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Artificial Intelligence for Antenna Design, Surrogate Modeling, And Optimization: A Review of Methods, Trends, And Open Challenges

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Abstract: The increasing complexity of modern wireless communication systems has significantly transformed the antenna design process. Conventional antenna development primarily relies on full-wave electromagnetic (EM) simulations combined with iterative optimization techniques. Although these methods provide accurate results, they often require extensive computational time, particularly when dealing with multi-parameter, multi-objective, or broadband antenna structures. In recent years, artificial intelligence (AI) has emerged as a promising alternative for accelerating antenna analysis and design. Machine learning (ML), deep learning (DL), surrogate modeling, inverse design, and generative approaches have demonstrated the ability to predict antenna performance with considerably fewer electromagnetic simulations while maintaining satisfactory accuracy. This review presents a comprehensive analysis of recent research on AI-assisted antenna design, covering studies involving microstrip patch antennas, ultra-wideband (UWB) antennas, antenna arrays, metasurfaces, horn antennas, and reconfigurable antenna structures. The reviewed literature is organized according to major AI methodologies, including classical machine learning algorithms, deep learning architectures, surrogate modeling techniques, inverse design frameworks, and hybrid optimization approaches. Their advantages, limitations, and practical applications are critically discussed and compared. Furthermore, this review identifies several challenges that continue to limit the widespread adoption of AI-driven antenna design, including the absence of standardized benchmark datasets, inconsistent reporting of computational efficiency, limited experimental validation, and the difficulty of developing generalized models that can perform well across multiple antenna topologies. Finally, potential research directions such as physics-informed learning, transfer learning, generative artificial intelligence, digital twins, and automated antenna design frameworks are highlighted. The objective of this review is to provide researchers and engineers with a structured overview of current developments while identifying opportunities for future advancements in intelligent antenna design.

Keywords: Artificial Intelligence; Machine Learning; Deep Learning; Antenna Design; Surrogate Modeling; Inverse Design; Antenna Optimization; Electromagnetic Simulation; Metasurfaces; Wireless Communication

1. INTRODUCTION

Antennas are one of the most essential components of modern wireless communication systems. They play a vital role in enabling reliable signal transmission and reception in applications such as fifth-generation (5G) and sixth-generation (6G) mobile communications, satellite systems, radar, wireless sensor networks, Internet of Things (IoT), wearable devices, autonomous vehicles, and aerospace communication. As wireless technologies continue to evolve, antenna designers are expected to achieve multiple performance objectives simultaneously, including high gain, wide impedance bandwidth, compact size, low mutual coupling, improved radiation efficiency, and reduced fabrication cost. Meeting all these requirements within a single antenna structure has made the antenna design process increasingly complex [1], [4], [15], [17].

Traditionally, antenna design relies on full-wave electromagnetic (EM) simulation software such as CST Microwave Studio, ANSYS HFSS, FEKO, and COMSOL Multiphysics. The design process generally involves repeated modification of antenna parameters followed by EM simulation until the desired performance is achieved. Although this trial-and-error approach provides accurate results, it is computationally intensive and time-consuming, particularly for antennas with multiple design variables or conflicting optimization objectives. Furthermore, optimization algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), and Simulated Annealing (SA) often require hundreds or even thousands of EM simulations before converging to an optimal solution, thereby increasing the overall computational cost [12], [14], [35], [40], [44].

To overcome these limitations, artificial intelligence (AI) has emerged as an effective tool for accelerating antenna analysis, modeling, and optimization. Instead of performing computationally expensive EM simulations during every optimization step, AI techniques learn the relationship between antenna geometry and electromagnetic characteristics from previously generated simulation data. Once trained, these models can accurately predict important antenna parameters such as resonant frequency, return loss (S_{11}), gain, bandwidth, radiation efficiency, and radiation pattern within a very short time. This significantly reduces the computational burden while maintaining acceptable prediction accuracy [9], [10], [15], [16], [20], [25].

Recent research has demonstrated the successful application of various AI techniques in antenna engineering. Classical machine learning algorithms, including Support Vector Machine (SVM), k-Nearest Neighbors (KNN), Random Forest (RF), Gaussian Process Regression (GPR), and Artificial Neural Networks (ANN), have been employed for antenna parameter prediction and optimization. More recently, deep learning models such as Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) networks, and Physics-Informed Neural Networks (PINNs) have shown excellent capability in modeling highly nonlinear electromagnetic problems. In addition, surrogate modeling, inverse design frameworks, and generative models such as Generative Adversarial Networks (GANs) have further expanded the application of AI by enabling rapid antenna optimization and direct geometry synthesis from target electromagnetic specifications [2], [3], [10], [11], [16], [18], [20], [21], [25], [26], [27].

