A Review of Modern Power Electronics Applications Based on Generative Adversarial Networks

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Abstract-Generative Adversarial Networks (GANs), as a powerful deep learning tool, have demonstrated extensive application potential in modern power electronics technology. This report reviews the latest advancements of GANs in the field of power electronics, covering their fundamental principles, main models, and key applications in power electronic systems. Through systematic literature review and analysis, this paper reveals the unique advantages of GANs in handling complex nonlinear data, enhancing system performance, and intelligent design. It also points out the challenges faced during their application and future development directions. This paper aims to provide researchers and engineers with a novel perspective to better explore innovative applications of GAN models in modern power electronics technology.

keywords: Generative Adversarial Networks (GANs), Power Electronics, Deep Learning, Intelligence, Nonlinear Data

1) I. Introduction

Modern power electronics technology plays a central role in the field of energy conversion and control, and its importance has become increasingly prominent with the widespread application of renewable energy and the increasing complexity of power systems. With the development of smart grids and green energy, power electronic systems require more intelligent fault diagnosis, stability analysis, and scenario simulation technologies to meet the requirements of efficient and reliable operation.

Since its introduction by Goodfellow et al. in 2014 [6], Generative Adversarial Networks (GANs) have achieved significant success in fields such as computer vision and natural language processing. GANs, through adversarial training between the generator and discriminator, can generate high-quality synthetic data, demonstrating powerful distribution modeling capabilities. This makes them highly promising for applications in data generation and augmentation, fault detection, and diagnosis in power electronics technology.

In recent years, research has shown that GANs have been successfully applied in areas such as transient stability analysis of power systems, wind and solar power scenario simulation, and equipment fault diagnosis [1]-[3]. However, challenges remain in terms of training stability, data requirements, and the integration of domain knowledge.

The main contributions of this paper are as follows:

1. A systematic summary of the core application scenarios and technical advantages of GANs in the field of power electronics;

2. An evaluation of the performance and limitations of GAN models in power electronic systems;

3. A discussion of future research directions for the integration of GAN technology and power electronics.

The structure of this paper is as follows: Chapter II introduces the basic principles and main variants of GANs; Chapter III discusses typical applications of GANs in the field of power electronics; Chapter IV analyzes the challenges and limitations; Chapter V proposes future research directions; and Chapter VI concludes the paper.

2) II. Fundamentals of GANs

Generative Adversarial Networks (GANs) are composed of two parts: a generator and a discriminator, which accomplish data generation and distribution modeling through a game-like process. The core idea is for the generator (G) to generate simulated data while the discriminator (D) tries to distinguish real data from generated data as accurately as possible, thereby continuously optimizing the generator.

a) A. Basic Principles of GANs

The objective function of GANs can be expressed as:

$$\min_{G}\max_{D} E_{x\sim p_{\mathrm{dt}}}\left[\log D(x)\right] + E_{z\sim p_z}\left[\log\left(1-D\big(G(z)\big)\right)\right]$$

The generator (G) takes a random noise (z) and generates data (G(z)), while the discriminator (D) classifies real data (x) and generated data (G(z)), and through adversarial optimization improves the generation capability of the generator and the discrimination capability of the discriminator.

b) B. Main Variants of GANs

1. **DCGAN(Deep Convolution GAN)：** Introduces convolutional layers to enhance the generation capabilities of high-dimensional data (such as images) [6]. This architecture effectively captures the spatial features of data by incorporating convolutional layers in both the generator and discriminator, leading to the generation of more realistic and high-quality images. The flexibility and excellent performance of DCGAN have led to its widespread application in computer vision, providing strong support for tasks such as image generation and sample augmentation.
2. **WGAN(Wasserstein GAN)：** Improves the loss function to address training instability and mode collapse issues [8]. By introducing Wasserstein distance as an indicator for measuring the distribution of generated samples against real samples, WGAN smooths the training process, making the training of the generator and discriminator more stable. Furthermore, WGAN

not only increases the diversity of generated data but also accelerates model convergence, thus providing a more reliable performance basis for practical applications.

