Artificial Intelligence Generative Model in Power System Security and Stability Analysis: An Overview

Yuxin Dai, Jun Zhang, Peidong Xu, Tianlu Gao, Haoran Zhang, Hao Liu, Ke Zhang, Hang Zhao, Zeyu Mu, and Chenglong Xu

***Abstract*—The field of artificial intelligence generated content (AIGC) is currently experiencing rapid development, attracting the attention of both academic and industrial communities. This article summarizes the development of several mainstream models in the AIGC field, as well as their research and application status in areas such as image generation and text generation. Additionally, as an emerging form of internet technology, this article analyzes the research status and application prospects of AIGC in traditional industrial fields using the power system as an example. Finally, this article summarizes in detail the shortcomings of generative models and identifies research directions for future study, to promote the development of AIGC technology and its deep integration with traditional industrial applications, to facilitate industrial technological transformation and upgrading.**

***Index Terms*—Artificial intelligence generated content (AIGC), diffusion model, generative adversarial network, variational auto-encoder, power system, steady-state security analysis, transient stability assessment**

I. Introduction

ARTIFICIAL intelligence generated content (AIGC) refers to content that is created through AI algorithms, such as image, text, audio, video, etc.

Early AIGC was content generated by professionals using software tools and fixed templates. It was mainly applied in industrial modeling, film creation, etc. However, the application scenarios were limited, and the degree of automation and efficiency was relatively low. In recent years, AIGC applications have also gained rapid growth in various scenarios with the development of AI algorithms and internet technology. The generative adversarial network (GAN) proposed by Goodfellow et al. [1] has greatly propelled the application of deep learning technology in AIGC technology. GAN employs a generator and a discriminator for adversarial training, which enables the two networks to engage in an antagonistic game and constantly iterate to improve the quality of the generated data samples. Ideally, the generator can generate new data that follow the same distribution as the real data. However, it is difficult to guarantee the stability and convergence of the GAN training process. Given the shortcomings of the original GAN, subsequent models such as conditional GAN (cGAN) [2] and information maximizing generative adversarial network (InfoGAN) [3] were developed, resulting in significant improvements in model performance. As a result, GAN-based models have become the mainstream generative models. In addition, generative models also include variational auto-encoders (VAEs) [4], flow-based models [5], and their derived models, also pushing the development of AIGC field to a certain extent. Over the past two years, the launch of various AI painting products, including OpenAI's DALL·E2, Google's Imagen, and Microsoft's NUWA, has garnered significant attention from the public. These tools can automatically generate high-quality images based on text and other input data. The products mentioned above are achieved based on diffusion model (DM). DM was originated from denoising diffusion probabilistic model (DDPM) proposed in 2020 [6]. Reference [7] pointed out that DDPM defeated GAN in image synthesis. The various improved diffusion models that have been subsequently introduced, especially the stable diffusion model [8], have received widespread attention and discussion.

Nowadays, the field of AIGC is booming. On the one hand, the automated production of art pieces and industrial products brings convenience to people's lives. With the help of AIGC, people's efficiency in living and working has been significantly improved. On the other hand, as an emerging form of internet technology, it is imperative for AIGC to leverage its advantages in data augmentation, enhance information support in industrial management and control, and drive the digital and intelligent development of relevant fields. This will guide profound technological changes. Based on the analysis provided above, this paper focuses on AIGC-related algorithms and their applications in power system security and stability analysis, while also examining some current issues that exist within these areas.

The rest of this paper is organized as follows. Section I briefly introduces the basic principles of several main AIGC models, and summarizes the status of their typical applications in the field. Section II introduces the fundamental physical

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models of power system security and stability analysis, and condenses the framework of data-driven power security and stability analysis. Section III overviews the research status of VAE and GAN models in power security and stability analysis. Section IV analyzes existing problems in current research and prospects for future research directions. Section V summarizes the whole paper.

II. Overview of Artificial Intelligence Generative Model (AIGM) Development

A. Introduction of AIGM

Artificial intelligence generative model refers to a kind of model that can randomly generate observed results according to some implicit parameters, mainly including VAE [4, 9], GAN [1, 10–12], DM [6, 7, 13, 14], etc. This section provides a brief introduction to these models and describes their key principles and technical characteristics.

VAE. VAE is a generative model that is based on the modification of the auto-encoder. After the model training is completed, the decoder can be used to simulate the generation of data that are similar in probability distribution to the training data.

As shown in Fig. 1, VAE is composed of encoders and decoders [4, 15], the same as auto-encoders.

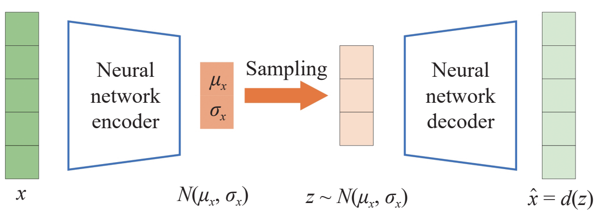

Figure 1 VAE.

Encoder, as a discriminative model $q_\varphi(z \mid x)$, encodes input data x and generates the hidden variable z, corresponding to input data; while decoder, as a generative model $p_\theta(x \mid z)$, receives hidden variable z as input and decodes it to get data $\bar{x}$. φ and θ are parameters (e.g., neural network weight and bias) of encoder model and decoder model, respectively.

In VAE, Kullback-Leibler (KL) divergence is used to measure the similarity between the discriminative model $q_\varphi(z \mid x)$ and the true posterior probability $p_\theta(x \mid z)$, i.e., the loss function of VAE is

$$L(\theta,\varphi,x) = \mathrm{KL}\{q_\varphi(z \mid x), p_\theta(z \mid x)\} - E_{q\varphi(z|x)}\{\log[p_\theta(x \mid z)]\} \tag{1}$$

where $\mathrm{KL}\{q_\varphi(z \mid x), p_\theta(z \mid x)\}$ refers to the similarity between the probability distribution of hidden variable z and prior distribution, and $E_{q\varphi(z|x)}\{\log[p_\theta(x \mid z)]\}$ refers to the error between reconstructed samples and original samples.

