International Conference on Applied Energy 2020
Dec. 1 - Dec. 10, 2020, Bangkok / Virtual
Paper ID: 0428

Data-Driven Scenarios Generation for Wind Power Profiles Using Implicit Maximum Likelihood Estimation

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ABSTRACT

The scenario generation of wind power profiles is of great significance for the economic operation and stability analysis of the distribution network. In this paper, a novel generative network is proposed to model wind power profiles based on implicit maximum likelihood estimation (IMLE). Firstly, the fake sample closest to each real sample is found to calculate the loss function used for updating weights. After training the model, the new wind power profiles are generated by feeding some Gaussian noises to the generator of the IMLE model. Compared with explicit density models, the IMLE model does not need to artificially assume the probability distribution of wind power profiles. The simulation results show that the proposed approach not only fits the probability distribution of wind power profiles well, but also accurately captures the shape, temporal correlation, and fluctuation of wind power profiles.

Keywords: wind power, scenario generation, deep learning, generative network

NONMENCLATURE

Abbreviations	
GAN	Generative Adversarial Network
VAE	Variational Automatic Encoder
IMLE	Implicit maximum likelihood estimation
Symbols	
$q(x)$	Approximate probability distribution of real samples
$p(x)$	Probability distribution of real samples
$q(z)$	Gaussian distribution
$q(x\|z)$	Conditional Gaussian distribution or Dirac distribution
$g(z)$	Generator of the IMLE model

1. INTRODUCTION

High penetrations of wind farms pose challenges in the scheduling, operation, and planning of distribution networks. Since wind power profiles are fluctuation and intermittent, accurately modeling the uncertainties of wind powers is the key to overcoming these challenges. One of the mainstream approaches to capture the uncertainty of wind power profiles is to generate a set of possible time series scenarios for wind farms [1]. For example, robust optimization attempts to find a conservative strategy that can guarantee the safe operation of the distribution network in any scenario.

The principle of methods for scenario generation is to generate some new wind power profiles similar to real samples by learning historical samples. With respect to whether it is necessary to assume the probability density function of real samples, the existing methods for scenario generation can be summarized into the following two categories: explicit density models and implicit density models [2]. Specifically, the explicit density models need to artificially assume the probability density function of real samples, which will limit the accuracy of new samples, because the probability density functions of some real wind power profiles are difficult to be accurately described with mathematical formulas [3]. Moreover, explicit density models are not universal, since the probability distributions of wind power profiles vary from region and time.

Recently, some deep generative networks such as the generative adversarial network (GAN) and

Selection and peer-review under responsibility of the scientific committee of the 12th Int. Conf. on Applied Energy (ICAE2020).

variational automatic encoder (VAE) have been used for scenario generation [4-6]. These generative networks are part of implicit density models which can capture the dynamic characteristics of wind power without explicitly fitting the probability density function. However, the performance of VAE is worse than that of GAN in many fields, because it does not use the adversarial for training [7, 8]. The weaknesses of the GAN, such as training instability, mode collapse, and vanishing gradients, still exist in preview publications [9, 10], and these problems lead to poor quality of new samples.

The implicit maximum likelihood estimation (IMLE) model is one of the implicit density models, and it is a well-known generative network after GAN and VAE. At present, the IMLE model has shown good performance in many fields such as image synthesis, data augmentation, style transfer, and missing data imputation [11, 12]. However, there is no report on the use of the IMLE model to generate wind power profiles. Theoretically, the IMLE model can effectively mine the natural course of wind power profiles and generate new samples similar to the real samples by using its strong learning ability. Specifically, how to design the structure of the IMLE model with high-performance according to the characteristics of wind power profiles needs further study.

In this paper, it is aimed to design an IMLE model to generate wind power profiles. The performance of the proposed method is tested by the real data set from the national renewable energy laboratory of the United States. The key contributions are as follows:

1) To the best of our knowledge, it is the first time to design the IMLE model for scenario generation of wind power profiles. After training, the IMLE model can generate any wind power profiles by feeding Gaussian noises to the generator.

2) The proposed approach uses historical samples to model wind power profiles without artificially assuming the probability distribution of real samples. It can accurately capture the volatility characteristics and temporal correlation of the wind power profiles. The simulation results show that the IMLE model has better performance than some existing methods.

