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Deep Learning-Enabled Generative Antenna Design: Review and Prospects

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***Abstract*— This paper explores generative antenna design (GAD) and optimization using neural network (NN)-based deep learning (DL) methods. We first outline traditional antenna design and the challenges of applying NN-DL synthesis, particularly with generative adversarial networks (GANs). While conventional approaches reach performance limits, applying NN-DL generative methods to designs with increased degrees of freedom offers new possibilities for enhanced performance, additional functionality, and knowledge discovery. We then review the historical development and diverse applications of NN-based antenna optimization, covering individual elements, multi-antennas, and periodic structures. Key algorithmic concepts such as conditional GANs and variational autoencoders (VAEs) are discussed, emphasizing the role of prior knowledge in GAD. Recent advancements demonstrate how DL-enabled synthesis can surpass phase shift limits, control dispersion, and enhance metalens antenna gain bandwidth by 52%. The approach also enables full-range amplitude and phase control, effectively reducing sidelobe levels to below −30 dB. Finally, we highlight the significance of prior knowledge in GAD, distinguishing GAD from conventional parametric optimization. We discuss the challenges, future trends, and broader impacts of NN-driven generative design in next-generation antenna and electromagnetic device engineering.**

***Index Terms*—Deep learning, generative antenna design, generative adversarial network, neural network, prior knowledge, metasurface, multi-antennas.**

I. Introduction

THE art and science of antenna design involve a number of challenges, and the degrees of freedom (DoFs) in the design play a critical role in addressing these challenges. The recent introduction of generative antenna design (GAD) and generative adversarial networks (GANs) enables more DoFs and thus offers the potential to take antenna design to a new level.

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1.1. Challenges in Antenna Design

Antennas are essential components for transmission and reception of electromagnetic waves (EMWs) in wireless systems. The design process traditionally begins with a rigorous study of the system-level specifications. Rather than reinventing the wheel, engineers typically select foundational antenna topologies or their variations that closely align with the requirements. These candidate designs are then iteratively modified or optimized to fulfill the specific needs.

However, this conventional approach is inherently bounded by the realities of the design process. Beyond physical laws and computational boundaries in antenna modeling, the constraints from limited material selection, volume restrictions, and feeding structure design narrow the choice of workable structures and tunable parameters. Consequently, the realized performance of an antenna is often significantly lower than the theoretical maximums permitted by physics.

On the other hand, the rapid advancement of wireless systems is widening the gap between the growing demand for high-performance, rapidly designed antennas and the ceilings of current design methods. To bridge this gap, engineers need innovative solutions, such as neural network (NN)-based deep learning (DL) for GAD, to explore a vast design space that was previously unreachable and to meet the evolving needs of modern wireless systems [1], [2], [3], [4].

1.2. Degrees of Freedom in Antenna Design

In addition to introducing new physical concepts like metamaterials [5] and mathematical tools like characteristic mode analysis [6], [7], [8], [9], increasing DoFs in antenna design is essential. It opens new opportunities and expands the design space to improve antenna performance. DoFs include geometrical parameters (dimensions, positions, orientations), materials, and platforms. The design space encompasses all potential solutions within the constraints such as volume, weight, cost, and environmental considerations [10]. The performance space includes key factors like operating bandwidth, radiation pattern, gain, and polarization.

Clearly, increasing the DoFs in antenna design enables expanding the design space, thereby enhancing antenna performance. While introducing new physical concepts and utilizing powerful mathematical tools have revolutionized antenna design, it is equally or even more important to explore approaches that permit more DoFs in the antenna design

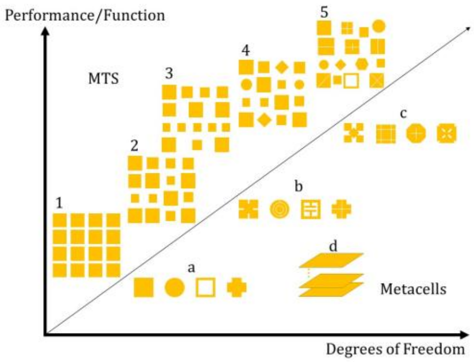

Fig. 1. Performance and functions against DoFs of metasurfaces and metacells.

process. Increasing DoFs allows engineers to explore a broader range of design parameters, configurations, and structures, leading to more innovative and optimal antenna solutions. This expanded space enables the development of antennas with new functionalities and improves performance. The DoFs enhanced by generative design techniques enable the synthesis of antenna designs with novel, previously unexplored solutions that surpass traditional approaches and human imagination.

Fig. 1 shows the evolution of DoF increase in the design of electromagnetic (EM) metasurfaces (MTSs) and the unit cells of MTS (referred to as metacells). The MTSs have been utilized to control the amplitude, phase shift, and polarization of transmitting or reflected EMWs through or by the MTS [11].

The DoFs in an MTS rely on the surface configuration and the metacell patterns. Conventional MTSs are periodic and consist of metacells with identical patterns (MTS 1), such as frequency selective surfaces (FSSs), or varying dimensions (MTS 2), such as metalens antennas. The DoFs of MTS design can be enhanced in three ways: aperiodic metacell arrangement (MTS 3), MTS with varying metacells (MTS 4), and combinations of these methods (MTS 5).

The DoFs in a metacell depend on its patterns, dimensions, material properties, and the number and arrangement of layers. Simple patterns (Metacell a) provide basic but limited performance, while modified patterns (Metacell b) increase DoFs and improve performance. More complex patterns (Metacell c) further enhance performance, and additional layers (Metacell d) also contribute to increasing DoFs. Similarly, conventional antenna design is often constrained by rigid array configurations and limited excitation methods. By increasing the DoFs in both individual element design and collective array synthesis, as seen in MTSs, engineers can significantly enhance antenna performance.

1.3. Generative Antenna Design

To surpass existing antenna design limitations, algorithm-based methods are being developed to automatically generate new topologies and structures. In general, algorithm-enabled antenna design methodologies are categorized into surrogate models, optimization methods, and generative models. Surrogate models address the forward problem by learning a direct mapping from antenna geometry or design parameters to EM performance. They are primarily used for rapid performance prediction and analysis. In contrast, both optimization methods and generative models target the inverse design problem, where desired EM specifications are mapped to antenna geometries capable of achieving those targets. Optimization methods, such as topology or adjoint optimization, are deterministic and iterative, relying on EM solvers to converge toward a single or limited set of optimal solutions through explicit minimization of a predefined loss function.

Generative models, including GANs, variational autoencoders (VAEs), and diffusion models, fundamentally differ in how they learn the conditional data distribution of antenna geometries given performance objectives. This probabilistic formulation enables stochastic sampling and diversity-aware inverse design, allowing multiple feasible solutions to be generated for the same target specification. The validity of generative solutions is assessed by their ability to satisfy target performance requirements rather than by direct loss minimization during inference. As a result, generative models can expand the DoFs in antenna design, capture underlying design patterns, and generate one or multiple feasible solutions, even beyond the training dataset.

The current antenna design space is limited to existing models, such as equivalent circuit models. Generative algorithms expand this space by significantly increasing DoFs, enabling GADs to offer new solutions that can meet or exceed current performance, though at the cost of increased design complexity. Importantly, the design space is essentially bound by physical laws and engineering constraints. If a gap exists between the existing design space and the theoretically maximal design space, one can expand the design space accordingly. For instance, the theoretical lower limit of a dipole antenna's directivity is 1.5, leaving no room for an ideal omnidirectional radiation design, even for electrically infinitesimal dipoles. However, a gap exists between the bandwidth constrained by Chu's limit [12] and the bandwidths achieved by existing single-mode electrically small antennas. Generative algorithms can explore this gap, pushing the bandwidth closer to the theoretical limit [13].