Although the number of publications on AI-assisted antenna design has increased rapidly during the past few years, the existing literature remains scattered across different antenna types, AI algorithms, optimization strategies, and application domains. Most studies focus on solving a specific design problem or evaluating the performance of an individual algorithm, making it difficult for researchers to obtain a comprehensive understanding of the strengths, limitations, and practical applicability of different AI techniques. In addition, variations in datasets, simulation environments, evaluation metrics, and validation methods make direct comparison among published studies challenging [15], [16], [17], [24].

Therefore, a comprehensive review is necessary to summarize the current state of research and identify future opportunities in this rapidly evolving field. This review presents a structured comparison of artificial intelligence techniques applied to antenna design, surrogate modeling, inverse design, and optimization. Instead of reviewing individual studies sequentially, the literature is organized according to major AI methodologies to facilitate meaningful comparison between different approaches. The advantages, limitations, and application areas of each technique are discussed, followed by an analysis of current research trends, existing challenges, research gaps, and future directions. The objective of this review is to provide researchers, engineers, and graduate students with a clear understanding of how artificial intelligence is transforming modern antenna design and where future research efforts are likely to have the greatest impact [15], [16], [17].

2. BACKGROUND OF ANTENNA DESIGN

The design of antennas has traditionally been based on electromagnetic (EM) theory and numerical simulation techniques. Commercial EM simulation software such as CST Microwave Studio, ANSYS HFSS, FEKO, and COMSOL Multiphysics enables designers to evaluate antenna performance before fabrication. During the design process, antenna dimensions are repeatedly modified and simulated until the desired characteristics, such as resonant frequency, impedance bandwidth, gain, radiation pattern, and return loss (S_{11}), satisfy the design requirements. Although this approach provides highly accurate results, it is computationally expensive and often requires numerous simulation iterations, particularly for complex antenna geometries and multi-objective optimization problems [12], [35], [40], [43], [44]. The increasing demand for compact, high-performance antennas in modern wireless communication systems has further increased the complexity of antenna design. Applications involving 5G/6G communication, Internet of Things (IoT), satellite communication, wearable devices, MIMO systems, and reconfigurable intelligent surfaces (RIS) require antennas capable of satisfying multiple performance objectives simultaneously. Designers must often balance parameters such as bandwidth, gain, efficiency, isolation, physical size, and fabrication constraints, making the conventional trial-and-error approach increasingly inefficient [1], [4], [5], [13].

To reduce computational complexity, optimization algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), and Simulated Annealing (SA) have been widely adopted in antenna engineering. These techniques automate the search for optimal antenna parameters and generally produce better solutions than manual parameter tuning. However, because every optimization step still requires repeated EM simulations, the overall computational cost remains high, particularly when dealing with antennas containing a large number of design variables [12], [14], [35], [41], [45].

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Figure 1 illustrates the conventional antenna design workflow adopted in electromagnetic-based antenna development. The process involves iterative stages of geometry design, EM simulation, performance evaluation, optimization, fabrication, and experimental validation until the required antenna characteristics are achieved.