2. METHODOLOGY

2.1 The principle of IMLE

Normally, implicit dense models can be naturally viewed as the distribution induced by the following sampling procedure [13]:

$$z \sim N(0, I), x = g(z) \tag{1}$$

where z denotes noises. $g(\cdot)$ denotes the generator of the IMLE model and x denotes the new samples. The probability distribution of x is as follows:

$$q(x) = \int q(z) q(x|z) dz \tag{2}$$

where $q(x|z)$ denotes the conditional Gaussian distribution or Dirac distribution. In theory, it can fit any distribution. It assumes that the probability distribution of real samples is $p(x)$, and the training process needs to maximize the following objectives:

$$E_{x\sim p(x)}[\log q(x)] = \int p(x) \log q(x) dx \tag{3}$$

The gradient descent method is often used to train neural networks. Therefore, the loss function of IMLE model is the opposite of formula (2). If $q(x|z)$ is a Dirac distribution, the formula (2) can be transformed into:

$$q(x) = \int \delta(x - g(z)) q(z) dz = E_{z\sim q(x)}[\delta(x) - g(Z))] \tag{4}$$

where $\delta(\cdot)$ denotes a Dirac function. In fact, the distribution of Dirac function is a Gaussian distribution whose variance tends to zero:

$$\delta(x) = \lim_{\sigma \to 0} \frac{1}{(2\pi\sigma^2)^{d/2}} \exp\left(-\frac{\|x\|^2}{2\sigma^2}\right) \tag{5}$$

where d denotes the dimension of z. σ denotes the variance. By substituting formula (5) into formula (4), the following results are obtained:

$$q(x) = \lim_{\sigma \to 0} E_{z\sim q(x)}\left[\frac{1}{(2\pi\sigma^2)^{d/2}} \exp\left(-\frac{\|x - g(z)\|^2}{2\sigma^2}\right)\right] \tag{6}$$

Furthermore, formula (6) is introduced into formula (2) to obtain the following results:

$$\text{loss} \approx E_{x\sim p(x)}\left[-\log\left\{\lim_{\sigma \to 0} E_{z\sim q(x)}\left[\exp\left(-\frac{\|x - g(z)\|^2}{2\sigma^2}\right)\right]\right\}\right] \tag{7}$$

where some constants which will not affect the results are ignored.

In the training process of the IMLE model, m real samples $X = (x_1, x_2, \cdots x_m)$ and n Gaussian noise samples $Z = (z_1, z_2, \cdots z_n)$ are input to the IMLE model for each iteration. By introducing them into formula (7), the loss function can be obtained as follows:

$$\text{loss} \approx \frac{1}{m} \sum_{i=1}^{m} \left(\min \sum_{j=1}^{n} \left(\|x_i - g(z_j)\| \right)^2 \right) \tag{8}$$

In this case, the back propagation algorithm can be used to update the weights of the IMLE model.

2.2 Scenario generation for wind farms

As is known to all, these deep generative networks are originally designed to generate image data with the same number of columns and rows. However, the wind power profile is a 1×n vector, which cannot be directly used as input data of these deep generative networks. Therefore, wind power profiles should be transformed into a square matrix before being fed to generative networks [2].

For scenario generation of a single wind power profile, an explanation is given by taking 144 sampling points per day as an example. Firstly, the original wind power profile is transformed into a matrix of 12×12 scales by a reshape function from Python. Then, the matrix is used as the input data of the IMLE model. In addition, the new samples generated by the IMLE model are also the matrixes of 12×12 scales, and they need to be converted into the wind power profiles of 1×144 scale through inverse transformation.

2.3 The process for scenario generation

To summarize the previous description, the steps to generate wind power profiles using the IMLE model are as follows:

1) Before feeding real samples into the IMLE model, they need to be normalized, and otherwise the performance of the IMLE model may be weak. Firstly, the minimum-maximum normalization method is utilized to transform the input data to the values that range from 0 to 1 in this paper. Then, the wind power profiles are reshaped into matrixes with the same number of rows and columns.

2) The Monte Carlo method is used to obtain a batch of Gaussian noises $Z=(z_1,z_2,\cdots z_n)$, which are fed into the generator of the IMLE model to generate a corresponding batch of fake wind power profiles $\hat{X}=(\hat{x}_1,\hat{x}_2,\cdots\hat{x}_n)$. Furthermore, a batch of real samples is randomly selected from the training set. For each real sample x_i, the closest fake wind power profile $\hat{x}_{p(i)}$ is found by calculating the Euclidean distance.

3) The loss function $\frac{1}{m}\sum_{i=1}^{m}\left(\left\|x_i-\hat{x}_{p(i)}\right\|\right)^2$ of the IMLE model is calculated to update the weights of the network by the back propagation algorithm.

4) If the set number of iterations is not reached, return to step 2). Otherwise, some Gaussian noises are fed to the generator to obtain new wind power profiles.

