

Day-ahead renewable scenario forecasts based on generative adversarial networks

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November 8, 2023

Abstract

With the increasing penetration of renewable resources, such as wind and solar, the operation and planning of power systems, especially in large-scale integration, are faced with great risks due to the inherent stochasticity of natural resources. Although this uncertainty is anticipated, their timing, magnitude and duration cannot be predicted accurately. In addition, the renewable power outputs are correlated in space and time and bring further challenges in characterizing their behaviors. To address these issues, this paper provides a data-driven method to forecast renewable scenarios considering its spatiotemporal correlations based on generative adversarial networks (GANs), which has the ability to generate realistic samples from an unknown distribution making them one of the hottest areas in artificial intelligence research. We first utilize GANs to learn the intrinsic patterns and model the dynamic processes of renewable energy sources. Then by solving an optimization problem, we are able to generate large number of day-ahead forecasting scenarios. For validation, we use power generation data from NREL wind and solar integration data sets. The experimental results of this present research accord with the expectations.

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Abstract

With the increasing penetration of renewable resources such as wind and solar, the operation and planning of power systems, especially in terms of large-scale integration, are faced with great risks due to the inherent stochasticity of natural resources. Although this uncertainty can be anticipated, the timing, magnitude, and duration of fluctuations cannot be predicted accurately. In addition, the outputs of renewable power sources are correlated in space and time, and this brings further challenges for predicting the characteristics of their future behavior. To address these issues, this paper describes an unsupervised method for renewable scenario forecasts that considers spatiotemporal correlations based on generative adversarial networks (GANs), which have been shown to generate high-quality samples. We first utilized an improved GAN to learn unknown data distributions and model the dynamic processes of renewable resources. We then generated a large number of forecasted scenarios using stochastic constrained optimization. For validation, we used power-generation data from the National Renewable Energy Laboratory wind and solar integration datasets. The experimental results validated the effectiveness of our proposed method and indicated that it has significant potential in renewable scenario analysis.

Index Terms

Artificial intelligence, generative adversarial networks, renewable energy, scenario generation

I. INTRODUCTION

To protect the environment and reduce the consumption of conventional energy resources, renewable energy will become progressively more important in the future. However, the intermittent and volatile nature of renewable power generation brings negative impacts for managing the operation of power systems, and additional reserves and facilities are required to accommodate the resulting power imbalances and aid network transmission, especially in the case of large-scale integration [1,2]. Scenario generation plays an important role in characterizing the uncertainties inherent in the use of renewable resources, and this technique is widely used in stochastic optimization problems such as establishing the optimal unit commitment, energy storage sizing, and electricity market trading [3–5]. For power-system operation and planning, accurate modeling of the output of renewable energy sources is therefore key to enforcing reliability criteria and increasing economic benefits.

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Extensive research has been conducted into scenario generation. A Gaussian copula has been proposed for the generation of statistical scenarios, and this accounts for both the interdependence structure of prediction errors and the predictive distributions of wind generation [6,7]. Moment-matching scenario generation from multivariate random variables with specified moments and correlations was introduced by Hoyland et al. [8], and Meibom et al. used a method based on an autoregressive moving average to generate scenarios for wind power [9]. An artificial neural network was presented by Vagropoulos et al. to create more representative scenarios for electric loads and photovoltaic and wind production [10]. These methods have been applied to a single site, and some of them may be extended to multisite datasets for capturing spatial correlations. Copula-based methods have been used to produce spatially correlated scenarios across different geographic sites [11–13], and time-series models have been applied to characterize multivariate stochastic processes pertaining to wind speed (or wind power) data coming from multiple sites [14,15]. Each of these scenarios embodies time dependencies and is spatially dependent on other stochastic wind processes.

Probabilistic models are usually based on statistical assumptions, and it is a challenge to capture all the salient features underlying renewable power-generation dynamics using these models. The generated scenarios can be used to represent future uncertainty but cannot represent the intrinsic patterns in the power output from renewable energy sources. Furthermore, the complex spatiotemporal behavior of the sources and the use of sampling from high-dimension joint distributions make it difficult to apply and scale these probabilistic methods in practice.

As a branch of unsupervised methods in machine learning, generative models can learn the distribution of a training dataset and generate datasets that exhibit similar characteristics to the real data. The most common deep-neural-network-based generative models are generative adversarial networks (GANs) [16], variational autoencoders (VAEs) [17], and generative moment-matching networks [18]. A model-free method based on GANs was proposed by Chen et al. for generating a scenario set that can capture the intrinsic patterns of renewable power generation [19]. Bayesian information has also been incorporated into these GANs to produce scenarios with different variances and mean values that capture different salient modes in the data [20]. In a previous work, we utilized an improved GAN to generate wind-power scenarios by applying alternative training techniques to improve the performance of the models [21]. Additionally, VAEs have been used for the generation of renewable scenarios [22,23]. These simulated scenarios can correctly characterize the temporal, spatial, and fluctuant characteristics of historical observations.

These data-driven models do not rely on any modeling assumptions and can characterize the stochastic processes with a full diversity of behaviors. However, although these methods can generate scenarios that correctly capture the intrinsic dynamics of historical data, they do not consider forecast information to characterize future uncertainties in renewable energy sources. Chen et al. presented a method based on unsupervised deep learning to generate future scenarios representing temporal correlations and fluctuation distributions [24]. This method has high flexibility, and it is easy to adjust the forecast horizon from hours to days for a particular geographical location.

