Synthesis of Realistic Load Data: Adversarial Networks for Learning and Generating Residential Load Patterns

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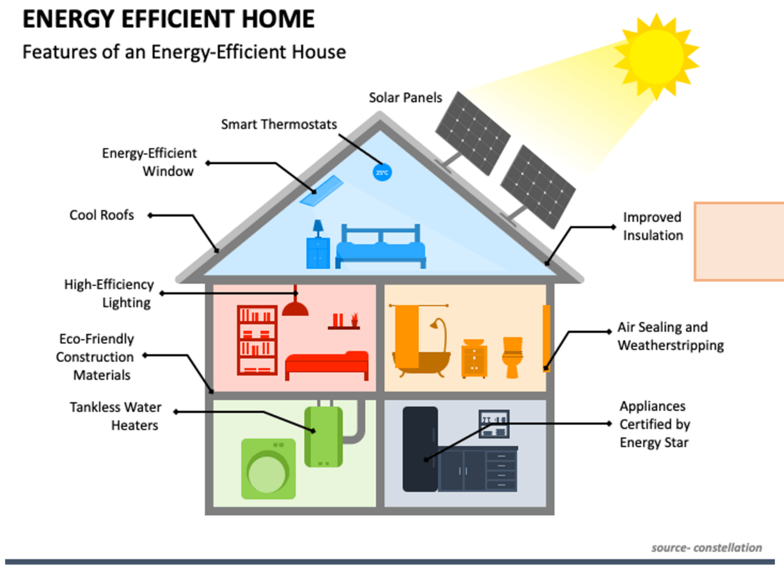
The important role of residential consumers in combating climate change

Residential energy use accounts for roughly 20% of greenhouse gas (GHG) emissions in the U.S



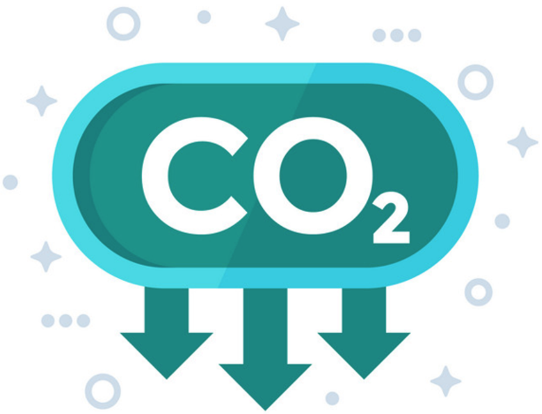
Understanding of residential electricity consumption

Responsible Energy Consumption

Energy saving

Energy efficiency upgrades

Increase renewable utilization via demand response



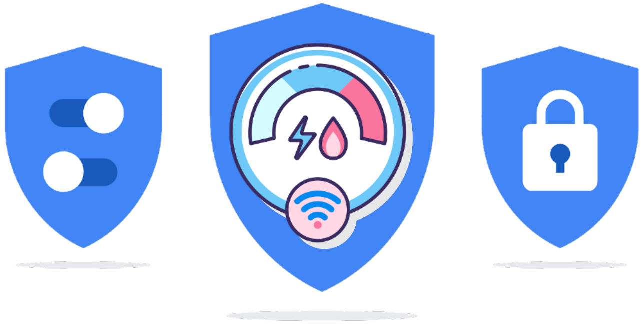
Reduce CO2 emissions

Importance of Residential Load Data

- Load Profiling
- Load Forecasting
- Demand Response
- ...

Barriers to Accessing High-Quality Residential Load Data

Time consuming and cost intensive
load data collection process



Privacy concerns for load data sharing

Lack of residential sector load dataset

Generating Residential Load Data - Related Works

Top-down Approach	Bottom-up Approach
Pros: Easy to model and scale with low computational cost	**Pros:** Able to generate diverse synthetic data with no information loss
Cons: Suffer from low diversity problems	**Cons:** Hard to scale up and be widely applied
Existing Works: • J. Dickert et al., IEEE Trondheim PowerTech 2011. • R. Subbiah et al., IEEE ISGT 2013. • T. Ding et al., 2016 IEEE Transactions on Smart Grid. • A. Marszal-Pomianowska et al., Energy 2016. • C. Klemenjak, et al. Scientific data 2020.	**Existing Works:** • G. Valverde et al., IET generation, transmission & distribution 2012. • W. Labeeuw et al., IEEE Transactions on Industrial Informatics 2013. • T. Zufferey et al., IEEE PSCC 2018. • Y. Gu et al., IEEE ISGT 2019.