3. CASE STUDY

3.1 Data description and details of the model

In order to fully verify the effectiveness of the IMLE model for scenario generation, simulations are carried out using the real data set from the national renewable energy laboratory of the United States [14]. After data cleaning, the data set includes 1825 wind power profiles with a resolution of 10 minutes. Eighty percent of the samples are randomly selected to form the training set, and the remaining samples are used to evaluate the performance of the model.

The programs of different generative models for scenario generation are implemented in the Spyder platform (Python 3.6) with Keras 2.2.2 and Tensorflow 1.10.0 library. The parameters of the computer are as follows: 6 GB of memory, Intel Core i3-3110M, The processor is dual-core 2.4 GHz.

After many experiments, the best structure of the generator of the IMLE model is shown in Tab.1. In addition, the batch size is 32 and optimizer is the RMSprop algorithms.

Table 1 Structure of the generator

Layer (type)	Output Shape
Input Layer	1×64
Dense, Unit=1152	1×1152
Batch normalization, Activation(ReLU)	1×1152
Reshape	6×6×32
Conv2DTranspose, Filter=3	12×12×1
Activation(Tanh)	12×12×1
Reshape	1×144

3.2 Result and analysis

In order to make it easier to observe the training stability of the IMLE model, Fig. 1 shows the evolution process of the IMLE model.

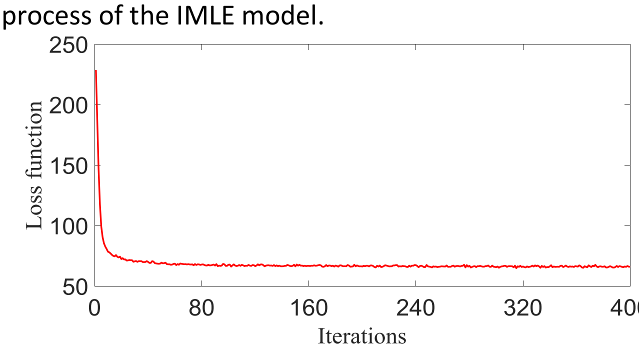

Fig 1 Training evolution for the IMLE model

It is obvious that the loss function of the IMLE model decreases rapidly with the increase of iteration. When the number of iteration is bigger than 60, the loss function tends to be stable, which indicates that the

IMLE model has matured. The loss function of GAN is difficult to converge [8], while the training process of IMLE is very stable and the convergence speed is fast.

To prove that the new samples generated by the IMLE model and the real samples have similar patterns, 1600 Gaussian noises are fed into the generator to obtain new samples, and a part of the real samples from the test set and the generated samples are shown in Fig. 2.

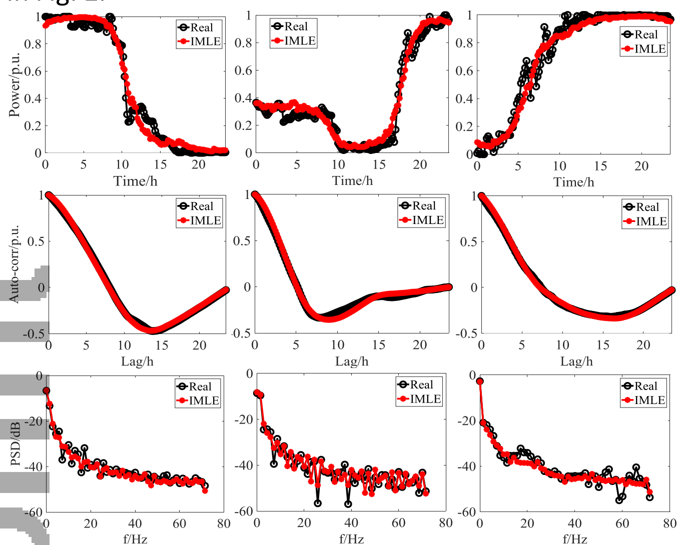

Fig 2 Comparison of new samples and real samples

1) As shown in the first row of Fig. 2, the shapes of generated samples are very similar to that of the real samples from the test set without used for training the IMLE model. The IMLE can capture the nonlinear dynamic characteristics of wind power profiles, such as large valley, fluctuation, and fast ramps. 2) Moreover, the second row of Fig. 2 shows the autocorrelation function to compare the temporal correlation between the real samples and the generated samples. The trends of autocorrelation functions between the real samples and the generated samples are basically the same, which indicates that the new samples generated by the IMLE model can fit the temporal correlation of the real samples well. 3) To visualize the fluctuation components of wind power at different frequencies, the third row of Fig. 2 shows the power spectral density of wind power profiles. Obviously, the power spectral density (PSD) of generated samples closely resembles that of real samples from the test set, which indicates that the IMLE model can accurately capture the frequency-domain characteristics of real wind power well.