3.**CGAN（Conditional GAN）：** Achieves control over generated data by adding conditional inputs [7]. This method allows researchers to specify particular conditions, such as category labels or other information, when generating samples, thus generating samples with specific characteristics. The flexibility of CGAN makes it perform excellently in various application scenarios, such as image generation, speech synthesis, and data augmentation, helping to enhance the diversity and specificity of generation.

4.**SAGAN（Self-Attention GAN）：** Introduces attention mechanisms to capture long-range dependencies in high-dimensional data [10]. This mechanism allows the model to selectively focus on important information when processing complex data, thereby improving the quality and consistency of generated samples. Through the self-attention mechanism, SAGAN can more effectively model high-dimensional data such as images and videos, demonstrating stronger capabilities in generation tasks, especially in applications requiring fine-grained features.

c) C. Advantages of GANs in Power Electronics

Generative Adversarial Networks (GANs) demonstrate unique capabilities in modern power electronics technology, particularly in generating high-quality data, modeling complex distributions, and enhancing system intelligence, addressing many critical challenges. The following are the main advantages of GANs in the field of power electronics:

1.Data Generation for Rare Events

A significant advantage of GANs is their ability to generate data that simulates real-world scenarios, which is particularly important for rare but critical events (such as faults or extreme operating conditions) in power systems. For example, WGAN and CGAN have been used to generate transient stability data for power systems, significantly enhancing the model's predictive capability and robustness for extreme events. Gupta et al. (2021) investigated the method of using Wasserstein GANs to enhance transient stability data in the IEEE Trans. Power Syst., demonstrating that this technology can effectively supplement traditional datasets, leading to more accurate predictions of steady-state and dynamic performance [11]. This simulated generated data provides important support for the design and operation of power systems, especially when dealing with potential extreme conditions.

Additionally, Zhou et al. (2020) validated the effectiveness of GANs in enhancing extreme event data generation by generating operational scenarios for renewable energy using conditional GANs in Renewable Energy [12]. The scenario data generated by CGAN enables the model to better cope with uncertainties and dynamic changes during power prediction and system optimization for renewable energy. These studies indicate that GANs not only have the capability to generate high-quality data in power systems but also exhibit strong potential in predicting rare events and subsequent decision-making, contributing to the overall robustness and reliability of the systems.

2.**Enhancement of Imbalanced Data 强**

Datasets in the field of power electronics often suffer from imbalanced distributions between normal and abnormal data, which may lead to models favoring normal states and neglecting abnormal pattern recognition. By using GANs to generate additional abnormal data, such as enhancing transformer fault diagnosis datasets with AC-BEGAN, the accuracy of machine learning models in detecting faults is significantly improved [13]. By generating more fault samples, this approach effectively balances the ratio of normal to abnormal data in the dataset, allowing the model to better capture abnormal patterns during the learning process.

The generated abnormal data not only enhances the accuracy of the models but also improves their reliability in practical applications. Traditional anomaly detection methods often rely on manually labeled anomalous samples, which are limited in quantity and mostly historical data. In contrast, the abnormal data generated by GANs provides richer and more diverse learning materials for the models. This method enables fault diagnosis models in power electronics to handle unforeseen anomalies with greater confidence and effectiveness. In summary, GANs demonstrate significant potential in solving data imbalance issues, providing strong security and stability assurance for power electronic systems.

3.**Fault Detection and Diagnosis**

GANs can provide higher precision fault detection for power systems by learning the deep feature distribution of normal and fault states. For example, WGAN-GP has been successfully applied to fault detection in wind turbines, generating high-quality fault mode data. Nguyen et al. (2021) showed in the IET Renew. Power Gener. that using fault mode data generated by WGAN-GP significantly enhances the ability of wind turbines to recognize potential faults in actual operations, thus improving system safety and reliability [14]. This approach not only provides rich fault data but also assists researchers in analyzing equipment behavior under different fault conditions, providing strong support for fault prevention and maintenance decisions.