RLPGen: Residential Load Pattern Generation Method

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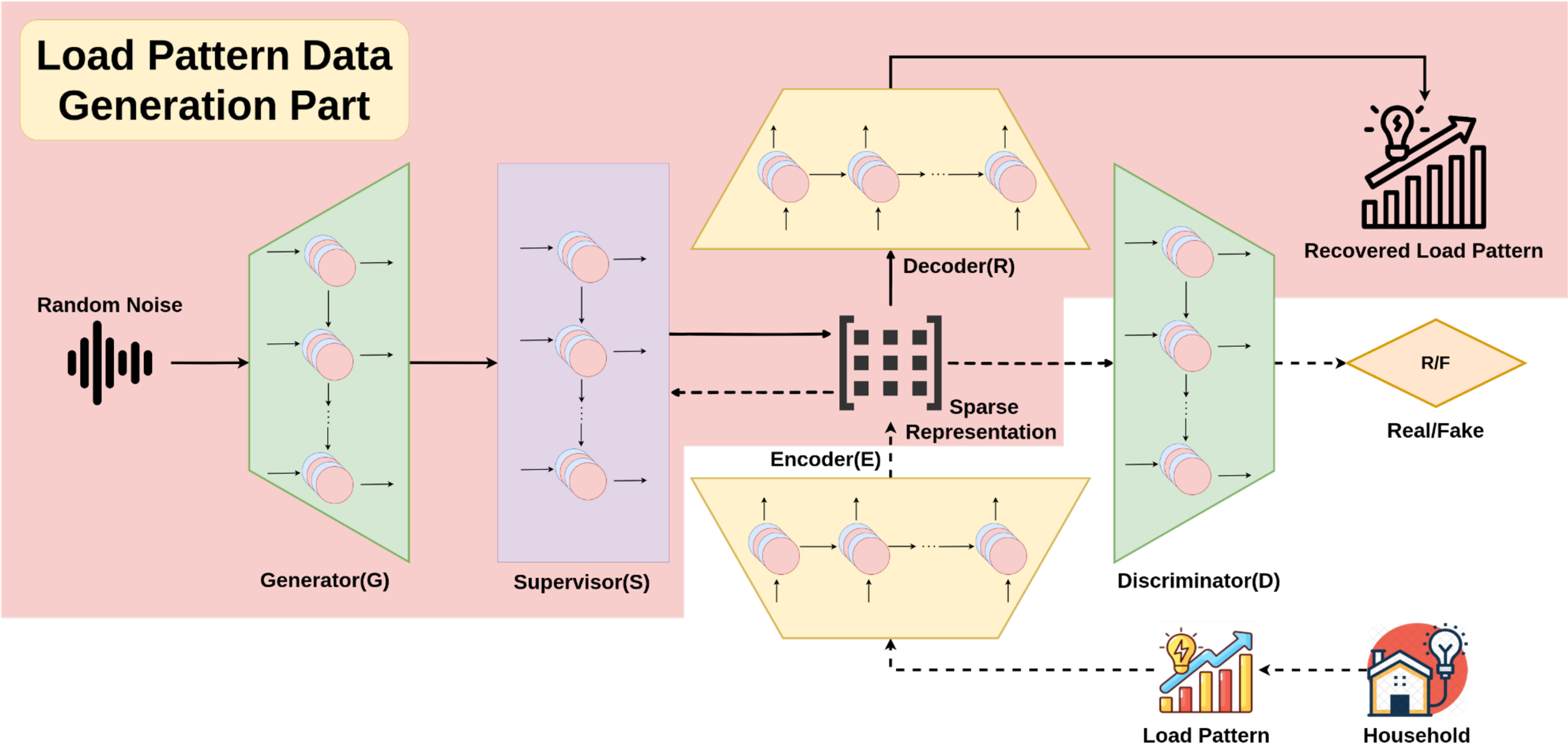
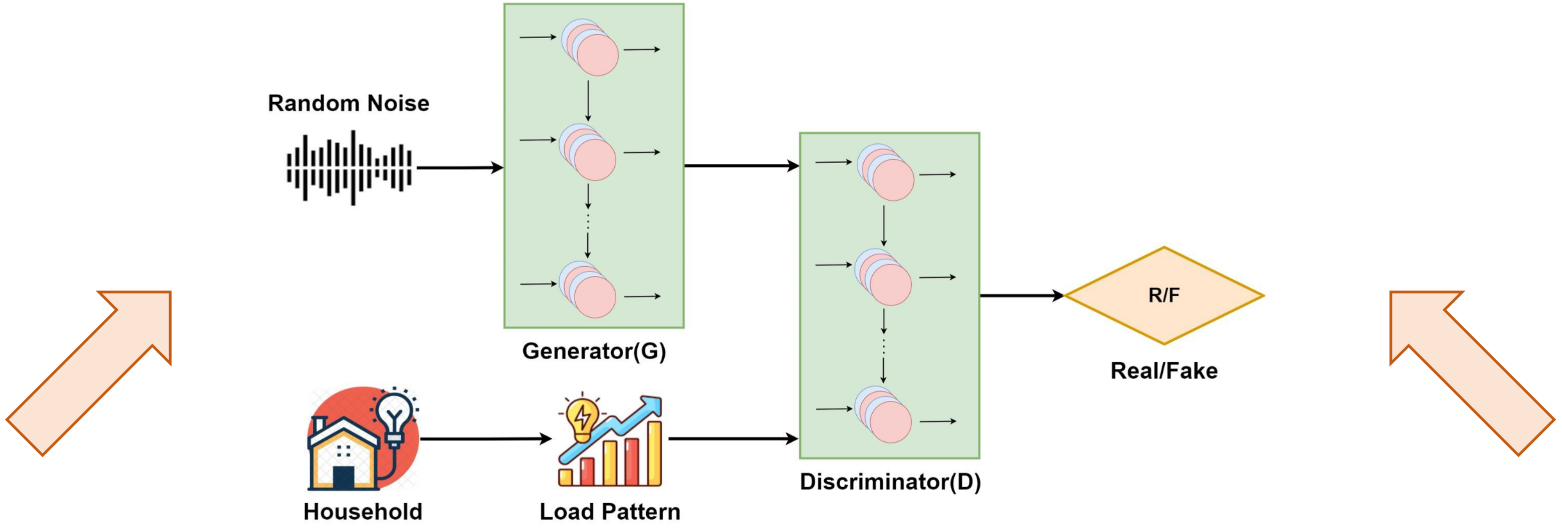
LSTM-based GAN model utilizing weakly-supervised training method