1.4. Generative Adversarial Network

With the rapid growth of computational capacity and advances in algorithms, a new wave of AI, especially large-scale model capabilities, has found successful applications in various social and technical fields. AI, as an all-encompassing term, describes a machine that incorporates some levels of human intelligence through computer algorithms. AI holds promise for innovating antenna design by applying algorithms to increase the DoFs, thereby expanding the design space beyond traditional approaches. Therefore, this offers potential to break performance limits of existing antennas, create antennas with multiple functionalities, and even discover new knowledge in antenna theory and design.

Machine learning (ML), NNs, and DL are all subsets of AI. NNs are a subset of ML, and DL is a subset of NNs. ML focuses on using data and algorithms to mimic how humans learn, gradually improving its accuracy over time. NNs, or artificial neural networks (ANNs), consist of layers of nodes, including an input layer, one or more hidden layers, and an output layer.

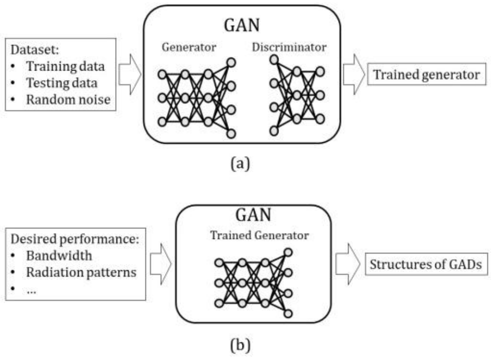

Fig. 2. The framework of GAN: (a) two components in training NNs: generator and discriminator, and (b) the design using a well-trained generator for GADs.

Each node, or artificial neuron, receives inputs through weighted connections, incorporates a bias term, and applies an activation function to produce its output.

DL, on the other hand, refers to NNs with multiple hidden layers that enable hierarchical feature representation. Due to significant advancements in computational capability and algorithms, DL has rapidly progressed and is now accelerating developments in various fields, such as computer vision, natural language processing, and speech recognition.

Generative design is an iterative design exploration process that leverages an AI-driven software program to generate a diverse range of design solutions, all of which fulfill a specific set of constraints or specifications. Unlike traditional design approaches, where engineers typically start with a model based on their expertise, generative design starts with design parameters and relies on AI or well-trained NNs to automatically generate the model. By doing so, generative design introduces a more innovative and efficient way to explore potential solutions, expanding the design space and often leading to multiple novel and even optimized designs that may not have been considered through conventional means.

This paper will primarily focus on generative algorithms, in particular Generative Adversarial Networks (GANs). GANs are an approach to generative modeling that utilizes DL methods. The aim is to employ GANs to model and generate highly complex antenna structures within a significantly expanded design space for the new GAD, despite the existence of various DL models.

The GAN framework [14], as shown in Fig. 2, includes two NNs: the generator and the discriminator, which engage in a zero-sum game. The generator is trained on a given dataset to generate new data similar to the training dataset, while the discriminator's role is to classify data as either "real" (obtained from the training dataset) or "fake" (generated by the generator). These two NNs are trained together in an adversarial manner, allowing the generator to improve its data generation capabilities until it can effectively deceive the discriminator about half the time. GANs hold great promise in providing sophisticated domain-specific data augmentation and generative solutions for antenna design. By leveraging GANs, we can explore new possibilities and achieve novel antenna designs that were previously beyond the capabilities of traditional methods. Fig. 2(a) illustrates the two key components involved in building and training a GAN model. The well-trained generator is then used for GADs as shown in Fig. 2(b). One crucial aspect of this process is the training and testing datasets, which form the foundation for training NNs.

Applying GANs to GAD poses unique challenges and requires tailored solutions, as antenna design is not inherently data-centric, requiring us to artificially generate massive amounts of data to train the NNs. This data can be generated through measurements, simulations using EM software tools, or a combination of both. As discussed above, an increased DoF or larger design space often requires a larger dataset for NN training. However, using all acquired data without selection can be extremely time-consuming. Hence, three primary challenges in training data generation should be addressed:

1. *Efficient generation of data*: Besides the development of fast full-wave algorithms for antenna modeling, developing efficient and accurate NN-enabled surrogate models for data generation is essential for the designs with high complexity, which helps increase data generation efficiency.
2. *Generation of effective data*: Within the vast pool of possible data used for training NNs, a portion, and often the majority, may violate physical laws or engineering constraints. Such data are irrelevant and introduce noise into the training process. Implementing rigorous filtering and selection mechanisms is essential to ensure the effectiveness of data used for training.
3. *Generation of efficient dataset*: There is an inherent trade-off between increasing the DoFs and maintaining a manageable dataset size. For instance, sensitivity analysis can reveal design parameters that contribute unequally to antenna performance. By focusing the dataset on these high-impact variables and pruning data that does not significantly influence the final solution, one can maintain a high DoF while keeping the dataset size within computationally acceptable limits.

To efficiently generate effective data and datasets for training NNs, the expanded design space needs to be carefully filtered using *prior knowledge*. This prior knowledge encompasses physical concepts and laws, engineering experience, and even results from previous GAD models. Specifically, physical concepts and laws include EM theorems such as the EM uniqueness theorem, reciprocity principle, and image theory. Engineering experience includes equivalent circuits, existing solutions, and constraints such as impedance matching, realized gain, radiation pattern requirements, and specification trade-offs between fabrication, material, cost, volume, shape, and environment. By applying prior knowledge, one can identify and remove "invalid" and/or "ineffective" data resulting from increased DoFs, ensuring that only relevant and meaningful data are used for training.

Prior knowledge's application is not limited to selecting training data; it also extends to the training procedure within GAD. With a limited yet effective dataset, incorporating prior knowledge can accelerate learning while maintaining acceptable accuracy.

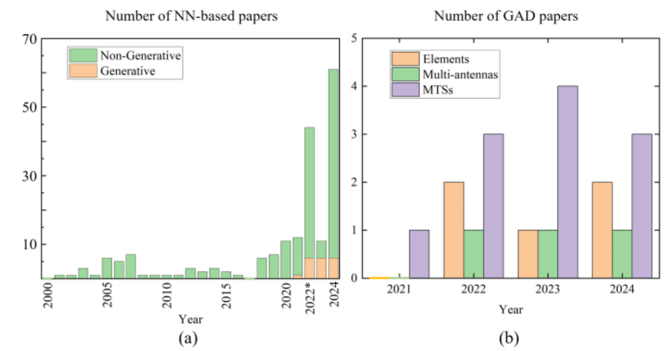

Fig. 3. The number of papers published in IEEE journals from 2000 to 2024 (Source: IEEE Xplore). (a) NN-based papers, and (b) GAD papers.
*IEEE Transactions on Antennas and Propagation published the special issue on Machine Learning in Antenna Design, Modeling, and Measurements in 2022.

Furthermore, when applying GANs to the synthesis and optimization of GAD, domain expertise plays a crucial role. Expert guidance is necessary to define the problems to be solved, set achievable targets, establish criteria for training convergence, and so on.

One more crucial feature of GANs is that GANs are capable of generating multiple solutions for a single set of specific inputs plus random noise. This perfectly fits the antenna design, as it typically aims to determine a solution that balances performance with other engineering considerations such as cost, weight, and profile.

By addressing these challenges and making use of appropriate prior knowledge, GANs can emerge as a powerful tool in GAD, offering innovative and optimized solutions for antenna engineering. Leveraging the potential of GANs in this field requires a combination of AI capabilities and expert domain knowledge to achieve truly groundbreaking results.