Due to the similarities in meteorological dynamics, outputs at different geographical locations will have natural correlations. Joint uncertainty modeling considering spatial dependence is crucial for power-system planning and operation studies, especially for transmission risk assessments and power-flow optimization. Furthermore, GANs

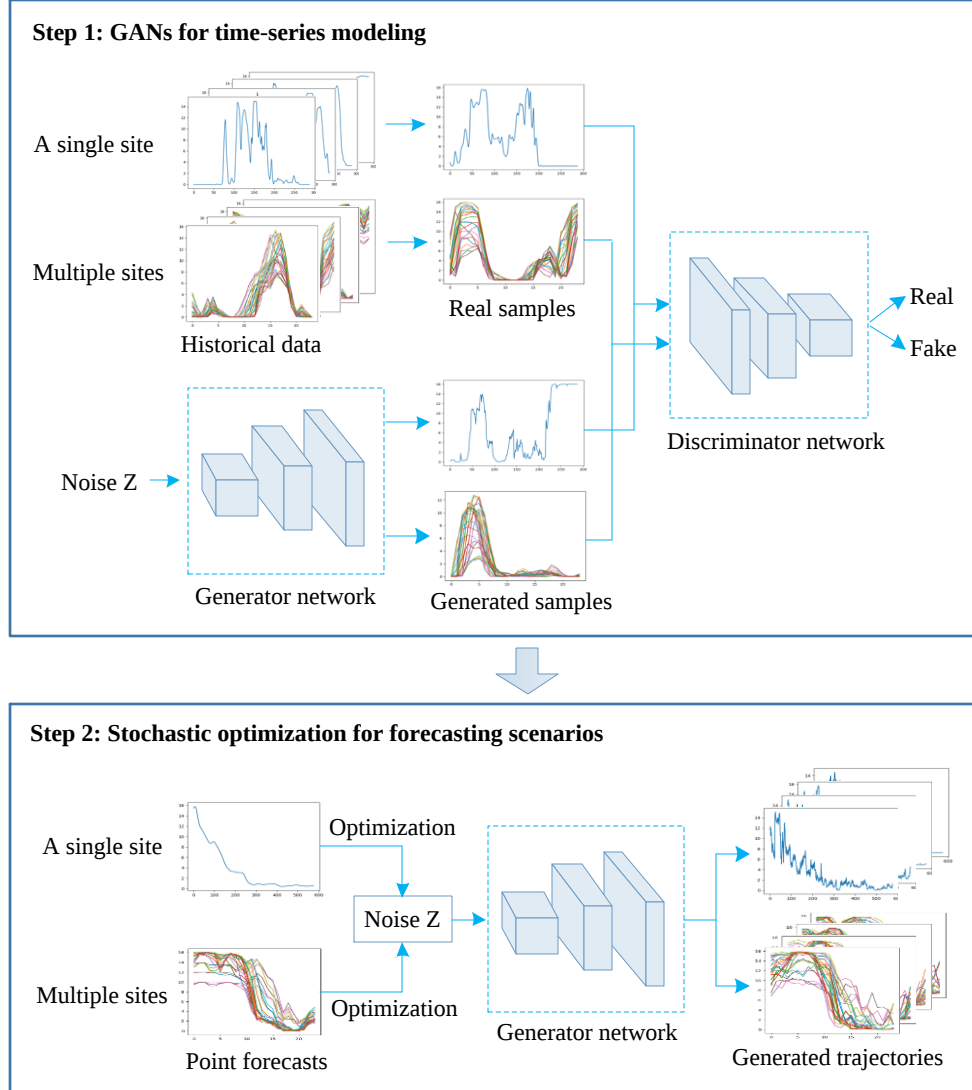


Fig. 1: Framework for the GANs used for different forecasting tasks.

can suffer from training instability, and this may result in failure of convergence in the training procedure. To address these issues, we propose an unsupervised method to forecast renewable scenarios for multiple geographical locations. Figure 1 shows the framework of the proposed method, which comprises two steps that proceed as follows. In step 1, based on deep learning, the GANs can learn and generate samples with the same properties as the training samples. The generator network tries to “cheat” the discriminator network by using random noise to imitate the real samples, and the discriminator network tries to distinguish the real and generated data as accurately as possible, thus forming a “game” process between the two networks. Once the training in step 1 is completed, an optimal generator is obtained that is able to generate realistic samples. Step 2 can further help us to incorporate forecast information to produce a group of future scenarios.

The contributions of this work can be briefly summarized as follows:

- An unsupervised learning method is proposed to generate future scenarios that can characterize the complex spatial and temporal correlations of stochastic power-generation processes. To our knowledge, this is the first work that has applied deep generative models to forecast spatiotemporal scenarios for wind and solar power.
- The proposed method can generate time-series trajectories without any changes to the model structure for different forecasting tasks. It also has high flexibility in terms of the number of generation sites and is not limited to forecasting day-ahead scenarios.
- The improved training techniques can achieve more stability in the training of the generative models, better utilizing the network capacity of the discriminator in the training and achieving faster convergence for scenario forecasts.

