). Because only **electrical distance** matters, which determined by **length** and **conductor material**.



Device-as-node: represent feeder as a **directed graph**, each **device as a node**, and edges just show the direction from feeder head to load node. Other information like 'length', 'conductor material' are represented as **node attributes**.



Ming Liang, Yao Meng, J. Wang, D. L. Lubkeman and Ning Lu, "FeederGAN: Synthetic Feeder Generation via Deep Graph Adversarial Nets," in *IEEE Transactions on Smart Grid*, vol. 12, no. 2, pp. 1163-1173, March 2021, doi: 10.1109/TSG.2020.3025259. A brief introduction of the paper can be found in Youtube at: https://youtu.be/r8cmSDyxIJ8

When conducting the GAN-based Training

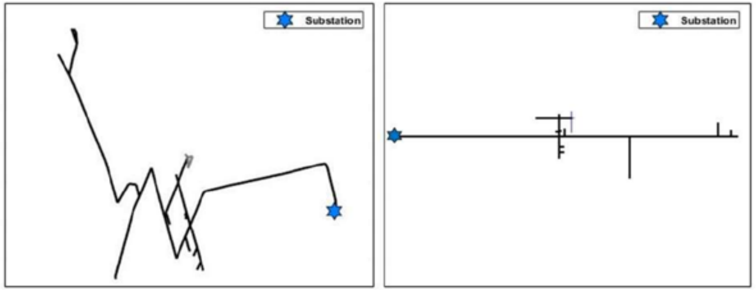


Fig.1 Topology representation: feeder using geographical coordinates (left) and using electrical distance (right)

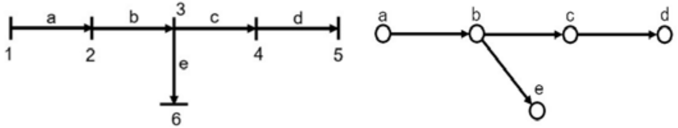
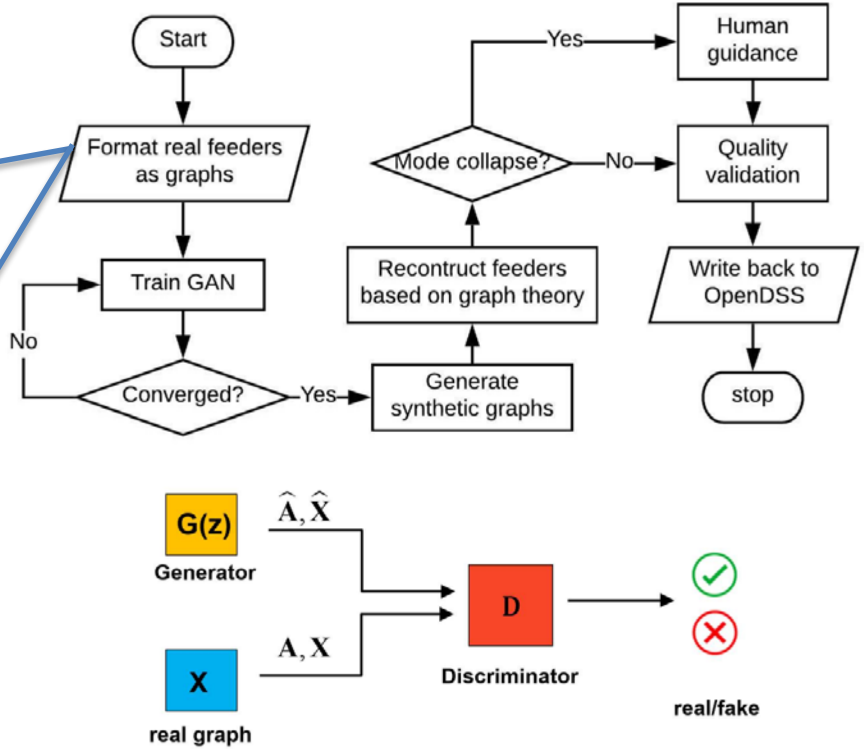


Fig. 2 Distribution feeder topology representation: Bus-as-node and device-as-edge (left) and device-as-node (right)



M. Liang, Y. Meng, J. Wang, D. L. Lubkeman and N. Lu, "FeederGAN: Synthetic Feeder Generation via Deep Graph Adversarial Nets," in *IEEE Transactions on Smart Grid*, vol. 12, no. 2, pp. 1163-1173, March 2021, doi: 10.1109/TSG.2020.3025259. A brief introduction of the paper can be found in Youtube at: https://youtu.be/r8cmSDyxIJ8

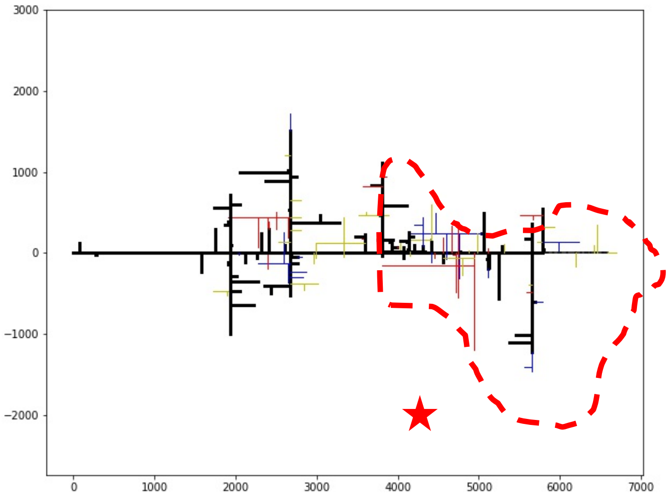
Uniqueness 2: Data Augmentation

How to handle data scarcity?

Our data sources: **14** real feeders most with equipment/device (nodes in a graph) from 1500 to 2000.

→ **need more graphs** to better learn the implicit topology and attributes information.

Our solution: sample subgraphs. Note that a subgraph of a chemical molecule may not be valid; but a subgraph of distribution feeder just represents a small part that exists in the system.



Sampling rules:

1. Only sample large graph, with nodes more than 500;
2. Choose a start node only in level 0 or level 1;
3. Extract its downstream (all the way to loads) as the subgraph;
4. Check whether #node is more than 100, if not resample;
5. Check whether #node of subgraph is more than 50% of #node in the original graph, if so resample;
6. Repeat 50 times to get 50 subgraphs for each feeder.

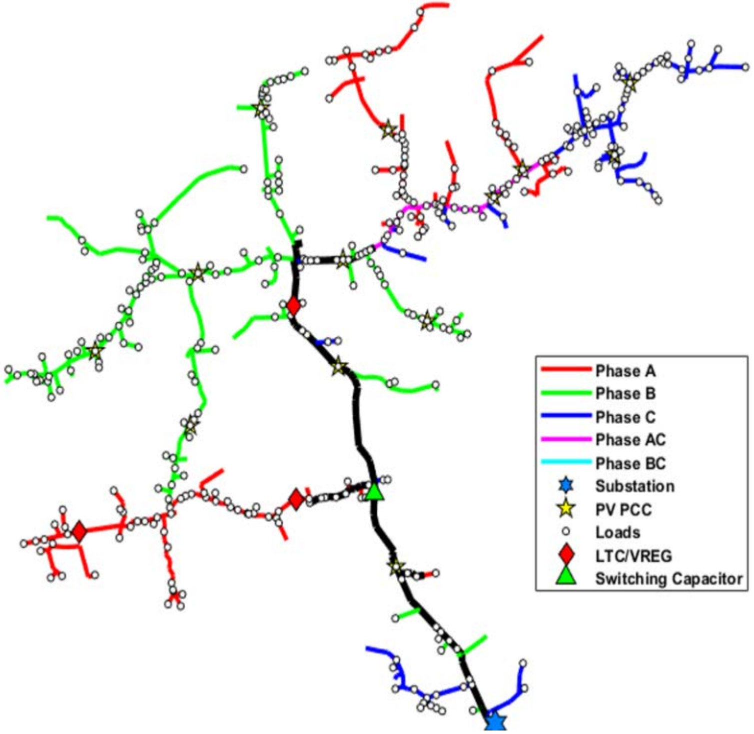
In total, we get **14+13*50=664** graphs to train our model.

Ming Liang, Yao Meng, J. Wang, D. L. Lubkeman and Ning Lu, "FeederGAN: Synthetic Feeder Generation via Deep Graph Adversarial Nets," in *IEEE Transactions on Smart Grid*, vol. 12, no. 2, pp. 1163-1173, March 2021, doi: 10.1109/TSG.2020.3025259. A brief introduction of the paper can be found in Youtube at: https://youtu.be/r8cmSDyxIJ8

Uniqueness 3: Select Attributes

Table I A summary of the attributes
$\mathcal{O}$: organic, $\mathcal{T}$: topological, $\mathcal{N}$: numerical, $\mathcal{C}$: categorical

Name	Definition	Type	Source
Length	The length of a device.	$\mathcal{N}$	$\mathcal{O}$
Norm Amps	Normal condition conductor amps, an indicator for the conductor materials.	$\mathcal{N}$	$\mathcal{O}$
Distance	Distance from feeder head to the device.	$\mathcal{N}$	$\mathcal{T}$
Pseudo Load	The sum of the capacity of all downstream customer side transformers.	$\mathcal{N}$	$\mathcal{T}$
Level	Start as Level 0 at the feeder head. When encountered a bifurcation leading to several children branches, level+1 if "norm amps" or "phase" of the child is different from that of the parent.	$\mathcal{C}$	$\mathcal{T}$
Phase	1 of the 7 options: *a, b, c, ab, ac, bc, abc*	$\mathcal{C}$	$\mathcal{O}$



Numerical: $\mathbf{X}_{num} \in \mathbb{R}^{m\times 4}$

- **Continuous** variable normalize to [-1, 1].