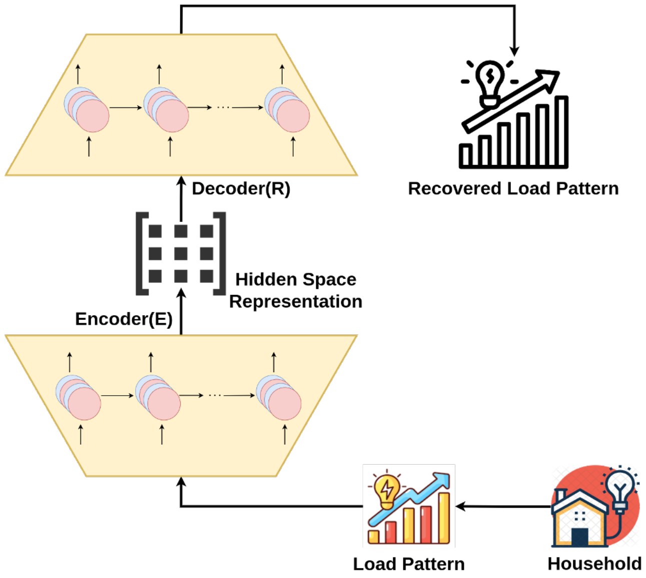
Model weight selection method for generator

$$D^2_{Frèchet}(X_{real}, X_{fake}) = \left|\mu_{X_{real}} - \mu_{X_{fake}}\right|^2 + tr\left(\Sigma_{X_{real}} + \Sigma_{X_{fake}} - 2\left(\Sigma_{X_{real}}\Sigma_{X_{fake}}\right)^{\frac{1}{2}}\right)$$