The remainder of this paper is organized as follows. Section 2 presents the GANs and the corresponding improved procedures, as well as the model training effects for renewable data. In section 3, the setup is detailed for an optimization problem using pre-trained GANs. In section 4, the experimental results are illustrated to test the proposed method using a comprehensive analysis comprising forecasting of renewable scenarios for single and multiple sites. Conclusions are presented in section 5.

II. GENERATIVE ADVERSARIAL NETWORKS

Generative adversarial networks offer a new framework for drawing realistic samples from an unknown data distribution, and they are therefore currently one of the most active research areas in artificial intelligence. Since their introduction by Goodfellow in 2014, GANs have become a popular approach for a variety of applications [25–27]. However, GANs can be remarkably difficult to train. The Wasserstein GAN (WGAN) makes progress toward stable training but can still generate low-quality samples or fail to converge in some scenarios [28,29]. In this section, we first introduce the WGAN and the improved training techniques, and then present the training effect for capturing the data distribution of renewable resources.

A. Wasserstein GAN

The idea of a GAN is to formulate the generative modeling problem as a competing game between two networks: a generator network G and a discriminator network D . Consider a historical dataset x with a data distribution denoted by P_r . To learn the generator's distribution P_G over data x , we define an input noise variable z and then represent a mapping of this to the data space as $G(z)$. The generator G can be trained by minimizing $-D(G(z))$, which indicates that the generator tries to output plausible samples. The discriminator D is alternately updated by the generator, and can be trained by maximizing between $D(x)$ and $D(G(z))$, which reflects that the discriminator is good at telling the difference between input samples. In a general form, the loss functions for G and D can be expressed as

$$\begin{aligned} L_G &= -\mathbb{E}_{z \sim P_z}[D(G(z))], \\ L_D &= -\mathbb{E}_{x \sim P_r}[D(x)] + \mathbb{E}_{z \sim P_z}[D(G(z))]. \end{aligned} \tag{1}$$

In the training process, the adversarial networks try to minimize each objective function in each training iteration. Formally, the game between the generator G and the discriminator D is represented by the minimax objective

$$\min_G \max_D V(G, D) = \mathbb{E}_{x \sim P_r} [D(x)] - \mathbb{E}_{z \sim P_G} [D(G(z))]. \quad (2)$$

The value function (2) of the game can be interpreted as the so-called Wasserstein distance, also known as the earth mover’s distance [30]. In terms of mode training, this distance is given a sensible cost function for learning distributions supported by low-dimensional manifolds. The Wasserstein distance is defined as

$$W(P_r, P_G) = \inf_{\psi \in \Pi(P_r, P_G)} \mathbb{E}_{(x,y) \sim \psi} [\|x - y\|], \quad (3)$$

where $\Pi(P_r, P_G)$ denotes the set of all joint distributions $\psi(x, y)$ whose marginals are P_r and P_G . Intuitively, $\psi(x, y)$ indicates the transport cost of transforming the distribution P_G into the distribution P_r . However, it is impractical to achieve the objective function in such a formula using neural networks. Considering the Kantorovich–Rubinstein duality [30], we find that

$$W(P_r, P_G) = \sup_{\|D\|_L \leq 1} \mathbb{E}_{x \sim P_r} [D(x)] - \mathbb{E}_{z \sim P_G} [D(G(z))], \quad (4)$$

where “sup” is the least upper bound, and the discriminator satisfies the 1-Lipschitz constraint.

B. Improved training techniques

The WGAN value function results in a discriminator function whose gradient with respect to its input is better behaved than its GAN counterpart, making optimization of the generator easier. However, it can still produce low-quality samples as a result of particular inputs or fail to converge in some settings. If the clipping parameter c is not carefully tuned, the optimization process can also result in either vanishing or exploding gradients. To overcome these issues, an alternative to clipping weights has been proposed to improve the performance of WGANs [29]. In particular, a gradient penalty term GP is introduced to penalize the gradient of the discriminator with respect to its input, such that

$$GP|_{\hat{x}} = \mathbb{E}_{\hat{x} \sim P_{\hat{x}}} [(\|\nabla_{\hat{x}} D(\hat{x})\|_2 - 1)^2], \quad (5)$$

where $\hat{x}$ represents uniform samples along straight lines between pairs of points from P_G and P_r .

It is better to utilize the gradient penalty for enforcing a Lipschitz constraint. Clear advantages of this when compared to weight clipping are its improved training speed and improved sample quality. Since the optimal discriminator has a unit gradient norm almost everywhere, enforcing this along straight lines between a pair of data points sampled from P_G and P_r seems sufficient and results in good performance [29].

Considering the real data points and the underlying manifold that supports the real distribution P_r , the sampled points $\hat{x}$ could be distant from the manifold in the early stage of the model training. The Lipschitz continuity over the manifold is not enforced until the data distribution P_G becomes close to the real distribution P_r . Therefore, an additional consistency term (CT) [31] is proposed to improve the training by additionally laying the Lipschitz continuity condition over the manifold of the real data. Instead of focusing on specific data points, data points near