During the process of model training, the objective is to minimize the reconstruction error between the reconstructed samples and the original samples. Additionally, the aim is to make the probability distribution of the hidden variable approach the prior distribution as closely as possible.

Based on VAE, many scholars have made improvements for various application scenarios, such as Nouveau-VAE [16], Control-VAE [17], and Robust-VAE [18]. But in theory, VAE needs to use variational inference for approximation, which introduces bias and therefore makes the generated images blurry.

GAN. GAN refers to a kind of deep learning model. As shown in Fig. 2, it is mainly composed of two parts [1], the generative model and discriminative model, separately corresponding to the generator and discriminator. D_{real} denotes the probability distribution of real data. $x_{\text{real}} \sim D_{\text{real}}$ means that x_{real} is sampled from the real data distribution D_{real}. Φ represents the parameter of the discriminator model.

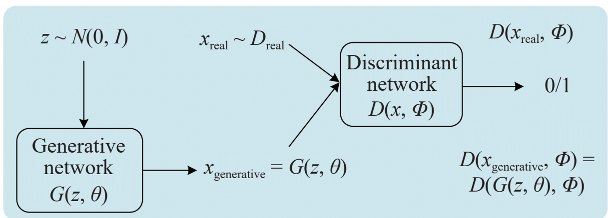

Figure 2 GAN.

(1) Generator It is used to generate data. The generator samples randomly from hidden space as input, and the output data need to imitate real samples as much as possible.

(2) Discriminator It is used to check whether the data are fake samples generated by the generator. The input of the discriminator is the real sample or output of the generator to distinguish the output of the generator from real samples as much as possible.

For the generator G, its input is $z \sim N(0, I)$, its output is $G(z,\theta)$.

For the discriminator D, it can be deemed as a binary classification. One is the input of the generator, i.e., $X_{\text{generative}} = G(z,\theta)$; the other is the real data X_{real}. By inputting the data $X = X_{\text{generative}} \cup X_{\text{real}}$ into the discriminator, the output results are $D(x_{\text{real}},\phi)$ and $D(x_{\text{generative}},\phi) = D(G(z,\theta),\phi)$, respectively. ϕ represents the parameter of discriminator model D.

From the perspectives of the generator and discriminator, we have standards as follows:

(1) Standard for generator The closer the generated data to the real data, the better, that is, the closer $D(x_{\text{generative}},\phi) = D(G(z,\theta),\phi)$ to 1, the better. Thus, the parameter for the generator meets

$$\max_{\theta}(E_{z\sim P(z)}[\log D(G(z,\theta),\phi)]) \tag{2}$$

where P indicates probability.

(2) Standard of discriminator Network can distinguish the real and false data accurately, that is, the closer the output $D(x_{\text{real}},\phi)$ to 1, the closer the output $D(x_{\text{generative}},\phi) = D(G(z,\theta),\phi)$ of generated data to 0.

For the discriminator, the cross entropy loss function can be used. For the binary classification, there are positive samples (label = 1) and negative samples (label = 0) only. The sum of the probabilities is 1. For the input x, it will be output as $p(x)$. We set y as the real label, and the loss function of the single sample is

$$L = -y \cdot \log(p(x)) + (1-y)\log(1-p(x)) \tag{3}$$

Calculate the average loss function of N samples as

$$L = \frac{1}{N}\sum_{i=1}^{N} y_i \cdot \log(p(x_i)) + (1-y_i)\log(1-p(x_i)) \tag{4}$$

where x_i and y_i represent the i-th input and output vectors of the model.

As the output $D(x,\phi)$ of $x \sim P_{\text{data}}(x)$ is real, where $P_{\text{data}}(x)$ represents the probability distribution of the dataset, i.e., the label is 1, the loss function is

$$L = -1 \cdot \log(D(x,\phi)) + (1-1)\log(1-D(x,\phi)) = \\ -\log(D(x,\phi)) \tag{5}$$

The average loss function is

$$L = -E_{x\sim P_{\text{data}}(x)}[\log(D(x,\phi))] \tag{6}$$

As the output $D(G(z,\theta),\phi)$ of $z \sim P(z)$ is false, i.e., the label is 0, the loss function is

$$L = -\log(D(x,\phi)) \tag{7}$$

The average loss function is

$$L = -E_{z\sim P_{\text{data}}(z)}[\log(1-D(G(z,\theta),\phi))] \tag{8}$$

To sum up, the loss function of GAN is

$$L(D,G) = E_{x\sim P_{\text{data}}(x)}[\log(D(x,\phi))] + \\ E_{z\sim P_z(z)}[\log(1-D(G(z),\phi))] \tag{9}$$

The optimization objective of GAN is

$$\min_G \max_D L(D,G) \tag{10}$$

During the training process, G is fixed and D is trained first

$$\max_D (E_{x\sim P_{\text{data}}(x)}[\log(D(x,\phi))] + \\ E_{z\sim P_z(z)}[\log(1-D(G(z),\phi))]) \tag{11}$$

where the objective of training D is to make the value of Eq. (11) as high as possible. The real data are expected to be classified into 1 by D, while the generated data are expected to be classified into 0. The objective of training G is to make the value of L as small as possible, so that D cannot distinguish real and false data.

Compared with VAE, GAN focuses primarily on restoring the distribution of the real data and generating new data through sampling. However, the original GAN suffers from several limitations, including divergent training, poor robustness, high sensitivity to the design of the discriminator and generator structures, and the selection of hyper-parameters. In view of these, some GAN-based derived models [10, 17–22] have been successively put forward, and good results have been achieved in different application scenarios, which have overcome the shortcomings of original GAN to a certain extent.

DM. DM is an emerging generative model in the past two years, which has achieved remarkable results in text generation, image generation, and other fields [6, 7, 13, 14].

The principle of DM is to apply noise gradually to the original data until the data are destroyed into complete noise and then restore from the noise to the original data through backward learning. Specifically, DM can be divided into the forward diffusion model q and the backward generative model p_θ. Taking DDPM for example, as shown in Fig. 3, x_0 is the original data, and there is a Markov chain from x_0 to x_T. x_T represents the noisy data at the T-th time step. For every time step t, in the forward direction, DM gradually adds noise to the data x_t to get the posterior probability $q(x_t \mid x_{t-1})$. When $t \to \infty$, $x_T \sim N(0, I)$. In the generative model p_θ, the network with the parameter θ is used to restore the noise into effective information.