Categorical: $\mathbf{X}_{cat} = \left[\mathbf{X}_{cat}^{1}, \mathbf{X}_{cat}^{2}\right] \in \mathbb{R}^{m\times(d_1+d_2)}$

- **Discrete** variable, one-hot representation.
- Phase a as [1 0 0 0 0 0 0]

Ming Liang, Yao Meng, J. Wang, D. L. Lubkeman and Ning Lu, "FeederGAN: Synthetic Feeder Generation via Deep Graph Adversarial Nets," in *IEEE Transactions on Smart Grid*, vol. 12, no. 2, pp. 1163-1173, March 2021, doi: 10.1109/TSG.2020.3025259. A brief introduction of the paper can be found in Youtube at: https://youtu.be/r8cmSDyxIJ8

Uniqueness 4: screening and feasibility check

- **Post-process screening:** comparing feeder topology statistics for realisticness
- **Feasibility check**: use power flow to check if it is solvable and has reasonable voltage profiles

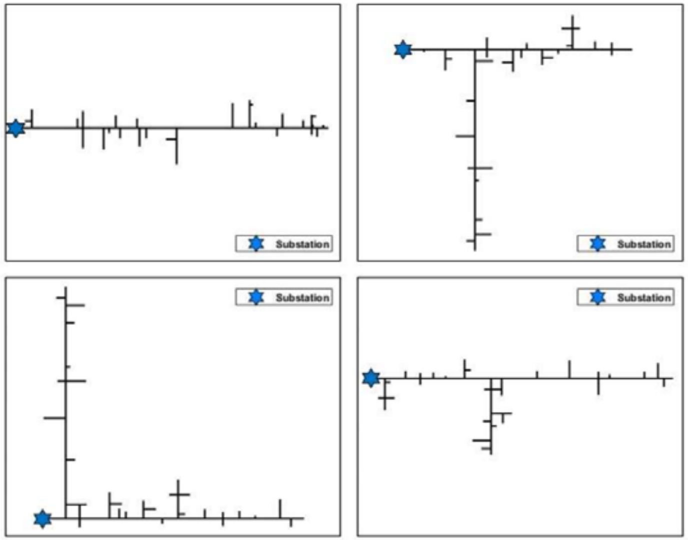


Fig. 9. Generated feeders

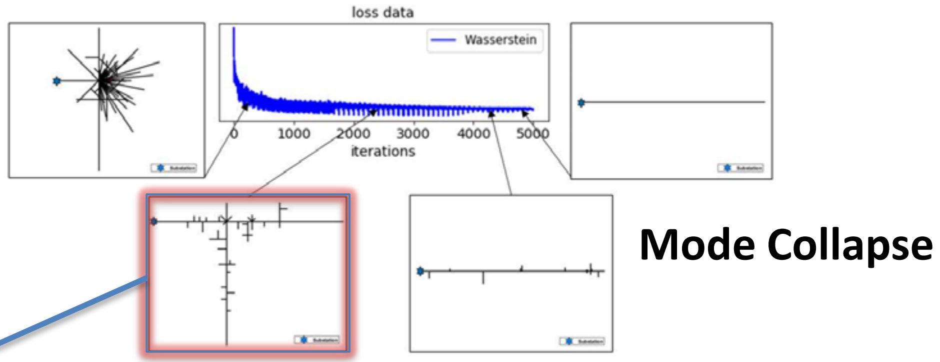


Fig. 13. Topology mode collapse

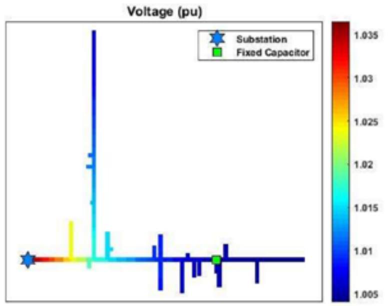


Fig. 10. Nodal voltage along the generated feeder

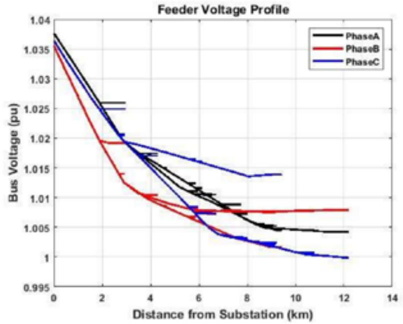


Fig. 11. Voltage profiles of nodes on phase a, b, and c (Nodes arranged ascendingly according to their distance to the substation)

Ming Liang, Yao Meng, J. Wang, D. L. Lubkeman and Ning Lu, "FeederGAN: Synthetic Feeder Generation via Deep Graph Adversarial Nets," in *IEEE Transactions on Smart Grid*, vol. 12, no. 2, pp. 1163-1173, March 2021, doi: 10.1109/TSG.2020.3025259. A brief introduction of the paper can be found in Youtube at: https://youtu.be/r8cmSDyxIJ8

Uniqueness 5: Realisticness Check

Performance Metrics: **Connectivity** (e.g., isolated nodes) and **Phase Transitions** (e.g., 3-phase circuit can be transitioned to 2- and 1-phase, ab followed by a or b.

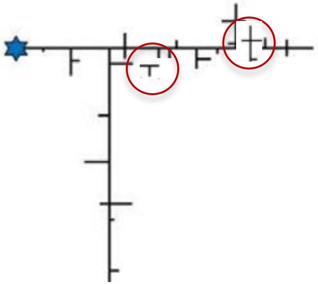


Table II Definition of the Success and Perfect metrics

Success		Perfect	
phase	subsequent neighbor's phase	phase	subsequent neighbor's phase
3-phases	3-phases, 2-phases, 1-phase	*abc*	*abc, ab, ac, bc, a, b, c*
		ab	*ab, a, b*
		ac	*ac, a, c*
2-phases	2-phases, 1-phase	*bc*	*bc, b, c*
		a	*a*
1-phase	1-phase	*b*	*b*
		c	*c*

Table IV Empirical statistics

Metrics	Empirical Statistics						
Level	4 ~ 7						
Phase distribution	*a*	*ab*	*abc*	*ac*	*b*	*bc*	*c*
	18%~ 28%	1%~ 3%	20% ~ 25%	1% ~ 3%	18%~ 28%	1% ~ 3%	18%~ 28%
Out-degree distribution	0	1	2	3	4	≥5	
	20%~ 40%	25%~ 45%	18%~ 26%	5%~ 7%	1%~ 3%	<1%	

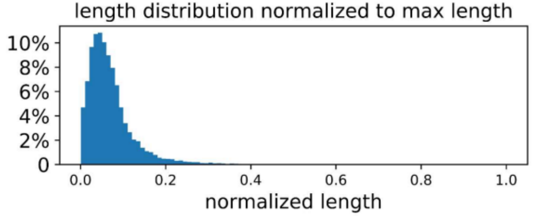


Fig. 14. Probability distribution function of the line segments

M. Liang, Y. Meng, J. Wang, D. L. Lubkeman and N. Lu, "FeederGAN: Synthetic Feeder Generation via Deep Graph Adversarial Nets," in *IEEE Transactions on Smart Grid*, vol. 12, no. 2, pp. 1163-1173, March 2021, doi: 10.1109/TSG.2020.3025259. A brief introduction of the paper can be found in Youtube at: https://youtu.be/r8cmSDyxIJ8

Part 2-1: GAN-based Methods

1. Synthetic Data Generation
2. Synthetic Topology Generation
3. **Super Resolution:** from Low-Resolution to High Resolution

GAN-based Method 1: Super Resolution

1-Minute data
- Not usually available
- Larger load and PV variations
- End use consumptions of appliances

15-minute Smart Meter Data
- Average kWH, kVar, Voltage
- Sensitive information

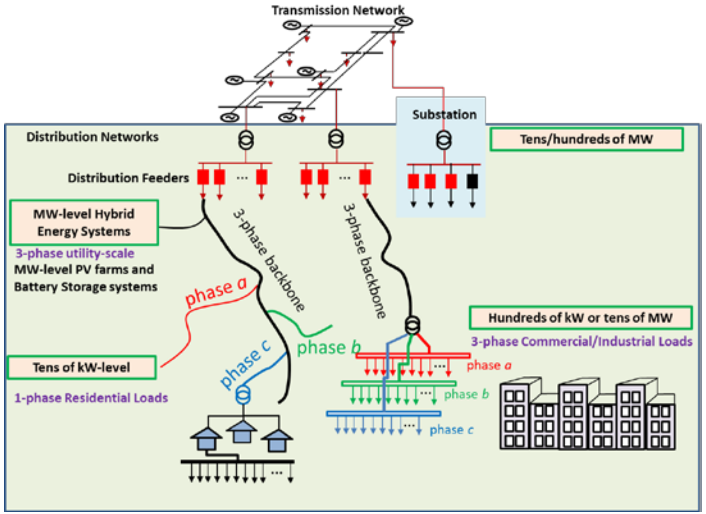
Super resolution

Hourly
- Temperature, irradiance
- Average kWH

Daily
- Peak hour
- DR events

Monthly
- Utility billing information
- Peak day peak hour

Time



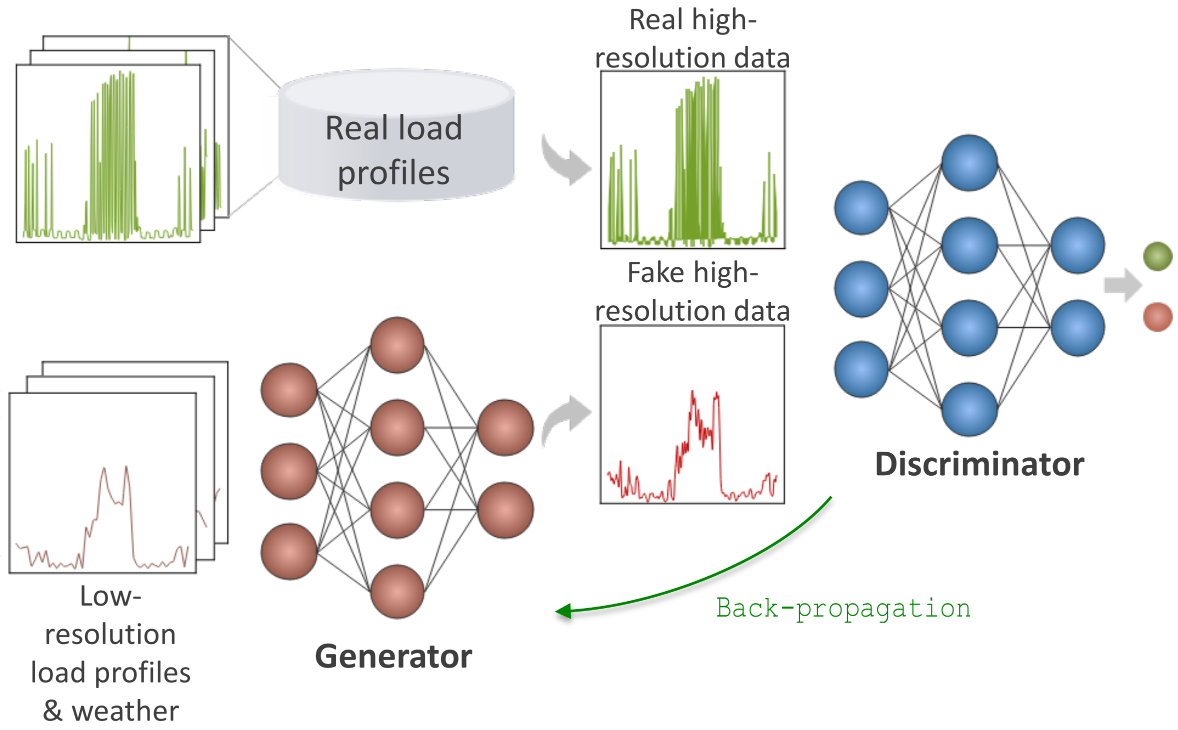
GAN-based Framework

training loop
for each step:

 # generate fake examples
- sampling LR inputs: z
- generate fake HR G(z)

 # train discriminator
- sampling real HR
- predict prob for real and fake HR
- calculate loss for D
- update θ_D using gradian descent

 # train generator
- calculate loss for G
- update θ_G using gradian descent

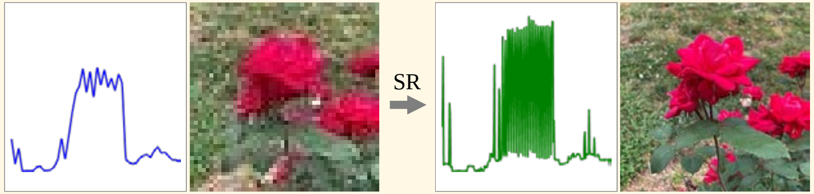


Lidong Song, **Yiyan Li** and N. Lu, "ProfileSR-GAN: A GAN Based Super-Resolution Method for Generating High-Resolution Load Profiles," in *IEEE Transactions on Smart Grid*, vol. 13, no. 4, pp. 3278-3289, July 2022, doi: 10.1109/TSG.2022.3158235. ProfileSR-GAN: https://www.youtube.com/watch?v=nBkwTqHplh8&t=30s

ProfileSR-GAN: Load Profile Super-resolution (SR)

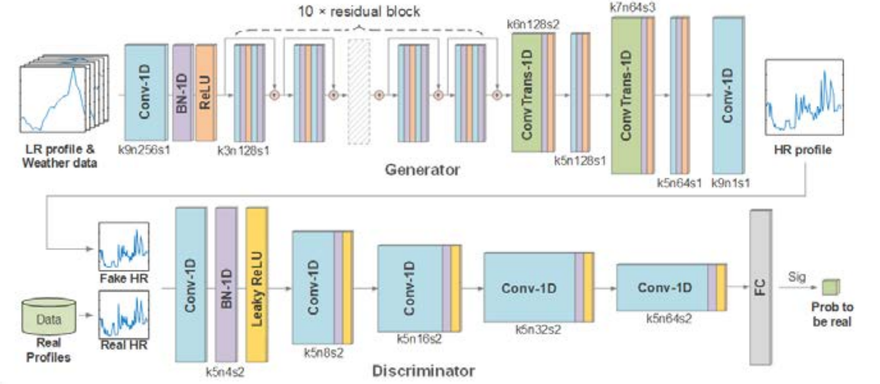
Develop high-resolution PV and load profiles

- Measurements uploaded from smart meter are usually averaged to **15-min** or **30-min** low resolution (LR)
- High-resolution (HR) load data is important in system situational awareness (e.g. peak load, load ramp)
- We restore the high-frequency load dynamics from the LR measurements using deep learning methods

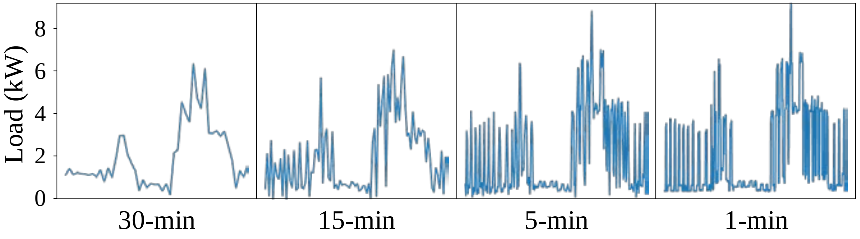


LR profile   Blurred image   HR profile   HR image

A GAN-based Super-resolution Method



From 15-minutes → Minute-by-minute→ intra-minute

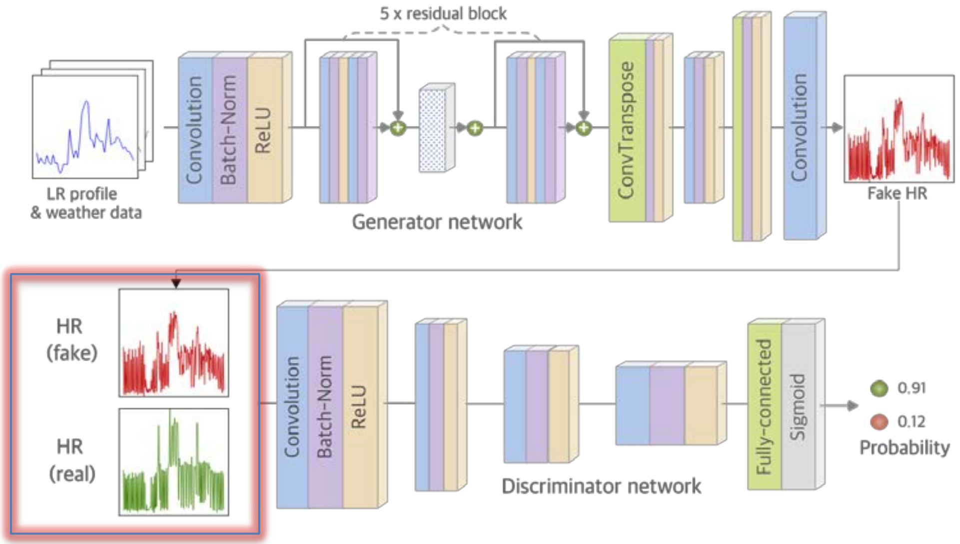


Lidong Song, **Yiyan Li** and N. Lu, "ProfileSR-GAN: A GAN Based Super-Resolution Method for Generating High-Resolution Load Profiles," in *IEEE Transactions on Smart Grid*, vol. 13, no. 4, pp. 3278-3289, July 2022, doi: 10.1109/TSG.2022.3158235. ProfileSR-GAN: https://www.youtube.com/watch?v=nBkwTqHplh8&t=30s

ProfileSR-GAN Framework

Stage 1: Inspired by the image processing applications

Loss function design and hyper-parameter tuning



$$L_{cont} = \frac{1}{N}\left\| G_{\theta_G}(P^{\mathrm{LR}}) - P^{\mathrm{HR}} \right\|_2^2$$

$$L_{advs} = -\log\left(D_{\theta_D}\left(G_{\theta_G}\left(P^{\mathrm{LR}}\right)\right)\right)$$

Generate the load profile that **CAN NOT** be distinguished as “fake” by the discriminator → make the generated high-resolution profile more realistic.

$$\min_{\theta_G} \; L_G\left(G_{\theta_G}(P^{LR}), P^{HR}\right) \tag{5}$$

$$L_G = L_{cont} + \lambda_1 L_{advs} + \boxed{\lambda_2 L_{feat}} \tag{6}$$

where L_{cont} is the content loss; L_{advs} is the adversarial loss; L_{feat} is the feature-matching loss; λ_1 and λ_2 are the weight coefficie

$$L_{feat} = \sum_{j=1}^{J} \left\| \varphi_j\left(G_{\theta_G}(P^{\mathrm{LR}})\right) - \varphi_j\left(P^{\mathrm{HR}}\right) \right\|^2$$

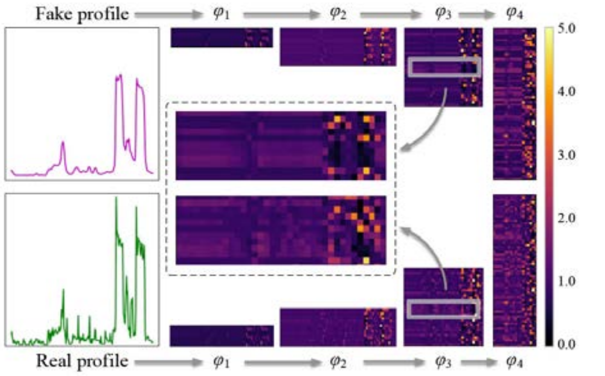


Fig. 6. Hidden feature maps extracted by the convolutional layers of the discriminator network. Load data source: Pecan Street [11].

Lidong Song, **Yiyan Li** and N. Lu, "ProfileSR-GAN: A GAN Based Super-Resolution Method for Generating High-Resolution Load Profiles," in *IEEE Transactions on Smart Grid*, vol. 13, no. 4, pp. 3278-3289, July 2022, doi: 10.1109/TSG.2022.3158235. ProfileSR-GAN: https://www.youtube.com/watch?v=nBkwTqHplh8&t=30s