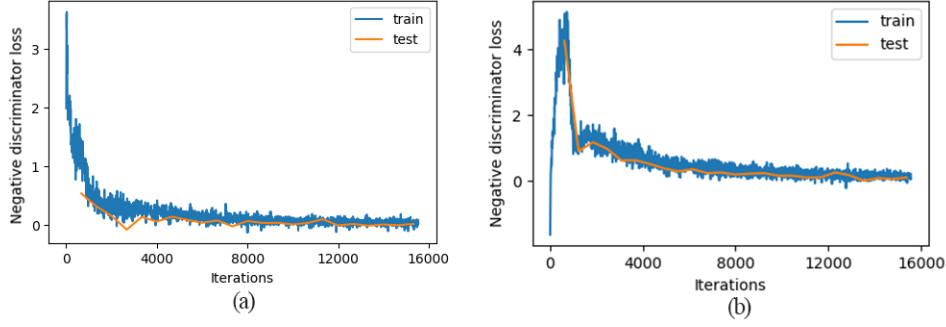


Fig. 2: Convergence curves of the generative model on (a) a solar dataset and (b) a wind dataset.

the manifold following the most basic definition of the 1-Lipschitz continuity are considered. The final additional term can be expressed as

$$CT|_{x',x''} = \mathbb{E}_{x \sim P_r} [\max(0, d(D(x'), D(x'')) + 0.1 \cdot d(D_-(x'), D_-(x'')) - M')], \quad (6)$$

where d denotes the ℓ_2 metric on an input space, M' is a bounded constant, $D_-(\cdot)$ denotes the second-to-last layer of the discriminator, and x' and x'' are two perturbed data points near observed data.

This new consistent regularization effectively complements and improves the gradient penalty used in the training of WGANs. Based on these improvements, the loss function of the discriminator can be reformulated as

$$L_D = \mathbb{E}_{z \sim P_z} [D(G(z))] - \mathbb{E}_{x \sim P_r} [D(x)] + \lambda_1 GP|_{\hat{x}} + \lambda_2 CT|_{x',x''}. \quad (7)$$

With the redefined function L_D , we can train the generative model to learn the real distribution of renewable data. An important benefit of a WGAN is that its value function is correlated with sample quality, which provides a useful metric for training the discriminator to optimality. To show that the generative model has the desired properties, we used power-generation data from the National Renewable Energy Laboratory (NREL) renewable integration datasets to train the model, and the convergence curves of the discriminator are shown in Figure 2. By training the two adversarial networks to an equilibrium, we can see that the two loss curves for wind and solar power gradually converge to minima and remain stable. To further check whether the discriminator overfits and provides an inaccurate estimate of a training point at which all bets are correlated with sample quality, we further explored the behavior of the loss curves from the test sets. It can be seen that the training and testing losses have almost the same trend for both wind and solar power, which indicates that the model can be well trained for renewable resources. When the training is completed, a generative model is obtained that captures the data distribution in the historical observations. In the next section, we will introduce how the pre-trained GANs can be used for scenario forecasts.

III. FORECASTING SCENARIOS USING GANS

Using a pre-trained generator G , we can generate realistic samples that reflect the intrinsic patterns of renewable power-generation dynamics. However, one more interesting problem is the generation of time series that can represent future uncertainty. This issue can be addressed by incorporating forecast information to formulate the scenario forecasts as a stochastic optimization problem. Since single-dimension data is a special case of multi-dimension data, we can formulate the problem for typical multiple renewable power-generation sites. We assume that at time node t , we are provided with the following point forecast for each site and each look-ahead time.

$$\hat{p}_{pred} = \begin{bmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,T} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,T} \\ \vdots & \vdots & \ddots & \vdots \\ p_{K,1} & p_{K,2} & \cdots & p_{K,T} \end{bmatrix}, \quad (8)$$

where T denotes the forecast horizon and K denotes the number of sites.

The unpredictability and variability of renewable energy sources is one of the fundamental issues associated with its integration into the power system. Point forecasts are able to provide deterministic information about uncertain future changes. Since we focus on the scenario-forecasting problem, this forecast information can be provided by any method, e.g., information from numerical weather prediction.

Given some input z , the forecasted trajectories will reflect the future dynamics and be volatile within a certain range. We can describe the fluctuations by defining a prediction interval [24,32]. A parameter θ can be used to control the interval with an upper bound $U_\theta(\hat{p}_{pred})$ and a lower bound $L_\theta(\hat{p}_{pred})$ such that

$$\begin{aligned} L_\theta(\hat{p}_{pred}) &= \frac{1}{\theta} \hat{p}_{pred}, \\ U_\theta(\hat{p}_{pred}) &= \theta \hat{p}_{pred}. \end{aligned} \quad (9)$$

Since the forecast information is a central-point forecast and will not fall outside the prediction interval, we can solve the following problem to obtain a starting point for $G(z)$.

$$\begin{aligned} \min_z & \left\| \mathbb{P}_{pred}(G(z)) - p_{init} \right\|_2 \\ \text{s.t.} \quad & z \in Z \end{aligned} \quad (10)$$

$$L_\theta(\hat{p}_{pred}) \leq p_{init} \leq U_\theta(\hat{p}_{pred}),$$

where p_{init} is sampled from an initial interval $[L_\theta(\hat{p}_{pred}), U_\theta(\hat{p}_{pred})]$.