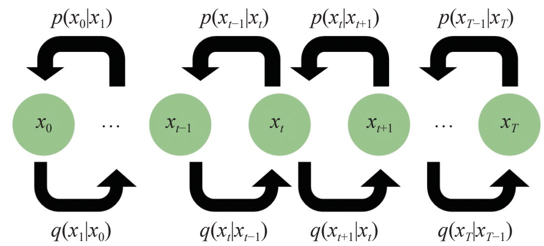

Figure 3 DM.

The forward process is also called the diffusion process, which is a Markov process, that is, the current state is only related to the previous state. We gradually add the Gaussian noise to the original data x_0. The standard deviation of the noise is determined by a fixed value β_t. The mean value is determined by the fixed value β_t and the data x_{t-1} at the step $t-1$, i.e., $q(x_t \mid x_{t-1}) = N(x_t, \sqrt{1-\beta_t}x_{t-1}, \beta_t I)$.

The backward process is also called the inverse diffusion process. It is expected to predict the target distribution x_0 gradually from the noise distribution x_T. The backward process is also a Markov process. The input x_t is used to get the distribution of x_{t-1}, namely to get $p_\theta(x_{t-1} \mid x_t)$, and finally to get the generated data $\bar{x}_0$, which are expected to be consistent in distribution with x_0.

The objective of DM is to make the approximate distribution $p_\theta(x_0)$ approach the real data distribution $q(x_0)$ as much as possible. Therefore, the objective function of the model is expressed by the cross entropy as

$$\begin{aligned} L &= -E_{q(x_0)}\log p_\theta(x_0) = \\ &-E_{q(x_0)}\log\left[\int p_\theta(x_{0:T})\mathrm{d}x_{1:T}\right] = \\ &-E_{q(x_0)}\log\left[\int q(x_{1:T}\mid x_0)\frac{p_\theta(x_{0:T})}{q(x_{1:T}\mid x_0)}\mathrm{d}x_{1:T}\right] = \\ &-E_{q(x_0)}\log\left[E_{q(x_{1:T}|x_0)}\frac{p_\theta(x_{0:T})}{q(x_{1:T}\mid x_0)}\right] \leqslant \\ &-E_{q(x_{0:T})}\log\left(\frac{p_\theta(x_{0:T})}{q(x_{1:T}\mid x_0)}\right) \end{aligned} \tag{12}$$

where $x_{0:T}$ is the sequence of variables from the initial time step to time step T.

Then, we have

$$L = -E_{q(x_0)}\log p_\theta(x_0) \leqslant \\ E_{q(x_{0:T})}\log\left(\frac{q(x_{1:T}\mid x_0)}{p_\theta(x_{0:T})}\right) \tag{13}$$

The right term of Eq. (13) is the lower bound of log-likelihood, which is denoted as L_{LB}. As long as we make it smaller, the cross entropy will be smaller.

As the model meets the condition of the Markov chain, we can get

$$q(x_{1:T} \mid x_0) = \prod_{t=1}^{T} q(x_t \mid x_{t-1}), \\ p_\theta(x_{0:T}) = p_\theta(x_T)\prod_{t=1}^{T} p_\theta(x_{t-1} \mid x_t) \tag{14}$$

By substituting Eq. (14) into L_{LB}, we can obtain

$$\begin{aligned} L_{\text{LB}} &= E_{q(x_{0:T})} \log\left(\frac{q(x_{1:T} \mid x_0)}{p_\theta(x_{0:T})}\right) = \\ &E_q\left[\log \frac{\prod_{t=1}^{T} q(x_t \mid x_{t-1})}{p_\theta(x_T)\prod_{t=1}^{T} p_\theta(x_{t-1} \mid x_t)}\right] = \\ &E_q\left[-\log p_\theta(x_T) + \sum_{t=1}^{T} \log\left(\frac{q(x_t \mid x_{t-1})}{p_\theta(x_{t-1} \mid x_t)}\right)\right] = \\ &E_q\left[\log \frac{q(x_T \mid x_0)}{p_\theta(x_T)} + \sum_{t=2}^{T} \frac{q(x_{t-1} \mid x_t, x_0)}{p_\theta(x_{t-1} \mid x_t)} - \right. \\ &\left. \log p_\theta(x_0 \mid x_1)\right] = \\ &E_{q(x_0)} D_{\text{KL}}[q(x_T \mid x_0) \| p_\theta(x_T)] + \\ &E_{q(x_0,x_t)} \sum_{t=2}^{T} D_{\text{KL}}[q(x_{t-1} \| x_0, x_t) \| p_\theta(x_{t-1} \mid x_t)] - \\ &E_{q(x_0,x_1)} \log p_\theta(x_0 \mid x_1) \end{aligned} \tag{15}$$

where D_{KL} indicates KL divergence. Then, L_{LB} is expressed by KL divergence as

$$\begin{aligned} L_{\text{LB}} &= E_{q(x_0)} D_{\text{KL}}[q(x_T \mid x_0) \| p_\theta(x_T)] + \\ &E_{q(x_0,x_t)} \sum_{t=2}^{T} D_{\text{KL}}[q(x_{t-1} \| x_0, x_t) \| p_\theta(x_{t-1} \mid x_t)] - \\ &E_{q(x_0,x_1)} \log p_\theta(x_0 \mid x_1) \end{aligned} \tag{16}$$

In Eq. (16), the first term corresponds to the regularization loss $D_{\text{KL}}(q_\phi(z \mid x) \| p_\theta(z))$ in VAE, the third term corresponds to the reconstructed loss $E_{q\phi(z|x)}[\log p_\theta(x \mid z)]$, and the second term refers to the sum of multiple KL divergences, which are used to separately measure the distance between the posterior distribution p and the posterior distribution q where x_0 is known.