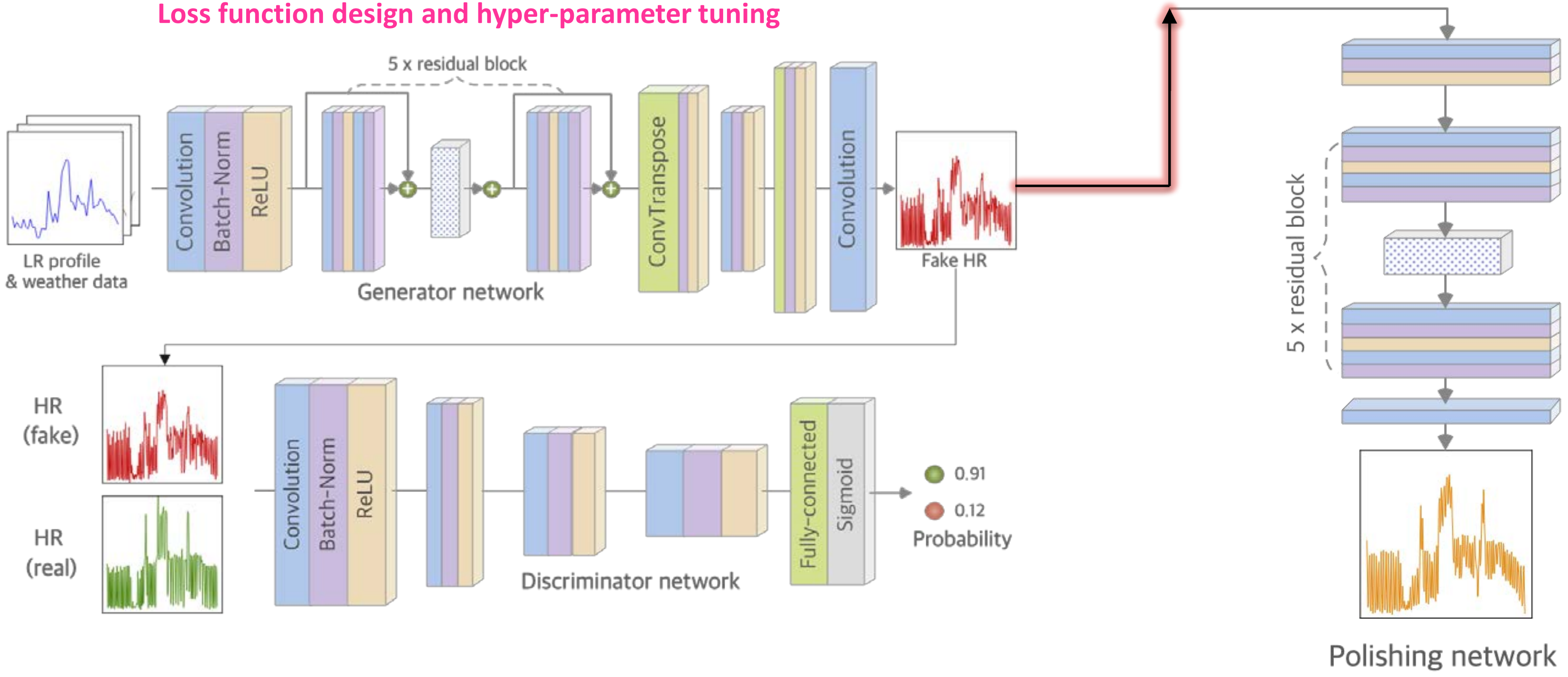
ProfileSR-GAN Framework

Stage 1: Inspired by the image processing applications

Loss function design and hyper-parameter tuning

Stage 2: fine-tuning

use power system domain expertise



Lidong Song, **Yiyan Li** and N. Lu, "ProfileSR-GAN: A GAN Based Super-Resolution Method for Generating High-Resolution Load Profiles," in *IEEE Transactions on Smart Grid*, vol. 13, no. 4, pp. 3278-3289, July 2022, doi: 10.1109/TSG.2022.3158235. ProfileSR-GAN: https://www.youtube.com/watch?v=nBkwTqHplh8&t=30s

ProfileSR-GAN Framework

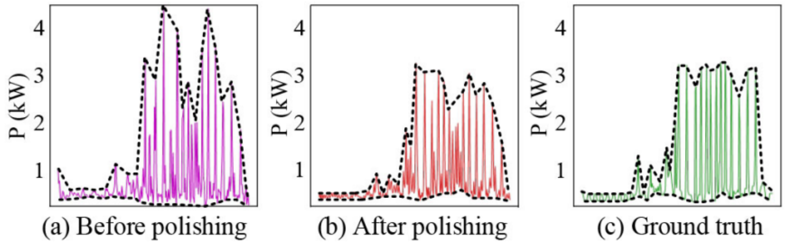


Fig. 7. An illustration of comparing the envelopes of the generated daily HR profiles (before and after polishing) with that of the actual daily load profile.

$$L_{pol} = L_{outl} + L_{swit} \tag{12}$$

$$L_{outl} = \frac{1}{N}\left\|\xi_{\max}\left(\hat{P}^{\mathrm{HR}}\right) - \xi_{\max}\left(P^{\mathrm{HR}}\right)\right\|_2^2 + \frac{1}{N}\left\|\xi_{\max}\left(-\hat{P}^{\mathrm{HR}}\right) - \xi_{\max}\left(-P^{\mathrm{HR}}\right)\right\|_2^2 \tag{13}$$

$$L_{swit} = \frac{1}{N}\left\|\xi_{\max}\left|\Delta\hat{P}^{\mathrm{HR}}\right| - \xi_{\max}\left|\Delta P^{\mathrm{HR}}\right|\right\|_2^2$$

$$\Delta\hat{P}^{\mathrm{HR}} = \hat{P}^{\mathrm{HR}}(n+1) - \hat{P}^{\mathrm{HR}}(n),$$

$$\Delta P^{\mathrm{HR}} = P^{\mathrm{HR}}(n+1) - P^{\mathrm{HR}}(n) \tag{14}$$

shape→outline loss

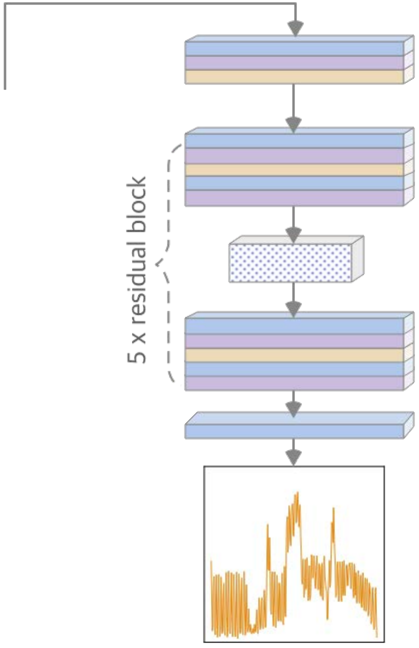
comparing the **local peaks and valleys** of the generated profile

Ramps → switching loss

focuses on comparing **the change of load** between two consecutive sampling intervals

Stage 2: fine-tuning

use power system domain expertise



Polishing network

Lidong Song, **Yiyan Li** and N. Lu, "ProfileSR-GAN: A GAN Based Super-Resolution Method for Generating High-Resolution Load Profiles," in *IEEE Transactions on Smart Grid*, vol. 13, no. 4, pp. 3278-3289, July 2022, doi: 10.1109/TSG.2022.3158235. ProfileSR-GAN: https://www.youtube.com/watch?v=nBkwTqHplh8&t=30s

Part 2-2: Automated forecasting methods

will be presented by Dr. Yiyan Li

PARS: three Main Platforms

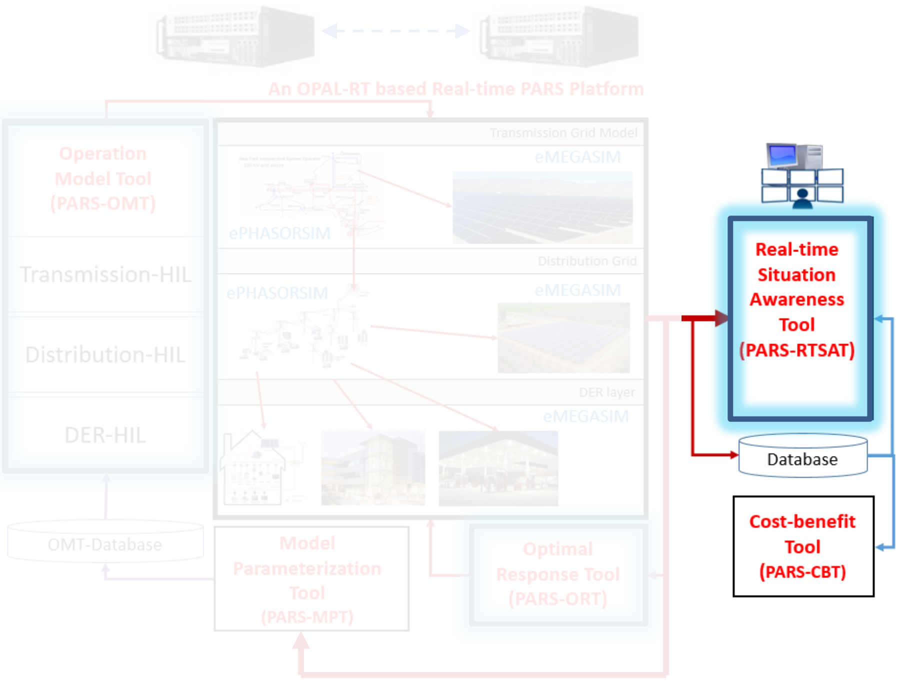
HIL: Hardware-in-the-loop

1. PARS Real-time HIL simulation platform

Requirement: Modeling the operation of **interconnected** physical systems in high-fidelity

Approaches:

1. Populate the model with **synthetic data and topology**
2. Develop automated parameterization



2. Situation Awareness

Requirement: Monitor the current status, **forecast** the future, authenticate the data, detect anomalies.

Approach:

1. **Meta-learning** for generalizable tool sets
2. **TCN** for capturing spatial and temporal correlation

3. Faster-than-real-time Optimal Response Tool (External to the HIL)

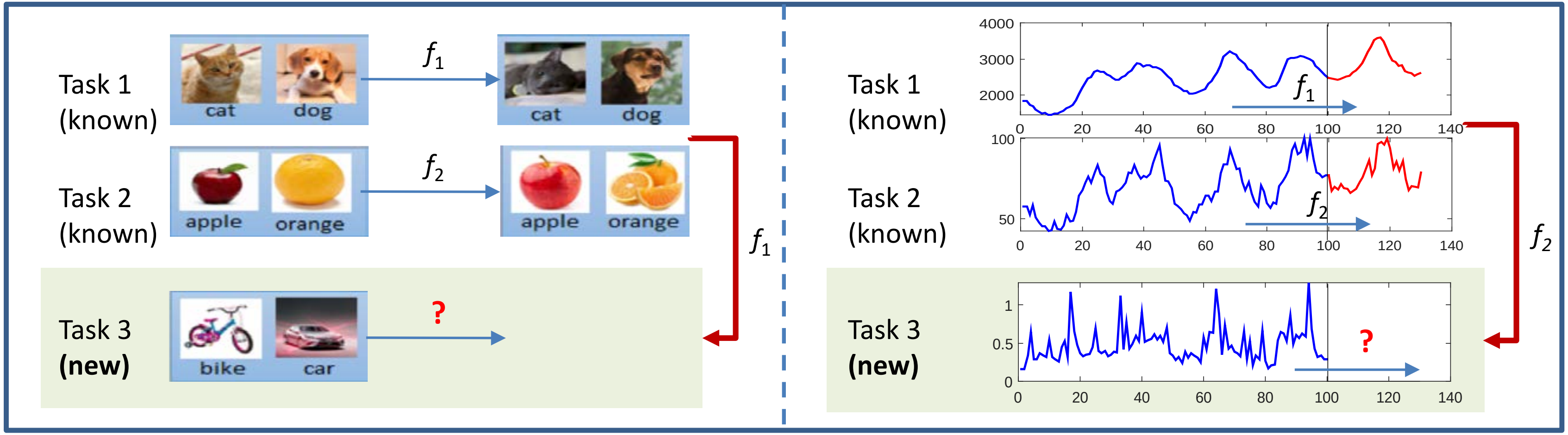
Requirement: energy and power management and response options (from 24-hour ahead to intra-hour to real-time)