1.5. Motivation and Contribution

While the use of DL in electromagnetics is expanding, a comprehensive review that clearly delineates the paradigm shift from parametric optimization to generative synthesis is strongly needed. Much of the literature emphasizes NNs as fast surrogate models, whereas the transformative potential of GANs, VAEs, and other generative approaches to create entirely new antenna topologies and explore design spaces deserve greater prominence. Key contributions of this paper:

1. To present a clear taxonomy and review of NN-based antenna design, distinguishing non-generative and generative methods, and highlighting the pivotal role of increased DoFs.
2. To elucidate the unique advantages of GANs and VAEs for GAD, explaining their probabilistic foundations and their ability to produce diverse, novel, and desired performance-conditioned solutions.
3. To demonstrate the critical role of prior knowledge in making GAD tractable, showing how it guides data generation, model training, and enforces physical feasibility.
4. To showcase state-of-the-art applications where GAD methods have exceeded existing performance limits, such as surpassing phase-shift boundaries in metacells and achieving exceptional sidelobe suppression in metalens antennas.
5. To offer a practical outlook on challenges, emerging trends, and future impact, providing actionable insights for researchers and practitioners entering this field.

II. Generative Antenna Design in Various Applications

Building upon the fundamental concepts and motivations for GAD introduced in the Introduction, we now review its practical applications. This section surveys the use of NNs across various antenna types, demonstrating the progression from non-generative surrogate models to generative synthesis. Fig. 3 provides the number of papers on this topic published in IEEE journals from 2000 to 2024. As shown in Fig. 3(a), the NN-based antenna designs are categorized into non-generative and generative antenna design methods (non-GAD and GAD). It is observed that since 2018 there has been a new wave of NN-based antenna design after the first peak in the period of 2005-2007. In particular, the second peak appeared in 2022 as GAD emerged in 2021. Fig. 3(b) highlights GADs in applications to antenna elements, multi-antennas, and MTSs. The limited number of existing publications shows that the majority of GAD studies focus on MTSs. It suggests that the MTSs with richer DoFs may be more suitable for GAD. Next, the state-of-the-art generative and non-generative antenna design methods are reviewed in detail.

2.1. Antenna elements

Our review begins with antenna elements, the most basic building blocks and the foundation of NN-based antenna design. An early paper about NN-based non-generative antenna element design, published in 2001, triggered the application of NNs to the analysis and design of antenna elements [15]. During the period from 2008 to 2017, on average, one or two relevant papers were published each year. Starting from 2018, this field regained prominence, becoming a research hotspot with an upward tendency in the number of papers published.

In the emerging phases, most of the work has utilized non-generative methods as a surrogate model [16], [17], [18], [19], [20], [21], [22], [23], where input data are the geometry parameters of different types of antennas, and output data are the performance, such as resonance frequencies [24], reflection coefficients [25], [26], [27], [28], [29], mutual coupling [30], operating bandwidths [31], [32], input impedances [33], radiation patterns [25], gain [25], [26], [29], [34], [35], axis ratios [26], and radar cross sections [36]. In these papers, NNs have been used to analyze geometric parameters of antenna elements. For example, some papers have applied NNs to the analysis of patch antennas [24], [31], [37], [38], [39], [40], dipole antennas [24], [36], [41], [42], [43], and monopole antennas [28]. Therewith, the research has focused on antenna designs with increased complexity, including slotting patches [26], cutting patch corners [44], and slotting a planar monopole antenna [30]. Recently, more complex antennas have been analyzed using NN-based methods, such as Yagi-Uda antennas

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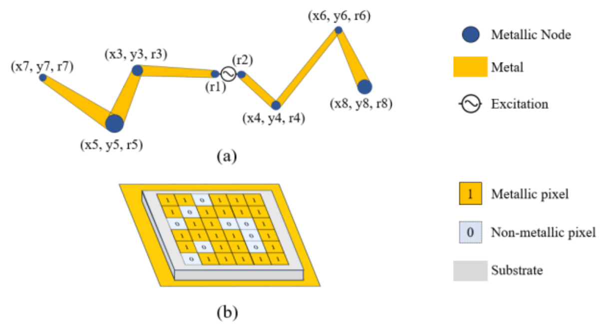

Fig. 4. Generated geometry diagrams of antenna elements. (a) Nodes-based model. (b) Pixelized model.

[35], dielectric-filled slotted waveguide antennas [45], and metasurface antennas [46], [47]. In addition, NNs are also utilized to accelerate antenna characterization [48] and the performance analysis of radomes [49].

Moreover, NNs have been used to map the inverse process, where antenna performance, such as voltage standing wave ratio (VSWR) [42], [50], reflection coefficient [40], [51], gain [52], electric field intensity [53], or the combination of some of the performance measures [40], [45], [52], is utilized as the input data of NNs, with antenna geometry parameters as the output. NN-based methods are also applied to other functions, such as mode recognition [54], near-field-to-far-field conversion [55], direction finding [56], and the design of a matching layer for field strengthening [43].

Recently, GAD methods have been used to enhance the performance of antennas [51], [57], [58], [59] and circuits [60]. An NN-based generative method was proposed for automating antenna design [57]. In this method, the antenna is modeled with nodes and characterized by the nodes' locations and radii, as indicated in Fig. 4(a). The training dataset is randomly sampled and simulated to achieve the intended performance. The proposed method consists of both discriminators and generators. The discriminators are used to predict the performance of geometric models, while the generators create new candidates that will pass the discriminators [57]. Two dual-resonance antennas were designed. Broadband optimization with minimal knowledge of the antenna verified the proposed generative method.

In another paper [58], a Tandem Neural Network was presented for the design of single- and dual-band microstrip antennas. In that work, a microstrip antenna is pixelized as shown in Fig. 4(b). A total of 500,000 antenna samples with the operating frequencies of interest are generated for training, validation, and testing. The NN inputs are return-loss responses, and the NN outputs a pixelated geometry pattern for antenna design. This study showcased two prototypes capable of producing both single- and dual-band antennas, with the first prototype demonstrating an area of 0.12 λ_0^2 and an achieved impedance matching bandwidth of 1.8%, while the second achieved a bandwidth of 1.7% with an area of 0.13 λ_0^2, where λ_0 is the operating wavelength.

Overall, before the advent of generative design methods, most of the antenna element designs utilize NNs for surrogate modeling, which inputs the geometry parameters of antennas

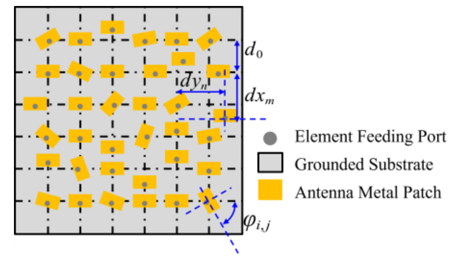

Fig. 5. Generative multi-antenna design with high DoFs, including element arrangements and rotation angles. Here, d_0 is the initial equal spacing, dx_m and dy_n are the unequal spacings, and $\varphi_{i,j}$ is the rotation angle.

and outputs the performance, such as operating frequencies of interest, radiation pattern and gain. The surrogate models contribute to predicting the antenna performance and can be combined with optimization algorithms for performance improvement. With limited DoFs in antenna geometries, the solution space has been expanded to some extent to improve antenna performance. Alternatively, GAD methods have been presented using nodes [57] and pixelization [58] to significantly increase the DoFs of antenna elements. Correspondingly, antenna elements are optimized to satisfy performance requirements, such as bandwidth [57] and compact size [58].

2.2. Multi-antennas

Extending from the complexity of single elements, multi-antenna systems introduce a higher-dimensional design space. Multi-antennas, including conventional antenna arrays and multiple-input-multiple-output (MIMO) antennas, have garnered significant attention in algorithm-based methodology research due to their high-DoF design space, including elements, configurations, and excitations, as well as high-dimensional solution space including radiation patterns, diversity, mutual coupling, channel capacity, and so on.