To verify the performance of the IMLE model, the existing methods such as VAE and an explicit density model (Gaussian copula method) are set up for comparison [5]. Fig. 3 shows the probability density functions of generated samples and real samples. It found that the probability density function of samples generated by the IMLE model is closer to that of real samples in comparison with other methods, which show that the IMLE model accurately captures the probability distribution characteristics of wind power profiles.

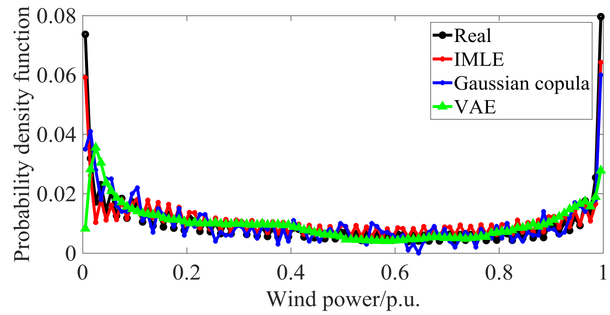

Fig 3 Probability density functions of the samples

4. CONCLUSIONS

In this paper, it is aimed to design an IMLE model to generate wind power profiles. The performance of the proposed method is tested by the real data set. After the simulation, the following conclusions are obtained:

1) Unlike GAN with unstable training problems, the training process of the IMLE model is very stable, and the convergence speed is very fast. In addition, the IMLE model can capture the probability distribution characteristics of wind power profiles more accurately than some existing methods such as the VAE and Gaussian copula method.

2) By comparing the simulation results, it is found that the IMLE model can capture the shape, temporal correlation, and fluctuation of real power profiles.

For future work, the IMLE model can be extended to generate scenario for multiple wind farms simultaneously. In addition, the spatial correlation between wind farms should be considered in the future.

ACKNOWLEDGEMENT

This manuscript is supported by the China Scholarship Council.

REFERENCE

[1] Ning C, You F. Data-driven adaptive robust unit commitment under wind power uncertainty: a bayesian nonparametric approach. IEEE Transactions on Power Systems.2019;34:2409–18.

[2] Ge L, Liao W, Wang S, Bak-Jensen B, Pillai J. Modeling daily load profiles of distribution network for

scenario generation using flow-based generative network. IEEE Access.2020;8:77587–97.
[3] Chen Y, Wang Y, Kirschen D S, Zhang B. Model-free renewable scenario generation using generative adversarial networks. IEEE Transactions on Power Systems.2018;33:3265–75.
[4] Tian C, Li C, Zhang G, Lv Y. Data driven parallel prediction of building energy consumption using generative adversarial nets. Energy and Buildings.2019;186:230–43.
[5] Hu W, Zhang H, Dong Y, Wang Y, Dong L, Xiao M. Short-term optimal operation of hydro-wind-solar hybrid system with improved generative adversarial networks. Applied Energy.2019;250:389-403.
[6] Pan Z, Wang J, Liao W, Chen H, Yuan D, Zhu W, Fang X, Zhu Z. Data-driven EV load profiles generation using a variational auto-encoder. Energies.2019;12:1-15.
[7] Jin G, Zhang Y, Lu K. Deep hashing based on VAE-GAN for efficient similarity retrieval. Chinese Journal of Electronics.2019;28:1191-9.
[8] Zhao Q, Liao W, Wang S, Pillai J. Robust voltage control considering uncertainties of renewable energies and loads via improved generative adversarial network. Journal of Modern Power Systems and Clean Energy.2020;8:1104-14.
[9] Wang C, Xu C, Yao X, Tao D. Evolutionary generative adversarial networks. IEEE Transactions on Evolutionary Computation.2019;23:921-34.
[10] Yang Y, Dan X, Qiu X, Gao Z. FGGAN: feature-guiding generative adversarial networks for text generation. IEEE Access.2020;8:105217-25.
[11] Hoshen Y, Li K, Malik J. Non-adversarial image synthesis with generative latent nearest neighbors.In. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition.CA.USA.2019;5811-9.
[12] Yang W, Zhang X, Tian Y, Wang W, Xue J, Liao Q. Deep learning for single image super-resolution: a brief review. IEEE Transactions on Multimedia.2019;21:3106-21.
[13] Li K, Malik J. Implicit maximum likelihood estimation. 2018. arXiv: Learning: 1809.09087v2. [Online]. Available: https://arxiv.org/abs/1809.09087
[14] Draxl C, Clifton A, Hodge B, McCaa. J. The wind integration national dataset (wind) toolkit. Applied Energy.2015;151:355-66.