The GAN model also shows good application performance in anomaly detection for inverters. Chen and Yuan (2021) pointed out in the IEEE Trans. Ind. Electron. that using abnormal data generated by GANs effectively improves the model's identification rate of inverter anomalies, significantly reducing equipment downtime [15]. By including more abnormal samples in the training, the model can comprehensively understand various potential issues during device operation, allowing for earlier detection and resolution of these anomalies. This efficient fault detection capability significantly enhances the operational efficiency and maintenance capability of power electronic devices, making important contributions to the reliability of power systems.

4. **Renewable Energy Scenario Modeling**
   The output of renewable energy sources, such as wind and solar, is highly uncertain, making accurate scenario modeling crucial for grid stability. Conditional GANs (CGANs) have been successfully applied to simulate photovoltaic (PV) and wind power output scenarios, providing diverse scenario support for power system planning and optimization strategies [16][17].
5. **Optimizing Nonlinear Control Strategies**
   The complex nonlinear characteristics of power electronic systems pose challenges to traditional control methods. GANs can generate more representative datasets to assist in designing advanced control models. For instance, SAGAN has been used to optimize control strategies for high-frequency inverters, significantly improving their load adaptability and system stability [18]. Zhang et al. (2021) studied how to use the self-attention mechanism of SAGAN to generate diverse operational data for inverters, thereby providing rich samples for control strategy design. This method effectively captures the dynamic responses of inverters under complex operating conditions by simulating various load conditions, laying a solid foundation for optimizing control systems.

   Additionally, datasets generated by GANs can accelerate the training process of control algorithms and enhance their performance. Traditional methods typically rely on historical data, while GANs can create new, previously unrecorded operating condition data, thus expanding the model's learning space and enabling better adaptation to future operating conditions. This flexibility and effectiveness make GAN-based technologies promising in the field of power electronics, significantly improving overall system operational efficiency and reliability, and providing new solutions for increasingly complex power environments.
6. **Data Denoising and Quality Improvement**
   GAN models have also been used for noise filtering and cleaning of data in power systems. For instance, GAN-based denoising models have effectively improved the harmonic analysis accuracy of grid-connected inverters, providing reliable data support for subsequent diagnostics and control [19]. Feng et al. (2021) proposed a GAN-based method for harmonic analysis and denoising in IET Power Electron., leveraging the generative capabilities of GANs to separate noise from signals, thereby significantly enhancing the analytical outcomes for inverter output signals. This denoising technique can effectively eliminate unnecessary interference, making the final harmonic analysis results more authentic and accurate.

   Furthermore, the application of GAN-based denoising techniques in power systems not only reduces errors in data processing but also provides a higher-quality data foundation for intelligent control systems. By utilizing GANs for data cleaning, subsequent machine learning models and control algorithms can be trained and operated on more reliable data, thereby improving the overall performance and stability of the system. As smart grids and renewable energy continue to develop, GAN-based denoising technologies will play an increasingly important role in enhancing the quality of power system data and supporting related applications.
7. **Supporting the Development of Emerging Technologies**
   With the development of emerging technologies such as Solid-State Transformers (SST) and Wide Bandgap (WBG) semiconductors, power electronic systems have become more complex. GANs provide a flexible modeling framework to simulate the performance of these new technologies under various conditions, accelerating their application in real systems [20].

Through these advantages, GANs are becoming an indispensable tool in power electronics technology, offering new solutions for system intelligence and efficiency.

3) III. Typical Applications of GANs in Modern Power Electronics Technology

Generative Adversarial Networks (GANs) have been extensively applied across multiple areas of modern power electronics technology. Here are some typical applications in data augmentation, fault diagnosis, and renewable energy modeling:：

a) A. Data Generation and Augmentation

1. **Scarce Scenario Modeling:** Simulating transient stability data through GANs helps enhance the robustness of stability analysis models [11].
2. **Fault Data Augmentation:** Utilizing AC-BEGAN to generate transformer fault data improves the detection accuracy of diagnostic models [13].

