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Opinion on enhancing diversity in photovoltaic scenario generation using weather data simulating by style-based generative adversarial networks

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1 Introduction

In 2023, the global installed capacity of photovoltaic (PV) power generation broke another record. The International Energy Agency recently released the 2023 annual report shows that last year, the global PV power generation new installed capacity of about 375 GW, an increase of more than 30 per cent (Szalóczy et al., 2024). Among them, China is the world's largest PV market and product supplier (Fu et al., 2024). However, the inherent intermittency and volatility of distributed PV power generation introduce considerable uncertainty, necessitating the modeling of PV scenarios to mitigate this uncertainty and support the growth of the PV industry. Among the various factors influencing PV output, weather conditions play a significant role in causing fluctuations and uncertainties in PV generation. However, the vast majority of the current PV scenario generation literature generates PV scenarios directly, which can overlook the important impact of weather on PV (Cai et al., 2023). To account for weather-related uncertainties and impose stricter physical constraints on PV power generation models, the PV scenario is modeled by simulating weather scenarios, enabling both specificity and generality in the models. Consequently, the development of a stochastic simulation model for year-round weather scenarios becomes essential to provide accurate weather information for PV power generation modeling (Rohani et al., 2014).

Current weather generation models mainly rely on mathematical approaches involving probabilistic calculations. The most common approach is to directly fit the distribution of weather data with probability distributions, such as sunlight intensity following a Beta distribution (Rathore et al., 2023) and wind speed following a Weibull distribution (Hussain et al., 2023). Li et la. proposed a two-stage scheme. In the first stage, weather sequences are simulated from a single-site multivariate weather generator, and in the second stage, the empirical Copula method is used to reproduce the inter-variable and inter-site dependencies as well as the temporal structure (Li et al., 2019). Richardson proposed WGEN based on a dynamic two-parameter Gamma distribution model and a two-parameter Beta distribution model (Richardson, 2018). WGEN is currently one of the widely used weather generator models, and many other weather generator models are developed based on improvements and extensions of WGEN, such as CLIGEN developed by the United States Department of Agriculture Agricultural Research Service. Sparks et al. proposed a novel method by transforming partial time series into an inferred linear function model, considering weather variables as Gaussian variables with temporal behavior (Sparks et al., 2018). Sun et al. utilized Copula for simulating multivariate joint distributions between observed and predicted weather variables, alongside Bayesian theory to derive conditional probability density functions for specific weather forecast scenarios, facilitating large-scale weather scenario generation (Sun et al., 2020). However, these probabilistic model-based approaches fail to fully capture the complexity of weather data.

In recent years, with the rapid advancements in artificial intelligence, deep learning has emerged as a pivotal technology in various domains, including electricity and agriculture (Fu and Zhou, 2023). Currently, several deep generative models tailored for time-series data have emerged to inform weather scenario generation. Yang et al. combined LSTM and Generative Adversarial Networks (GAN) to generate health time series data (Yang Z. et al., 2023). Li et al. fused transformer and GAN to ensure temporal consistency in generating time-series data (Li et al., 2022). Yi et al. utilized a diffusion model based on U-net with attention mechanism to generate time-series data, preserving frequency features (Yi et al., 2023). In PV scenario generation, Li et al. used a time series correlation evaluation mechanism and a GAN-based generator-assisted updating mechanism to generate PV scenarios with long and short time scale time series correlation (Li et al., 2023). Xu et al. used Deep Convolutional GAN (DCGAN) to generate high-accuracy PV scenario (Xu et al., 2023). Zhang et al. used Spectral Normalization GAN (SNGAN) to improve the training stability and generate PV scenarios with probabilistic characteristics. However, these methods primarily focus on preserving the temporal characteristics and uncertainty of the generated data, neglecting the diversity aspect. We believe that diverse weather data is crucial for generating PV scenarios and analyzing uncertainty in PV systems, enabling comprehensive performance simulation across various environmental conditions. This aids in optimizing the design and operational strategies of PV systems, enhancing their stability and reliability under diverse climate conditions. Hence, generating diverse weather data remains pivotal for weather generation in the context of power applications.

In recent years, style-based GAN (StyleGAN) has become a research and application hotspot due to its ability to ensure diversity in generated image data (Karras et al., 2020). Sauer et al. utilized StyleGAN to meet the specific requirements of large-scale text-to-image synthesis (Sauer et al., 2023). Xiong et al. utilized StyleGAN to achieve fast generation of high-quality 3D digital humans (Xiong et al., 2023). Yang et al. utilized StyleGAN to implement flipping and editing operations on real face images (Yang S. et al., 2023). StyleGAN excels at disentangling images, separating different image features in a hierarchical manner to generate images with diverse and realistic styles. In the context of weather scenario, we utilize style-based learning to enhance the level of refinement and granularity in weather simulations. Style-based learning enables the separation of various levels of image features (Karras et al., 2019). We believe that, in the case of weather data, it allows the matching of overall trend features and local random features, respectively. This allows for the generation of weather scenarios that capture the accurate overall trend while incorporating nuanced variations. However, style-based learning relies on convolutional neural networks (CNNs) for data processing, which may limit StyleGAN's ability to learn temporal features from weather data. To address this limitation, replacing the 2-dimensional CNNs in StyleGAN with 1-dimensional CNNs could better model the temporal characteristics of weather data.