For optimizing Eq. (16), the first term is constant, and the third term can be deemed as the result when the first term $t = 1$. Therefore, the second term is mainly taken into account. The reparameterization method is used to make x_0 directly calculate x_t at any step without iteration step by step [23]. By setting $p_\theta(x_{t-1} \mid x_t) = N(x_{t-1}, \mu_\theta(x_t, t), \sigma_t^2 I)$, according to Ref. [23], we have

$$\begin{aligned} L_{t-1} &= E_{q(x_0,x_t)} \sum_{t=2}^{T} D_{\text{KL}}[q(x_{t-1} \| x_0, x_t) \| p_\theta(x_{t-1} \mid x_t)] = \\ &E_q\left[\frac{1}{2\sigma_t^2} \|\tilde{\mu}_t(x_t, x_0) - \mu_\theta(x_t, t)\|^2\right] + C \end{aligned} \tag{17}$$

where μ_θ denotes the mean function predicted by the neural network parameterized by θ. σ_t^2 denotes the variance parameter used in the Gaussian transition at time t, specifying the noise level. L_{t-1} denotes the loss term corresponding to step $t-1$ in the optimization objective. $\tilde{\mu}_t(x_t, x_0)$ is the posterior mean of x_{t-1} given x_t and x_0, computed from the forward process. C denotes a constant irrelative to the model.

In order to minimize Eq. (17), it is necessary to optimize μ_θ, making it approach $\tilde{\mu}_t$ as much as possible. In Ref. [15], Eq. (17) is further simplified in practice, which is detailed in Ref. [6].

At present, DM has achieved remarkable results in image generation, text generation [6, 23], and other fields. However, DM suffers from several inherent issues, including long sampling time, challenges in reducing data dimensionality, and limited capacity to handle only a single data type. As a result, there is an urgent need for a new model that can overcome these shortcomings and enhance overall performance.

Other generative models such as normalized flow models and energy-based models are shown in Fig. 4 [24]. $f(x)$ denotes the transformation function (or mapping) performed by the encoder in a normalizing flow model. $G_w(x, z)$ denotes the generator function parameterized by w. Due to the limited space, it will not be described here, and reference can be seen in Refs. [25, 26].

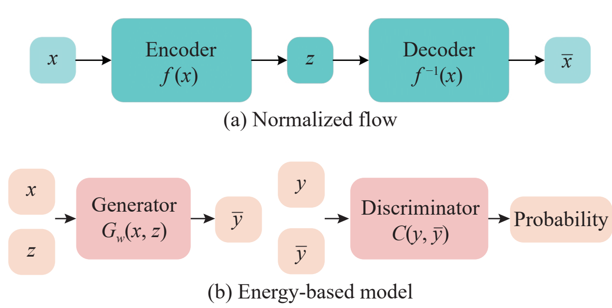

Figure 4 Other generative models.

B. Application of AIGM in Typical Field

a. Image Generation

Image generation is an important application direction of AIGM. The main task of image generation is to generate images that meet human needs. Generally speaking, image generation mainly includes two fields, text-to-image (T2I) and image-to-image.

Text-to-image refers to generating an image based on a text description, which has always been a research hot topic in the field of AI. The first step is to extract semantic features from the text description, which are then input into the image generation model. The model needs to be able to accurately extract the key semantics in the text description, and make the image meet the description of the extracted semantic features while ensuring that the image is as real as possible during its generation [27]. The method of generative adversarial T2I [28] first puts forward the use of GAN for text-to-image. The method incorporates random variables into adversarial networks and employs a deep convolutional GAN generator to produce images. As a result, it can generate multiple images that correspond to the same text description. After that, a lot of research has achieved text-to-image based on GAN and its variants. StackGAN [29] decomposes the generation of high-resolution images into subproblems that are easier to solve, which improves the quality of the generated images. The method StackGAN++ [30] sets a bilayer structure based on StackGAN. Layer 1 generates the original scenario shape and color according to the text description, while layer 2 generates higher-resolution images according to the results and text description of layer 1.

AttnGAN [31] introduces the attention mechanism into GAN. With the help of the attention-driven mechanism, the network can be used to evaluate keywords in text descriptions and synthesize details in different sub-domains of images. Considering that initial images generated by the network may have quality issues, dynamic memory generative adversarial network (DMGAN) [32] adopts the “dynamic memory” mechanism. In case of poor quality of initial images, the dynamic storage module can be used to refine image content. ControlGAN [33] puts forward the use of the word discriminator, allowing the model to focus on generating sub-domains corresponding to the most relevant words.

All in all, the above GAN-based improved methods enhance the performance of text-to-image conversion from different angles. However, due to the limited expressive ability of GAN, these methods are usually used to generate scenarios with a limited dataset only, where the application scope is narrow.

Apart from GAN, other AI generative models have also found applications in text-to-image. CogView [34] uses vector quantized (VQ)-VAE model to establish tokenizer, and uses transformer that contains 4 billion parameters for image generation. The VAE-GAN [35] uses VAE model to extract the basic layout and color of text-based images and uses conditional GAN to improve the generated result of VAE and restore missing details, to generate vivid images. DALL·E [36] model is used to achieve image generation in unrestricted scenarios based on the auto-regression model. In addition, DM [6, 7] has been increasingly studied in recent years and has also achieved excellent results in text-to-image.

The primary task of image-to-image is to convert existing images into other images as required, such as image restoration, portrait extraction, image style transfer, etc. Pix2Pix [37] is the most classic one in this field. Pix2Pix adds regularization, U-net, and other structures based on conditional GAN to achieve a universal image conversion framework and image style transfer. CycleGAN [38] introduces the concept of loop consistency, where two GAN networks are arranged in mirror symmetry to form a loop network. Additionally, it designs a loss function to enforce loop consistency, which helps to avoid potential mode collapse during image conversion using GAN networks. DualGAN [39] uses the GAN of dual learning mode to achieve one-to-one image translation. Unsupervised image-to-image translation network (UNIT) [40] uses VAE-GAN to model every image domain based on the shared-latent space hypothesis, which achieves unsupervised image-to-image translation. The above methods are one-to-one image-to-image, but there are also tasks requiring the conversion of one image to multiple images. Multimodal UNIT (MUNIT) [41] divides images into content encoding and space encoding, retains content decoding of images, and samples different style encodings of images to generate a multimodal output sample. BiCycleGAN [42] combines conditional variational auto-encoder (cVAE)-GAN and conditional latent regressor (cLR)-GAN models and samples different noise signals in source space to achieve one-to-many image generation.

b. Natural Language Generation

Natural language generation is an important branch of natural language processing (NLP). The aim of natural language generation is to automatically produce understandable texts based on key information, including abstract summary, article writing, dialogue system, etc. In recent years, many scholars have attempted to apply AI generative models to the field of natural language generation.

