Deep Generative Models for Renewable Resources

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Introduction

Background:
- Growing needs for analysis of renewables generation (e.g., wind, solar)
- Scenarios: possible realizations of power production
- Existence of "big data": historical generation profiles;
- Previous research on scenario generation: complicated statistical methods; highly dependent on data volume and statistical assumption.

Objective:
- Design and implement Generative Adversarial Networks (GANs) for renewables scenarios generation
- Formulate and solve optimization problem for scenario forecasts

Datasets:
- *Wind Integration Dataset* and *Solar Integration Dataset* by National Renewable Energy Laboratory (*NREL*).
- 5-minute interval; 24 wind farms 3-year records

Methods

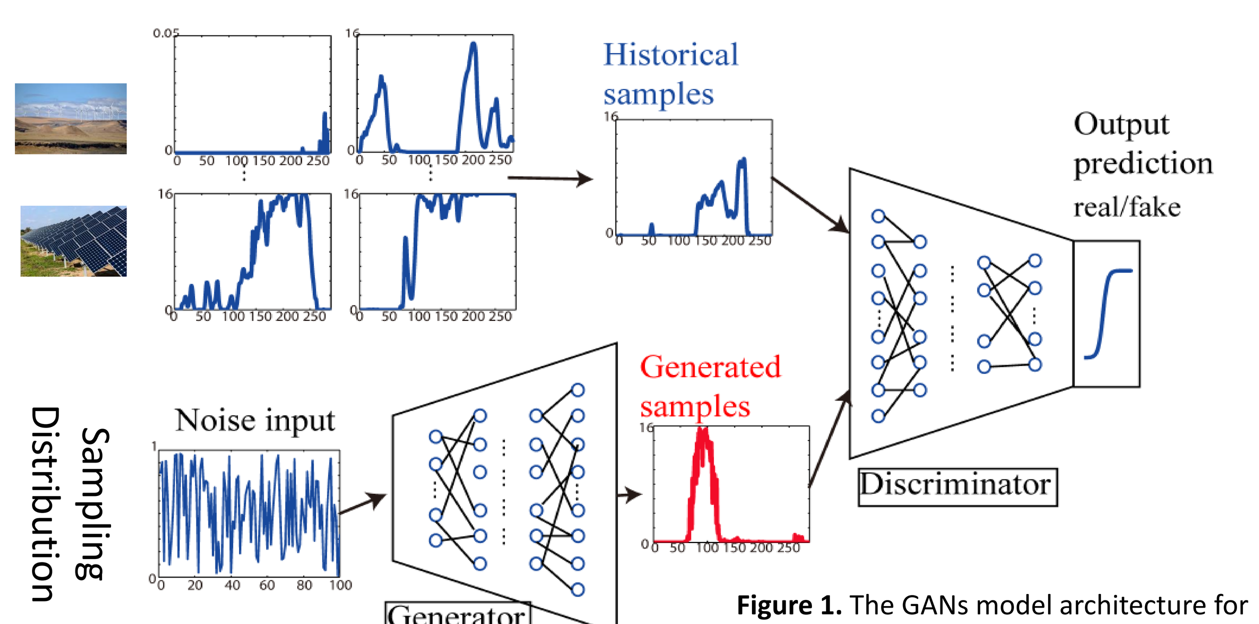

Figure 1. The GANs model architecture for renewables scenario generation

GANs with Wasserstein distance

*__Generator *G*__: trained to synthesize images G(Z) resembling to a given distribution $\mathbb{P}_X$;

G(Z): generative function that takes a random vector Z∈ $\mathbb{R}^d$ sampled from a prior noise $\mathbb{P}_Z$ to output time-series.

*__Discriminator *D*__: trained to distinguish samples from $\mathbb{P}_X$ and G(z);

D(X): discriminative function that for $X \in \mathbb{R}^d$ outputs probability of X being a real sample.

Training objective formulated as a minimax game:

$$\min_G \max_D V(G,D) = E_X[D(X)] - E_Z[D(G(Z))]$$

Iterative training of G and D:

Update G: $\min_G \; -E_Z[D(G(z))]$

Update D: $\min_D \; -E_X[D(X)] + E_Z[D(G(z))]$

Conditional GANs

As an extension of Wasserstein GANs, give extra label information y pertained to the input X/Z

Label encodes class/event information(e.g., forecast error, power generation mean value) into generated samples (tensors) by GAN