Approaches: 1) Optimization, and 2) Machine learning based (reinforcement learning for adaptability)

Approach 1: meta-learning based load forecasting

Traditional machine learning, single task

Meta-learning, cross-task

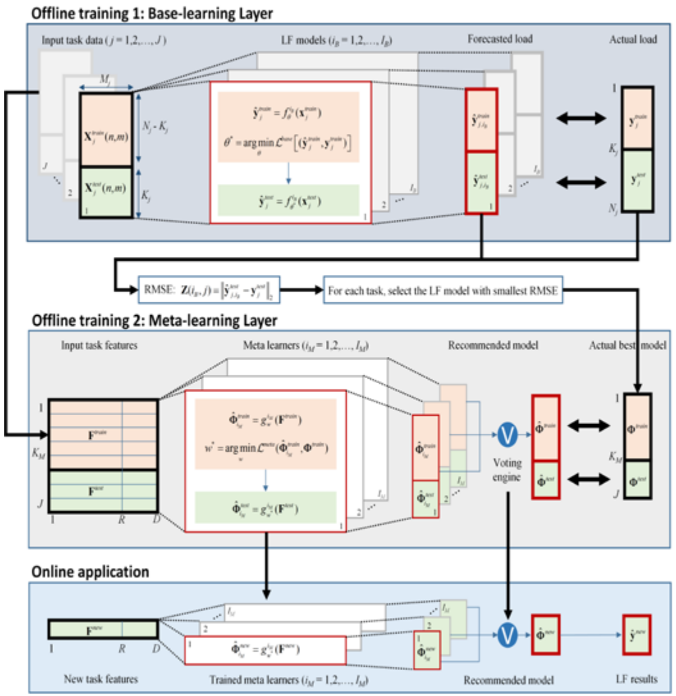


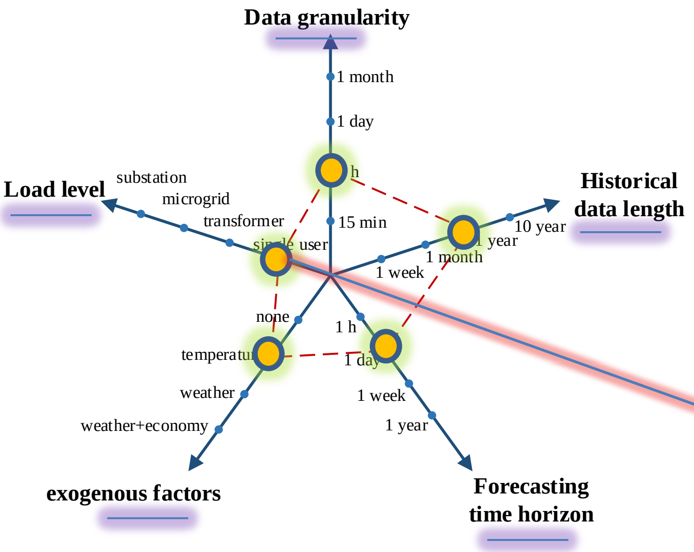
Li, Yiyan, Si Zhang, Rongxing Hu, and Ning Lu. "A meta-learning based distribution system load forecasting model selection framework." *Applied Energy* 294 (2021): 116991. [Meta-learning based load forecasting tool](https://www.youtube.com/watch?v=hiUMqhTXOLM): https://www.youtube.com/watch?v=hiUMqhTXOLM

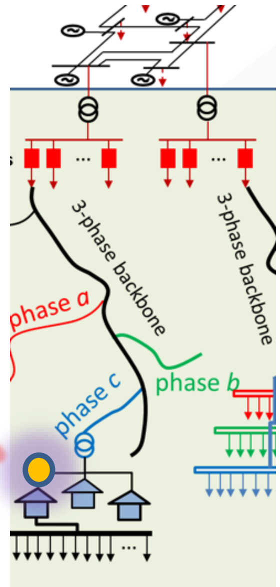
Approach 1: meta-learning based load forecasting

- Using **meta learning** to identify the best-fit forecasting model
- The framework is highly **automated** and **extendable**

Goal: Handle heterogeneous forecasting tasks







Data source: Wilson Energy, Pecan Street

Li, Yiyan, Si Zhang, Rongxing Hu, and Ning Lu. "A meta-learning based distribution system load forecasting model selection framework." *Applied Energy* 294 (2021): 116991. Meta-learning based load forecasting tool: https://www.youtube.com/watch?v=hiUMqhTXOLM

Approach 1 : meta-learning based load forecasting

- **677 tasks for training, 169 tasks (20%) for validation**

Results :

1. Achieve **46% (now > 70%)** accuracy to hit the best LF model among 10 candidates
2. Achieve **76% (now > 90%)** accuracy to recommend a model that among top-3
3. Forecasting accuracy improved:

   MAPE: **0.188 → 0.143**

   SER: **1.40 → 1.14**

Averaged accuracy of LF models on different rankings

Ranking	1	2	3	4	5	6	7	8	9	10
Classification accuracy	46	17%	13%	6%	4%	3%	3%	3%	2%	3%
SER	1.14	1.27	1.34	1.46	4.18	2.89	4.48	3.61	2.61	3.09
Failure count	0	0	2	10	10	12	12	17	14	11

Comparison of averaged LF accuracy

	Average SER	Average MAPE	Failure Count
Proposed meta-learning mechanism	1.14	0.143	0
Best-performed single LF model	1.40	0.188	0

Ref: Li, Yiyan, et al. "A meta-learning based distribution system load forecasting model selection framework." Applied Energy 294 (2021): 116991.

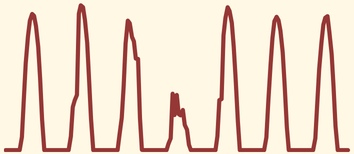
Approach 2: spatial-temporal PV forecasting

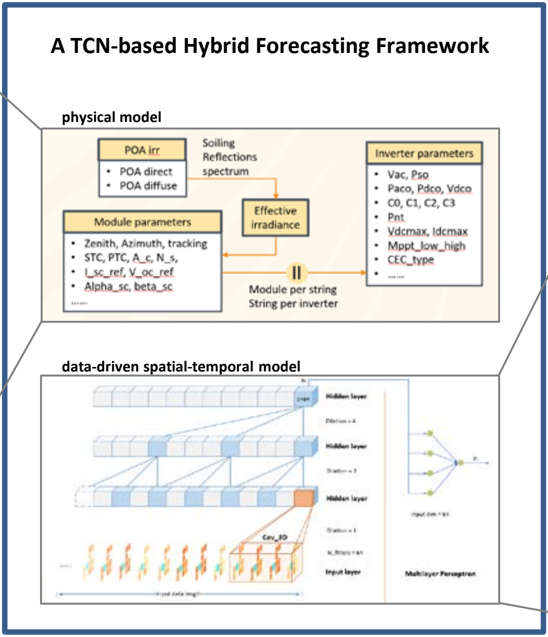
1. Background

Data-driven model vs physics-based model

Physics-based model

- Supported by NWP
- Can catch the trend of weather (irradiance) change
- But fail to predict intra-hour fluctuations

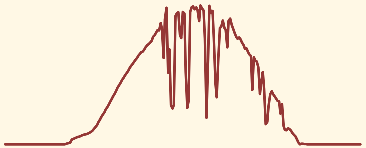




Data source: Strata Solar

Data-driven model

- Learned from historical data and correlation among neighbors
- Can catch very short-term fluctuations caused by cloud, but only works for a few hours ahead



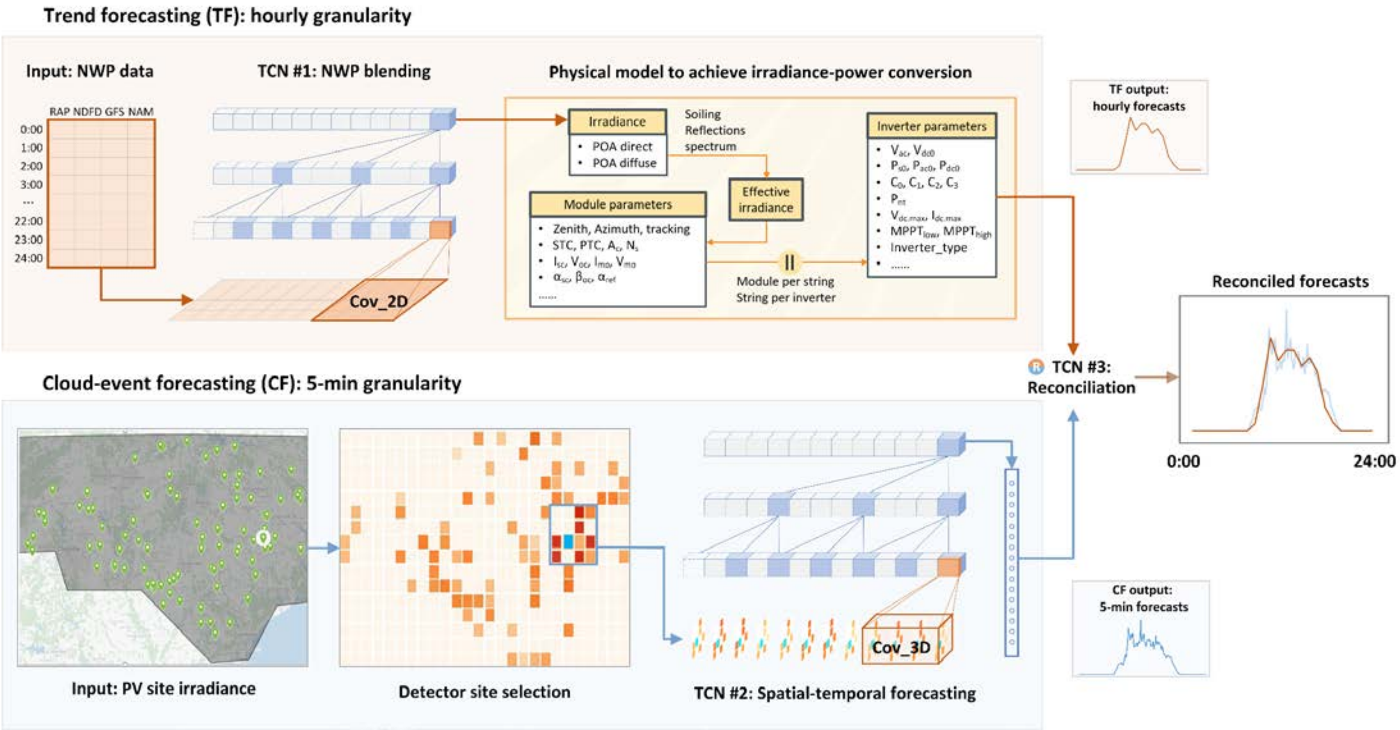
How to combine their advantages?