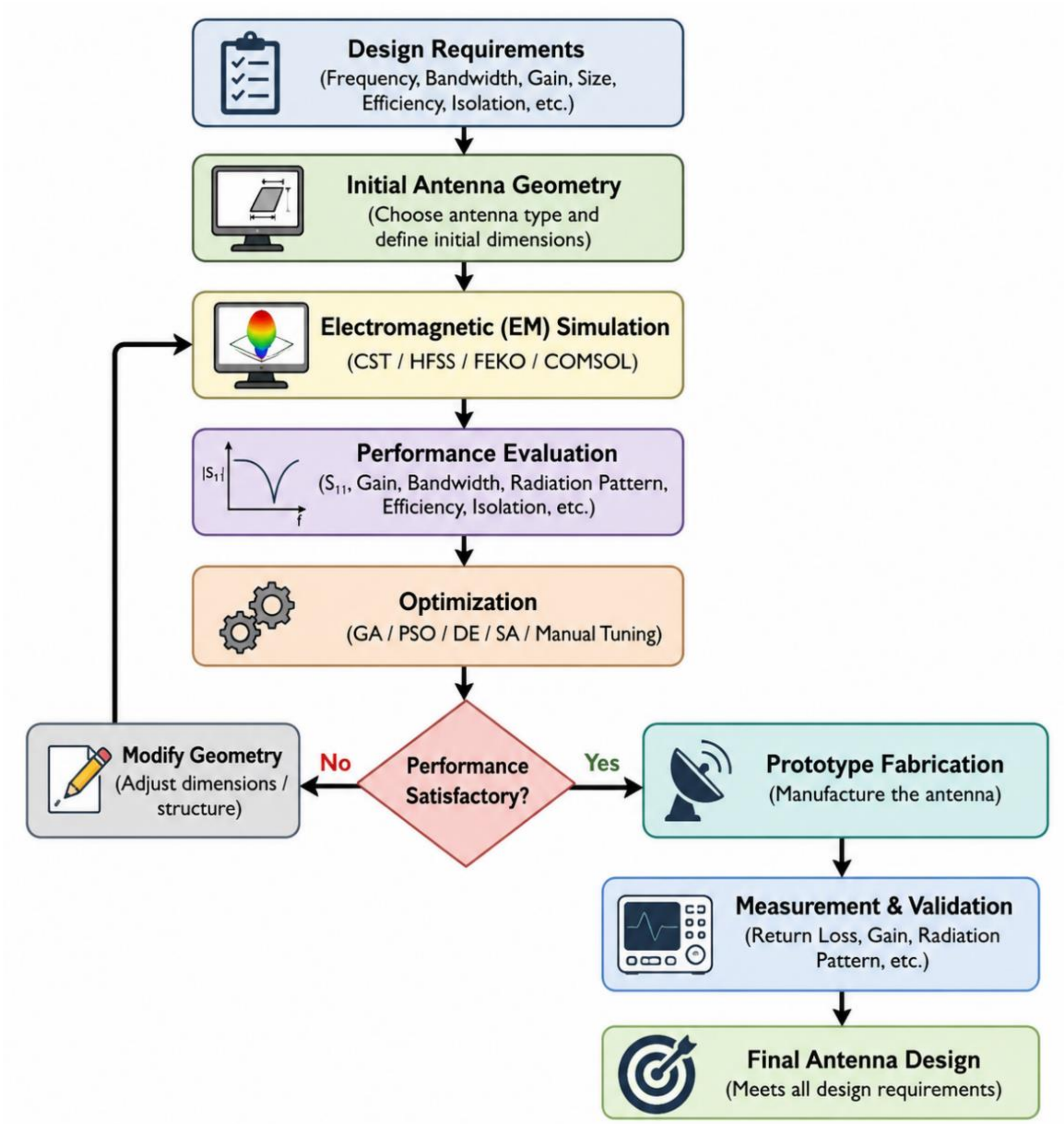

Figure 1. Conventional antenna design workflow illustrating the iterative process involved in antenna modeling, optimization, fabrication, and performance validation.

Recent advances in artificial intelligence have provided an effective alternative to conventional optimization techniques. Instead of relying solely on repeated electromagnetic simulations, AI-based approaches learn the relationship between antenna geometry and electromagnetic performance from previously generated simulation data. Once trained, these models can rapidly predict antenna characteristics and significantly reduce the number of expensive EM simulations required during the design process. Consequently, artificial intelligence has become an important tool for antenna modeling, optimization, surrogate modeling, and inverse design [9], [10], [15], [16], [17], [20]. Among the various AI-based approaches, surrogate modeling has received considerable attention because it replaces computationally intensive EM simulations with predictive models that provide similar outputs at a much lower computational cost. Likewise, deep learning models have demonstrated strong capability in modeling complex nonlinear electromagnetic relationships, while inverse design frameworks directly estimate antenna geometries from desired electromagnetic specifications. These developments have transformed the conventional antenna design workflow from a simulation-intensive process into a faster and more intelligent data-driven methodology [10], [11], [16], [20], [25], [27].

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3. ARTIFICIAL INTELLIGENCE TECHNIQUES FOR ANTENNA DESIGN

Artificial intelligence has become an important component of modern antenna engineering by enabling faster analysis, accurate performance prediction, and efficient optimization. Unlike conventional electromagnetic simulation-based methods, AI techniques learn the relationship between antenna geometry and electromagnetic characteristics from previously generated simulation data. Once trained, these models can rapidly estimate antenna parameters such as resonant frequency, return loss (S_{11}), gain, bandwidth, radiation efficiency, and radiation pattern with significantly reduced computational effort [9], [10], [15], [16], [17], [20].

Over the past few years, numerous AI techniques have been investigated for different antenna design tasks. The choice of an appropriate AI model depends on several factors, including antenna complexity, dataset size, computational resources, and the specific design objective. While some algorithms are more suitable for parameter prediction and surrogate modeling, others perform better in inverse design or multi-objective optimization. Figure 2 illustrates the major categories of artificial intelligence techniques currently employed in antenna engineering.