Scenario Generations

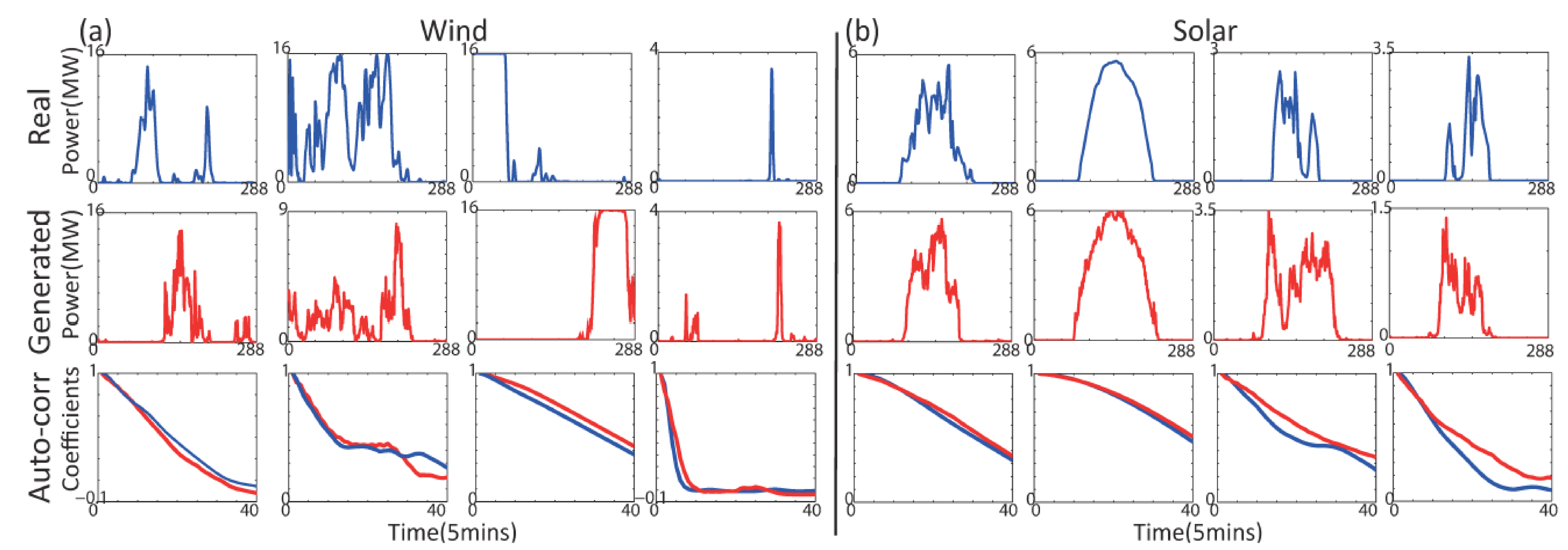

Figure 2. Wind and solar power generation scenarios synthesized by GANs (Blue: historical records, Red: generated samples). X-axis is time-step while y-axis is power strength.