2 Model for weather simulation

As shown in Figure 1, we present a novel stochastic simulation approach for generating year-round PV scenarios utilizing weather scenarios generated on Conditional Style-based Generative Adversarial Networks (C-StyleGAN). The weather scenarios consist of three variables, temperature, direct radiation and diffuse radiation, which are placed side by side during the training of the model to facilitate the neural network to learn the correlation between the variables. An increase in temperature causes a decrease in the power generation efficiency of the PV panels because high temperatures increase the resistance to electron flow within the PV panels. Direct radiation is the main source of energy for PV panels, while diffuse radiation affects the propagation path of light and indirectly affects the amount of radiant energy received by the PV panels. This method leverages real weather data as a foundation for simulating weather scenarios. The weather data generated using C-StyleGAN exhibits comprehensive diversity and effectively captures temporal correlations through active learning. The proposed method employs a Conditional Generative Adversarial Network (CGAN) as the primary framework, and the underlying neural network architecture is an enhanced version of the style-based Generative Adversarial Network (StyleGAN2). In Sections 2.1, 2.2, we will introduce the CGAN and the improved StyleGAN2, respectively. The generated PV scenarios can be obtained by inputting the temperature, direct radiation and diffuse radiation generated by C-StyleGAN into the PV model (Yano et al., 2009).

2.1 CGAN using weather features as labels

CGAN is the main framework of this model and provides the overall idea for the training and optimization of the model (Zhang et al., 2021).

In a GAN framework, the primary components are the generator and the discriminator. The objective of generator is to learn the underlying distribution $P_{ori}(w)$ of the real data by randomly sampling from real data. It takes a random noise $P_z(z)$ as input and converts it into a synthesized data $P_{gen}(\hat{w}\colon \theta)$ using a network parameter θ. The primary objective of the generator is to produce weather data samples that closely resemble real data, with the intention of deceiving the discriminator. On the other hand, the discriminator is a binary model responsible for distinguishing between the data samples. Its role is to classify the weather data samples, with the objective of labeling the generated weather data samples $P_{gen}(\hat{w}\colon \theta)$ by the generator as "false" and the real weather data samples $P_{ori}(w)$ as "true" to the best of its ability. In the training process, both the discriminator and the generator are trained using an adversarial approach. The generator's primary objective is to enhance its generation performance in order to deceive the discriminator, while the discriminator aims to improve its discrimination ability to accurately classify the weather data samples.

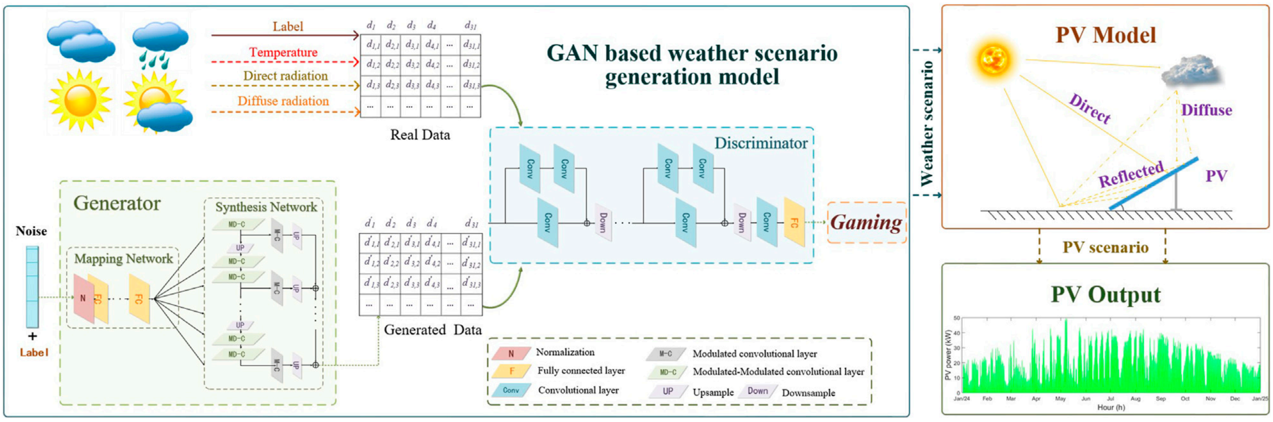

FIGURE 1
Conditional style-based generative adversarial networks model for weather simulation of PV scenario.