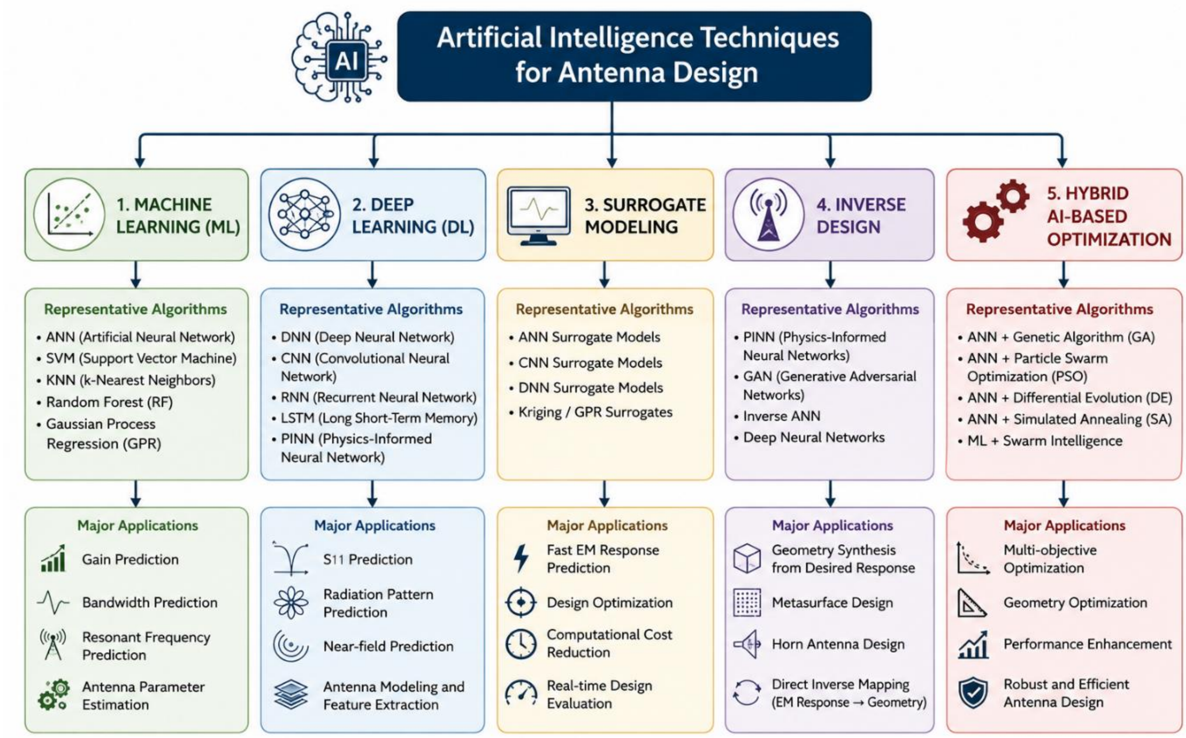

Figure 2. Classification of artificial intelligence techniques used in antenna design and optimization.

The AI techniques reported in the literature can generally be classified into five major categories:

- Machine Learning (ML): Classical machine learning algorithms such as Support Vector Machine (SVM), k-Nearest Neighbors (KNN), Random Forest (RF), Gaussian Process Regression (GPR), and Artificial Neural Networks (ANN) are widely used for predicting antenna parameters, resonance frequency, gain, bandwidth, and impedance characteristics. These methods generally require relatively small training datasets and offer good prediction accuracy for low- to medium-dimensional antenna design problems [15], [17], [35].
- Deep Learning (DL): Deep learning models, including Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) networks, and Physics-Informed Neural Networks (PINNs), have demonstrated excellent capability in modeling highly nonlinear relationships between antenna geometry and electromagnetic performance. These models are particularly effective for complex antenna structures and large-scale datasets [10], [11], [16], [20], [25], [26].
- Surrogate Modeling: Surrogate models replace computationally intensive electromagnetic simulations with predictive models that approximate antenna performance using previously generated simulation data. This approach significantly reduces optimization time while maintaining acceptable prediction accuracy, making it one of the most widely adopted AI techniques in antenna optimization [9], [16], [20], [40], [44].

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- Inverse Design: Unlike conventional forward modeling, inverse design predicts antenna geometry directly from the desired electromagnetic response. This approach reduces iterative optimization and enables rapid antenna synthesis using deep learning and generative models [11], [27], [28], [32], [39].
- Hybrid AI-Based Optimization: Hybrid approaches combine artificial intelligence models with optimization algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), and Simulated Annealing (SA). The AI model predicts antenna performance, while the optimization algorithm searches for the best antenna geometry, thereby reducing the number of computationally expensive EM simulations [12], [14], [33], [36], [45].

Each of these techniques offers unique advantages depending on the antenna design problem. Classical machine learning algorithms generally provide faster training with relatively small datasets, whereas deep learning models achieve higher prediction accuracy for complex nonlinear problems. Surrogate modeling considerably reduces computational cost, inverse design accelerates antenna synthesis, and hybrid optimization methods improve both design efficiency and solution quality. Consequently, selecting an appropriate AI technique depends on the complexity of the antenna, the availability of training data, computational resources, and the desired design objectives.

