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

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Abstract

Responsible energy consumption plays a key role in reducing carbon footprint and CO2 emissions to tackle climate change. A better understanding of the residential consumption behavior using smart meter data is at the heart of the mission, which can inform residential demand flexibility, appliance scheduling, and home energy management. However, access to high-quality residential load data is still limited due to the cost-intensive data collection process and privacy concerns of data sharing. In this paper, we develop a Generative Adversarial Network (GAN)-based method to model the complex and diverse residential load patterns and generate synthetic yet realistic load data. We adopt a generation-focused weight selection method to select model weights to address the mode collapse problem and generate diverse load patterns. We evaluate our method using real-world data and demonstrate that it outperforms three representative state-of-the-art benchmark models in better preserving the sequence level temporal dependencies and aggregated level distributions of load patterns.

1 Introduction

Residential energy use accounts for roughly 20% of greenhouse gas (GHG) emissions [11] in the United States. Responsible energy consumption promotes energy saving, energy efficiency upgrades, and consuming more renewable energy when available, thus reducing carbon footprint and CO2 emissions to tackle climate change. Load profiling, load forecasting and demand response can be performed by analysing residential load data [1, 3, 23, 30] so that the industry can better understanding the residential consumption behavior to greatly inform responsible energy consumption [14]. However, due to the cost-intensive data collection process and privacy concerns of data sharing, the lack of access to diverse and high-quality residential load data becomes a barrier to enabling responsible energy consumption [12, 15, 22].

A lot of effort has been made to study the modeling and generation of residential load to overcome the aforementioned challenges due to the lack of access to residential load data. One category of studies [7, 8, 16, 20, 25] followed a bottom-up approach where individual appliances' electricity consumption is modeled first and then aggregated to model and generate load data at a household level. Household-level load data can be further aggregated to a group level. Bottom-up approaches are able to generate diverse synthetic data. However, intrusive sensors are often required during the

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data collection process, which is costly and time-consuming, making bottom-up approaches hard to scale up and be widely applied. The other category of studies [17, 26, 31] followed a top-down approach where the residential load is modeled and generated at the household level directly, for example, using Gaussian Mixture Model or Markov Chain Model. Recently, Generative Adversarial Network (GAN) has attracted much attention for generating synthetic energy data. Gu et al. [13] proposed a conditional GAN-based generative model using the Auxiliary Classifier GAN [21] for residential load data generation, which is promising for the low cost and high scalability. However, residential load data can be very diverse because of various housing properties and lifestyles of energy users. Most results generated using the top-down approaches suffer from low diversity problems.

To overcome the challenges of GAN-based methods, we develop a novel Residential Load Pattern Generation method (called RLPGen). Our method can better capture the time dependencies within the daily load patterns and generate diverse load data reflecting different lifestyles. We evaluate our method's performance against three representative benchmarks using real-world data. Our method outperforms all the benchmarks by achieving higher similarity to the real data and better diversity within the generated load patterns.

2 Data Description

We use real-world data from the Pecan Street database [24] to train and evaluate our RLPGen method. This database contains smart meter data of hourly load recordings (in kWh). After data cleaning, we obtain the hourly load data of 417 households from Jan. 1, 2017 to Dec. 31, 2017. In our work, we focus on load patterns using normalized hourly smart meter data and develop a novel method (presented in Section 3) to generate diverse daily load patterns reflecting all kinds of real-world consumption behaviors. For our future works, a more comprehensive comparison including non-GAN and non-ML based method can be conducted and further extension can be done on our approach to perform residential load demand data generation.

3 Methodology

As existing top-down methods can hardly capture diverse load patterns across various households, whiles existing bottom-up methods are not suitable to overcome the load data shortage and privacy concerns of load data collection, we develop an LSTM-based GAN model along with the weight selection method to learn and generate residential load patterns. Inspired by TimeGAN [28], we 1) introduce autoencoders in the model allowing adversarial training at the hidden space level, and 2) perform weakly-supervised training for finer control over temporal dynamics. We use LSTM units across the model to improve the ability of learning time-series load data. We present the detailed model design and implementation as follows.

