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Advance Generative Model for Scenario Generation of Wind Power Distributions With Hight Granularity

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1 Abstract

The current wind farm control schemes qualify wind power producers (WPPs) to provide balancing services in modern electricity markets. Accordingly, WPPs are responsible for real-time deviations in the reserve market, settled every few seconds within a market period [1]. Therefore, WPP require to integrate intra-period wind variability in energy trading framework. As a main ingredient of such frameworks, in this work, we devise a novel scenario generation technique, i.e., Auxiliary Classifier Wasserstein Generative Adversarial Networks (ACWGAN), to produce intra-period wind power distribution with high-temporal-resolution. Notably, the generator of the neural network is appropriately constrained to return temporal distributions as the output.

2 Introduction

The recent advancements in generative adversarial networks (GANs) draw wide attention to their application regarding model-free scenario generation for renewable energy sources [2]. In [3], CWGAN is used to model load forecast uncertainty based on historical load measurements. However, the performance of CWGAN can be further improved by exploiting an auxiliary classifier (ACWGAN) in the network design to predict the class labels instead of feeding them as an input to the network. It is shown in [2] that such a design can return high-quality outputs for wind trajectories. This advanced architecture will be used and optimized in this paper to generate representative forecast scenarios of wind distribution, which requires advanced adaptation based on wind power expertise.

3 Methodology

A GAN consists of an interconnected network comprising a generator $G_\alpha(\cdot)$ and discriminator $D_\beta(\cdot)$ which compete in a zero-sum game. The neural networks' parameters are shown by subscripts. The generator $G_\alpha(\cdot)$ samples a latent noise vector z from the latent space with the probability distribution $\mathcal{P}_Z$, as input and attempts to map it to realistic-looking data s_g in the output $G_\alpha(z)$. Conventional CWGAN learns a representation of z that depends on class labels as it receives them as input to the network. In other words, CWGAN requires D_β to return an estimate of the distance between generated and real joint distributions of class labels c and samples, by merging c to either z or s_r (real samples), since it receives them as input. The complicated task of D_β, measuring the discrepancy between the real and generated joint distributions, and G_α, mapping the latent space to real data distribution, can be alleviated by incorporating a new agent into the adversarial training process. The additional agent, which is a classifier $C_\varsigma(\cdot)$ and cooperates with $D_\beta(\cdot)$ and $G_\alpha(\cdot)$, estimates the conditional probability of the class labels given the received samples.

The input-output diagram of ACWGAN is shown in Fig. 1. It is seen that the critic of ACWGAN, has two outputs, shown by green arrows. The first output, $D_\beta\big(H_h(\cdot)\big)$, obtains the WD between real and generated distributions while the second output, $\mathcal{C}_\varsigma(H_h(\cdot))$, predicts the class label of the provided sample (H_h is the hidden layers of the critic). Finally, ACWGAN is trained by sequentially updating the parameters of the new critic and generator through loss feedbacks $\mathcal{L}_{AW}^{D}$ and $\mathcal{L}_{AW}^{G}$. The loss function of critic and generator are respectively represented by (1) and (2):

$$\begin{aligned}\mathcal{L}_{AW}^{D} = &\max_{\{h,\beta,\varsigma\}} \mathbb{E}_{s_r\sim\mathcal{P}_r}\left[D_\beta\left(H_h(s_r)\right)\right]\\ &- \mathbb{E}_{s_g\sim\mathcal{P}_g}\left[D_\beta\left(H_h(s_g|c)\right)\right] - \eta_{GP}\mathbb{E}_{\hat{s}\sim\hat{\mathcal{P}}}\left[\left(\nabla_{\hat{s}}\left\|D_\beta\left(H_h(\hat{s}|c)\right)\right\|_2 - 1\right)^2\right]\\ &+ \eta_c\mathbb{E}_{s_r\sim\mathcal{P}_r}\left[\log\mathbb{P}\left(\mathcal{C}_\varsigma\left(H_h(s_r)\right) = c\right)\right]\\ &+ \eta_c\mathbb{E}_{s_g\sim\mathcal{P}_g}\left[\log\mathbb{P}\left(\mathcal{C}_\varsigma\left(H_h(s_g)\right) = c\right)\right]\end{aligned} \quad (1)$$

$$\begin{aligned}\mathcal{L}_{AW}^{G} = &\max_{\alpha} \mathbb{E}_{s_g\sim\mathcal{P}_g}\left[D_\beta\left(H_h(s_g|c)\right)\right]\\ &+ \eta_c\mathbb{E}_{s_g\sim\mathcal{P}_g}\left[\log\mathbb{P}\left(\mathcal{C}_\varsigma\left(H_h(s_g)\right) = c\right)\right]\end{aligned} \quad (2)$$

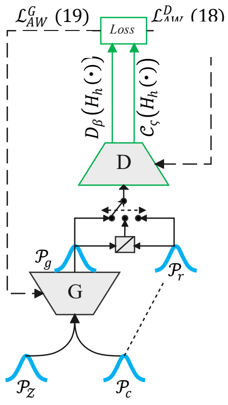

Fig.1. The training of the proposed ACWGAN

where η_{GP} is the gradient penalty coefficient concerning the 1-Lipschitz regularity condition and $\hat{s}$ symbolizes the linearly interpolated data points belonging to $\mathcal{P}_r$ and $\mathcal{P}_g$. $\nabla\|\,.\,\|_2$ is the gradient norm and η_c is the classifiers scale coefficient. $\log\mathbb{P}(\,)$ is the log-likelihood loss.

The generator's output layer should satisfy the conditions imposed by general distributions' shape. To do so, we use a SoftMax layer at the output of G_α to guaranty that the generated mass on each interval sums up to 1 and is non-negative. The standard (unit) softmax function $\sigma(z)\colon \mathbb{R}^K \to (0,1)^K$ is defined when K is greater than one by $\sigma(z)_i = \frac{e^{z_i}}{\sum_{j=\{1,\dots,K\}} e^{z_j}}$.

The output of generator after training for a given condition is given in Fig.2. In this figure scenarios corresponding to the predicted trajectory (in black) is given by coloured curves. In future, the proposed method will be used to generate wind distribution scenario using real data.

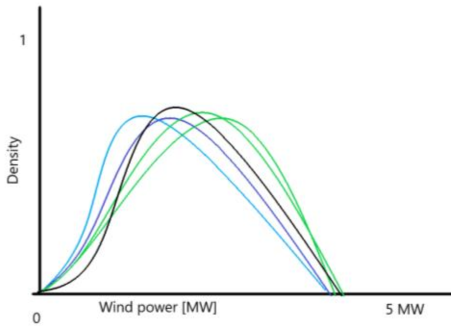

Fig. 2. The candidate scenarios generated with respect to black wind distribution.

References

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