The training process of a GAN can be characterized as a minimax game, which is formulated as a value function $V(D,G)$ by Eq. 1. In this game, the objective is to maximize $V(D,G)$ with respect to the generator G, while minimizing the value function V with respect to the discriminator D. This minmax game provides a clear understanding of the GAN training process.

$$\min_G \max_D V(D,G) = E_{x \sim P_{ori}}(x)\left[\log D(P_{ori}(w))\right] + E_{x \sim P_{gen}(x:\,\theta)}\left[\log\left(1 - D\left(P_{gen}(\hat{w}:\,\theta)\right)\right)\right] \quad (1)$$

However, the data generated by GAN is inherently random and lacks control over specific output. To address this limitation, the concept of Conditional GAN (CGAN) has been proposed, incorporating the principles of supervised learning into GAN. The fundamental idea behind CGAN is to introduce conditional information into both the generator and discriminator. In our model, we utilize weather features as conditional labels, such as sunny, cloudy, overcast, and rainy/snowy, to steer and facilitate the training. This approach enables us to generate weather data sequences that align with specific desired features. The objective function of our model (Eq. 2) is derived by adapting Eq. 1.

$$\min_G \max_D V(D,G) = E_{x \sim P_{ori}(w)}\left[\log D\left(P_{ori}(w)\middle|y\right)\right] + E_{x \sim P_{gen}(\hat{w}:\,\theta)}\left[\log\left(1 - D\left(P_{gen}(\hat{w}:\,\theta)\middle|y\right)\right)\right] \quad (2)$$

where, y denotes the condition and corresponds to the weather features.

2.2 Style-based learning model

We draw inspiration from StyleGAN2, which leverages the concept of style migration to learn from image data. The style-based learning generator incorporates two main parts, namely the Mapping network and the Synthesis network, to facilitate its functionality. The Mapping network plays a crucial role in decoupling complex features that are coupled together. On the other hand, the Synthesis network incorporates two important components for data processing: modulation-demodulation convolutional layers (MD-C) and modulation convolutional (M-C) layers. Eqs 3–6 (Karras et al., 2019) illustrate the functioning of MD-C network blocks, while for M-C the operation of Eq. 5 is omitted. y incorporating style-based learning from StyleGAN2, we are able to enhance the fidelity and realism of weather simulations. This approach enables us to capture not only the overall global trends but also the localized variations in the generated weather scenarios.

$$\boldsymbol{s} = \boldsymbol{\omega}^{f} \cdot w + \boldsymbol{b}^{f} \quad (3)$$

$$\boldsymbol{\omega}^{c'} = \left[s_i \cdot \omega^{c}_{ijmn}\right] \quad (4)$$

$$\boldsymbol{\omega}^{c''} = \left[\frac{\omega^{c'}_{ijmn}}{\sqrt{\sum_{i,m,n}\left(\omega^{c'}_{imn}\right)^2 + \epsilon}}\right] \quad (5)$$

$$\hat{w} = \boldsymbol{\omega}^{c''} * \boldsymbol{x}^{c} + \boldsymbol{b}^{c} \quad (6)$$

where, the w decoupled by the Mapping Network is first passed through a fully connected layer with a weight of $\boldsymbol{\omega}^{f}$ and a deviation of $\boldsymbol{b}^{f}$ to obtain the style information $\boldsymbol{s}$. The resulting $\boldsymbol{s}$ is then multiplied element-wise with the convolution kernel ω^{c}, producing modulation weights $\boldsymbol{\omega}^{c'}$. Subsequently, a demodulation weight $\boldsymbol{\omega}^{c''}$ is computed using a root mean square operation, incorporating an infinitesimal constant ϵ. Utilizing $\boldsymbol{\omega}^{c''}$ and the convolutional bias $\boldsymbol{b}^{c}$, a convolutional operation is performed on $\boldsymbol{x}^{c}$ which is the original input. This operation enables the extraction of complicated features from weather scenario.