3.1 Model Design With Weakly Supervised Adversarial Training

Suggested in TimeGAN framework [28] and several other studies [10, 18, 19] adopting autoencoders with GAN to perform adversarial training with the trained representation can improve learning similarity measure, inference efficiency, and generative capability during adversarial training. As shown in Figure 1, we integrate an over-complete autoencoder into the standard GAN, where the encoder (E with weight parameters θ_E) encodes the original load pattern into a sparse representation (h) in the hidden space, and the decoder (R with weight parameters θ_R) recovers the hidden representation back to the load pattern format. This approach allows the data generation to be performed in a more feature-rich hidden space so that the diverse household level load pattern can be more efficiently captured. The encoder and decoder will be trained in the first step of model training by updating θ_E and θ_R using the recovery loss (L_r), e.g., the mean square error of the estimated load patterns.

Relying solely on the feedback from the discriminator is not sufficient enough to help the generator capture the stepwise conditional distributions in the data. Hence, a supervisor unit (S with weight parameters θ_S) is employed following the generator (G with weight parameters θ_G) as an additional step to finely adjust the temporal dynamics of the output sequence of the generator to form a two-step data generation process. The supervisor will be pre-trained in a supervised manner in the second step of the model training, where part of the hidden representation will be taken as the input for the

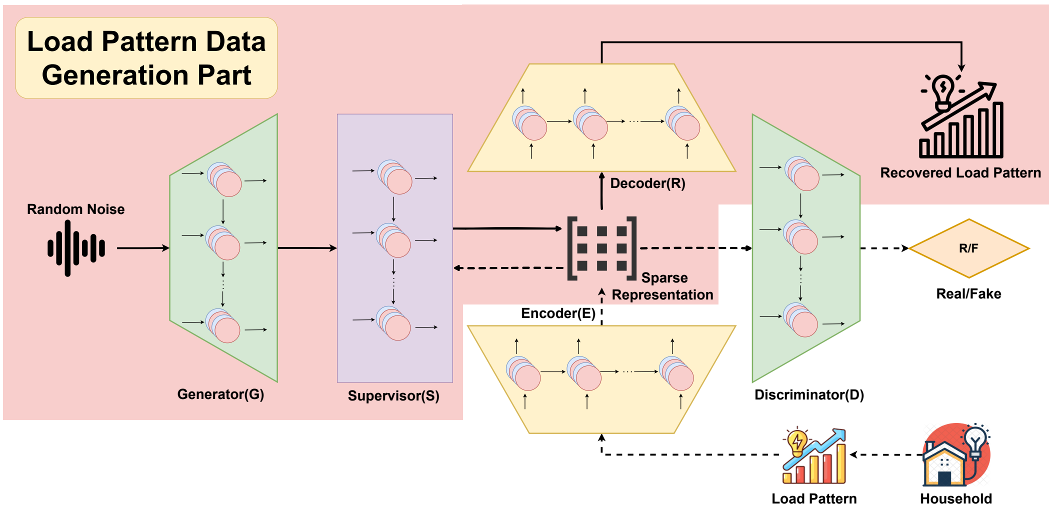

Figure 1: Model structure of RLPGen. The dashed arrow represent inference in training process only and solid arrow represent inference in both training and generation process.

supervisor to predict the one-step ahead value. The supervisor loss (L_s) is calculated using MSE of the predicted one-step ahead value to update θ_S.

The discriminator (D with weight parameters θ_D) and the generation process (i.e., generator with supervisor) are trained against each other to perform the adversarial training in the feature-rich hidden space. The sparse representation can ensure that the complex and diverse structure of the load pattern can be better reflected, which is more suitable for the top-down approach to residential load pattern generation. During the third step of the training process, the standard adversarial loss (L_a) will be calculated to update θ_G, θ_S and θ_D, where a standard adversarial training of GAN is performed.