VAE has a wide range of applications in natural language generation. VAE-recurrent neural network (RNN) [43] proposes a kind of RNN-based VAE generative model, which uses the sequential structure characteristics of RNN for text generation modeling. Conditional VAE [44] captures discourse-level diversity in encoders based on its framework, which achieves diversified dialog generation. The transformer-based conditioned variational auto-encoder [45] uses transformers to replace the encoders and decoders in VAE. The encoder and decoder share the attention layer, enabling the model to generate text for story continuation tasks. Apo-VAE [46] adopts the original dual formula of KL divergence and introduces an adversarial learning mode, which enhances the stability of text generation training. Topic-guided variational auto-encoder (TGVAE) [47] builds upon the VAE framework and incorporates a topic guide to improve its performance. It also introduces the use of the Householder manifold to enhance posterior reasoning, resulting in promising outcomes for both unconditional and conditional text generation tasks. Polarized-VAE [48] is used to explain sentence semantics or grammar based on the proximity measurement reflecting similarity between data points.

GAN models are originally designed to generate continuous data. But NLP requires generating the sequence of discrete words. Moreover, GAN can be used to evaluate the generated complete sequence only, which lacks the function of evaluating partial sequence. To solve these problems, SeqGAN [49] casts the generator within a GAN as a randomized policy in reinforcement learning. This approach directly updates the gradient and circumvents the differential problem associated with the generator. The reward signal used in reinforcement learning is derived from the evaluation of complete sequences by discriminator. LeakGAN [50] is a model designed for long-text generation. It achieves this by using a hierarchical generator, which allows the discriminator to provide the generator with more information. This approach helps to overcome the issue of sparse information in the discriminator, as the additional guidance provided to the generator results in more accurate and effective long-text generation. In addition, there are also methods that use policy gradient for GAN training and achieve the GAN-based dialog system in combination with the training method of teacher forcing [51].

Other methods have also been used in various subfields of natural language generation. Structured denoising diffusion model in discrete state-space (D3PM) [52] adds the Gaussian noise to discrete variables and improves the loss function of DM, enabling it to be applied to discrete variables, which allows DM to be used for text generation. In regards to the image-to-text problem, dual encoder (DualEnc) [53] establishes a dual coding model that incorporates not only the structure of the image but also the linear structure of the output text.

c. Other Fields

Besides image generation and natural language generation, AIGM finds extensive applications in various other domains.

In the audio generation field, MIDI-VAE [54] can deal with chord music with multi-instrument tracks based on VAE, and simulate music dynamics in combination with note duration and speed, so as to achieve music style transfer. MidiNet [55] uses GAN for rhythm generation. Similarly, MuseGAN [56] is also a GAN-based model, but it incorporates a sequence generative model to generate music with multiple tracks in the symbolic domain. Its aim is to capture the harmonic rhythm structure, the association between audio tracks, and the temporal structure of music. When it comes to code generation, GANcoder [57] proposes an automatic programming method based on GAN that can generate functional and logical programming language code from the given natural language discourse. The model is capable of producing code that is equivalent to the meaning of the input discourse. In terms of three-dimensional (3D) model generation, there are a lot of researches focused on using GAN for generation or reconstruction [58, 59]. Also, there are researchers who use cGAN [60] to achieve the generation of 3D medical images, or use the VAE [61] model to directly generate 3D coordinates of immune globulin.

III. Power System Security and Stability Analysis

This section introduces the problems of steady-state security and transient stability in power systems and summarizes the framework of data-driven power system security and stability analysis.

A. Steady-State Security Analysis

The power system flow equation is fundamental to static security analysis [62]. In a power system with N nodes, each node i has four state variables P, Q, V, and θ, representing the active power injection, reactive power injection, voltage magnitude, and phase angle, respectively. The state between nodes meets the flow equation [63]

$$\begin{cases} \Delta P_i = P_i^{\mathrm{sp}} - V_i \sum_{j=1}^{N} V_j (G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}) = 0, \\ \Delta Q_i = Q_i^{\mathrm{sp}} + V_i \sum_{j=1}^{N} V_j (B_{ij}\cos\theta_{ij} - G_{ij}\sin\theta_{ij}) = 0 \end{cases} \tag{18}$$

where $i = 1, 2, ..., N$, sp indicates setpoint, G_{ij} and B_{ij} are the admittance values between node i and node j, and θ_{ij} refers to the phase angle difference between node i and node j.

In the actual solving process, there are usually two known state variables under each node for solving the other two state variables. Nodes can usually be divided into PV nodes, PQ nodes, and $V\theta$ nodes by different known state variables. The flow equation is usually used for solving based on iteration methods, including the Newton-Raphson method, the Gauss-Seidel method, etc. [63].

The steady-state security of power systems means that if the operating point of the current system meets the flow equation and various operating security constraints, the operating point is statically secure, so that it is usually expressed as

$$\begin{cases} \phi(x, y) = 0, \\ V_i^{\min} \leqslant V_i \leqslant V_i^{\max},\ \forall i \in N; \\ P_i^{\min} \leqslant P_{\mathrm{g},i} \leqslant P_i^{\max},\ \forall i \in N_{\mathrm{g}}; \\ Q_i^{\min} \leqslant Q_{\mathrm{g},i} \leqslant Q_i^{\max},\ \forall i \in N_{\mathrm{g}}; \\ -P_{b,i-j}^{\max} \leqslant P_{b,i-j} \leqslant P_{b,i-j}^{\max},\ \forall i, j \in N \end{cases} \tag{19}$$

where $\phi(x, y) = 0$ refers to the flow equation of alternating current (AC) system, N refers to the bus node set of the system, N_{g} refers to the generator node set of the system, $V_i^{\min}$ and $V_i^{\max}$ refer to the lower and upper voltage limits of the i-th node, $P_i^{\min}$ and $P_i^{\max}$ refer to the lower and upper limits for the active power output of the i-th system generator node, $Q_i^{\min}$ and $Q_i^{\max}$ refer to the lower and upper limits for the reactive power output of the i-th system generator node, and $P_{b,i-j}^{\max}$ and $-P_{b,i-j}^{\max}$ refer to the forward and backward transmission power limits of the transmission line connecting node i and node j in the system, respectively. $P_{g,i}$ denotes the active power output of the generator at node i, $Q_{g,i}$ represents the reactive power output of the generator at node i, and $P_{b,i-j}$ denotes the active power flow on the branch connecting node i to node j.