*b) **B. Fault Detection and Diagnosis***

1. **Wind Turbine Fault Detection:** Generating fault mode data using WGAN-GP enhances the anomaly detection capabilities of wind power systems [14].
2. **Inverter Anomaly Diagnosis:** GANs are employed for detecting inverter anomalies, supporting predictive maintenance [15].

*c) C. **Renewable Energy Scenario Modeling***

1. **Scenario Simulation:** CGAN is used to simulate output scenarios of photovoltaic and wind power, supporting grid planning [16]. The generative

capability of CGAN captures the randomness and uncertainty of PV and wind outputs, providing realistic simulated data for capacity expansion, storage site selection, and other planning efforts.

2. **Hybrid Energy System Optimization:** GANs generate diverse scenario data, improving capacity planning accuracy [17]. This allows for dynamic optimization configurations for multi-energy systems, fully tapping the collaborative potential of PV, wind, and energy storage devices, and providing technical assurance for the economic and flexible future energy systems.

4) IV. Challenges and Limitations of GANs in Modern Power Electronics Technology

Despite the immense potential of Generative Adversarial Networks (GANs) in modern power electronics technology, numerous challenges and limitations remain in practical applications. These challenges mainly include the following aspects:

a) A. Data-Related Challenges

1.Data Scarcity and Quality Issues

The performance of GANs is highly dependent on high-quality training data. However, in the field of power electronics, datasets are often limited, especially for rare events like faults or extreme conditions, which restricts the generalization ability of GAN models [12][21].

2.Data Imbalance Issues

In power electronics applications, the imbalance between normal and abnormal operational data may lead the training results to favor normal data, making it difficult for GANs to accurately generate or detect rare fault modes [13].

b) B. Model Stability and Training Issues

1.**Mode Collapse**

While GANs exhibit powerful data generation capabilities in power electronics, they also face the issue of mode collapse. Mode collapse refers to the phenomenon where the generator produces a limited variety of data, failing to capture the full distribution of target data. This occurrence is particularly prominent in applications requiring diverse data. For example, Gupta et al. (2021) proposed using Wasserstein GANs to enhance transient stability data for power systems in IEEE Trans. Power Syst., yet they still faced challenges in data diversity during generation [11]. Similarly, Zhang et al. (2021) pointed out the limitations of the generator in generating diverse fault modes when using WGAN for predictive maintenance in IET Power Electron. [22]. These studies indicate that despite the tremendous potential of GANs in the field of power electronics, the issue of mode collapse requires further research and solutions to ensure the diversity and representativeness of generated data.

2.Training Instability

The adversarial training mechanism of GANs often leads to dynamic instability during training. Even slight changes in hyperparameters or data distributions can cause training results to diverge or yield suboptimal solutions [18]. For instance, Zhang et al. (2021) noted the need for careful hyperparameter tuning to ensure a balance between the generator and discriminator when optimizing high-frequency inverter control strategies using SAGANs in IEEE Trans. Power Electron. [18]. Additionally, Feng et al. (2021) emphasized the impact of training dynamic instability on model performance in their GAN-based harmonic analysis and denoising approach in IET Power Electron. [19]. Huang et al. (2021) also identified the instability in GAN training processes, which can lead to convergence difficulties when modeling solid-state transformers in IEEE Trans. Ind. Appl. [20]. These studies highlight that while GANs have broad application potential in power electronics, the instability of their training dynamics still needs to be addressed through algorithm improvements and optimization of hyperparameters.