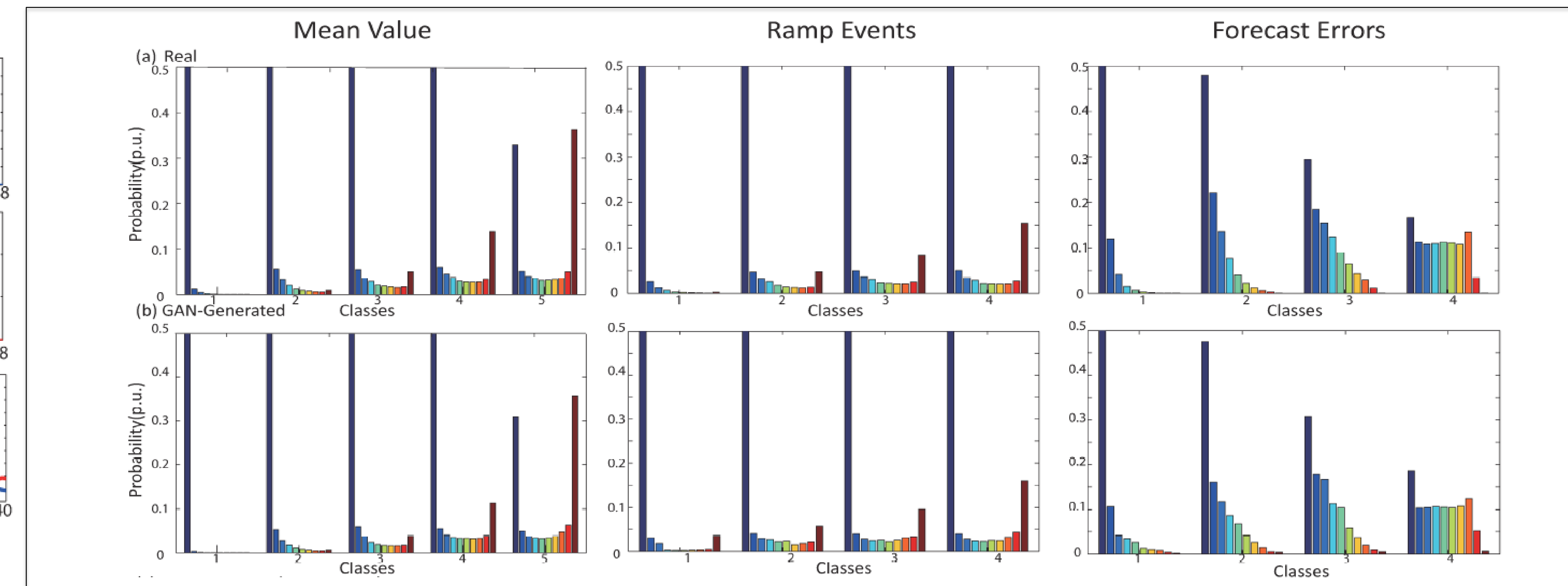

Figure 3. Data distribution in original and generated scenarios based on three conditional labels

Model-Free Scenario Generations

The architecture in Fig.1 is used in all 3 models with minor modifications.

GPU-enabled training for 100 epochs.

z drawn from p_{noise} were passed into G to synthesize samples (Fig. 2).

Generated samples exhibit diversity and complex temporal dependencies.

Conditional labels are adopted for event-based scenario generation (e.g., ramp events, forecast errors) (results shown in Fig. 3).

Spatiotemporal Scenario Generations

Inputs X are re-organized for group of spatiotemporal samples.

GAN-generated scenarios preserve both the temporal and spatial dependencies.

(results shown in Fig. 4)

Scenarios generated by GAN are also robust to noise injection (results shown in Fig. 5)

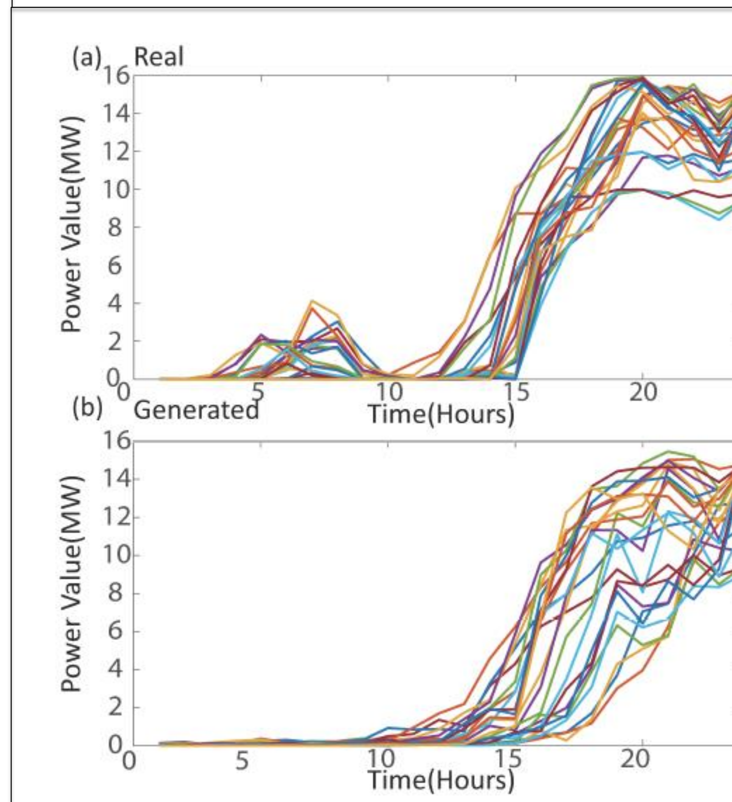

Figure 4. A group of 24 wind farms one-day scenarios.