NN-based methods have been developed to address nonlinear problems in multi-antenna systems and surpass the capabilities of conventional methods. The early development of NN-empowered multi-antenna designs began in 2002 [61], leveraging the data analysis capabilities of NN-based algorithms. From then until 2019, both NN-based and non-NN algorithms drove the evolution of ML-enabled multi-antenna designs and optimizations [62]. Since the introduction of DL-based algorithms in 2020, NN-enabled multi-antenna research has reached its first peak [63], [64], [65], [66], [67], [68], [69], [70], [71], [72], [73], [74], [75], [76]. Furthermore, starting in 2022, generative DL-based algorithms have emerged for multi-antenna designs [77], [78], [79], offering higher DoFs for more customized and critical performance.

Researchers have attempted to apply generative algorithm-based DL approaches to the design and optimization of multi-antennas, particularly for configurations and inter-element mutual coupling. As shown in Fig. 5, a generator-predictor NN was proposed to realize real-time two-dimensional (2-D) beamforming with an array using rotatable dielectric slabs [77]. In this work, ideal dielectric slabs are excited by a point source, and the scattered fields are used as prior knowledge, thereby revealing the nonlinearity of the proposed 2-D beamforming and guiding the upper limit of the sampling step. The proposed generative NN architecture comprises a pre-trained predictor and a generator, both consisting of multi-layer fully connected NNs. The predictor inputs the rotational angles of different slabs and outputs the directivity. The generator takes desired beamforming patterns as input and produces a set of predicted rotation angles. The generator's outputs are then fed into a pre-trained predictor to generate a predicted pattern. As the discrepancy between the predicted and desired patterns decreases, the proposed generative NN-enabled method successfully achieves a 2-D beamforming capability. With the proposed generative DL-based approach, the researchers realized a real-time beamforming system with limited computing power and alleviated the EM synthesis issues with less analysis.

In 2023, using Masked Autoencoders (MAEs), a multi-objective generative design for decoupling structures was achieved to enhance wideband isolation between two planar monopole ultra-wideband (UWB) antennas [78]. The proposed approach involves two stages: pre-training and fine-tuning, each consisting of an encoder and a decoder sub-network. During the pre-training stage, the entire model is trained, primarily learning basic mappings and generating new samples to complement existing models. The results of the pre-training stage act as prior knowledge to improve the modeling in the fine-tuning stage. In the fine-tuning stage, only the decoder is updated using a few samples and iterations. The MAE-based optimization employs the image information of pixelated decoupling structures as the input and has multiple desired targets, including port coefficients and gains. This generative approach reduces the number of samples required for multi-objective optimization in pixelated array decoupling designs.

Besides GAD, there are ML-based non-generative design methods for multi-antenna systems. With the non-generative methods, researchers have also optimized and synthesized the structures, arrangements, and excitation configurations of multi-antennas. These ML-based methods have efficiently addressed challenges in multi-antenna systems, including radiation pattern control [80], [81], [82], [83], platform effects [81], mutual coupling [84], [85], phase delay [86], and bandwidth enhancement [87], [88]. The employed algorithms include support vector regression (SVR) [80], Gaussian process regression (GPR) [81], support vector machine (SVM) [86], and deep neural network (DNN) [88].

Overall, non-generative methods have mainly provided multi-antenna systems with multi-objective optimization capabilities and computational cost reduction over the past two decades. In recent years, generative approaches have been introduced into the multi-antenna design, which features the possibility of solving nonlinear configuration issues and synthesizing the structural topology of multi-antennas.

2.3. MTSs

With the highest design DoFs, MTSs represent the frontier of GAD and are particularly amenable to generative approaches. An MTS is a two-dimensional, electrically thin sheet or surface composed of an array of unit cells, termed as *metacells*, which are usually subwavelength metal or dielectric scatterers [11]. In

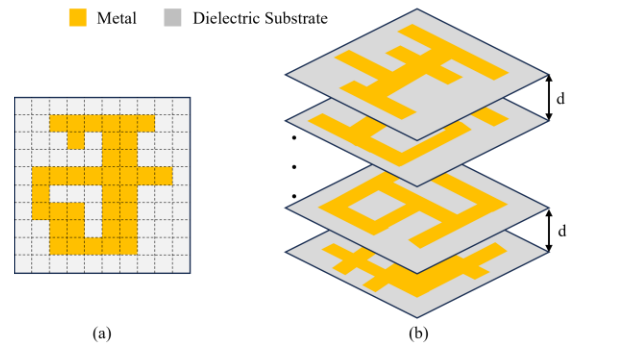

Fig. 6. Degrees of freedom enhancement using generative metacell design method: (a) Pixelization of geometry pattern, and (b) a multilayer metacell having several layers with different pixelized geometry patterns.

2012, ANNs were utilized for optimizing contoured-beam reflectarray antennas [89]. Since then, NN-based non-generative ML methods have been introduced into the research of MTSs [48], [90], [91], [92], [93], [94], [95], dielectric lens antennas [97], [97], FSSs [98], [99], [100], rasorbers [101], and absorbers [102]. The algorithms include ANN [103], [104], [105], [106], [107], back-propagation neural network (BPNN) [108], dynamic graph convolutional neural networks (DGCNNs) [109], convolutional neural network-long short-term memory-deep neural network (CLD) hybrid algorithm [110], statistical learning [111], support vector regression (SVR) [112], nonlinear regression learning [113], particle swarm optimization (PSO) [114], and global surrogate-assisted optimization [115]. Since 2020, DL-based methods have been proposed to design reconfigurable [116] and coding programmable MTSs [117], [118].

Over the past few years, more and more DL-based studies have focused on the optimization and synthesis of metacells using generative methods [119], [120], [121], [122], [123], [124], [125], [126], [127], [128], [129], which have been used to greatly increase the DoFs of MTS design. Fig. 6(a) shows an example of pixelating the geometry pattern of a metacell to increase the DoFs. Moreover, as shown in Fig. 6(b), different pixelated layers can be combined to further increase the DoFs of MTS design.

A generative approach was proposed in 2021 for the inverse design of multilayer metasurfaces using VAE and PSO algorithms [119]. Six kinds of primitives, including Jerusalem cross, complementary Jerusalem cross, rectangular patch, complementary rectangular patch, circular slot, and complete ring, were utilized for training. The method enabled evaluation of the MTS using new combinations of these primitives without simulating the entire structure. This approach enabled optimization problems with single or multiple constraints.

Generative methods have advantages in solving non-unique mapping issues. An adversarial-network regularized inverse design approach was proposed to alleviate the non-uniqueness in mapping and the difficulty in incorporating fabrication constraints [120]. Both frequency and time were utilized as prior information of the data space, which was followed by a pseudo-twin network to constrain the geometry space satisfying fabrication requirements. To verify the design strategy, an inverse-designed passive absorber and a switchable absorber

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were proposed. The measured $|S_{11}|$ met the requirements of less than −5 dB over a specified frequency range and achieved a minimum of less than −20 dB in the absorption band, while the measured transmissions were almost unchanged under different incident angles.

A solution based on conditional generative adversarial network (cGAN) was proposed to solve the problem of nonunique mapping between inputs and outputs in FSS design [121]. This work formulated and discussed the problem of nonunique mapping from the new perspective of information loss caused by data dimensionality reduction and pointed out the limitations of discriminative models in the FSS inverse design. Generative models were used to deal with the dilemma of non-unique mapping. Two specific cGAN-based implementations were proposed for FSS design. One is based on joint inverse network and cGAN while the other one is based on an end-to-end GAN. This work obtained the FSS cell design that meets the targeted specifications without complex NN processing or repeated iterations. As a comparison, the execution time of the proposed method is 0.004 seconds while that of the genetic algorithm (GA) is 10 minutes [121].