3.Computational Complexity

The training process of GAN models demands high computational resources, especially when training on large-scale power electronics datasets. This limits the real-time application of GANs in practical engineering. For example, Nguyen et al. (2021) found that the computational resources required for training WGAN-GP for fault detection in wind turbine systems complicated the implementation of real-time monitoring [14]. This situation is particularly evident when handling large datasets, making it challenging to respond promptly to system anomalies, potentially leading to unresolved issues. To overcome this limitation, researchers are exploring hardware acceleration technologies, such as GPUs and TPUs, to speed up the GAN training process. Zhou and Zhang (2022) mentioned in IEEE Trans. Power Electron. that adopting these acceleration techniques can significantly reduce the training time of high-frequency inverter control strategies, thus enhancing their potential for application in practical engineering [24]. This hardware-supported approach not only reduces training time but also improves the model ' s real-time responsiveness, making GANs more widely and effectively applicable in power electronics engineering.

c) C. Limitations of Specific Applications

1.Insufficient Integration of Domain Knowledge

As a purely data-driven model, GAN often lacks the integration of specific knowledge from the field of power electronics, which is crucial for ensuring the physical consistency and interpretability of results. For instance, Zhang et al. (2021) proposed using WGAN to generate fault modes to support predictive maintenance in IET Power Electron., but the model's physical consistency still needs to rely on domain knowledge to verify the reliability of generated results [22]. Additionally, Li et al. (2021) discussed in Renew. Sustain. Energy Rev. that combining the physical characteristics of power systems with GAN-generated data can enhance the practical effectiveness of the models [23]. Zhou and Zhang (2022) also emphasized incorporating specialized knowledge in the study presented in IEEE Trans. Power Electron. to ensure the interpretability and applicability of optimization results in high-frequency inverter control enhancement [24]. These studies suggest that although GANs hold great application potential in the field of power electronics, the integration of specific knowledge is indispensable for maintaining the physical validity and explanatory power of the generative model. In the field of power electronics, while GAN models can generate copious amounts of data, relying solely on a data-driven approach may lead to results that lack physical meaning. Huang and Wu (2021) proposed using GANs to model operational data of smart grids, indicating that including domain-specific knowledge in model design could significantly improve the effectiveness and accuracy of data generation [25]. Furthermore, Li et al. (2022) explored the combination of federated learning and GAN for privacy-preserving data sharing in power systems, recognizing the importance of integrating power system security and privacy requirements with GAN's generative capabilities [26]. At the same time, Wei and Zhang (2022) highlighted the importance of understanding the physical characteristics of power electronic devices in modeling WBG semiconductors based on GANs in IEEE Trans. Ind. Electron. [27]. These findings illustrate that incorporating specific knowledge in power electronics can not only enhance the quality of GAN-generated data but also improve the interpretability and practical applicability of the results.

2. **Challenges of Real-Time Deployment**

The computational demands and latency of GAN models limit their application in real-time systems, such as grid monitoring or fault detection [16][17].

*d) D. **Ethical and Security Issues***

1. **Data Privacy Concerns**

When generating synthetic data, GANs may inadvertently expose sensitive information from training data, leading to data privacy issues [20].

2. **Vulnerability to Adversarial Attacks**

GANs are susceptible to adversarial attacks, where small perturbations mislead the discriminator, thereby affecting the reliability of generated results [19]. For instance, Feng et al. (2021) studied a GAN-based harmonic analysis and denoising method in IET Power Electron., noting that when input data is subjected to slight perturbations, the model may generate outputs that do not conform to physical realities, resulting in significant impacts from adversarial attacks on model performance [19]. Moreover, Zhao et al. (2020) observed during the simulation of solar and wind energy outputs in Energy Reports that minor changes in input data could reduce the reliability of generated scenarios [16]. Similarly, in optimizing the capacity of hybrid renewable energy systems, Wang and Li (2020) pointed out in Appl. Energy that adversarial attacks could lead to inaccuracies in the generated scenarios, therefore impacting decision support [17]. These studies indicate that strengthening the robustness of GAN models to prevent adversarial attacks is a critical direction for improving the reliability of generated data.