In the past, the steady-state security analysis of power systems typically utilized a point-by-point method [64], which is known for its high computational requirement and low efficiency. Recently, some scholars have explored the use of security region methods [65–67] to address steady-state security problems in power systems, and some progress has been made. However, it remains challenging to apply these methods to the high-dimensional static security domain analysis of large power grids.

B. Transient Stability Analysis

The transient stability of power systems can be defined as the ability of each synchronous generator to maintain synchronous operation and transition to a new stable operation mode or restore to the original stable operation mode after the power system is subjected to serious disturbances such as short circuit [68]. The process is shown in Fig. 5.

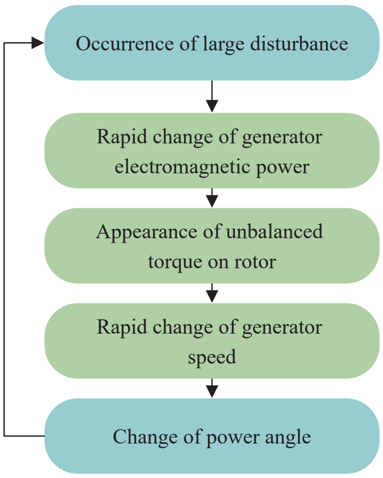

Figure 5 Transient process of power system.

In theory, the transient stability of power systems can be judged by equal-area criteria [63]. The sufficient and necessary condition for transient stability is that the transient stability of generator can be guaranteed if the maximum deceleration area is greater than or equal to the acceleration area. Otherwise, the generator will experience a loss of stability.

Taking one machine infinity bus for example, as shown in Fig. 6, point a refers to a normal operating point of the system. Points a to h describe the complete transient process of a power system subjected to a large disturbance, such as a short circuit fault. P_{I} and P_{II} denote the normal operating power and fault-on power of the grid. P_{III} denotes the post-fault power. P_0 denotes the mechanical input power of the generator. $a \to b$ means that the power changes from P_{I} to P_{II} at the short circuit moment of the system, the power of system drops, and the rotor angle δ_0 has no mutation due to inertia. $b \to c$ is the short circuit period. δ_1 denotes the initial rotor angle at fault onset. The short circuit fault is cleared at c moment. At this moment, the surplus power of rotor is $\Delta P = P_0 - P_{\mathrm{II}} > 0$. As the rotor accelerates, the rotor angle δ increases along P_{II} curve until the fault is cleared. $c \to e$ means that power changes from P_{II} to P_{III} at the moment of fault clearing, and the rotor angle δ_c remains unchanged. $e \to f$ means that the surplus power of the rotor is $\Delta P = P_0 - P_{\mathrm{III}} < 0$ after the fault is cleared, the rotor slows down, and the rotor angle increases to point f along P_{III} curve. At this time, the rotor speed is $\omega = 1$. However, as $\Delta P = P_0 - P_{\mathrm{III}} < 0$, the rotor speed will still slow down, δ will swing along P_{III} curve and finally stop at point k, and the system makes a transition to a new stable operation mode. If it takes too long to clear a fault, δ_c becomes greater, resulting in $\delta_f > \delta_h$, where δ_f and δ_h denote the rotor angle at the maximum excursion and the critical rotor angle, and the system will face a loss of stability. The equal-area criterion can be used to obtain the system acceleration area.

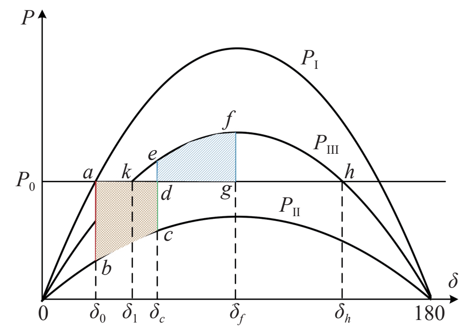

Figure 6 P-δ curve.

$$S_{abcd} = \int_{\delta_0}^{\delta_c} (P_0 - P_{\mathrm{II}})\,\mathrm{d}\delta \tag{20}$$

The physical significance is the kinetic energy obtained for the rotor, and the system deceleration area is

$$S_{edgf} = \int_{\delta_c}^{\delta_f} (P_{\mathrm{III}} - P_0)\,\mathrm{d}\delta \tag{21}$$

The physical significance is the kinetic energy that the rotor loses. As the rotor speed is 1 at points b and f, it is known that $S_{abcd} = S_{edgf}$ by the law of conservation of energy, the system can maintain transient stability. After the fault is cleared, the maximum deceleration area of the rotor is

$$S_{-\max} = \int_{\delta_c}^{\delta_h} (P_{\mathrm{III}} - P_0)\,\mathrm{d}\delta \tag{22}$$

Therefore, if $S_{-\max} > S_{abcd}$, $\delta_f < \delta_h$ can be guaranteed, and the and system can maintain transient stability. On the contrary, the system will face a loss of stability.

In the actual research and application of transient stability evaluation for power systems, there are three main methods:

(1) Time-domain simulation method [69]. This method uses the steady-state power flow as an initial value and solves differential algebraic equations by numerical integration to obtain the swing curve of each generator rotor under disturbance. Then, it determines the transient stability of the system by analyzing the rotor power angle difference. Although this method provides reliable results, it is time-consuming and therefore only suitable for offline analysis.

(2) Direct method [70]. This method is used for transient stability analysis based on energy viewpoints, mainly including the extended equal-area criterion and the Lyapunov-based transient energy function method. Such methods have definite physical significance but conservative computational results, so it is difficult to determine the energy function.