Table I. Comparison of Artificial Intelligence Techniques Used in Antenna Design

AI Technique	Representative Algorithms	Primary Application	Major Advantages	Limitations	References
Machine Learning (ML)	ANN, SVM, KNN, Random Forest (RF), Gaussian Process Regression (GPR)	Antenna parameter prediction, gain estimation, bandwidth prediction, resonance frequency prediction	Simple implementation, faster training, suitable for small and medium datasets	Performance decreases for highly nonlinear and complex antenna structures	[4], [13], [15], [17], [35]
Deep Learning (DL)	DNN, CNN, RNN, LSTM, PINN	S_{11} prediction, radiation pattern estimation, antenna modeling, feature extraction	High prediction accuracy, capable of learning complex nonlinear relationships	Requires large datasets and higher computational resources	[9], [10], [11], [16], [20], [25], [26]
Surrogate Modeling	Deep Learning Surrogates, ANN Surrogates, CNN Surrogates	Fast electromagnetic response prediction, design optimization, computational cost reduction	Significantly reduces EM simulation time while maintaining good accuracy	Accuracy depends on the quality and diversity of the training dataset	[9], [16], [20], [40], [43], [44]
Inverse Design	PINN, GAN, Inverse ANN, Deep Neural Networks	Direct prediction of antenna geometry from desired electromagnetic specifications	Eliminates repeated trial-and-error design iterations and accelerates antenna synthesis	Requires high-quality datasets and careful model training	[11], [21], [27], [28], [32], [39]
Hybrid AI-Based Optimization	ANN + GA, ANN + PSO, ANN + Simulated Annealing, ML + Swarm Intelligence	Multi-objective antenna optimization, geometry optimization	Combines AI prediction with optimization algorithms to improve design efficiency	Increased implementation complexity and parameter tuning requirements	[12], [14], [23], [33], [36], [45]

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4. MACHINE LEARNING METHODS

Machine learning (ML) has become a practical tool for improving antenna design by reducing the dependence on repeated electromagnetic (EM) simulations [15], [17]. Instead of evaluating every antenna configuration through computationally expensive simulations, ML models are trained using previously generated datasets to estimate antenna characteristics such as resonant frequency, return loss (S_{11}), gain, and bandwidth [4], [8], [35]. This significantly shortens the antenna development cycle while maintaining acceptable prediction accuracy.

Several classical ML algorithms have been investigated for antenna applications. Artificial Neural Networks (ANNs) are widely used for nonlinear antenna modeling, while Support Vector Machines (SVMs) are preferred for problems involving relatively small datasets [12], [15], [22]. Other techniques, including Random Forest (RF), k-Nearest Neighbors (KNN), and Gaussian Process Regression (GPR), have also been employed for antenna parameter prediction, surrogate modeling, and optimization because of their simplicity and reliable performance [8], [17], [35].

Machine learning has been successfully applied to various antenna structures, including microstrip patch antennas, wideband antennas, 5G MIMO antennas, and antenna arrays [1], [4], [13]. These studies demonstrate that ML-based approaches can considerably reduce computational effort while providing prediction accuracy suitable for practical antenna design and optimization tasks [14], [36].

Although machine learning offers faster prediction and reduced computational cost, its performance is strongly influenced by dataset quality and feature selection [15], [17]. As antenna structures become increasingly complex, conventional ML algorithms may struggle to capture highly nonlinear relationships, encouraging researchers to adopt deep learning models for more sophisticated antenna design problems [16], [20].

5. DEEP LEARNING METHODS

Deep learning (DL) has become an important artificial intelligence technique in antenna engineering because of its ability to model complex nonlinear relationships between antenna geometry and electromagnetic characteristics [15], [17]. Unlike conventional machine learning algorithms, deep learning models automatically extract meaningful features from large datasets, resulting in improved prediction accuracy and reduced dependence on manual feature engineering [20], [24]. Consequently, DL has been widely applied in antenna modeling, performance prediction, surrogate modeling, and inverse design [16], [20], [25].

Among various deep learning architectures, Deep Neural Networks (DNNs) are the most commonly used due to their excellent approximation capability [16], [20]. DNN-based models have been successfully employed for predicting resonant frequency, return loss (S_{11}), gain, and bandwidth while significantly reducing computational time compared with repeated electromagnetic simulations [9], [10], [16]. Similarly, Convolutional Neural Networks (CNNs) have demonstrated promising performance in image-based antenna modeling, radiation pattern prediction, and antenna frequency estimation [7], [10], [18].

Recent studies have also explored Physics-Informed Neural Networks (PINNs) and Generative Adversarial Networks (GANs) for antenna design [2], [3], [11], [27]. PINNs incorporate electromagnetic knowledge into the learning process, improving prediction reliability, whereas GANs enable inverse design by generating antenna geometries directly from desired performance specifications [11], [27].

Despite their advantages, deep learning models require large training datasets, higher computational resources, and careful hyperparameter tuning [15], [20]. Nevertheless, their ability to achieve high prediction accuracy and accelerate antenna optimization has made deep learning one of the most promising approaches for next-generation intelligent antenna design [16], [20], [25].