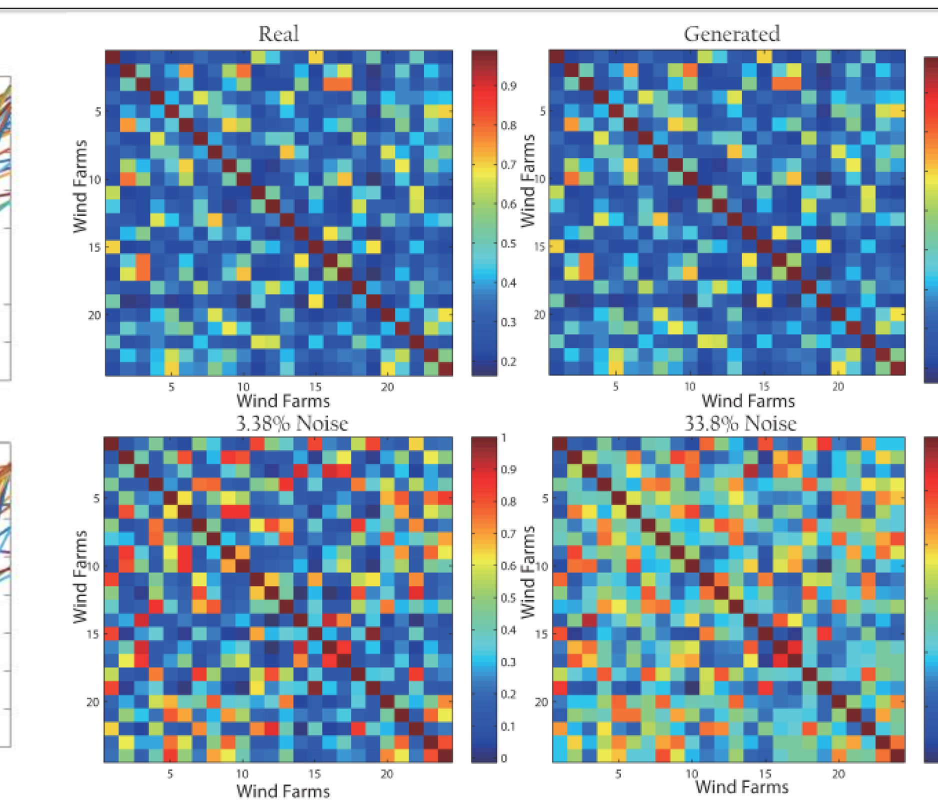

Figure 5. The spatial correlation coefficients matrix for spatiotemporal scenario generation

Scenario Forecasts

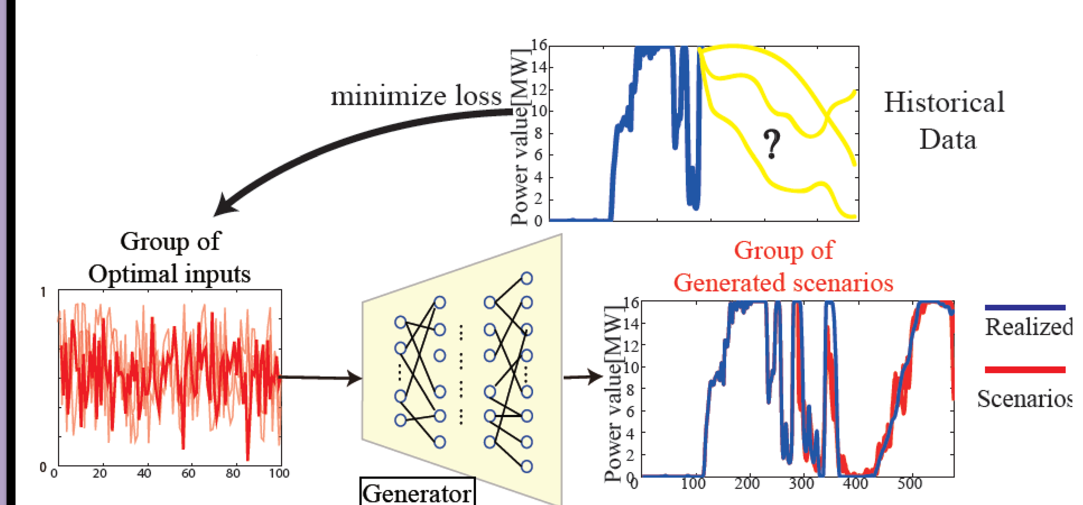

Figure 6. The pipeline for forecasting scenarios based on historical observations.