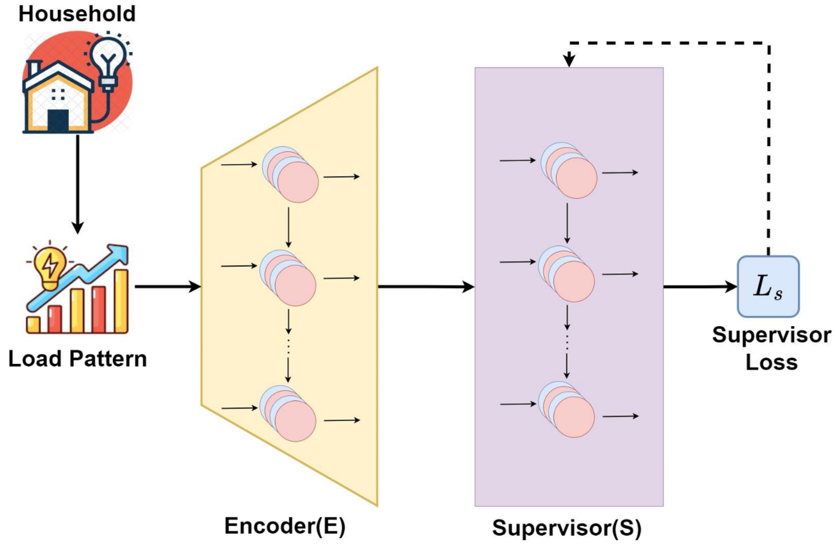
Model Structure With Weakly-Supervised Training