An equivalent circuit theory-assisted DL approach was proposed to accelerate the design of MTSs [122]. By combining filter equivalent circuit theory, a VAE model, and genetic algorithms, designers achieved an efficient MTS design. This work adaptively generated highly relevant, low-noise training samples guided by filter equivalent circuit theory, resulting in a narrower target solution space and improved model training efficiency.

In 2022, a prior-knowledge-guided deep-learning-enabled (PK-DL) method was proposed for synthesizing pixelated metacells with arbitrary geometries [123]. This generative method is based on the conditional deep convolutional generative adversarial network (cDCGAN) algorithm. Owing to pixilation, the DoFs of the metacell design are greatly increased. Prior knowledge, including EM theorems and experience in antenna engineering, are purposely integrated into the DL-based generative algorithm to strategically guide and speed up the proposed PK-DL method. Using this method, the −1-dB phase shift limit of a triple-layer metacell was improved from a theoretically derived limit 308° to 330° by increasing the DoFs of metacell design. It also provided additional DoFs for simultaneously tuning both center and off-center frequency responses in metacell synthesis. Thus, a broadband DL-enabled metalens antenna was proposed. Compared to the metalens antenna using conventional Jerusalem cross metacells with three identical layers, the 1-dB and 3-dB gain bandwidths of the DL-enabled metalens antenna were improved by 52.2% and 42.6%, respectively.

In 2023, the PK-DL method was further expanded to a full-range 2-D coverage of metacell's dispersion properties [124]. Both amplitude and phase responses of metacells can be simultaneously synthesized using the PK-DL method. Based on this method, a metacell dataset was built to demonstrate the 2-D coverage performance. Moreover, a metalens antenna was proposed with outstanding sidelobe suppression performance. Measured results of the metalens antenna showed that the first sidelobe levels (SLLs) in the E- and H-plane are −33.2 dB and −30.9 dB, respectively.

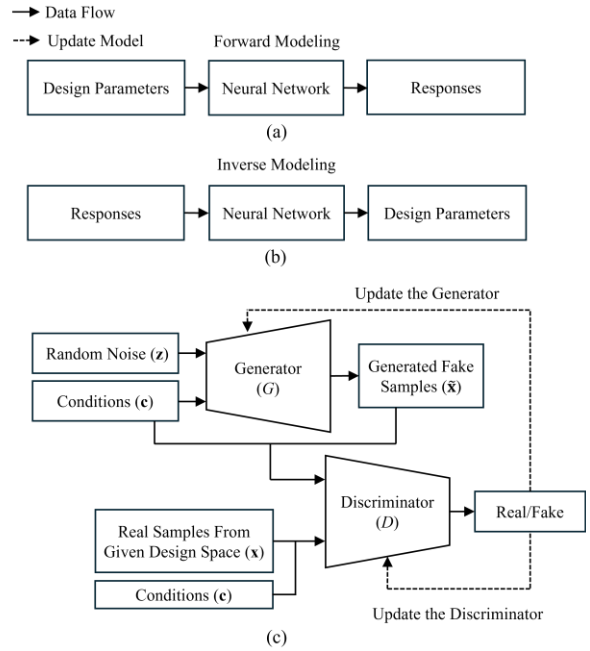

Fig. 7. Schematic diagrams of (a) NN-based forward modeling, (b) NN-based inverse modeling, and (c) conditional generative adversarial network (cGAN).

In short, VAEs and GANs (including cGAN and cDCGAN) have been employed in generative methods for MTS optimization and synthesis to solve non-unique mapping problems [119], [120], [121] and to surpass existing performance ceiling [123], [124], [129]. The tendency of generative MTS optimization and synthesis is to introduce prior knowledge to guide and accelerate the generative methods for multiple performance targets, including bandwidth, execution time, phase-shift range, and SLL suppression.

III. Algorithms in Generative Antenna Design

As demonstrated in the previous section, the effectiveness of GAD hinges on the choice of algorithms. This selection aims to match the strengths of the algorithms to the features of the antenna to be designed. It first introduces the algorithms in GAD, particularly the unique features of GANs and VAEs algorithms. The significant role of prior knowledge in GAD is then discussed. Moreover, a brief review of non-generative algorithms in antenna design is presented.

3.1. Generative Adversarial Networks

Deep generative networks have been an active topic in the computer science community for the past decade and have produced impressive and notable achievements. The allure of GANs stems from their capacity to enable computers not only to comprehend but also to create things through DL algorithms. Applying generative algorithms to antenna design generates one or more design solutions that meet desired specifications, rather than necessarily finding the optimal solution.

Fig. 7 shows schematic diagrams of NN-based and cGAN-based design processes. The traditional NN algorithms are

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grouped into two categories: 1) training forward NN as surrogate models to replace the full-wave EM simulator for acceleration as shown in Fig. 7(a); and 2) training inverse models to propose new candidate designs as shown in Fig. 7(b). GANs work well for generating solutions with statistics similar to those of the training dataset. However, original GANs are not related to desired antenna responses or specifications. In GAD, cGAN is more suitable for generating new antenna designs by labelling the desired antenna performance as its conditions. Fig. 7(c) shows the schematic diagram of a cGAN model where the random noise vector **z** is concatenated with the condition vector **c** before feeding them into the generator (*G*) to produce the required samples. Additionally, for the discriminator (*D*), both real samples from the given design space and fake samples from the generator must be concatenated with their corresponding conditions before being fed into the discriminator for recognition. The generator (*G*) captures the data distribution of training samples and generates samples to fool the discriminator (*D*), while the discriminator (*D*) estimates the probability whether the input sample is from real data or the generator (*G*).

The objective function of cGAN [130] is described by the value function $V(G, D)$ as:

$$\min_G \max_D V(D,G) = \mathbb{E}_{\mathbf{x}\sim p_{\text{data}}(\mathbf{x})}[\log D(\mathbf{x}|\mathbf{c})] \\ +\mathbb{E}_{\mathbf{z}\sim p_z(\mathbf{z})}[\log(1-D(G(\mathbf{z}|\mathbf{c})))] \tag{1}$$

where **x** is the data vector sampled from the training data distribution $P_{\text{data}}(\mathbf{x})$, **c** is the condition vector, and **z** is the random noise vector sampled from a prior distribution $P_z(\mathbf{z})$. $E_{\mathbf{x}\sim P_{\text{data}}(\mathbf{x})}$ is the expected value over real data under the training data distribution $P_{\text{data}}(\mathbf{x})$. $E_{\mathbf{z}\sim P_z(\mathbf{z})}$ is the expected value over random noise under the noise prior distribution $P_z(\mathbf{z})$. To learn the distribution $P_{\text{data}}(\mathbf{x})$ of the real training data space, the generator (*G*) constructs a generator function $G(\mathbf{z}|\mathbf{c})$, which produces synthetic data given the random noise vector **z** and conditional vector **c**. $D(\mathbf{x}|\mathbf{c})$ represents the discriminator function outputting the probability that the input samples and conditions are from the given design space (real) or from the generator (fake).

Conventional antenna modeling is deterministic, mapping design parameters to fixed outcomes. In contrast, cGANs adopt a probabilistic approach, enabling the generation of new antenna designs that differ from the training samples. For GAD, cGANs offer several advantages:

- Learn a mapping from a latent prior distribution to the antenna design distribution, which is inferred from the training data, enabling generation of diverse antenna structures.
- Model conditional design distributions by incorporating explicit constraints, enabling controlled generation.
- Generate new antenna designs from the conditioned design distribution.
- Produce multiple designs that satisfy target specifications while exhibiting performance diversity.

These features enable designers to efficiently explore innovative solutions and select optimal designs based on additional criteria such as cost and manufacturability.