6. SURROGATE MODELING

Surrogate modeling has emerged as one of the most effective artificial intelligence approaches for accelerating antenna design by replacing computationally expensive electromagnetic (EM) simulations with predictive models [9], [15], [16]. Instead of performing repeated full-wave simulations during every optimization iteration, surrogate models learn the relationship between antenna geometry and electromagnetic responses from previously generated simulation data [20], [40], [44]. Once trained, these models can rapidly predict antenna performance, thereby reducing computational cost and significantly shortening the overall design cycle [9], [16]. Various machine learning and deep learning techniques have

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been employed to construct surrogate models for antenna applications. Artificial Neural Networks (ANNs), Deep Neural Networks (DNNs), Convolutional Neural Networks (CNNs), and Gaussian Process Regression (GPR) are among the most commonly used approaches because of their ability to model highly nonlinear relationships between antenna design parameters and electromagnetic characteristics [9], [10], [16], [20]. These surrogate models have been successfully applied to predict return loss (S_{11}), resonant frequency, gain, bandwidth, and radiation patterns with prediction accuracy comparable to full-wave EM simulations [9], [16], [20].

Table II. Comparison of commonly used surrogate modeling techniques for antenna design and electromagnetic performance prediction.

Surrogate Model	Typical Applications	Advantages	Limitations	References
Artificial Neural Network (ANN)	S_{11} prediction, gain prediction, antenna optimization	Fast prediction and simple implementation	Requires sufficient training data	[12], [16], [22]
Deep Neural Network (DNN)	Surrogate modeling, EM response prediction	High prediction accuracy for nonlinear problems	High computational cost during training	[9], [16], [20]
Convolutional Neural Network (CNN)	Near-field prediction, image-based antenna modeling	Automatic feature extraction from complex antenna features	Requires large datasets and longer training time	[10], [18]
Gaussian Process Regression (GPR)	Surrogate modeling, uncertainty estimation	High prediction accuracy with uncertainty estimation	Computationally expensive for large datasets	[8], [35]

Figure 3 illustrates the general workflow of AI-based surrogate modeling for antenna design. Initially, electromagnetic simulation data are generated using commercial software and subsequently used to train an AI surrogate model. The trained model predicts antenna performance parameters rapidly, thereby reducing computational cost and accelerating the antenna optimization process.

Recent studies have demonstrated the effectiveness of surrogate modeling in the design of horn antennas, microstrip patch antennas, wideband antennas, metasurfaces, and antenna arrays [9], [10], [16], [40]. Compared with conventional optimization methods, surrogate-assisted design significantly reduces simulation time while maintaining satisfactory prediction accuracy, making it highly suitable for multi-objective antenna optimization and real-time design applications [14], [40], [45]. Despite its advantages, the performance of surrogate models largely depends on the quality and diversity of the training dataset [15], [17]. Poor dataset coverage may lead to inaccurate predictions, particularly for antenna geometries that differ significantly from the training samples [16], [20]. Therefore, careful dataset generation, feature selection, and model validation remain essential for developing reliable surrogate models for antenna design.

Surrogate modeling not only accelerates antenna analysis but also enables designers to explore a larger design space within a shorter period. Since the trained model can instantly predict antenna performance for new design parameters, engineers can evaluate multiple design alternatives without performing repeated electromagnetic simulations. This capability is particularly beneficial during the early stages of antenna development, where rapid design exploration and efficient optimization are essential. As a result, surrogate modeling has become an increasingly valuable approach for developing accurate, cost-effective, and time-efficient antenna design frameworks.