Reference : Li, Yiyan, et al. "A TCN-based Spatial-Temporal PV Forecasting Framework with Automated Detector Network Selection." arXiv preprint arXiv:2111.08809 (2021).

Approach 2: spatial-temporal PV forecasting

2. Methodology

A hybrid PV forecasting framework

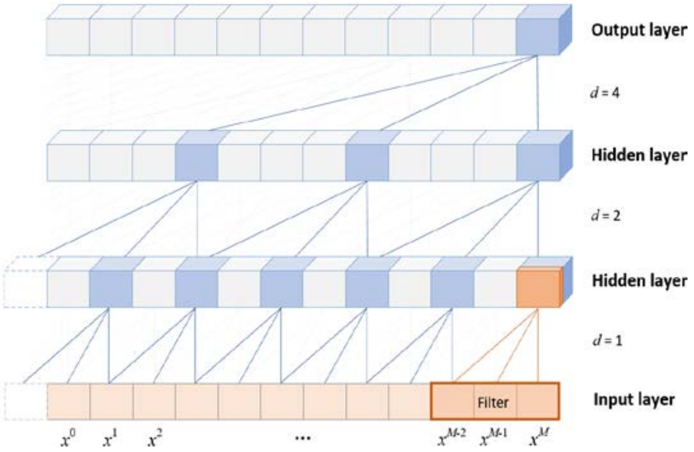


Reference : Li, Yiyan, et al. "A TCN-based Spatial-Temporal PV Forecasting Framework with Automated Detector Network Selection." arXiv preprint arXiv:2111.08809 (2021).

Approach 2: spatial-temporal PV forecasting

2. Methodology

Key Algorithm 1: Temporal Convolutional Network



- **Dilated convolution: longer receptive field with limited complexity**
- **Causal structure: good fit for forecasting**

Application 1: NWP blending

- Blend different NWP data sources to improve the NWP performance

Application 2: Spatial-temporal forecasting

- Learn the spatial-temporal correlations among neighbors

Application 3: forecasting reconciliation

- Reconcile the forecasts from physics-based model and data-driven model

Reference : Li, Yiyan, et al. "A TCN-based Spatial-Temporal PV Forecasting Framework with Automated Detector Network Selection." arXiv preprint arXiv:2111.08809 (2021).

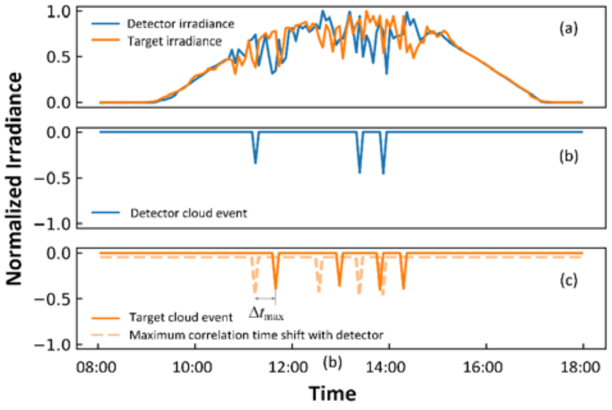
Approach 2: spatial-temporal PV forecasting

2. Methodology

Key Algorithm 2: neighbor selection to identify most contributive neighbors

Definition of successful detection rate of a detector site for a given target site

- Extract cloud events from historical data
- For each day, find the time shift $\Delta t_{\max}$ that has the maximum correlation coefficient $\beta_{\max}$ between target and detector
- Define successful detection when $0 < \Delta t_{\max} < T_{thre}$ (leading correlation), and successful detection rate φ



Example of correlation calculation

Different correlation scenarios

Scenario No.	Detector sites	Target site	Δt	Definition
1	Sunny	Sunny	\	Ignored
2	Cloudy	Sunny	\	detect
3	Sunny	Cloudy	\	Fails to detect
4	Cloudy	Cloudy	$\Delta t_{max} \leq 0$	Fails to detect
5	Cloudy	Cloudy	$0 < \Delta t_{max} \leq T_{thre}$	Successful detection
6	Cloudy	Cloudy	$T_{thre} < \Delta t_{max}$	Irrelevant

$$\varphi = \frac{\sum_{j=1}^{N} I_{s_j=5}}{\sum_{j=1}^{N} I_{s_j \in [2,6]}} \times 100\%$$

Reference: Li, Yiyan, et al. "A TCN-based Spatial-Temporal PV Forecasting Framework with Automated Detector Network Selection." arXiv preprint arXiv:2111.08809 (2021).

Approach 2: spatial-temporal PV forecasting

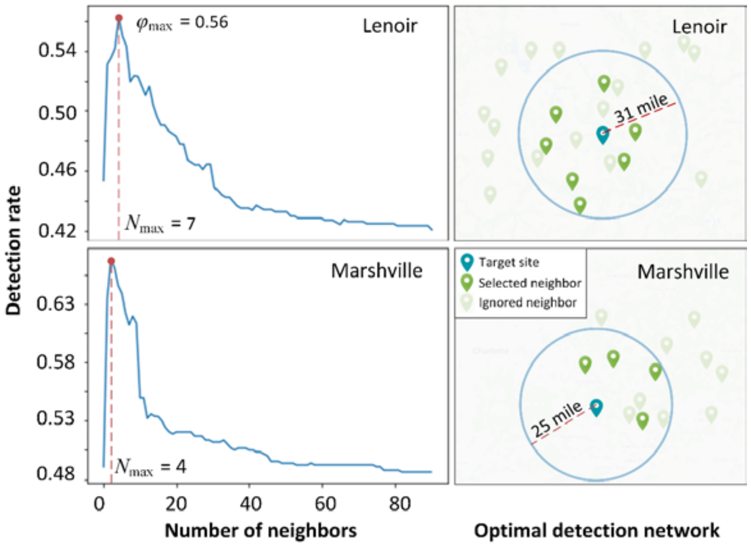
2. Methodology

Key Algorithm 2: neighbor selection to identify most contributive neighbors

Greedy-based optimal detector network searching

- Select optimal detector network that can maximize φ
- Is an NP-hard problem, solved by greedy-search algorithm

Example of detector selection results



Detector network selection algorithm

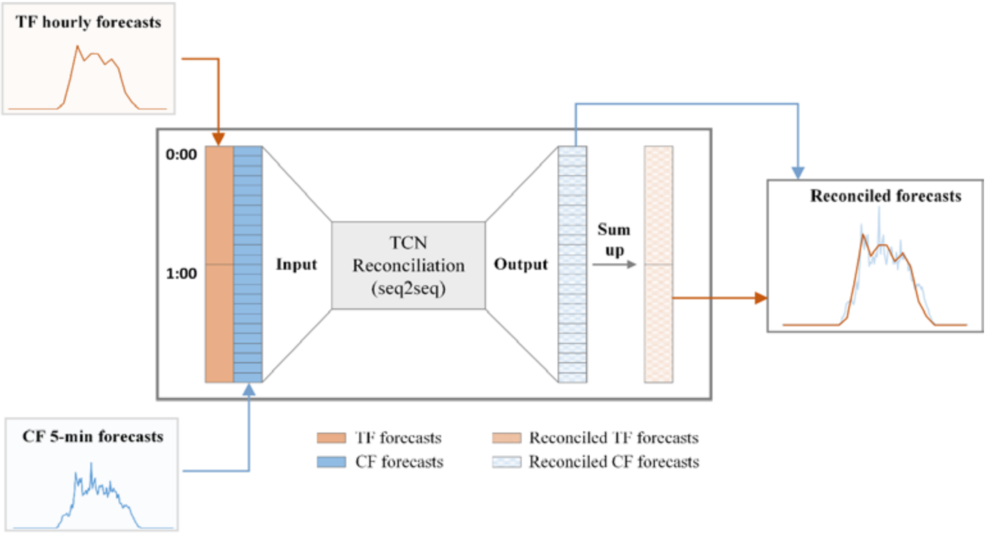
1. Calculate the time-lagged correlation value and Δt_{max} between the target site and each detector site.
2. Add the detector with the highest correlation value to the detector network, and remove it from candidates
3. Calculate φ. If φ increases, then go back to 2. Else go to 4
4. Delete 1 site from the selected detector network, and calculate φ. If φ increases, repeat this process. Else go back to 2
5. If the detector network stabilized, we can obtain the near-optimal detector network

Reference: Li, Yiyan, et al. "A TCN-based Spatial-Temporal PV Forecasting Framework with Automated Detector Network Selection." arXiv preprint arXiv:2111.08809 (2021).

2. Methodology

Key Algorithm 3: forecasting results reconciliation

- Set TCN working in Seq2seq mode to reconcile forecasts from physics-based model and data-driven model
- Can remove the inconsistency and improve forecasting performance



Forecasting reconciliation framework

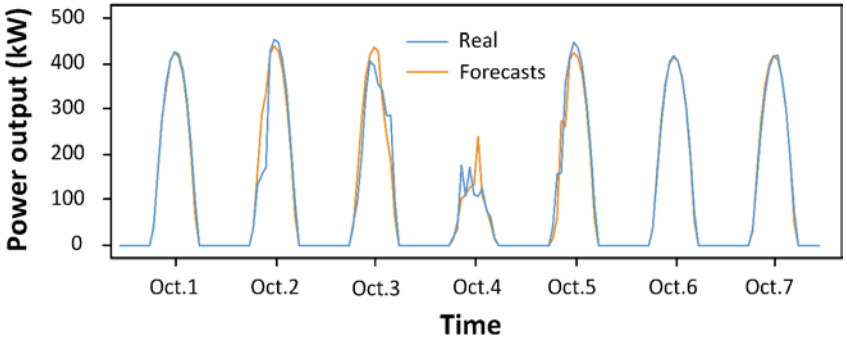
Reference : Li, Yiyan, et al. "A TCN-based Spatial-Temporal PV Forecasting Framework with Automated Detector Network Selection." arXiv preprint arXiv:2111.08809 (2021).