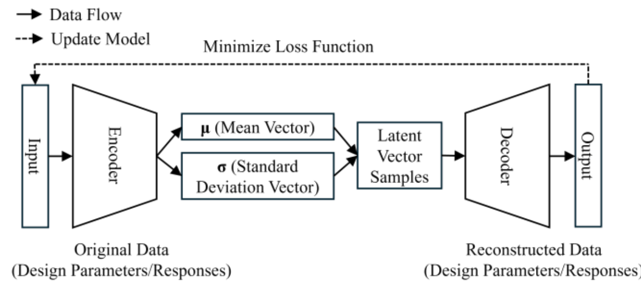

Fig. 8. Schematic of a variational autoencoder (VAE).

3.2. Variational autoencoders

Besides cGANs, NN-based VAEs are also widely used in GAD. As shown in Fig. 8, a VAE comprises an encoder NN and a decoder NN. The encoder maps input data to a distribution in the latent space. This distribution is often represented by a mean vector **μ** and a standard deviation vector **σ**, which parameterize a Gaussian distribution. The encoder compresses the input data into a lower-dimensional latent space, capturing the data's essential features in a compact form. The decoder then samples a vector from this latent-space distribution and maps it back to the original data space, reconstructing the data as accurately as possible. This process allows the model to learn meaningful representations and generate new samples from the latent space.

The optimization of the VAE's loss function, which typically includes a reconstruction loss term and a regularization term, encourages the latent space to follow a specific distribution (e.g., a Gaussian distribution). Through this optimization, the encoder and decoder networks collaboratively learn an optimized latent space of the input data. This latent space captures the data's essential characteristics, facilitating accurate reconstruction by the decoder. Additionally, the regularization term constrains the latent space to follow a specific distribution, enabling meaningful interpolation and sampling, which allows for the generation of novel data samples that resemble the input data.

In GAD, VAEs are often combined with evolutionary optimization methods to leverage the strengths of both techniques [119], [122], [131]. Initially, a VAE is trained using a dataset of antenna designs with complex geometries. This VAE learns to map these designs to a lower-dimensional latent space while preserving important design characteristics. This allows the VAE to effectively encode the high-dimensional design space into a more manageable and structured latent space. Once the VAE is trained, the learned latent space serves as a search space for evolutionary optimization algorithms. These algorithms explore the latent space to find optimal solutions that maximize or minimize certain objectives, such as antenna performance metrics (e.g., gain, bandwidth, impedance matching). After the optimization process converges on a solution in the latent space, the corresponding latent variables are decoded by the VAE's decoder network to reconstruct the optimized antenna design. This reconstructed design is then evaluated using a full-wave EM simulator or a surrogate model to assess its performance against the desired criteria. The whole process continues iteratively until a stopping criterion is met,

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TABLE I
COMPARISON BETWEEN REPRESENTATIVE GENERATIVE ANTENNA DESIGN METHODS

Algorithm	Model Size	Dataset Information	Key Words
Tandem NN	Inverse Network: 3 fully connected layers [58] Pre-Trained Forward Network: 3 convolutional layers and 3 fully connected layers [58]	500,000 samples [58]	• Antenna element rapid design [58].
Generative NN	Predictor: 7 fully connected layers [77] Generator: 9 fully connected layers [77]	40,000 samples [77]	• Multi-antenna real-time beamforming [77].
Masked Autoencoder	Encoder: 24 blocks [78] Decoder: 8 blocks [78]	3,000 samples [78]	• Multi-antenna decoupling [78].
VAE	Encoder: 3 convolutional layers [122] Decoder: 4 transpose convolutional layers [122]	34,000 samples [119] 400 samples [122] 2,400 samples [131]	• Solve the one-to-many mapping issue in MTS design [119]. • Equivalent circuit theory-assisted MTS rapid design [122]. • Small-scale data-selection method for MTS design [131].
GAN	Generator: 4 fully connected layers [57], [59] Discriminator: 4 fully connected layers [57], [59]	50 to 700 samples [57] 500 samples [59]	• Automate antenna element design and optimization [57]. • Antenna element rapid design [59].
	Generator: 3 fully connected layers [79] Discriminator: 2 convolutional layers and 2 fully connected layers [79]	20,000 samples [79]	• Conformal multi-antenna real-time diagnosis [79].
	Inverse Network: 5 fully connected layers [121] Generator: 5 fully connected layers [121]; 4 deconvolutional layers [123], [124]; 8 deconvolutional layers [128] Discriminator: 4 fully connected layers [121]; 5 convolutional layers [123], [124]; 8 convolutional layers [128]	3,500 samples [120] 7,144 samples [121] >6,000 samples [123] >15,000 samples [124] 1,200 samples [128] >5,000 samples [129]	• Frequency-temporal method for MTS design [120]. • Solve the information loss dilemma in MTS design [121]. • Break phase shift limit; broadband MTS [123]. • Full-range amplitude and phase control; low SLL MTS [124]. • MTS design for radar cross section reduction [128]. • TE–TM balanced wide-angle transmission MTS [129].

such as reaching a certain level of performance improvement, convergence of the optimization algorithm, or a predefined number of iterations. This integrated approach streamlines the design process, accelerates the discovery of optimized antenna designs, and facilitates the exploration of the design space in a systematic and efficient manner.

Table I compares the representative GAD methods from the literature, categorizing each work by the generative algorithm employed, model size, training dataset size, and key words. The comparison highlights the breadth of applications and demonstrates the effectiveness of the algorithms across various contexts, offering a concise overview of the state of the art.

3.3. Prior knowledge in algorithms of GAD

One of the key advantages of GAD is its ability to efficiently model antenna designs with extremely high DoFs. The design space of GAD is incredibly expanded with numerous parameters and variables that influence antenna performance. It suggests that GAD can inherently deal with large-scale, complex, and computationally expensive optimization problems. To take this advantage, leveraging prior knowledge is essential for balancing efficiency and accuracy in generative algorithms.

Generative algorithms can benefit from prior knowledge in the following aspects:

- Prior knowledge helps efficiently generate effective data for training generative models. Prior knowledge enables algorithms, such as cGANs and VAEs, to learn the probability distribution from relevant and meaningful training data, thereby enhancing the efficiency of antenna design across an extremely large design space.
- Prior knowledge plays a crucial role in defining problems suitable for GAD. Only when the complexity and variability of the antenna design space, as well as the objectives and constraints of the antenna design task, are well understood can designers identify problems well-suited to GAD.
- Prior knowledge is crucial for formatting and pre-processing data from antennas to make them suitable for generative algorithms, which are not initially proposed specifically for GAD.
- Prior knowledge is instrumental in guiding the modification and adaptation of generative algorithms to suit the specific requirements and characteristics of GAD. Every component of the generative algorithm, such as network layers, connections, and the loss function [132], can be adjusted based on prior knowledge, ensuring physically consistent and reliable outputs that meet engineering requirements.
- Prior knowledge also significantly affects the convergence of the algorithms. Our experience indicates that setting targets too high can make convergence very slow, or even impossible. Prior knowledge helps set realistic targets that balance accuracy and time consumption.

3.4. Non-generative algorithms in antenna design

Besides generative algorithms, non-generative algorithms including both NN-based and non-NN-based ones have also been used in antenna design.

A. Non-NN-based machine learning methods

Over the past decades, various non-NN-based ML techniques, e.g., support vector machine (SVM) [86], support vector regression (SVR) [80], enhanced extreme gradient boosting (E-XGBoost) [133], and Gaussian process regression (GPR) [81], have been implemented to reduce the computational cost of antenna modeling and surrogate-assisted optimization processes.