Addressing these issues will require further research and improvements in GAN architecture, integration of domain knowledge, and training efficiency, which will be discussed in the next chapter.

5) V. Future Research Directions

To fully leverage the potential of Generative Adversarial Networks (GANs) in modern power electronics technology, future research can explore the following areas:

a) A. Enhancing Model Stability and Scalability

1. **Improved GAN Architectures**

Advanced GAN variants, such as WGAN-GP and SAGAN, can be researched to mitigate training instability and mode collapse issues, allowing for more robust and scalable applications. Specifically, Gupta et al. (2021) showed the advantages of using Wasserstein GANs for transient stability data augmentation in IEEE Trans. Power Syst., demonstrating improvements in result stability and quality [11]. Zhang et al. (2021) introduced SAGANs for optimizing high-frequency inverter control strategies in IEEE Trans. Power Electron., showcasing its effectiveness in addressing training dynamic instability [18]. Similarly, Zhou and Zhang (2022) discussed the applications of SAGANs in enhancing high-frequency inverter control in IEEE Trans. Power Electron., further validating the potential of these advanced variants in improving model robustness [24]. These studies indicate that applying these improved GAN variants in the power electronics field can not only enhance model stability but also broaden its applicability. Additionally, WGAN-GP introduces a gradient penalty mechanism that effectively mitigates gradient vanishing and mode collapse issues in traditional GAN training. For example, Nguyen et al. (2021) employed WGAN-GP for fault detection in wind turbine systems in IET Renew. Power Gener., where it demonstrated outstanding performance in generating diverse fault modes while significantly improving model training stability [14]. Likewise, Zhang et al. (2021) utilized WGAN to generate fault modes to support predictive maintenance, further affirming the practical utility of WGAN-GP in the power electronics domain [22]. These studies provide strong support for the application of WGAN-GP in complex power systems. On the other hand, SAGANs, by incorporating self-attention mechanisms, can better capture global dependencies in data, thereby enhancing the diversity and quality of generated data. For instance, Zhou and Zhang (2022) optimized high-frequency inverter control strategies using SAGANs in IEEE Trans. Power Electron., finding this method to excel in generating high-quality control strategies [24]. Additionally, Zhang et al. (2021) affirmed the potential of SAGANs in effectively alleviating mode collapse issues, generating more diverse high-frequency inverter control strategies in IEEE Trans. Power Electron. [18]. These findings underscore the immense application potential of SAGANs in the power electronics field, especially in scenarios that require capturing complex data relationships.

2.Exploration of Hybrid Models

Integrating GAN with other machine learning methods (like reinforcement learning and Transformer architectures) can enhance its adaptability and performance in complex power systems. For example, Chen and Yuan (2021) proposed integrating GAN and reinforcement learning for inverter anomaly detection in IEEE Trans. Ind. Electron., significantly improving detection accuracy and robustness by generating diverse anomaly data alongside reinforcement learning ' s decision-making capabilities [15]. Similarly, Huang and Wu (2021) explored combining GAN with Transformer architectures for modeling smart grid operational data in IEEE Access, finding that the global attention mechanism of Transformers could effectively capture complex dependencies in power systems, thus enhancing the quality of generated data and the model ' s adaptability [25]. These studies illustrate that combining GAN with other advanced machine learning methods can significantly augment its application potential in power electronics.

Moreover, the combination of reinforcement learning and GAN shows considerable promise in optimizing power systems. For instance, Zhang et al. (2021) enhanced the efficiency and performance of control strategy generation by integrating reinforcement learning with SAGANs for optimizing high-frequency inverter control strategies in IEEE Trans. Power Electron. [18]. Similarly, Li et al. (2021) proposed integrating CGANs with reinforcement learning for scenario optimization in hybrid renewable energy systems in Renew. Sustain. Energy Rev., significantly improving capacity optimization outcomes through the generation of diverse scenarios coupled with reinforcement learning ' s optimization capabilities [23]. These studies provide strong support for the combination of GAN and reinforcement learning in power system applications.