Approach 2: spatial-temporal PV forecasting

3. Case study _ Physics based model

- Can provide “trend” forecasts with hourly granularity
- Forecasting performance can be improved after blending different NWPs by TCN
- Unable to catch intra-hour fluctuations due to the NWP data granularity limitation

Example of physics-based model forecasting results



FEATURES OF DIFFERENT NWP DATA SOURCES AND THEIR FORECASTING PERFORMANCE

	HRRR	GFS	NAM	NDFD	RAP
Spatial resolution	3km	28-44km	12km	2.5km	13km
Dara granularity	1h	3h	1-3h	1h	1h
Forecasting horizon	15h	16days	4days	36h	1day
Forecasting bias	23.74	6.89	14.99	1.31	16.11
Forecasting RMSE	76.14	82.37	80.30	61.72	68.81

PERFORMANCE COMPARISON OF DIFFERENCE BLENDING METHODS

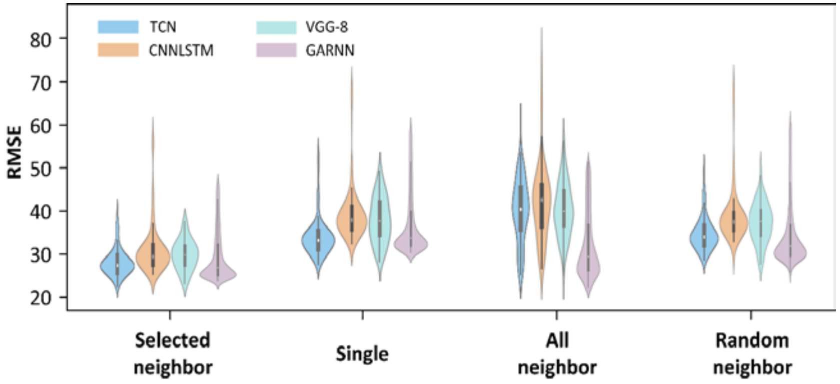
Blending methods	Forecasting RMSE	Forecasting bias
LR	52.39	-9.81
RF	50.57	-13.79
SVR	50.96	4.97
MLP	54.42	-2.33
LSTM	48.01	1.52
TCN	**43.17**	**0.47**

Reference : Li, Yiyan, et al. "A TCN-based Spatial-Temporal PV Forecasting Framework with Automated Detector Network Selection." arXiv preprint arXiv:2111.08809 (2021).

3. Case study _ data-driven model (1h ahead)

- Tested on 95 PV sites in NC state for 1h ahead forecasting
- 4 neighbor selection strategies are compared
- 4 deep-learning based spatial-temporal forecasting methods are tested
- TCN with selected neighbors yields the best performance

Example of physics-based model forecasting results



STATISTICS OF THE 1-HOUR AHEAD FORECASTING RMSE ON 95 PV SITES

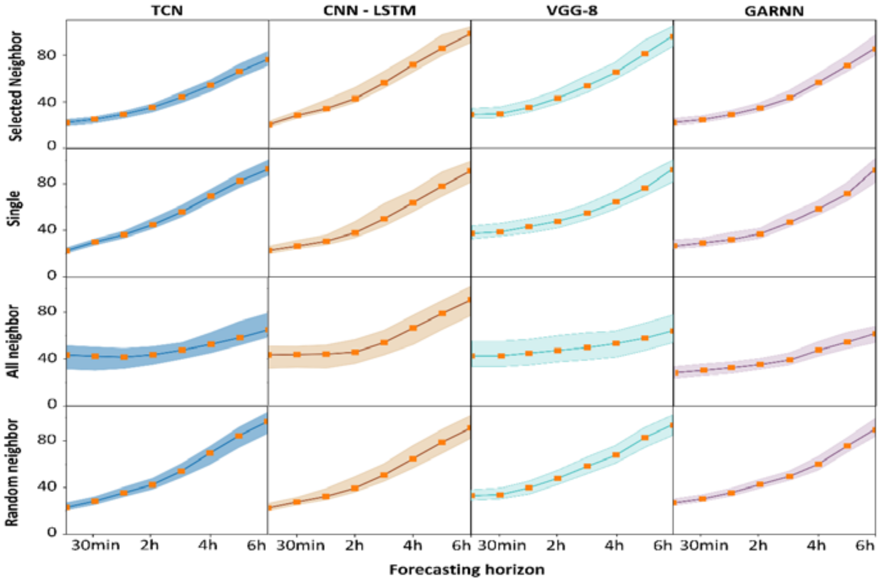
Scenarios	Evaluation Metrics	TCN	CNN-LSTM	VGG-8	GARNN	Average
Selected neighbors	Media	27.53	29.11	29.50	27.60	**28.44**
	IQR	4.78	5.65	4.77	8.41	**5.90**
Single site	Media	33.41	38.29	37.95	33.98	35.91
	IQR	3.92	6.84	9.08	7.22	6.77
All sites	Media	40.18	43.02	40.01	29.20	38.10
	IQR	11.77	10.55	8.56	10.59	10.37
Random neighbors	Media	34.05	37.88	37.91	31.96	35.45
	IQR	5.11	6.72	5.93	9.21	6.74

Reference: Li, Yiyan, et al. "A TCN-based Spatial-Temporal PV Forecasting Framework with Automated Detector Network Selection." arXiv preprint arXiv:2111.08809 (2021).

3. Case study _ data-driven model (varying forecasting horizon)

- Further tested for different forecasting horizons: 5min – 6h
- TCN with selected neighbors has best performance and computation efficiency

Forecasting results under different forecasting horizon



FORECASTING PERFORMANCE EVALUATION (AVERAGED ON 95 SITES)

Scenarios	Evaluation Metrics	TCN	CNN-LSTM	VGG-8	GARNN
Selected neighbors	RMSE	**39.80**	51.88	48.52	43.81
	CI-90%	**10.37**	15.81	16.25	10.89
Single site	RMSE	**52.86**	55.80	61.77	56.71
	CI-90%	**11.67**	18.00	15.03	12.66
All sites	RMSE	49.92	57.74	54.30	**42.15**
	CI-90%	17.84	23.33	25.69	**14.52**
Random neighbors	RMSE	54.60	52.26	58.11	**49.77**
	CI-90%	13.96	16.07	15.22	**11.33**
Average computation time		**≈ 6min**	≈ 22min	≈ 31min	≈ 164min

Reference: Li, Yiyan, et al. "A TCN-based Spatial-Temporal PV Forecasting Framework with Automated Detector Network Selection." arXiv preprint arXiv:2111.08809 (2021).

Approach 2: spatial-temporal PV forecasting

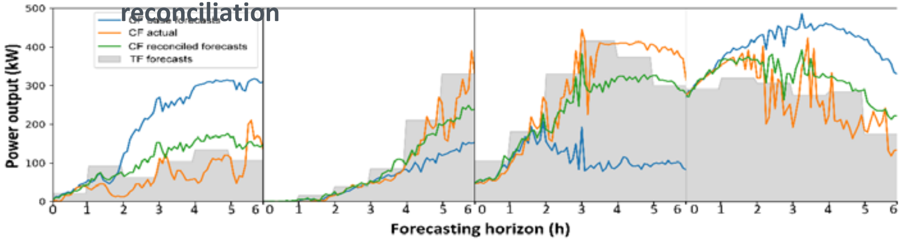
3. Case study _ forecasting results reconciliation

- Reconciling forecasts from the two models can correct trend errors , especially after 2 hours.

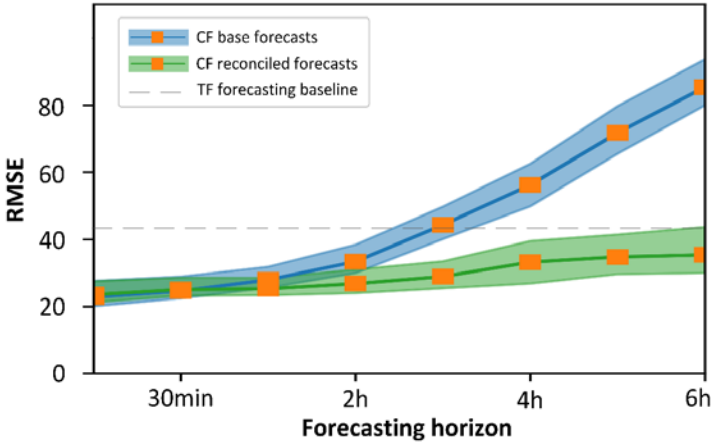
AVERAGE FORECASTING RMSE BEFORE AND AFTER RECONCILIATION

Forecasting horizon	5min	30min	2h	4h	6h	Average
Before reconciliation	**27.60**	**30.55**	35.07	52.13	79.64	45.00
After reconciliation	28.30	30.68	**32.71**	**36.84**	**38.07**	**33.22**
Improvement	-2.54%	-0.43%	6.73%	29.33%	52.20%	25.95%

Examples of forecasting results before and after reconciliation



Error distribution on different forecasting horizons



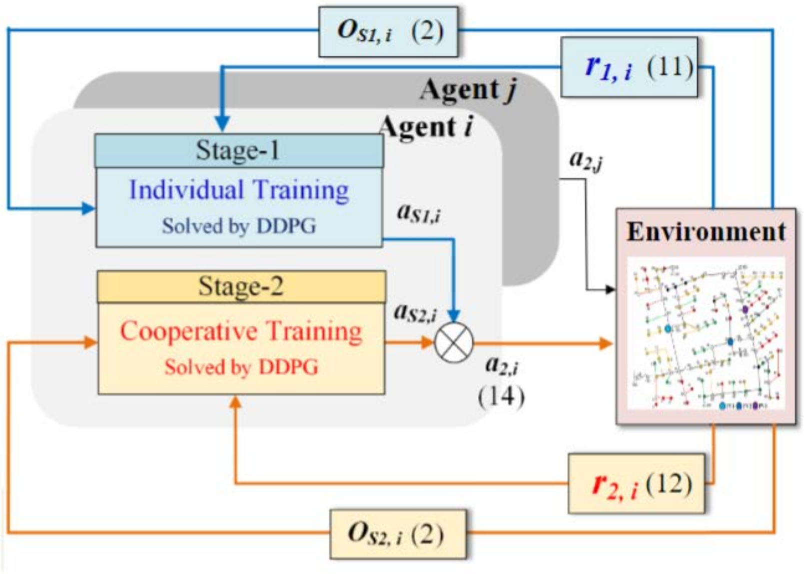
Reference : Li, Yiyan, et al. "A TCN-based Spatial-Temporal PV Forecasting Framework with Automated Detector Network Selection." arXiv preprint arXiv:2111.08809 (2021).