The discriminator is predominantly implemented using a residual Convolutional Neural Network (CNN). This choice of architecture enables the discriminator to effectively identify abstract features and uncover hidden invariant structures within the weather data sequence. Within each residual block, average pooling down-sampling is employed to reduce the temporal resolution of the samples by half. Pattern collapse, a common issue in GAN structures where only a subset of data patterns are captured, is addressed by incorporating a small batch standard difference layer into the network structure. This addition aims to increase the diversity of reproducible samples generated, mitigating the problem. Towards the end of the discriminator, two fully connected layers are applied to adjust the output shape. The discriminator's discriminant results being closer to 1 indicate a more realistic weather scenario. These discriminant results are then utilized to construct loss functions for both the generator network and the discriminator network, as described by Eqs 7, 8. The purpose of computing these losses is to optimize the parameters of each component in the neural network using backpropagation, thereby continuously improving the realism of the weather data generated by the generator.

$$LossG = \mathrm{Relu}\Big(1 - D\big(G(z \mid y)\big)\Big) \tag{7}$$

$$LossD = \mathrm{Relu}\Big(1 + D\big(G(z \mid y)\big)\Big) + \mathrm{Relu}\big(D(w \mid y)\big) \tag{8}$$

where the function denoted as Relu is represented by $\mathrm{Relu}(x) = \max\{0, x\}$ and has the capability to be smoothed.

3 Discussion

Currently, almost all GAN-based PV scenario generation models are directly based on renewable energy generation data such as PV data or wind power data, and the proposed model is also theoretically applicable to the direct modelling of the PV scenario and the wind power scenario, as they are both essentially time series data. However, these approaches often overlook the crucial factor of weather scenarios. Weather conditions significantly impact PV power generation, and PV power models rely on factors such as direct radiation, diffuse radiation, and temperature to simulate PV power output. Solar radiation levels and temperature directly influence the performance of PV modules, and the uncertainty in weather scenarios contributes greatly to the uncertainty in PV power generation. Therefore, solely relying on direct PV data simulation neglects the physical constraints imposed by weather scenarios on PV power generation, limiting the generalizability of PV scenario modeling approaches. To address this limitation, we propose a weather-based PV generation scenario simulation that first models weather scenarios to accurately capture their realism. By incorporating weather-based simulations, we can enforce strict physical constraints on PV scenarios, thus ensuring a higher level of generality in PV scenario simulation models.

Traditional methods for modeling weather scenarios primarily rely on explicit methods based on probabilistic statistical approaches. These explicit methods require formulating probability distribution functions for PV generation data, leading to limitations such as small capacity, poor generalization capability, and difficulties in handling high-dimensional data. With the advancements in artificial intelligence algorithms, deep learning methods, particularly unsupervised learning methods based on GAN, have gained prominence. GAN-based models do not necessitate explicit specification of probability distribution functions for scenario data, nor do they require explicit likelihood estimation. GAN is capable of capturing complex data distributions due to its data-driven approach. GAN has the flexibility to generate realistic weather simulations while effectively capturing spatial and temporal dependencies. In addition, GANs have the ability to generate high-resolution simulations and estimate uncertainty, providing a powerful tool for weather prediction and climate research. However, one limitation of GANs is the lack of control over the generated data, as it is random and unpredictable. CGAN enable GANs to transition from unsupervised to supervised learning, allowing better control over the network's output. In our proposed model, we utilize weather features as labels, such as sunny, cloudy, overcast, and rainy/snowy, to generate weather scenarios based on specified weather conditions. By incorporating weather features as labels, we can generate weather scenarios according to our specific requirements. To achieve better control over the overall probabilistic, temporal, and correlation characteristics of weather scenario data, as well as the diversity represented by local differences, we propose a style-based weather data simulation algorithm. This algorithm enables us to learn the trend characteristics and local uncertainty random variation characteristics of weather data, representing high and low image characteristics, respectively. By separating these characteristics, we can generate weather scenarios with consistent trends but diverse variations.

4 Conclusion

For PV scenario modeling, generating weather data sequences with specific features is crucial. We propose a conditional style-based generative adversarial network for stochastic weather scenario simulation.

In conclusion, two key points stand out. Firstly, methods based on weather data for generating PV scenarios can comprehensively consider weather's impact on PV system performance, enhancing simulation accuracy. This aids in understanding PV system behavior under various conditions and supports system design and operation. Secondly, current time-series data generation models and PV scenario generation models often lack scenario diversity consideration. StyleGAN, an advanced image generation technology, holds significant potential for weather data generation. Leveraging its hierarchical feature control and continuous latent space, StyleGAN can generate richer, more diverse, and realistic weather scenarios. This increases data diversity and enhances simulation realism.

Moreover, AI advancements, like ChatGPT, are promising for weather scenario generation. It can automate dataset annotations, improve data quality, and analyze discrepancies between generated and real data, aiding GAN training and refining generated results. This opens avenues for processing higher-dimensional and larger-scale weather data.

Author contributions

JD: Conceptualization, Data curation, Investigation, Writing–original draft. JZ: Funding acquisition, Investigation, Visualization, Writing–review and editing.

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Conflict of interest

Authors JD and JZ were employed by Guangzhou Power Supply Bureau of Guangdong Power Grid Co., Ltd.

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