Standard GAN

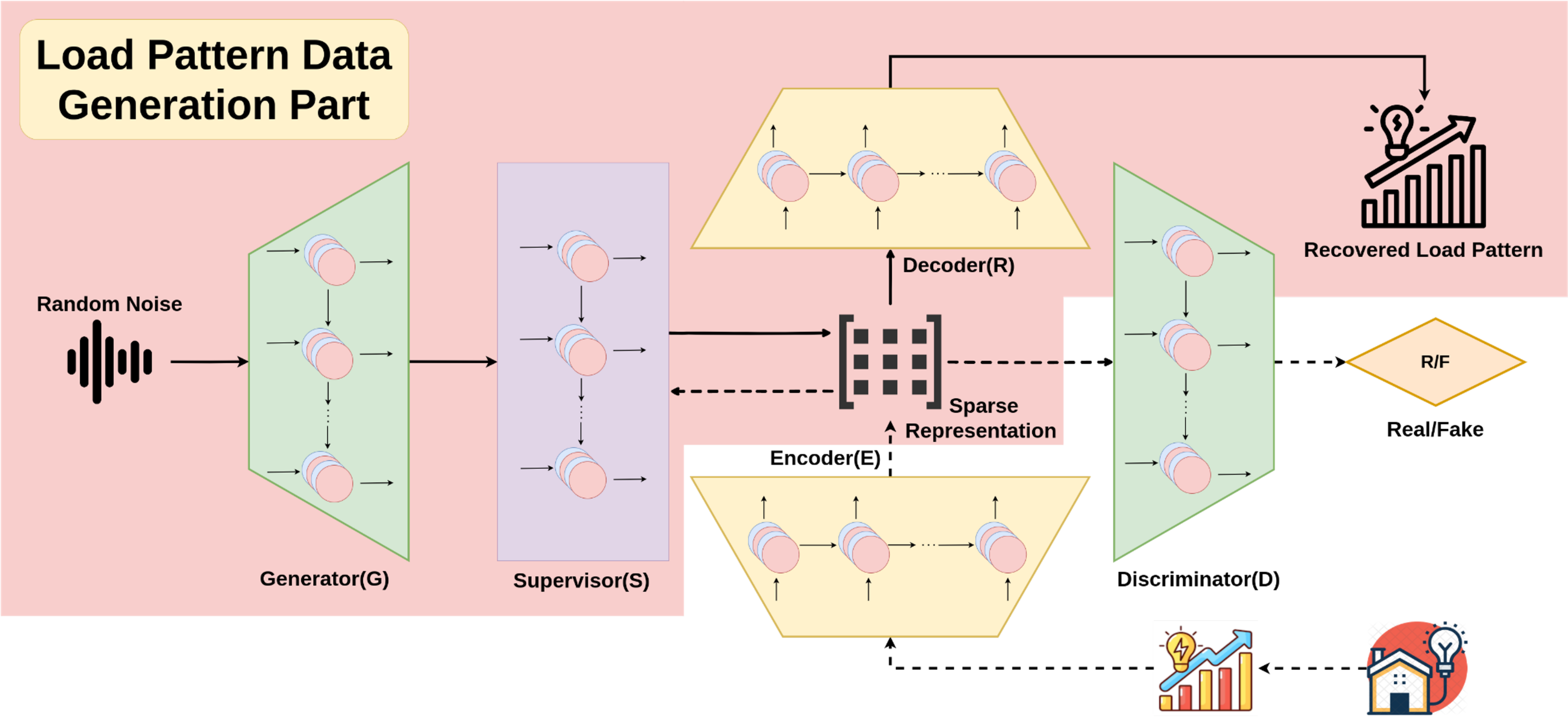


Step 1: Overcomplete Autoencoders Training



Step 2: Supervisor and Supervised Training

Model Structure With Weakly-Supervised Training



Step 3: Joint Training

Weight Selection Method

$D^2_{Frèchet}$: Fréchet distance between two multivariate Gaussian distributions

$$D^2_{Frèchet}(X_{real}, X_{fake}) = \left|\mu_{X_{real}} - \mu_{X_{fake}}\right|^2 + tr\left(\Sigma_{X_{real}} + \Sigma_{X_{fake}} - 2\left(\Sigma_{X_{real}}\Sigma_{X_{fake}}\right)^{\frac{1}{2}}\right)$$