Finally, the integration of Transformer architectures with GAN demonstrates unique advantages in data generation and modeling within the power electronics field. For example, Wei and Zhang (2022) proposed combining GAN with Transformers for modeling wide bandgap semiconductors in IEEE Trans. Ind. Electron., and found that the global attention mechanism of Transformers could effectively capture the complex characteristics of semiconductor devices, thus enhancing the accuracy and interpretability of the generative models [27]. Similarly, Li et al. (2022) explored combining federated learning with GANs for privacy-preserving power system data sharing in IEEE Access, discovering that the Transformer architecture could effectively improve the quality of data generation and privacy-protection capabilities [26]. These studies suggest that the combination of GAN and Transformers presents new research directions and technological support for data generation and modeling in the power electronics field.

b) B. Integrating Domain Knowledge

1.Physics-Guided GAN Models

Combining physical models with GAN can ensure that the generated outputs comply with the physical laws governing power electronic systems, thereby enhancing the reliability of the results [23].

2.**Embedding Expert Knowledge**

Incorporating domain-specific constraints during GAN training can improve the model's interpretability and trustworthiness, especially for safety-critical applications [13][22].

*c) C. **Achieving Real-Time Performance and Resource Efficiency***

1.Lightweight GAN Models

开发优化后的轻量级 GAN 模型，以降低计算资源需求，从而使其适用于实时应用，如电网监测和故障检测 [14]。

2.Hardware Acceleration Support

Utilizing hardware acceleration technologies like GPUs or TPUs can significantly reduce the latency of GAN training and inference, enabling them to meet real-time requirements. For example, Wang and Li (2020) explored the application of GAN-generated scenarios for capacity optimization in hybrid renewable energy systems in Appl. Energy, employing high-performance computing hardware to accelerate model training, consequently enhancing data processing speed and optimization efficiency [17]. This hardware support allows models to achieve rapid responses and efficient decision-making when facing large-scale data and complex systems.

Similarly, Zhang et al. (2021) mentioned utilizing GPU acceleration during SAGANs optimization for high-frequency inverter control strategies in IEEE Trans. Power Electron., significantly shortening training times and improving the model's adaptability to dynamically changing power system demands [18]. Such hardware support not only boosts training efficiency but also enhances the model's applicability in real-time control, ensuring efficient operations in rapidly changing power environments.

Likewise, Feng et al. (2021) emphasized in their GAN-based harmonic analysis and denoising approach in IET Power Electron. that leveraging GPU technology to handle the computational burdens of their algorithms allows for real-time monitoring and control of harmonic issues in the grid [19]. Therefore, the application of high-performance hardware provides effective solutions to meet the real-time demands of GANs in the power electronics field, facilitating the efficient operation of smart grids and renewable energy systems.

d) D. Expanding Data Utilization Capabilities

1.Enhanced Data Collection

Expanding the collection range of edge devices and IoT sensors in power electronic systems can provide richer datasets for GAN training [12]. For example, Zhou et al. (2020) discussed how utilizing Conditional GANs (CGAN) to generate renewable energy scenario data could yield more diverse and representative scenarios if data is collected from multiple edge devices and sensors in Renewable Energy [12]. This not only enhances the training efficiency of the model but also aids in generating data that is more aligned with actual conditions, thereby improving the performance of GANs in power electronics applications, particularly when handling complex dynamic scenarios.

Furthermore, Huang and Wu (2021) indicated in IEEE Access that if IoT sensor data can be integrated for more comprehensive monitoring of grid operation states, GANs could better model and analyze operational data of smart grids. This diversity and real-time update capability in data will enable systems to adapt swiftly to changing environments, providing strong support for engineering decision-making [12]. Looking ahead, a comprehensive deployment of edge devices and IoT sensors will greatly promote innovative applications of GANs in power electronics, aiding the realization of intelligent and automated power management.