3.2 Model Weight Selection

The GAN training process can be unstable and suffer from mode collapse problems (i.e., consistently generating data with low diversity regardless of the generator input) if overtrained [2]. However, the quality of generated load pattern can hardly be fully reflected by the generator loss only. Hence, we incorporate a model weight selection method by choosing the model weight with the lowest measured distribution distance between the real and generated data. We assume the load pattern data follow a multivariate Gaussian by only considering the mean and covariance. We adopt the method in [9] to calculate the Fréchet distance using

$$\mathcal{D}^2_{Fr\acute{e}chet} = ||\mu_{X_{real}} - \mu_{X_{fake}}||^2 + tr\left(\Sigma_{X_{real}} + \Sigma_{X_{fake}} - 2\left(\Sigma_{X_{real}}\Sigma_{X_{fake}}\right)^{\frac{1}{2}}\right), \quad (1)$$

where X_{real} denotes load pattern samples from real dataset, X_{fake} denotes load pattern samples from generated dataset, $\mathcal{D}^2_{Fr\acute{e}chet}$ denotes the Fréchet distance between two multivariate Gaussian distributions with means $\mu_{X_{real}}$ and $\mu_{X_{fake}}$ and covariance matrices $\Sigma_{X_{real}}$ and $\Sigma_{X_{fake}}$.

3.3 Evaluation Methods

We validate our RLPGen method using the real-world data presented in Section 2. To evaluate the generated results, we develop a set of comprehensive evaluation methods to measure the generated data with two criteria: diversity and similarity. Our evaluation methods can address the two criteria at both sequence level (i.e. evaluate individual load data sequence) and aggregated level (i.e. aggregate all load data sequences in the dataset and evaluate the mean profile). We visually compare the difference between load patterns along with their auto-correlation by selecting real and fake sample sets with the minimum Euclidean distance, and dimension-reduced data points (i.e., perform dimension reduction using PCA [4], and T-SNE [27]) across the original and generated datasets to evaluate the framework performance at the sequence level. We further calculate distances, such as root mean square error (RMSE) and Jenson-Shannon distance (J-S) between the mean profile of generated and original load pattern samples to evaluate the model performance at the aggregated level.

4 Results and Discussions

To compare with our method, we select three state-of-the-art benchmark models, including ACGAN, WGAN, and C-RNN-GAN. These methods have been adopted to solve similar problems, such as time-series data generation. All selected benchmark models are considered to be good representations of different types of GAN models (with details discussed in the Supplementary section).

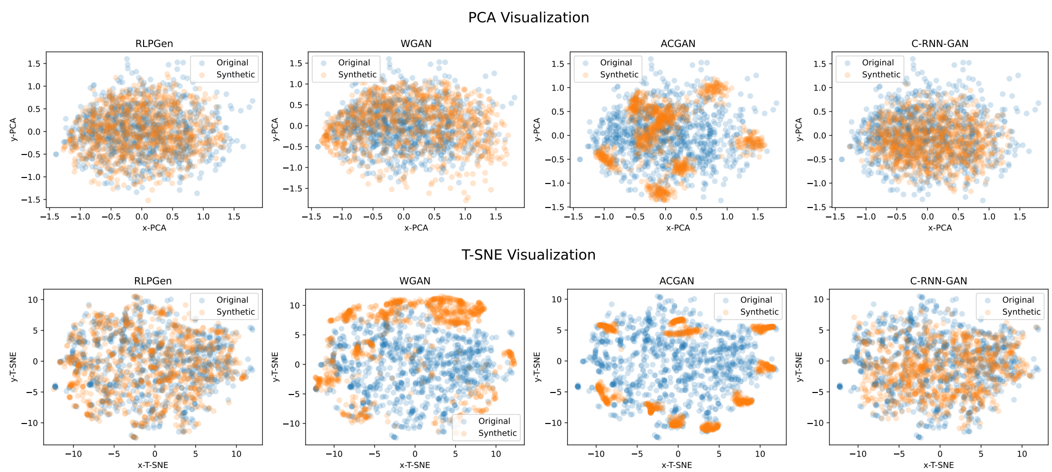

Figure 2: Similarity and Diversity comparisons using dimension reduction data visualization technique. The top four plots use PCA and the bottom four plots use T-SNE.

As shown in Figure 2, all the tested models are able to capture certain levels of temporal correlation and data distributions from original data. However, our RLPGen method is more capable of generating residential load patterns with well-retained temporal feature correlation against original data while still being able to capture the diverse patterns from real-life load patterns. Data points generated by our RLPGen method are significantly more diverse than the two CNN-based GAN models (i.e., WGAN and ACGAN) and achieve better coverage than the other RNN-based model (i.e., C-RNN-GAN). Our method achieves a considerable amount of performance gain against the other three benchmark models, by achieving the lowest distance from the original samples, as shown in Table 1.