X_{real} : load pattern samples from original dataset

X_{fake} : load pattern samples from generated dataset

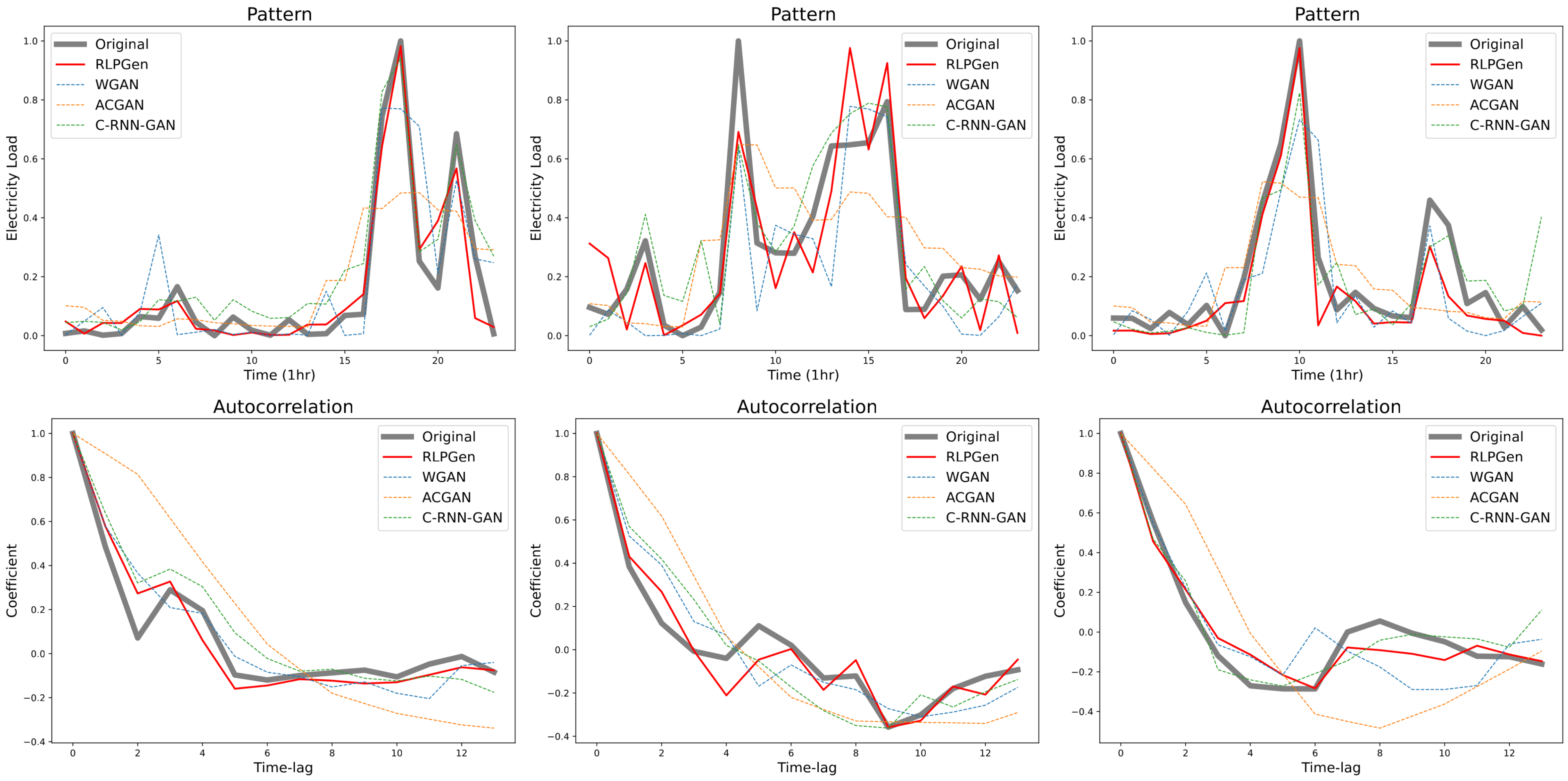
$\mu_{X_{real}}$: mean of load pattern samples from original dataset

$\mu_{X_{fake}}$: mean of load pattern samples from generated dataset

$\Sigma_{X_{real}}$: covariance matrices of load pattern samples from original dataset

$\Sigma_{X_{fake}}$: covariance matrices of load pattern samples from generated dataset