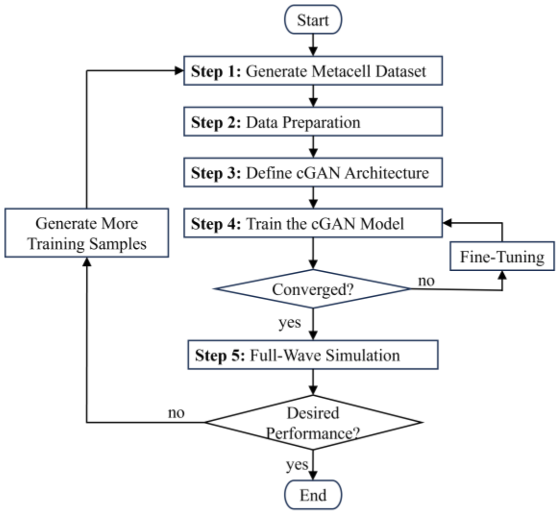

Fig. 9. Flowchart of the GAD method for metacell synthesis in [123], [124].

The SVM algorithm is primarily used for classification [86], [134]. It can predict whether antenna designs satisfy or fail to satisfy specified goals. The SVR algorithm is a regression analysis method. The goal of SVR is to find a function that approximates the relationship between the input variables and a continuous target variable while minimizing the prediction error. It is widely used in antenna modeling with limited training samples [80], [112], [135], [136], [137]. The GPR (Kriging) method establishes a surrogate model for samples and their corresponding responses. Based on the GPR algorithm, various methods, such as machine learning-assisted optimization (MLAO) [81], [138], [139], [140], [141], surrogate model assisted differential evolution for antenna synthesis (SADEA) [84], [87], [142], [143], and trust-region parallel Bayesian optimization (TRPBO) [144], have been proposed for efficient antenna optimization.

B. NN-based machine learning methods

Among non-generative NN methods, feedforward neural networks (FFNNs) feature unidirectional information flow between layers. Multilayer perceptron (MLP), a widely used FFNN architecture, have been extensively applied to forward modeling of antenna elements [24], [33], [34], [36], [39], [41], [42], [43], [44], [54], [55], [145], multi-antennas [61], [146], [147], [148], and MTSs [89], [103], [149] to accelerate optimization and reduce computational cost, as well as to inverse modeling of various antenna structures [37], [53], [103], [148]. Another common FFNN is the radial basis function neural network (RBF-NN) [53], [151], [152], [153], [154], [155], which employs RBF activations and is effective in capturing localized input-output behaviors [156].

With advances in NN techniques, architectures have evolved from shallow networks to deep neural networks (DNNs). Over the past decade, DNNs have outperformed shallow NNs in antenna design and optimization, particularly for highly complex and nonlinear modeling tasks. Representative DNN approaches include deep MLPs [35], [157], [158], convolutional neural networks (CNNs) [117], [159], deep belief networks (DBNs) [30], and reinforcement learning [29], [160], [161], [162]. For strongly nonlinear input-output relationships, incorporating transfer functions as prior knowledge can further enhance DNN modeling performance [40].

IV. Generative Method-Enabled Metacell Synthesis

This section presents the latest advances in cGAN-based GAD, showcasing a specific example using the prior-knowledge-guided deep-learning-enabled (PK-DL) method for metacell synthesis. It demonstrates the potential of cGAN-based GAD in breaking the performance limits of metacells, thereby improving the performance of metalens antennas.

Fig. 9 shows the flowchart of the GAD method for metacell synthesis [123], [124]. The development process is summarized in the following stepwise algorithm.

Step 1: Metacell Dataset Generation.

A: An initial geometry pattern, such as a square patch, is placed on a 30×30-pixel grid to define the metacell's design space.

B: Pixelate the pattern and randomly add pixel blocks based on prior knowledge of EM expertise [123].

C: Obtain S_{21} responses of the generated metacells by full-wave EM simulation. Then, sample the S_{21} responses to create condition vectors.

D: Label geometry matrices of metacells with the corresponding S_{21} response condition vectors to form the complete dataset. The final dataset comprised over 6,000 [123] and 15,000 [124] unique metacell geometries and their responses.

Step 2: Data Preparation.

Normalize magnitude and phase for fair evaluation in the cGAN loss function. For the magnitude error less than 0.1 and the phase error less than 10°, scale phase responses by 0.01.

Step 3: cGAN Model Definition.

A: The generator is a deconvolutional NN. It takes a concatenated vector of random noise and the condition vector as input. As detailed in [123], the network comprised four deconvolutional layers with channel sizes of 256, 128, 64, and 1, respectively. In subsequent work [124], the architecture was adapted for a two-channel output, using layers with 256, 128, 64, and 2 output channels to simultaneously generate the top/bottom and middle-layer geometries for a triple-layer metacell.

B: The discriminator is a convolutional neural network that classifies input-condition pairs as real or fake. In both [123] and [124], it comprised five convolutional layers with channel sizes of 64, 128, 256, and 512, followed by a final classification output channel of 1. The key difference in [124] was the processing of a two-channel geometry input.

C: ReLU or Leaky ReLU activation functions are commonly used in the hidden layers while Sigmoid activation function in the output layer to make sure the value of output data is in the range of (0,1). Binary cross-entropy is a commonly used loss function for GAN-based models. Adam or stochastic gradient descent (SGD) are popular choices for optimizer.

Step 4: cGAN Model Training.

The metacell dataset is split into training, validation, and test sets.

A: Train the cGAN using the training dataset. For the model in [123], the training on an NVIDIA Tesla V100 GPU took approximately 48 hours to converge over 5,000 epochs.

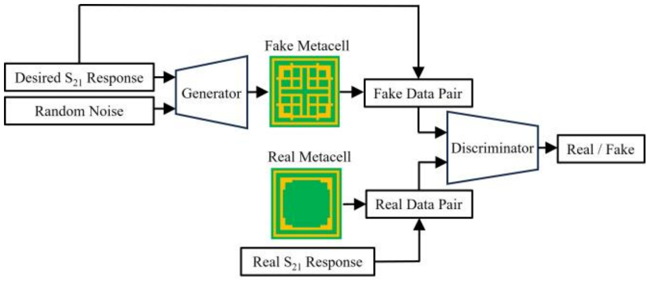

Fig. 10. Schematic diagram of the cGAN model for metacell synthesis.

B: Validate performance and fine-tune hyperparameters.

C: Test on unseen data for final evaluation.

D: Save the trained generator and discriminator models.

Step 5: Full-Wave Simulation Verification.

A: Use the well-trained generator to produce metacell geometries for desired S_{21} responses. Filter the geometry matrix and convert it to binary format.

B: Simulate generated metacells. If performance is unsatisfactory, refine the dataset and repeat from **Step 1**, incorporating prior knowledge to accelerate training.

This PK-DL synthesis method can generate metacells with arbitrary geometric patterns, thereby greatly increasing the DoFs of metacell design. Fig. 10 shows the schematic diagram of the cGAN model. During training, the desired performance, i.e., S_{21} responses in metacell synthesis, and random noise are fed into the generator. The generator network learns probability distributions from the training dataset and predicts the geometric patterns of metacells that satisfy the desired S_{21} responses. In this framework, a generated metacell and its desired S_{21} response are treated as a 'fake' data pair. Conversely, a metacell sourced from the training dataset, generated by full-wave EM simulation, along with its corresponding S_{21} response, constitutes a 'real' data pair. The discriminator evaluates whether a given piece of data is real or fake.

During training, the generator learns to map the desired S21 responses to realistic data, while the discriminator is trained to improve its ability to distinguish between real and generated data. Based on the PK-DL synthesis method, two metalens antennas are proposed by using the generated metacells. In the first design [123], the PK-DL method is utilized to synthesize triple-layer metacells with −1-dB phase-shift range of 330°, which breaks the limit of 308° derived by existing techniques. Moreover, it flexibly controls the phase shift not only at the center frequency but also over an off-center frequency range of interest. Compared to the metalens antenna using the well-known Jerusalem cross metacells, the 1-dB and 3-dB gain bandwidths of the generative method-enabled metalens antenna are improved by 52.2% and 42.6%, respectively.