(3) Data-driven method [71–74]. In this method, transient stability evaluation is modeled as a classical binary classification problem in machine learning. This approach does not require the establishment of a complex mathematical model. Instead, it involves offline fitting of the mapping relationship between physical quantities and the transient stability state of the system using historical data. Once well-trained models are obtained, they can be deployed for online applications. While online processing is fast, it requires massive amount of historical operating data for support.

The data-driven method for power system security and stability analysis is a model-free approach that is characterized by simple principle, high accuracy, and fast online computation speed. In recent years, it has received significant attention and research, and considerable progress has been made.

C. Principle and Shortcoming of Data-Driven Power System Security and Stability Analysis

In the analysis of security and stability in power systems, data-driven methods usually model them as binary or multiclass classification problems [71–75], ignoring their complex mathematical models and expressing them as

$$\mathcal{F}(X) \to Y \tag{23}$$

where $\mathcal{F}(\cdot)$ represents machine learning model such as support vector machine, neural network, decision tree, etc. X represents physical variable of the system, also known as feature in the field of machine learning. The specific relevant variables are selected according to the task. Y represents the system state set, usually, which is {security, unsecurity} as a binary task or {nromal, alert, urgency, collapse} as a multi-class task. $\mathcal{F}(X) \to Y$ represents the complex mapping relationship between many physical variables of the system and the system state, obtained through fitting using $\mathcal{F}(\cdot)$.

With the rapid development of artificial intelligence algorithms, various types of supervised learning models have emerged, including those for data-driven transient stability assessment. However, one of the main challenges currently faced by these methods is the availability of data. The data collected from actual power systems during operation mainly consist of samples that are in a secure and stable state. This results in a significant imbalance between the number of samples in different categories, which can hinder model training. Generating data through simulation software is an option, but it is time-consuming and can be biased towards specific operating scenarios, making it difficult to apply data-driven methods to the safety and stability assessment of power systems in practice.

In recent years, generative models, specifically GAN, have emerged as a convenient method for producing large-scale datasets [22, 76, 77]. These models are capable of generating a vast amount of data with the same distribution as real samples, while only requiring a small amount of actual system operation data. This approach effectively reduces the obstacles to the practical application of data-driven methods and holds great potential for future research.

IV. Application of AIGM in Security and Stability Analysis of Power System

As a branch of deep learning models, AIGM has achieved impressive results in multi-modal data generation tasks in various fields. They can also be utilized for power system security and stability analysis, such as renewable energy and load modeling, system anomaly detection, and fault diagnosis, as shown in Table 1.

Regarding renewable energy scenario generation, to address the problem of uncertainty in photovoltaic systems, a deep generative convolutional graph rough VAE algorithm is proposed to provide accurate spatiotemporal photovoltaic predictions [78]. An improved VAE is used to model the uncertainty of concentrating solar power systems. The generated operating scenarios can help with the subsequent power system operation planning [79]. A large-scale regional wind energy prediction method based on VAE and mixed learning is proposed, which takes into account the volatility, intermittency, and non-linearity of wind power output [80]. A VAE method is applied to improve the single-step and multi-step prediction accuracy of solar power generation [81].

Table 1 Application of AIGM in security and stability analysis.

Application field	Method	References
Renewable energy scenario generation	VAE	[78–81]
	GAN	[76, 82–88]
Load modeling	VAE	[89, 90]
	GAN	[91–94]
Anomaly detection and fault diagnosis	VAE	[95, 96]
	GAN	[97, 98]
State assessment	GAN	[22, 77, 99]
Others	VAE	[100]
	GAN	[101]

In the field of renewable energy scenario generation, GAN is utilized to generate different specific scenarios conditioned on weather events and specific dates [76]. To address the uncertainty of renewable energy day-ahead generation, conditional style based GAN is proposed to generate reliable day-ahead scenarios directly from historical data, and to better characterize the spatiotemporal features of renewable energy [82]. To address the volatility of renewable energy, controllable GAN is utilized to generate controllable scenarios covering a variety of statistical features. This method can even generate new scenarios different from previous ones [83]. Controllable GAN with transparent latent space is proposed to address the uncertainty of renewable energy generation, which is applied to the time series data generation in wind power and photovoltaic fields [84]. An improved GAN for wind power generation scenarios is proposed. This method utilizes a gradient penalty term to improve the training speed and alleviates overfitting problems by imposing the Lipschitz constraint on networks [85]. A distribution-free wind power generation scenario generation method based on GAN and reinforcement learning is proposed, which generates scenarios characterizing the variability of wind power generation and reducing uncertainty risk [86]. An improved GAN is utilized to extract spatiotemporal correlations between wind power and photovoltaic power stations from measured data, and to generate renewable energy scenarios for short-term optimization of hydro-wind-solar complementary systems [87]. A wind power scenario generation framework based on conditional improved Wasserstein GAN is proposed to generate typical wind power scenarios containing multiple wind power stations [88].

Regarding the problem of load modeling in power systems, a load generation method based on VAE is proposed to address the difficulty of modeling electric vehicle charging loads in distribution networks. The simulation results demonstrate that the generated data conform to the time correlation and probability distribution characteristics of real load data [89]. A conditional VAE method is utilized to generate multi-variable load states in power systems [90]. 3D convolutional GAN is used to model electric vehicle load demand. The method reduces the model error compared with traditional methods [91]. In the prediction of large-scale building power demand, the performances of original GAN, cGAN, semi-supervised generative adversarial network (SGAN), InfoGAN, and auxiliary classifier generative adversarial network (ACGAN) are compared. The results show that cGAN and original GAN work better on large-scale building power demand prediction [92]. To address the difficulty in obtaining datasets in power systems, a dataset for energy consumption prediction models is constructed using a small amount of real data based on RGAN [93]. A scenario generation method based on GAN is proposed to model the uncertainty of loads and to evaluate the effect of uncertainty modeling from different perspective [94].

Regarding anomaly detection and fault diagnosis in power systems, the uncertain information of measurement data is modeled using probabilistic deep auto-encoders to achieve anomaly detection and reconstruction in power systems [95]. Based on phasor measurement unit (PMU) monitoring data, VAE is used in the field of voltage stability evaluation in power systems. The method improves the accuracy and online calculation speed of the model [96]. A fault detection and diagnosis method for distribution networks based on VAE is proposed to detect and locate faults in distribution networks. This method has strong robustness [96]. A real-time event detection algorithm based on bidirectional GAN is proposed to monitor power system events online [97]. The data with the same distribution are generated as real bus features, including bus voltage, frequency, phase angle, etc., for fault diagnosis in power systems using GAN [98].