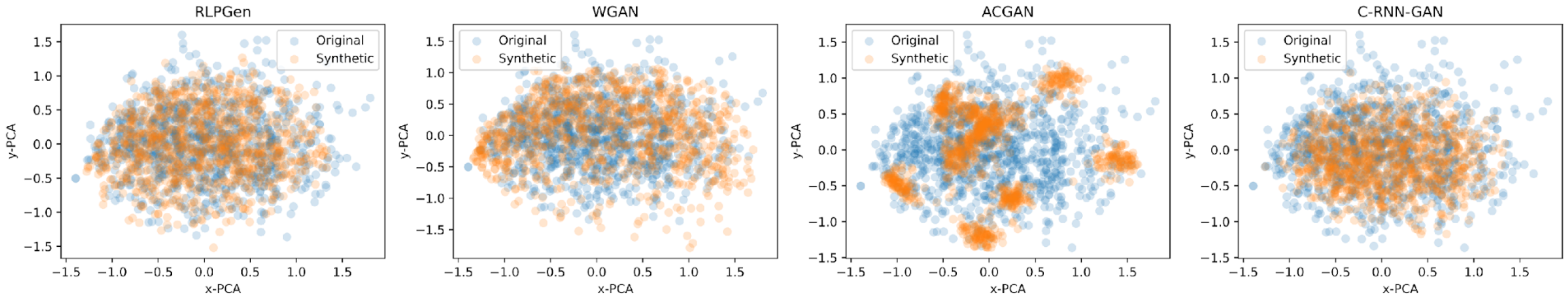
Results



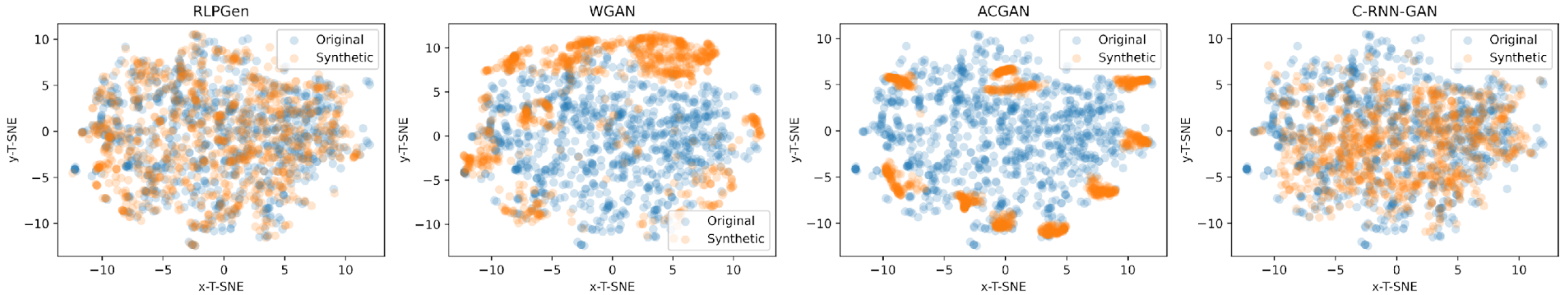
Pattern
Pattern
Pattern
Original
RLPGen
WGAN
ACGAN
C-RNN-GAN
Electricity Load
Time (1hr)
Autocorrelation
Autocorrelation
Autocorrelation
Coefficient
Time-lag

Results

PCA Visualization



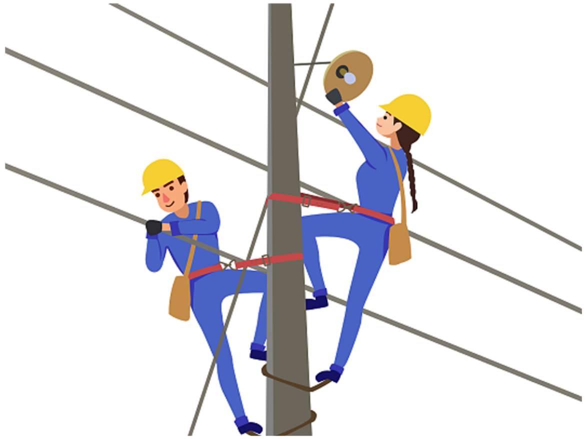
T-SNE Visualization



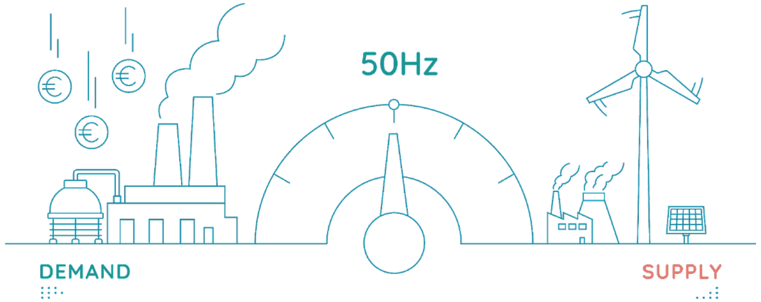
Distance Measuremen	**RLPGen**	ACGAN	WGAN	C-RNN-GAN
J-S Distance	**0.00770**	0.18363	0.05576	0.04277
RMSE	**0.03522**	0.56700	0.26113	0.19247

Pathway to Impact

Grid Planning



Grid Construction



Demand Response

Utilization of Renewable Energy

Response consumption and production

Contact Us

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