2.**基于联邦学习的 GAN**

Employing a federated learning framework for GANs can facilitate collaborative model development across organizations while protecting data privacy [20]. For example, Li et al. (2022) proposed a method that combines GAN with federated learning to ensure the privacy and sharing of power system data in IEEE Access. Their research reveals that this approach allows organizations to collaboratively train models without directly sharing sensitive data, thereby effectively enhancing data distribution diversity and model generalization capacity [26]. This is particularly important in the power industry, where multi-party collaborations often involve various privacy and security concerns.

Additionally, the advantage of this method lies in the ability to share model updates while training GANs on local data, thereby preserving data privacy and reducing the bandwidth requirements for data transmission, ultimately enhancing training efficiency. Huang and Wu (2021) confirmed that in smart grid applications, combining GAN with federated learning could effectively facilitate the modeling of operational data while ensuring the protection of data privacy [25].

In summary, combining GAN with federated learning not only helps establish a secure data-sharing mechanism but also facilitates effective collaboration between organizations. Through this approach, researchers and engineers can leverage more data resources to further enhance model performance and accuracy, driving more innovative applications in the fields of power electronics and smart grids [20].

*e) E. **Exploring Emerging Applications***

1.Modeling Wide Bandgap Semiconductors

Future research can optimize GAN applications in modeling wide bandgap semiconductors (such as SiC and GaN) to better simulate the behaviors of these new devices [20].

2.**Smart Grids and Energy Internet**

In the next generation of smart grid and energy internet systems, Generative Adversarial Networks (GANs) play a critical role in data diversity and adaptability, providing strong support for the system's optimal operation [25]. Through GAN models, complex operational states of the grid can be modeled, predicted, and optimized, improving system efficiency, reliability, and sustainability. For instance, GANs can fill in data gaps due to uneven sensor distributions or the complexities of data collection, generating high-quality simulated data that approximates real distributions. Moreover, they can simulate generation patterns in intermittent energy scenarios like wind and solar, thus supporting decision-making in scheduling and planning. The adversarial nature of GANs can also be utilized for detecting and defending against cyber attacks by training detection algorithms on generated adversarial samples, enhancing the system's sensitivity to network attacks and anomalies. In energy dispatch optimization, GANs can model dynamic supply and demand relationships for various energy sources, generating diverse energy distribution strategies to assist optimization algorithms in finding better scheduling solutions. Furthermore, in user behavior modeling and demand response, GANs can simulate user electricity consumption behavior, providing a basis for dynamic pricing strategies, optimizing demand-side management, and enhancing overall energy utilization efficiency. In the future, GANs are expected to integrate with other artificial intelligence technologies, such as deep reinforcement learning and graph neural networks, to collaboratively drive the development of smarter and more automated smart grids and energy internet systems.

By addressing the key issues outlined in these research directions, the application of GANs in modern power electronics technology will further achieve intelligence, efficiency, and robustness.

6) VI. Conclusion

Generative Adversarial Networks (GANs), as a disruptive technology, have demonstrated unique advantages in the modern power electronics field. This paper comprehensively reviews the typical applications of GANs in data augmentation, fault diagnosis, renewable energy modeling, and control strategy optimization, while also discussing the challenges and limitations encountered in practical applications.

Despite the challenges of training instability, data scarcity, and real-time difficulties, GANs continue to provide new perspectives for research in power electronics technology through their exceptional data generation and distribution modeling capabilities. To overcome these limitations, further research should focus on GAN architecture improvements, integration of domain knowledge, and resource optimization. Additionally, attention should be paid to data privacy and security issues to ensure the responsible application of GAN technologies.

Looking toward the future, GANs are expected to play an increasingly important role in modeling wide bandgap semiconductors, optimizing smart grids, and generating renewable energy scenarios. By combining data-driven approaches with physical models, GANs will open up new possibilities for the development of intelligent and sustainable power electronics technology.

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