Table 1: Result of Distance Measurements.

Distance Measurement	**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

5 Conclusion

In this paper, we developed a comprehensive method called RLPGen to generate residential load patterns. Compare to existing methods, RLPGen has demonstrated significant improvement in generated load pattern data quality and can be further adapted as a promising method to produce representative household load patterns for different regions globally. The generated load pattern can help the field of research to better understand residential consumption and greatly inform utilization of renewable energy and responsible energy consumption. RLPGen method includes a GAN-based model with weakly-supervised training and a weight selection method that can effectively select generator weight with the highest quality of data generation while overcoming mode collapse issues. We validated the performance of RLPGen against three state-of-the-art models, including ACGAN, WGAN, and C-RNN-GAN, showing that RLPGen outperformed all the benchmarks.

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6 Supplementary

6.1 Details of Benchmark Models

The details of selected benchmark models are discussed as follows:

1. **Auxiliary Classifier Generative Adversarial Network (ACGAN)** is a specialized CNN-based GAN, which can perform data generation based on given class labels. Proposed by Gu [13] to pre-label all load data using K-Means Clustering and then perform training and generation using ACGAN, can further ensure the diversity of the model. Hence, we choose ACGAN as the baseline to compare with our framework, to assess both the capability of the CNN-based approach and the pre-clustering method.
2. **Wasserstein Generative Adversarial Network (WGAN)** uses Wasserstein distance to replace the original loss function in standard CNN based GAN to solve the mode collapse problem. Since existing energy related studies [5, 29] have also suggested to use CNN based GAN method to perform time series data generation, we choose WGAN as a representation used in our benchmarks to compare with the RNN-based models and pre-clustering method.
3. **Continuous RNN-GAN (C-RNN-GAN)** is an RNN-based GAN method. For the comparison purposes, we use LSTM units in the C-RNN-GAN model to compare the performance of LSTM-based GAN against CNN-based GAN and evaluate the performance differences by further incorporating overcomplete autoencoders and weakly-supervised training method.

The benchmark evaluation has been done under the following model training and data generation conditions:

1. To ensure all selected models are being evaluated under the same condition, we perform the model weight selection process for all selected models to generate the best possible benchmark result.
2. During the preprocessing before ACGAN model training, we carefully select the K value for K-Means clustering with the lowest Davies-Bouldin Index (DBI) [6] which evaluates the goodness of split of the clustering algorithm. In our study, DBI starts to stabilize when the K value reaches 10. Therefore, we choose K = 10 to perform K-Means clustering.
3. To ensure the distribution of original data can be accurately reflected, we generate the same number of data points as the sampled evaluation dataset from original load pattern data. For the ACGAN model, we further ensure the number of data points from each cluster stays the same as the sampled evaluation dataset.

6.2 Similarity comparison of selected original and generated sample sets

In this section, we provide the pattern plots along with the auto-correlation plots for similarity comparison. We randomly selected three typical load patterns from original data that can represent different household electricity consumption. The peak hours generally suggest the residents start to use appliances while during lower consumption periods the residents are more likely to rest or not at home. Figure 3(a) demonstrates 2 load peaks from 7:00 to 9:00 and 17:00 to 24:00, where the first peak period can reflect the time when the residents wake up and prepare for breakfast, and the second peak period at night matches with the time when residents go back home after work or school. In Figure 3(b), the electricity consumption peak starts from 12:00 until 20:00 which can potentially due to the residents are working in night shift so that the activities are concentrated during the afternoon and in the early evening. The third representative load pattern shown in Figure 3(c) demonstrates three peak periods in the morning, noon, and night which matches the preparation time of three meals.

In each figure, the matched generated load pattern samples are selected within the synthetic datasets generated using different models with the lowest Euclidean Distance. From the plot, we can see that patterns generated by our model are able to more accurately capture peaks within the daily load pattern shown in the pattern comparison graph and better retain temporal dynamics shown in the auto-correlation graph.