Note that our goal is to generate time series that can capture the intrinsic patterns and represent the future uncertainty of stochastic power generation. The fluctuation of the produced time series can be controlled by the pre-determined confidence interval θ . Meanwhile, a larger discriminator output for the generated samples indicates more realistic samples. Using all these objectives, with the pre-trained generator G and discriminator D , we can

formulate the scenario-forecasting problem to be a stochastic optimization problem where

$$\begin{aligned}
& \min_z -D(G(z)) \\
& s.t. \quad z \in Z \\
& L_\theta(\hat{p}_{pred}) \leq \mathbb{P}_{pred}(G(z)) \leq U_\theta(\hat{p}_{pred}).
\end{aligned} \tag{11}$$

To start with a good initial z , the parameter θ in (10) can be slightly smaller than in the main optimization problem (11). This can help $G(z)$ to generate time series that fluctuate within an appropriate range. To deal with the inequality constraints, we can use two log barriers to substitute them into the main objective. The optimization can then be expressed as

$$\begin{aligned}
& \min_z -D(G(z)) - \tau(\mathbb{P}_{pred}(G(z)) - L_\theta(\hat{p}_{pred})) - \nu(U_\theta(\hat{p}_{pred}) - \mathbb{P}_{pred}(G(z))) \\
& s.t. \quad z \in Z,
\end{aligned} \tag{12}$$

where τ and ν are weighting parameters.

Since the two adversarial networks G and D are highly nonconvex, there are many local optima in (11). By solving the stochastic optimization in (12), we can start at different initial points $z_i \in Z$ in (10) to generate a group of realistic scenarios $\mathbb{P}_{pred}(G_{z_i}^*)$ representing different uncertainties in volatile power generation according to the actual needs of risk management using θ in (9).

IV. EXPERIMENTS

In this section, we describe our experiments using two renewable datasets. We show that the proposed method can produce realistic trajectories that are able to represent the future uncertainty both for a single site and multiple spatially correlated sites. The simulation results indicate that our method is an effective tool for renewable scenario forecasts.

A. Data description

To test the performance of the proposed method, we used actual data from a previous publication as the input [19]. These data were collected from public datasets provided by NREL [33], which provides data and tools for the analysis of grid technologies and strategies, including power-system models and renewable datasets. This includes seven years' historical data with a 5-min temporal resolution. Wind data from 24 sites and solar data from 32 sites, all located in the US state of Washington, were chosen to construct the training and test data. For different modeling tasks, we randomly selected 80% of the input data as the training set, and the remaining 20% was used as the test set. Along with the historical data, forecast information was used for stochastic optimization based on the pre-trained GANs. All of the chosen sites were in geographical proximity, and the corresponding data were normalized into the range $[0, 1]$.

B. Training algorithm

The algorithm for using GANs for scenario forecasts contains two steps, as shown in Figure 1. The time-series modeling of renewable energy sources can be trained using step 1. The network structure we used was based on our previous work [21]. In this system, a generator with three deconvolutional layers is used to find a function that transforms a well-defined noise distribution z to generate realistic time series. A discriminator with a reverse structure is used to distinguish whether the input data come from the generator or the real samples. ReLU and LeakyReLU are used as activation functions. Stochastic dropout is applied to the hidden layers of the discriminator. Since batch normalization changes the form of the mapping between the input and the output, it can simply be omitted in our generative models. Once the model is well trained, the generator can generate realistic profiles that preserve the same distribution as historical observations.

With a pre-trained generator and discriminator, we can easily generate a large number of realistic time series. Using step 2, the forecast information can be incorporated for future uncertainty forecasting. First, an appropriate initial z needs to be found according to the point forecast $\hat{p}_{pred}$. This z is then fed to the trained generator to generate future trajectories according to different prediction intervals θ . This parameter can be set according to actual needs. The Momentum and RMSprop optimization algorithms have long been popular for different deep-learning structures, but the Adam algorithm combines the advantages of these two methods and is suitable for application to a wide range of non-convex optimization problems [34]. Therefore, we used Adam for the gradient-based stochastic optimization. All the experiments were implemented using the open-source machine learning framework TensorFlow [35].

C. Scenario forecasts

The model structure shown in Figure 1 can be used to implement different forecasting tasks. First, we used solar data to validate that the proposed method can generate volatile profiles that accurately represent different levels of uncertainty for a single site. The historical data with a 5 min resolution were used for training. Repeatedly inputting real samples allows our GAN model to automatically learn the distribution of historical observation data. Figure 2(a) shows the training curves for our GAN model using solar data. At the early stage, L_D is large because the model has not yet captured the distribution of power-generation dynamics. The generator and the discriminator are continuously updated, and the generator gradually captures the intrinsic underlying patterns in the historical observations. In the figure, it can be seen that after about 6000 iterations of training, the loss functions have decreased to near zero. After the model has been trained to converge, the generator can generate realistic time series representing the stochastic dynamics of solar power.

With the pre-trained G and D , we can use constraint optimization in (12) to generate a group of future trajectories. Figure 3 shows the simulation results at different prediction intervals θ of 1.5, 2, and 3 for solar power. We can see that the forecasted trajectories can correctly preserve the intermittent and volatile characteristics of solar power generation. By choosing different values of the confidence parameter θ , the resulting trajectories can be used to represent different degrees of uncertainty. With a larger θ , the profiles will have larger fluctuations. The prediction