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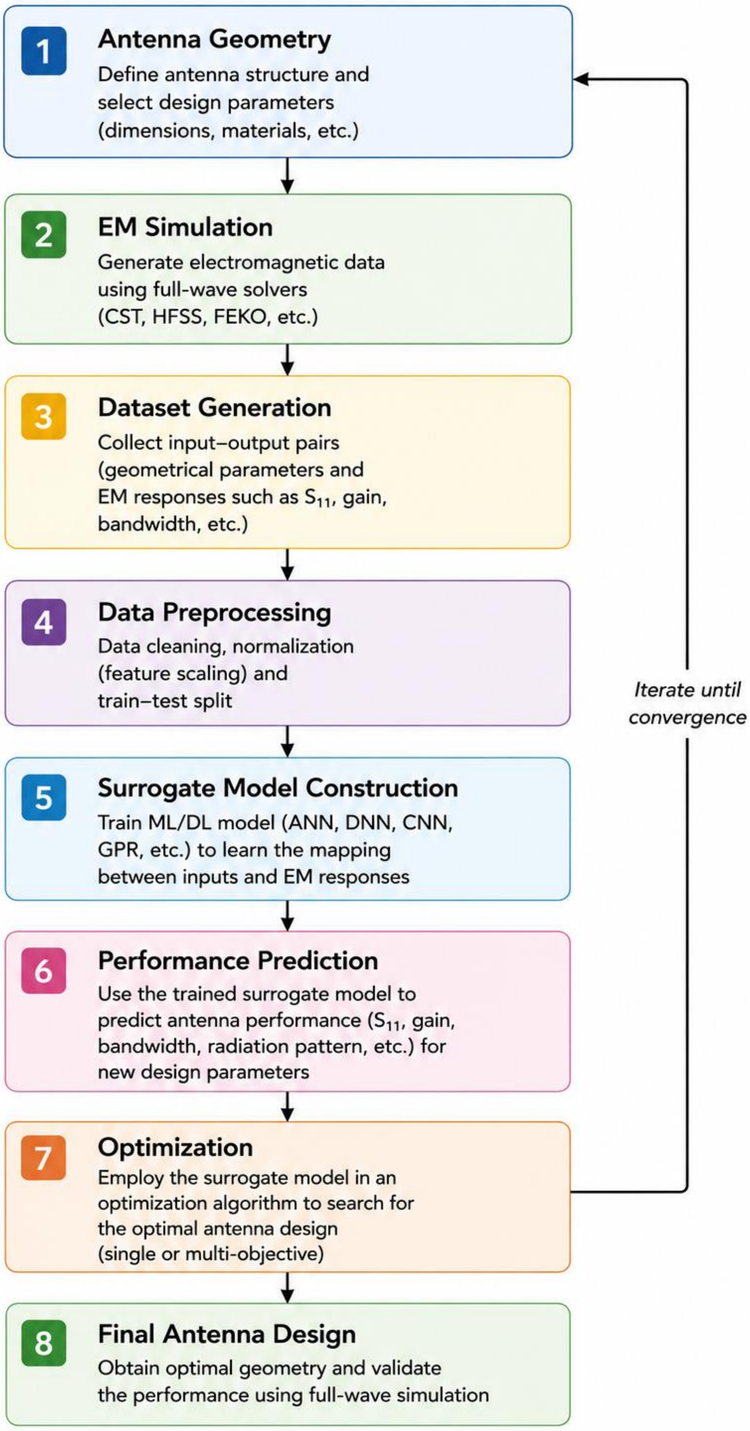

Figure 3. General workflow of AI-based surrogate modeling for antenna design, illustrating the process from electromagnetic simulation and dataset generation to performance prediction and antenna optimization.

7. INVERSE DESIGN

Inverse design has become an emerging approach in AI-assisted antenna engineering because it reverses the traditional antenna design process [11], [27]. Instead of starting with antenna geometry and predicting its electromagnetic performance, inverse design begins with the desired antenna specifications, such as resonant frequency, return loss (S_{11}), gain, and bandwidth, and directly estimates the corresponding antenna dimensions [11], [28]. This approach minimizes the need for repeated trial-and-error optimization and significantly reduces the antenna design time.

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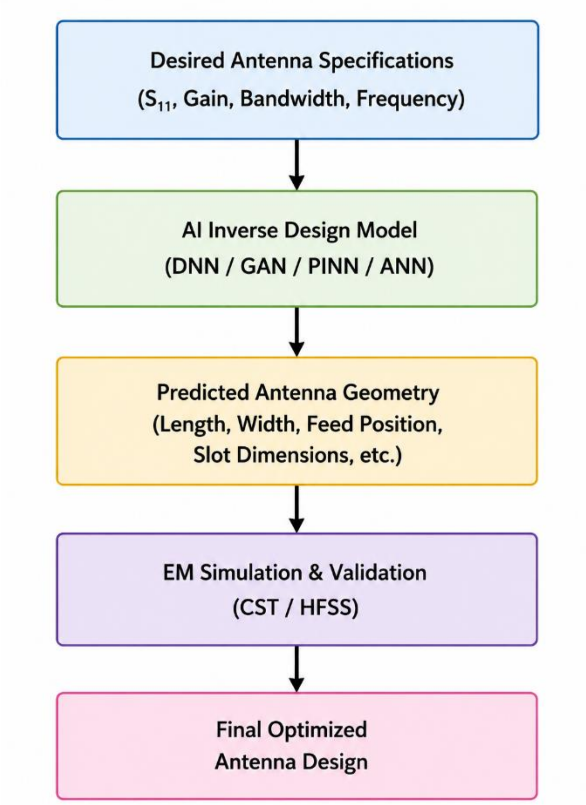

Figure 4. General Workflow of AI-Based Inverse Antenna Design

Recent studies have employed various artificial intelligence techniques, including Deep Neural Networks (DNNs), Generative Adversarial Networks (GANs), and Physics-Informed Neural Networks (PINNs), for inverse antenna design [2], [3], [11], [27]. These models learn the relationship between electromagnetic responses and antenna geometry, enabling rapid generation of optimized antenna structures for different wireless communication applications [21], [28], [32].