In the field of power system state assessment, a GAN-based approach is proposed to handle PMU data incompleteness, which shows the effect in power system dynamic security assessment [22]. A model-free data-driven method based on conditional GAN is used for power system state estimation. The method can accurately estimate the corresponding system states with given raw measurement values [77]. In the field of data-driven transient stability assessment, where sample scarcity and imbalance are common problems, a controllable sample generation framework based on conditional tabular GAN is proposed to balance the transient stability samples and significantly improve the performance of transient stability assessment models [99]. A conditional auto-encoder and synchronized measurement vectors are utilized to calibrate generator parameters [100]. A long-term intelligent power generation controller combines GAN and reinforcement learning for microgrids. The method solves the problem of economic dispatch and control time mismatch and exhibits higher control performance and lower economic costs compared to traditional methods [101].

Despite the success of diffusion models in other fields, their applications in the power systems domain are still limited and require further research.

V. Problem and Prospect

AIGM, represented by techniques such as VAE, GAN, and DM, has been extensively applied in areas such as image and natural language generation, significantly altering the content production mode in the internet domain. Nevertheless, various types of generative models exhibit some inadequacies and research-worthy problems in different aspects.

VAE is the result of combining variational inference and deep learning techniques in theory. As a generative model, it has gained significant attention and widespread use in generating continuous data. However, the generated images by VAE can suffer from issues such as blurriness, and there is still ample space for improvement in their practical performance.

GAN introduces the idea of adversarial games to design a generator that samples data directly and learns a function that approximates the distribution of real data. The discriminator is used to distinguish between real and generated data, which can fit the distribution of the sampled data by optimizing the network parameters. It has been theoretically proven that under the guidance of the objective function, the most ideal training result for GAN is to generate data that are completely consistent with the distribution of real data. While GAN has shown impressive results in practice, ensuring its convergence and stability during training can be challenging in theory. This can result in GAN generating insufficiently diverse samples and struggling to capture the entire distribution of real data.

Based on recent advancements in research, with notable releases of AI painting products such as Stable Diffusion, DM has garnered substantial interest from researchers in academia and industry. DM can generate high-quality data, but there are still some outstanding issues that need to be addressed. Firstly, due to the large number of sampling steps required to generate data, it is challenging to compare its data generation speed with other generation models such as VAE and GAN. Secondly, most current diffusion-based models use the evidence lower bound (ELBO) of the negative log-likelihood as the objective function for model training, as shown in Eq. (13). However, there is currently no theoretical proof that the negative log-likelihood and its ELBO are optimized simultaneously. Therefore, the inconsistency between the actual optimization objective and the theoretical objective may reduce the effectiveness of the model.

In addition, generative models have been extensively employed in power system security and stability analysis, including modeling uncertainties in renewable energy and load, fault diagnosis, sample enhancement, etc. Nevertheless, several pressing issues still need to be addressed. In the domain of power system security and stability analysis, it is essential to enhance the quality of data generated by generative models and establish scientific and unified evaluation criteria for the generated data. Additionally, the training objectives, optimization processes, and interpretability of generative models demand further research.

Therefore, concerning the future artificial intelligence generative models and their applications in the field of power system safety and stability analysis, the following points merit further research:

(1) Unified evaluation method for generative model. Currently, when evaluating the quality of data generated by generative models, researchers typically compare the generated data with real data and use various statistical indicators based on specific application requirements and prior experience to assess the accuracy of the generated samples. However, there is no unified indicator for a certain type of generative model or a specific application. This results in inconsistent and incompatible evaluation criteria when assessing the effectiveness of the model. Therefore, developing a unified evaluation method for generative models is a crucial problem that requires further research and exploration.

(2) General optimization method for artificial intelligence generative model. During the training process of GAN, issues such as gradient disappearance or overfitting are common, making it difficult to ensure the convergence and stability of training. These problems demand higher requirements for the network structure and objective function design of GAN. Despite the development of diffusion models, there are still many issues worth researching. Firstly, the sampling process is time-consuming and requires further optimization. Secondly, the objective function design issue mentioned above merits further investigation. Therefore, there is a large scope for optimization in the model structure, objective function, and implementation mechanism of artificial intelligence generative models, which demands exploring and researching.

(3) Adaptation of AIGM to complex mechanism constraint of power system. Unlike industries such as film and art, the industrial sector represented by power systems often requires the system to satisfy massive and complex constraint conditions during operation. When using artificial intelligence generative models to support power grid security and stability analysis, the generated data need to ensure that they are distributed within the secure region allowed by the mechanism constraints. Thus, integrating the mechanism constraint information of power systems into existing general generative models to accomplish the efficient and stable generation of feasible samples is a crucial issue that necessitates exploration.

(4) Application path design of AIGM in power system security and stability analysis. In the field of power system security and stability analysis, significant progress has been made in applying artificial intelligence generative models. However, further research is needed to address critical issues such as generating directional power samples based on generative models, including samples distributed near the secure boundary of the power system and samples with certain typical power system characteristics. In addition, how to overcome the problem of sample imbalance in power systems using artificial intelligence generative models, and how to design a unified and scientific model evaluation standard that combines the characteristics of power system application scenarios are all worth exploring and researching.

VI. CONCLUSION

This paper provides an overview of the development of AIGM, its mainstream algorithmic principle, and current application in various fields. Additionally, the paper focuses on the research status, key issues, and application prospects of generative models in the field of power system security and stability analysis.

Finally, this paper presents several issues that merit exploration in the realm of AIGM, along with a summary of the technical hurdles that need to be addressed for the effective application of these models in power system security and stability analysis. Hopefully, this paper will serve as a useful reference for researchers interested in the intersection of AIGM and power system security and stability analysis.

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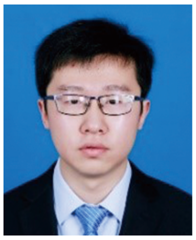

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