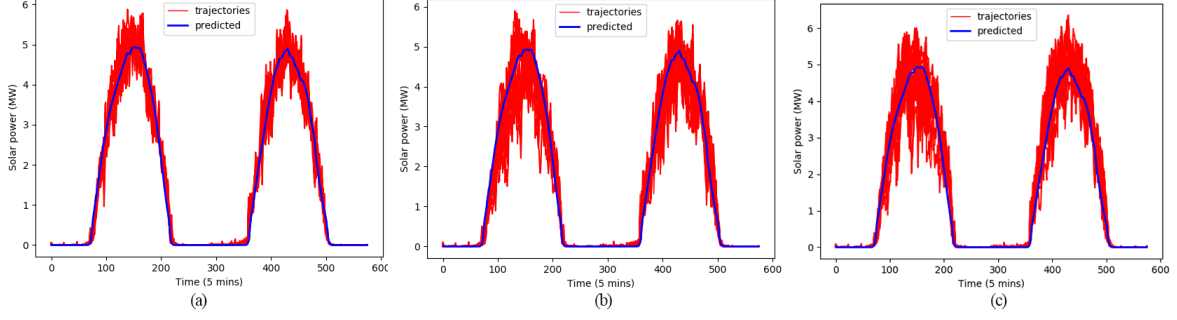


Fig. 3: Forecasted trajectories for solar power with a θ value of (a) 1.5, (b) 2, and (c) 3.

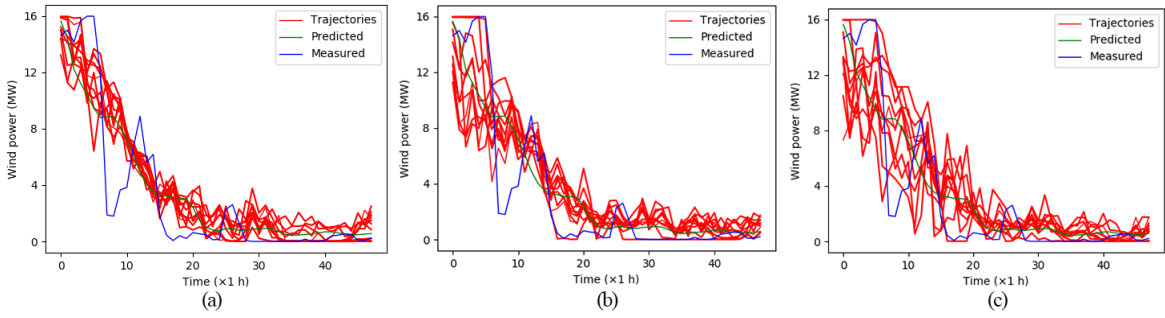


Fig. 4: Forecasted trajectories for wind power with a θ value of (a) 1.5, (b) 2, and (c) 3.

interval can be selected according to the actual situation. For power-system operation, a larger θ will improve forecast reliability but reduce operational economics.

To verify that a group of generated trajectories is representative of future uncertainty, the scenarios should cover the actual values of real power generation. Since solar power has much simpler intermittent and volatile properties than wind power, we can use wind power data for presentation. Historical wind data were randomly and repeatedly input to train our GAN model, and the training losses are plotted in Figure 2(b). We can see that the model was well trained after 10 000 iterations. We then generated trajectories using the stochastic optimization in (12). Figure 4 shows an sample whose point forecast is deviating a lot from the measurements. It can be seen that the generated trajectories are able to reflect the diversities and reliabilities when different prediction confidence values θ are selected. When the parameter θ is 1.5, the trajectories are close to the point forecast but fail to cover the actual power measurement. When θ is 3, the trajectories have a larger degree of volatility and can cover the measurements but are less concentrated. The range of the prediction confidence can be chosen according to the accuracy of forecast information and the required level of risk management. At the same time, the weight parameters τ and ν in (12) can be adjusted so that the generated trajectories can better meet actual needs.

To further verify the temporal statistical characteristics of the produced time series, we used an autocorrelation coefficient $R(h)$ to measure the degree of correlation of a time series in two periods. This coefficient at lead time

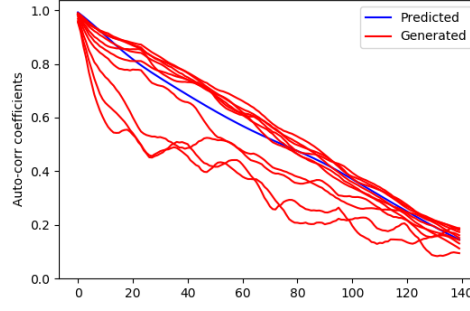


Fig. 5: Autocorrelation plots for predicted values and produced trajectories.

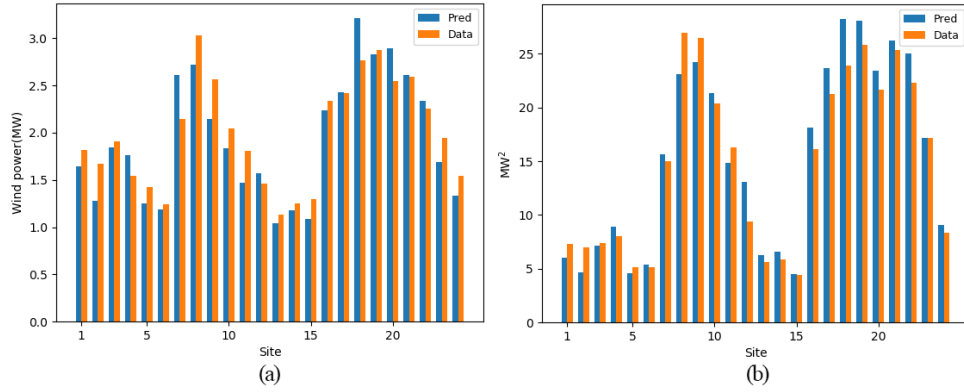


Fig. 6: Wind power mean (a) and variance (b) for the 24 sites.

h can be calculated from

$$R(h) = \frac{\sum_{i=1}^{n-h} (s_i - \mu)(s_{i+h} - \mu)}{\sum_{i=1}^n (s_i - \mu)^2}, \quad (13)$$

where μ denotes the mean of a single scenario s .