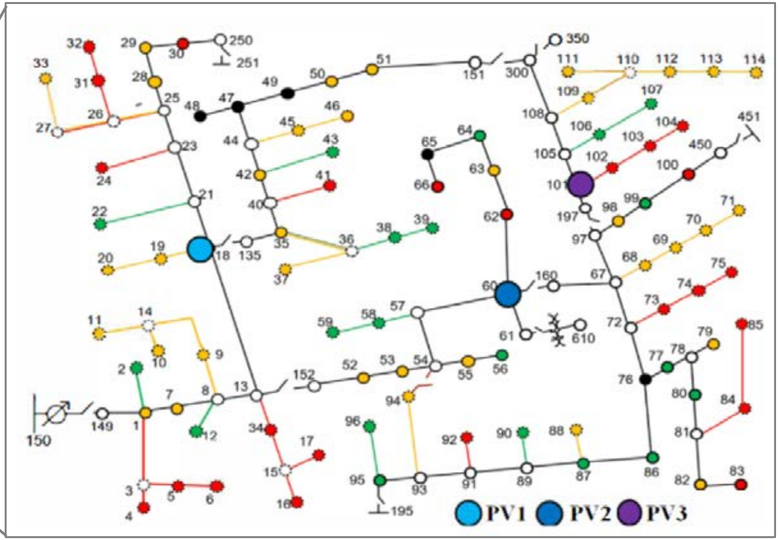
Part 3: Reinforcement Learning based Volt/var Control

2-Stage Learning Process

Stage-1: **Individual training** - learn to react to voltage drops properly

Stage-2 Cooperation among – learn to share the response with the other PV controllers





Si Zhang, Mingzhi Zhang, Rongxing Hu, David Lubkeman, Yunan Liu, and Ning Lu, "*Reinforcement Learning for Volt-Var Control: A Novel Two-stage Progressive Training Strategy*," Proceeding of the 2022 PES General meeting, Denver, USA, 2022

Stage 1: Individual Training

$$Cost_i = w_{cost} \times |Q_i^t|$$

$$r_{1,i} = r_s - Cost_i + r_{DN}$$

Reward need to consider the cost of taking action

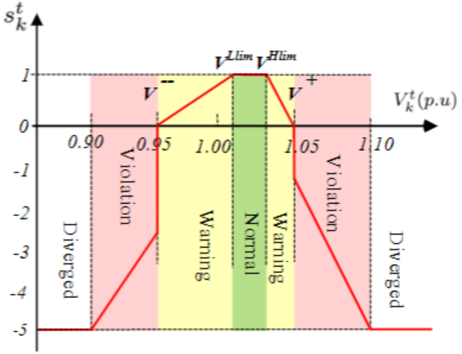
$$r_s = Score_A^{AS} - Score_{DN}^{AS}$$

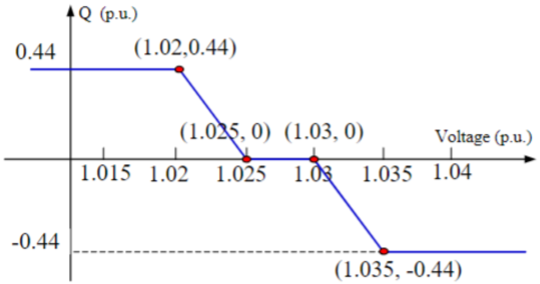
$$r_{DN} = \begin{cases} 10^{-3}, & |a_i^t| \leq a^{th} \\ 0, & otherwise \end{cases}$$

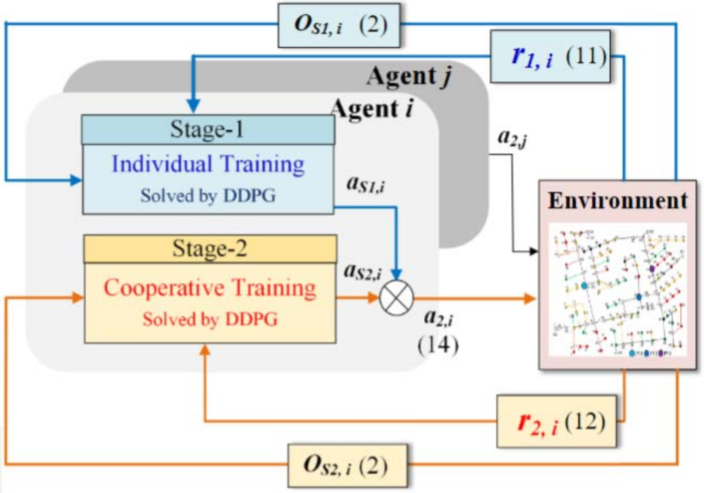
Do nothing is a good strategy

$$Score_A^{AS} = \frac{1}{M}\sum_{k=1}^{M} s_k^t,$$

$V_k^t(p.u)$	s_k^t
$[V^{\mathrm{Llim}}, V^{\mathrm{Hlim}}]$	1.0
$[V^{\mathrm{Hlim}}, V^{+}]$	$\frac{1.05-V_k^t}{1.05-V^{\mathrm{Hlim}}}$
$[V^{-}, V^{\mathrm{Llim}}]$	$\frac{V_k^t-0.95}{V^{\mathrm{Llim}}-0.95}$
[1.05, 1.10]	$\frac{5\times(V_k^t-V^{\mathrm{Hlim}})}{V^{\mathrm{Hlim}}-1.10}$
[0.90, 0.95]	$\frac{5\times(V^{\mathrm{Llim}}-V_k^t)}{0.9-V^{\mathrm{Llim}}}$
$[1.10, +\infty]$	-1×5
$[-\infty, 0.90]$	-1×5







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Stage 2: Cooperative Training

- Reward allocation
- Goal: decide action magnitude for cooperation

Reward need to be shared properly among agents to know who will take more/less actions

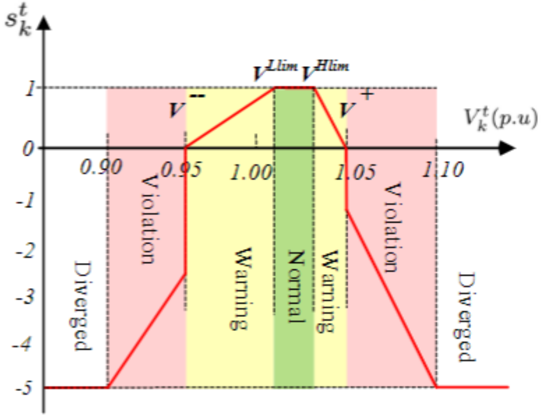
$$r_{2,i} := CF_i \times r_s - Cost_i$$

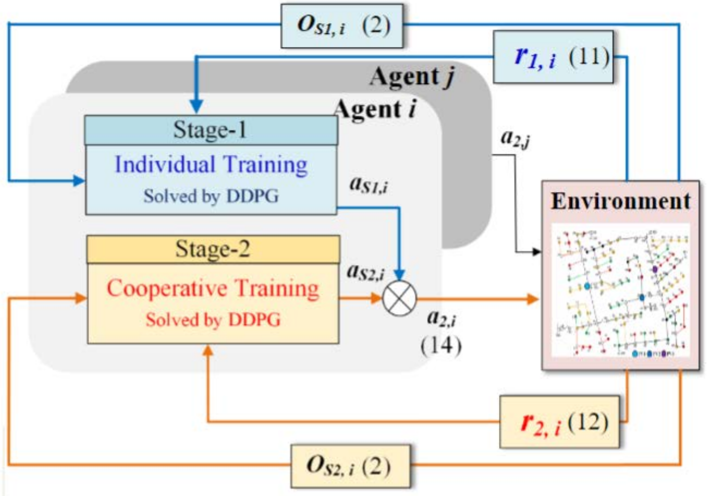
$$a_{2,i} := sign(a_{S_1,i}) \times \mathbb{1}(|a_{S_1,i}| > a_{th}) \times a_{S_2,i},$$

$$Score_A^{AS} = \frac{1}{M}\sum_{k=1}^{M} s_k^t,$$

$$CF_i := \frac{|Q_i^t|}{\sum_{j=1}^{N}|Q_j^t|}$$

$V_k^t(p.u)$	s_k^t
$[V^{\mathrm{Llim}}, V^{\mathrm{Hlim}}]$	1.0
$[V^{\mathrm{Hlim}}, V^{+}]$	$\frac{1.05-V_k^t}{1.05-V^{\mathrm{Hlim}}}$
$[V^{-}, V^{\mathrm{Llim}}]$	$\frac{V_k^t-0.95}{V^{\mathrm{Llim}}-0.95}$
$[1.05, 1.10]$	$\frac{5\times(V_k^t-V^{\mathrm{Hlim}})}{V^{\mathrm{Hlim}}-1.10}$
$[0.90, 0.95]$	$\frac{5\times(V^{\mathrm{Llim}}-V_k^t)}{0.9-V^{\mathrm{Llim}}}$
$[1.10, +\infty]$	-1×5
$[-\infty, 0.90]$	-1×5





Si Zhang, Mingzhi Zhang, Rongxing Hu, David Lubkeman, Yunan Liu, and Ning Lu, "*Reinforcement Learning for Volt-Var Control: A Novel Two-stage Progressive Training Strategy*," Proceeding of the 2022 PES General meeting, Denver, USA, 2022

Part 3: Conclusion

Conclusions

- High-fidelity Digital Twins are important for developing new grid support functions
  - **Benefits:** compared with field tests, testing on digital twins are safer, cheaper, faster, and scalable
  - **Challenges**: Data requirements are high (require realistic network topologies; require PV and load data sets for populating the network models; require manufacture data sheets; require field tests for benchmarking the model dynamic responses; ….)
- **Challenges** for Developing Machine Learning Applications:
  - **High-fidelity**
    - Data scarcity → are the result representative?
    - Visual inspections is not sufficient to tell fake/real → How to evaluate realisticness?
  - **Trustworthy** applications
    - Explainable, repeatable, and replicable (especially if we need to take actions)
    - Human-machine interface (when, how often, and who)
    - Eliminate bias in data sets (e.g., data availability is geographically, demographically uneven)
    - Cyber security considerations
  - **Open sources** to accelerate the development

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Publications: https://sites.google.com/a/ncsu.edu/ninglu/mypublicatons?authuser=0

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