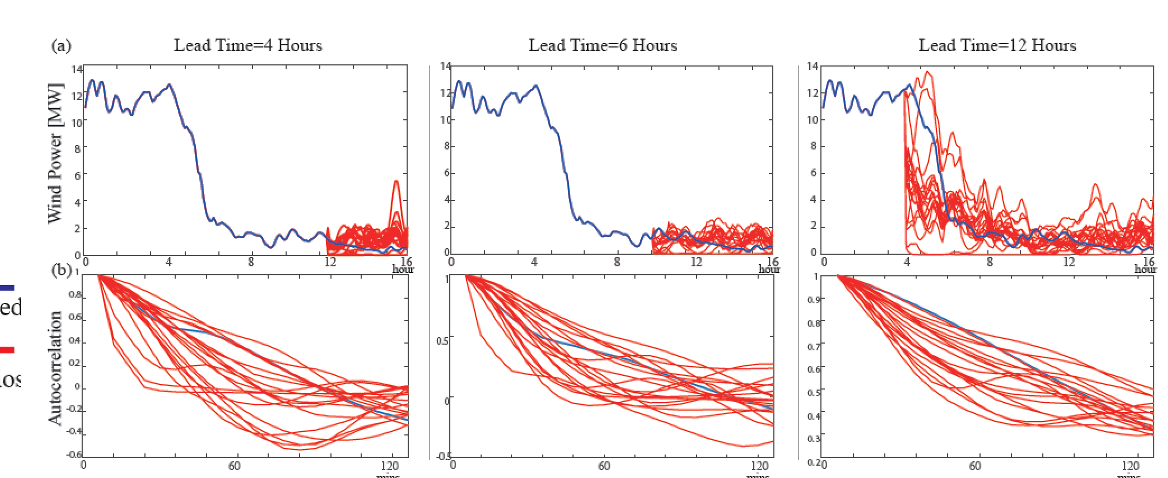

Figure 7. Our method is scalable to a variety of forecasting lead time.

Objective: Given historical observations $\mathbf{p}_{hist}$, point forecasts $\widehat{\mathbf{p}}_{pred}$ find scenario $\mathbb{P}_{pred}(G(z))$

Form the optimization problem for finding a future scenario:

$$\min_Z \; \|\mathbb{P}_{hist}(G(z)) - \mathbf{p}_{hist}\|_2 - \gamma D(G(z))$$
$$s.t. \;\; Z \in \mathbb{P}_Z$$
$$\text{LowerBound}(\widehat{\mathbf{p}}_{pred}) \le \mathbb{P}_{pred}(G(z)) \le \text{UpperBound}(\widehat{\mathbf{p}}_{pred})$$

- Solve optimization problem for DNN: SGD
- Scalable and informative of temporal dynamics

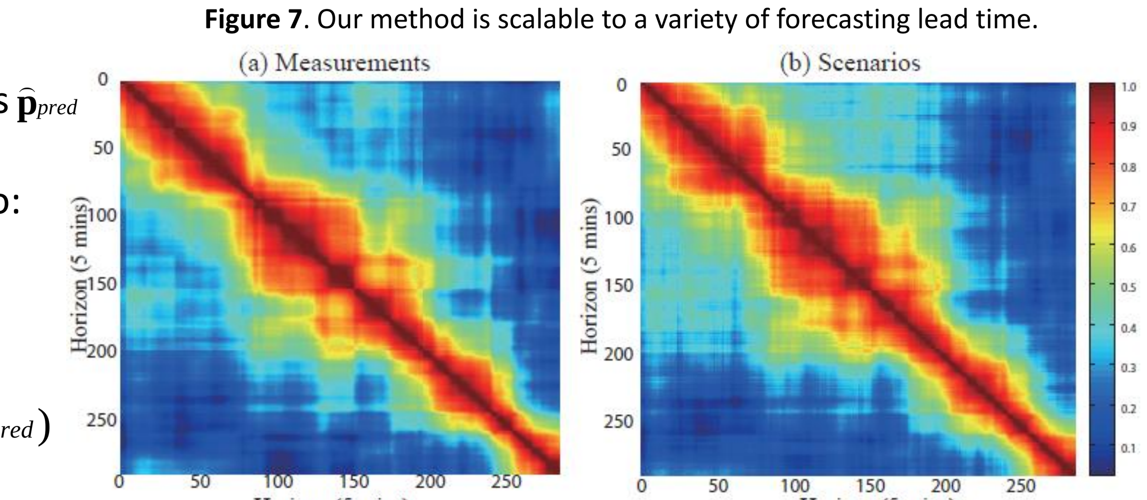

Figure 8. Comparison of correlation matrix for real measurements and generated scenarios..

Conclusions

- GANs is a powerful deep-learning model for depicting complex spatiotemporal dynamics in renewables generation
- GANs-generated scenarios both preserve statistical properties of wind/solar power generation and diversity
- Incorporate GANs into an optimization problem would give us scenario forecasts
- Scenarios "conditioned" on history is to be examined
- Generative models in physical system

References

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