We computed and compared these autocorrelations for the predicted values and produced trajectories. As shown in Figure 5, the autocorrelation plots of the produced trajectories are able to cover the range of the prediction, which means that the produced trajectories are able to represent the temporal dependence of the real observations.

D. Spatial correlation

To examine forecasting scenarios for multiple sites, we used historical data with a size of $K = 24$ and $T = 24$ and a resolution of 1 h to train the generative model. After training the model to converge, the forecasted time series can be produced from the stochastic optimization objective in (12). We first verified the statistical properties for individual locations. We randomly generated 50 samples and plotted the mean and the variance for the predicted and generated data, as shown in Figure 6. It can be seen that the power magnitude and fluctuations for the 24 sites

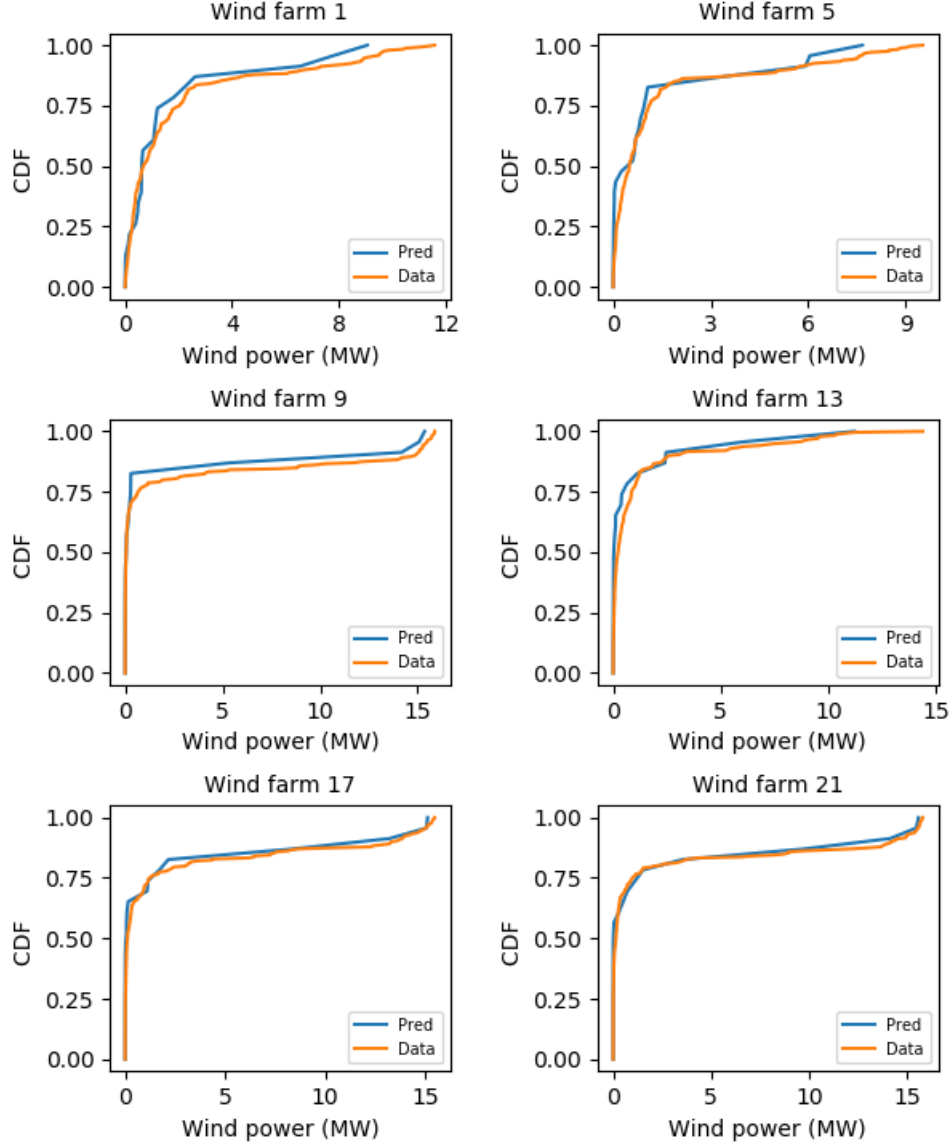


Fig. 7: Comparisons of the cumulative distribution function (CDF) of generated and predicted data for multiple sites.

are basically consistent with the predicted data. In probability and statistics, the cumulative distribution function (CDF) of a random variable X , evaluated at x , is the probability that X will take a value less than or equal to x . We computed the CDFs of some of these sites, and these are plotted in Figure 7. It is clear that the generated trajectories preserve the correct marginal distributions of the predicted data.