The second design [124] realizes the independent control of amplitude and phase responses of metacells. The proposed PK-DL synthesis method expands metacell design from the conventional one-dimensional space to a new two-dimensional amplitude- and phase-space. Based on the PK-DL method, a metalens antenna is designed with high sidelobe suppression. Measurement results show that the first sidelobe level of the metalens antenna is suppressed to below −30 dB.

Fig. 11. Solutions generated by three techniques against DoFs.

V. Notes for Generative Antenna Design

Antenna design involves determining the configuration and excitation distribution of the radiating structure. To develop innovative and high-performance GADs, further research should address key issues informed by our experience.

- *Roles of prior knowledge in GAD include:*

a) Crucially, antenna design challenges must be well paired with the most suitable DL-enabled algorithms. The success of this matching depends heavily on the designer's cross-disciplinary expertise, integrating prior knowledge from both antenna engineering and deep learning theory.

b) GAD advancement proceeds along two distinct fronts: algorithmic development and practical application. The former requires substantial prior knowledge for efficient NN development, while the latter focuses on minimizing required domain expertise by creating intelligent antenna design tools.

- *Unique features of GANs:* GANs generate diverse and novel outputs by incorporating random noise as input. This noise functions as an exploration mechanism, enabling the synthesis of complex designs and the coverage of different regions in the design space.
- *Generative design, reformed design, and parametric optimization:* Traditional optimization seeks the best solutions by adjusting predefined parameters within a fixed topology. Generative methods create new data samples that capture the underlying characteristics of training data, fostering design creativity and structural innovation. Key differences include:

a) *Objective*: Parametric optimization refines a known design to its best performance. GAD seeks novel designs that meet or exceed targets, often creating families of diverse solutions.

b) *Process*: Optimization relies on iterative improvement of a single candidate using algorithms such as gradient-based or evolutionary methods. GAD leverages a trained generative model, such as GAN or VAE, to instantaneously propose new design candidates that are statistically likely to perform well, based on the statistic patterns learned from the training datasets.

c) *Output Nature*: Optimization yields deterministic, finely tuned instances of a chosen topology. GAD produces probabilistic, diverse, and often unconventional geometries, offering multiple viable pathways to meet specifications.

Fig. 11 illustrates solutions versus DoFs in antenna design, using parametric optimization for comparison. The three techniques, applied with varying DoFs, generate distinct solutions. The parametric optimization solution with the lowest DoFs maintains the original antenna design with optimal dimensions (e.g., a and b of a patch). The generative solution with the highest DoFs meets the performance goals but presents a complex and unpredictable pattern. With moderate DoFs, the reformed design generates solutions similar to the original with some improvements.

VI. Prospects and Conclusions

Antenna design must evolve to enhance performance and functionality by increasing DoFs, but this expansion challenges current computational capacity. Prior knowledge, such as physical laws and engineering expertise, can help filter training samples. DL techniques enable generative design, using iterative algorithms to refine antenna topology, including shapes, structures, and materials. Key attributes include automated design generation, rapid iteration, and the ability to discover innovative solutions, such as those enabled by cGANs.

6.1. Challenges

GAD is fast developing with various challenges. These challenges include but are not limited to:

A. General Challenges of GAD:

- *Defining Effective Problem Statements*: The problem statements need to be suitable for GAD and beneficial from GAD. Formulating well-defined antenna design problems and precise specifications remains challenging for GAD implementation.
- *Data Effectiveness*: Acquiring raw data for highly effective antenna data or training samples for training GAD can be challenging due to limitations in computational capability as well as physical laws and engineering constraints.
- *Dataset Generation and Integration*: Efficiently generating vast amounts of effective antenna data or training samples for the training process poses significant logistical and computational challenges.
- *Training Stability*: A stable training process is concerned with the convergence of GAD, which can be more difficult than modeling and optimization.
- *Interpretability*: Understanding and interpreting antenna designs generated by GAD can be challenging, making it difficult to extract meaningful insights.
- *Proper Integration of Prior Knowledge*: Integrating prior knowledge into generative AI models in all steps can be time-consuming, thus impacting efficiency and performance.
- *Computational Resources*: GAD requires significant computational power and memory, which can be costly and time-consuming, especially for large antenna designs.

B. Specific Challenges of cGANs:

- *Prior Knowledge*: Capturing prior knowledge, selecting effective prior knowledge, and integrating prior knowledge are not trivial in every step of the process. GANs may struggle to capture domain-specific knowledge and constraints relevant to antenna design, requiring careful integration of expert knowledge.
- *Mode Collapse*: GAD, especially GANs, may converge to a limited set of antenna designs, known as mode collapse, thus hindering the exploration of diverse design solutions.
- *Model Versatility*: Enhancing the adaptability and versatility of trained generative networks for diverse antenna design scenarios is essential.
- *Scalability*: Extending GAN-based approaches to large-scale antenna arrays or complex antenna systems may pose scalability challenges in terms of both computational resources and model complexity.

6.2. Impact on Antenna Technology and Applications:

Generative AI, particularly in antenna engineering, holds immense potential for revolutionizing traditional practices. It streamlines design processes, enhances prediction accuracy, and fosters adaptability, ultimately improving overall performance and efficiency across various applications.

Furthermore, it serves as a catalyst for exploring new phenomena and pushing the boundaries of antenna design, giving rise to novel antenna types that not only enhance existing systems but also pave the way for innovative architectural designs to meet emerging application demands. With ample DoFs, generative AI can undertake tasks beyond human limitations, driving exploration in areas previously deemed too time-intensive or challenging.

6.3. Trends

With the rapid advancement of AI, particularly in generative approaches, GAD is experiencing notable trends in its development, including:

1. *Addressing Performance Limitations*: Generative design challenges existing technology by tackling performance limitations of antenna designs to narrow the significant gap between their performance limits and the theoretical upper bound of antenna performance.
2. *Handling Complexity Beyond Current Capabilities*: Generative approaches tackle complex antenna problems beyond current modeling, optimization, and design capabilities.
3. *Knowledge Accumulation*: The intersection of engineering and generative design leads to the accumulation of new knowledge.
4. *Integration of Prior Knowledge*: Prior knowledge is increasingly being integrated into all aspects of antenna engineering to improve design efficiency and reliability. EM principles and accumulated domain expertise can be embedded into GAD frameworks to reduce solution space,

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improve data efficiency, and enhance model interpretability. The appropriate level and form of prior-knowledge integration, however, depend on the specific design objectives and problem formulation, and should therefore be determined on a case-by-case basis.

5. *Advanced Algorithms*: An emerging trend in GAD lies in leveraging more advanced and powerful generative algorithms, exemplified by diffusion models and transformer models.
6. *Cross-Border Cooperation*: Cooperation across academic, research, and industrial organizations fosters the development of powerful algorithms.
7. *Interdisciplinary Collaboration*: Collaboration across disciplines facilitates innovation and advancement in GAD.
8. *Rapid and Accurate Modeling*: Generative techniques enable fast and accurate modeling of ultra-large and intricate antenna problems, including platform effects in real-world applications.
9. *Cost-Effective Optimization*: AI-assisted optimization, utilizing surrogate models, reduces costs of computation and design, as compared to full-wave EM simulations.
10. *Setting New Design Targets*: GAD sets new targets by breaking performance limits, creating multifunctional antennas, and developing new knowledge and materials.

In summary, we anticipate that AI-enabled antenna technology, namely Antenna + AI, will accomplish tasks that are challenging or impossible for humans, particularly in the realm of innovative design with superior performance, additional functionalities, and novel insights. Furthermore, it will facilitate the modeling and optimization of highly complex antennas with remarkable precision and efficiency.

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