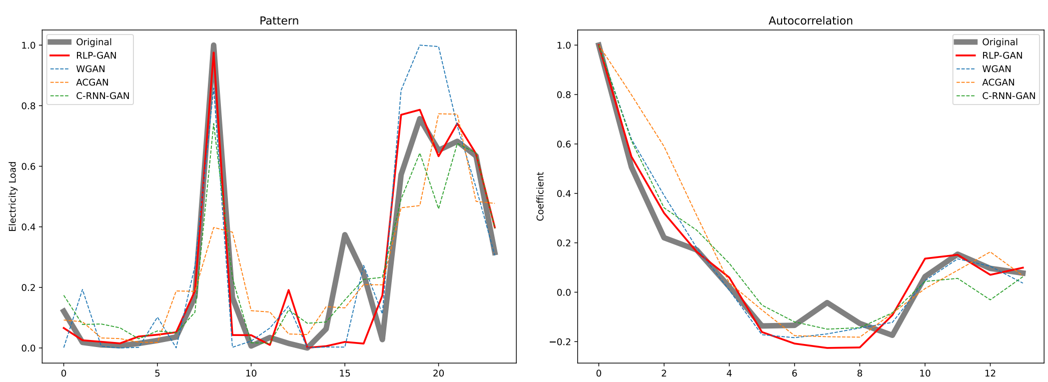

Figure 3(a): Representative load pattern 1.

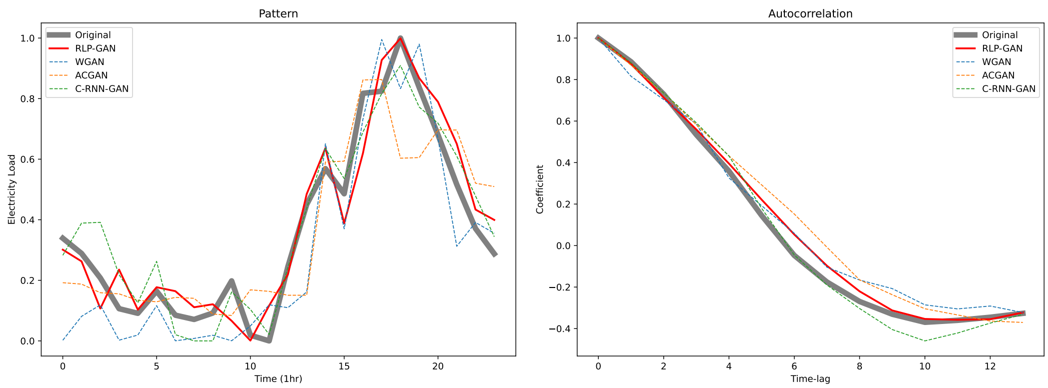

Figure 3(b): Representative load pattern 2.

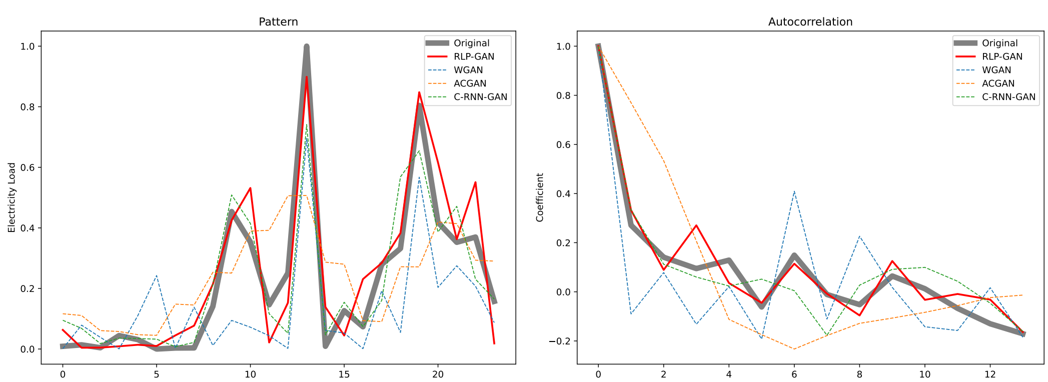

Figure 3(c): Representative load pattern 3.