To show the correlations between individual locations, a pair of real and generated samples for the 24 wind farms is shown in Figure 8. By visual inspection, it can be seen that they have similar behaviors and features. The produced trajectories preserve the spatial and temporal correlations of the historical observations. From the

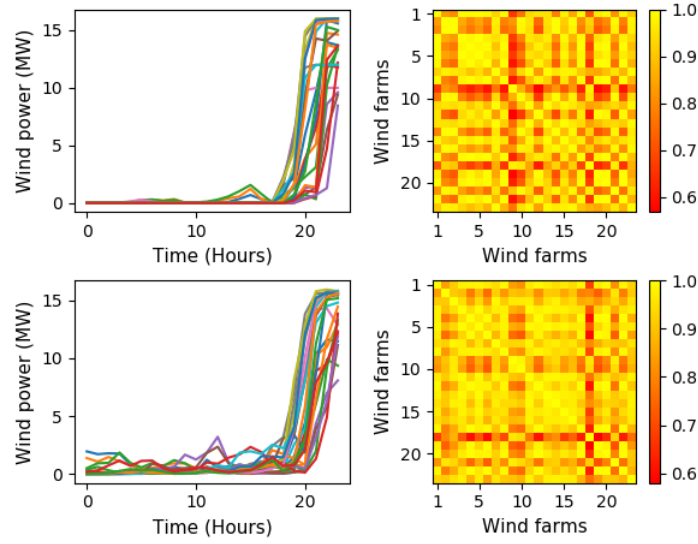


Fig. 8: The results of training the GAN with multiple wind-site data. Left: a pair of one-day training (top) and produced (bottom) samples; right: their respective spatial correlation coefficient matrices.

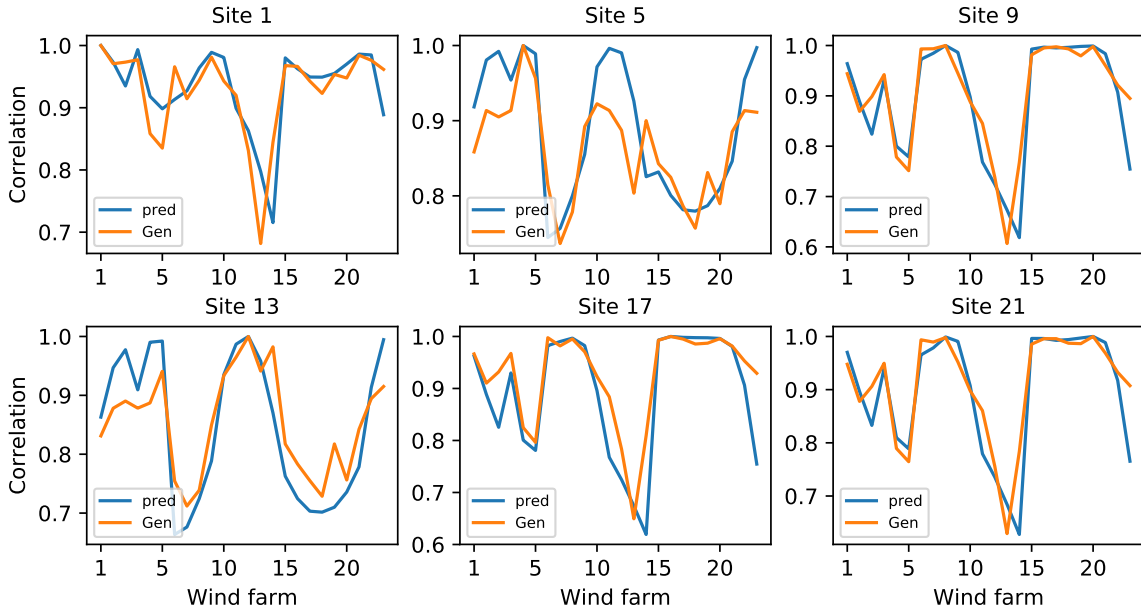


Fig. 9: Correlations between a given site and all other sites for wind power data.

visualizations on the right of the figure, it can be seen that the coefficient matrices of the two samples have relatively large values. This indicates that all sites have relatively high correlations and the similarity between the upper and lower correlations suggests that the proposed method can correctly capture the stochastic dynamics for multiple power-generation sites.

To further examine the spatial correlations for multiple sites, we compared the correlations between each site and all other sites. The correlation coefficient matrix for each of the samples was computed for all different sites. In this matrix, the diagonal positions represent the auto-correlation of a site, and the other positions represent the cross-correlations between sites. Each row and column of a matrix represents the correlation between that particular site and the other sites. Figure 9 illustrates some of the elements of the correlation matrix for multiple power-generation sites. It can be seen that the correlation curves of the generated data are basically consistent with the forecasted values, demonstrating that the spatial correlations in stochastic power generation can be correctly captured.

V. CONCLUSION

This paper presents an unsupervised learning method to generate future scenarios for multiple renewable power processes. The improved training techniques detailed here can achieve more stable training and improve the performance of the deep generative model. The proposed method is able to characterize the uncertainty and variability characteristics of both a single site and multiple spatially correlated sites. It can not only generate a group of future realizations but can also capture the intrinsic dynamics of historical observations. Comprehensive case studies were used to validate the effectiveness of our proposed method for generating scenarios within a stochastic programming framework. The marginal distribution for each stochastic process was preserved by the data that were produced. The temporal correlations were examined at each site and the cross-correlations were verified at different geographical sites. With its high flexibility and reliability, our method provides a meaningful tool for the analysis of renewable scenarios in sustainable energy systems.

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