Inverse design has been successfully applied to microstrip antennas, horn antennas, metasurfaces, and antenna arrays, where multiple design parameters must be optimized simultaneously [11], [21], [27]. Compared with conventional optimization techniques, inverse design provides faster design exploration and allows engineers to obtain suitable antenna geometries with fewer simulation iterations [28], [32].

Despite these advantages, inverse design remains challenging because multiple antenna geometries may produce similar electromagnetic responses [11], [27]. Therefore, the accuracy of inverse models largely depends on the quality of the training dataset and the capability of the AI model to generalize unseen design conditions. As research continues to advance, inverse design is expected to become an important component of intelligent antenna development for future wireless communication systems.

8. OPTIMIZATION TECHNIQUES

Optimization plays an important role in antenna design by identifying the most suitable antenna dimensions that satisfy multiple performance requirements simultaneously. Traditional optimization methods often require a large number of electromagnetic (EM) simulations, making the overall design process computationally expensive [14], [45]. To overcome this limitation, researchers have increasingly combined artificial intelligence with optimization algorithms to improve design efficiency and reduce simulation time.

Among the commonly used optimization techniques, Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), and Simulated Annealing (SA) have been widely applied for optimizing antenna parameters such as resonant frequency, return loss (S_{11}), gain, bandwidth, and radiation efficiency [12], [14]. These algorithms efficiently search the design space and identify optimal antenna configurations without relying solely on manual parameter tuning.

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Recent studies have demonstrated that integrating AI models with optimization algorithms further improves antenna design performance [8], [33]. In these hybrid approaches, machine learning or deep learning models rapidly predict antenna responses, while optimization algorithms determine the optimal design parameters. This combination significantly reduces the number of full-wave EM simulations required during the optimization process and enables faster convergence toward high-performance antenna designs [14], [36].

Despite their effectiveness, AI-based optimization techniques still depend on appropriate parameter selection and reliable training data to achieve accurate results [15]. Nevertheless, their ability to accelerate antenna optimization while maintaining good prediction accuracy has made them an essential component of modern intelligent antenna design frameworks [16], [20].

9. COMPARATIVE ANALYSIS

Various artificial intelligence techniques have been investigated for antenna design, each offering unique advantages depending on the application and design objectives. Classical machine learning algorithms provide simple and efficient solutions for parameter prediction, whereas deep learning models achieve higher accuracy in complex nonlinear problems. Similarly, surrogate modeling significantly reduces computational cost by replacing repeated electromagnetic simulations, while inverse design and hybrid optimization techniques accelerate the overall antenna development process. Therefore, selecting an appropriate AI technique depends on factors such as dataset availability, computational resources, antenna complexity, and the desired design accuracy. The comparative analysis presented in the following tables summarizes the major characteristics, advantages, limitations, and typical applications of the AI techniques discussed in this review.

The following table presents a general comparison of the major artificial intelligence techniques used in antenna design. It highlights their primary applications, strengths, and limitations, providing a clear overview of how different AI approaches contribute to antenna modeling, optimization, surrogate modeling, and inverse design.

Table III. Comparison of Classical Machine Learning Methods Used in Antenna Design

Method	Typical Use	Data Requirement	Strength	Limitation	Reference
K-Nearest Neighbors (KNN)	Parameter/resonance prediction	Low	Simple, few assumptions on function shape	Scales poorly to high dimensions	[35]
Ensemble Learning	Multiobjective optimization	Low-moderate	More robust than a single learner	Added model-management overhead	[19]
Broad Learning System	Fast antenna optimization surrogate	Low-moderate	Faster training than deep networks	Less representational depth	[23]
Regression (ANN/SVM-type, shallow)	Compact microstrip antenna modeling	Low	Fast, interpretable for simple geometries	Limited to narrow geometry class	[30]
Multistage Collaborative ML	Antenna modeling and optimization	Moderate	Reduces sample needs via staged learning	Requires careful stage design	[36]

Table III shows that no single AI technique is suitable for every antenna design problem. Instead, the choice of a particular method depends on the antenna complexity, available dataset, computational resources, and the required prediction accuracy.

To better understand the practical applications of artificial intelligence, recent research works published between 2018 and 2026 are comparatively analyzed. The comparison includes the adopted AI techniques, antenna types, objectives, and the key outcomes reported by different researchers.

Table IV. Comparison of Deep Learning Methods Used in Antenna Design.

Method	Typical Use	Data Requirement	Strength	Limitation	References
Convolutional Neural Network (CNN)	Near-field prediction, image-based modeling	Moderate-high	Exploits spatial feature structure	Needs image-like data encoding	[10], [18]
Physics-Informed Neural Network (PINN)	Horn antenna inverse design	Moderate	Embeds physical constraints	Physics embedding is antenna-specific	[11]
Domain-Confined / Pyramidal DNN	Behavioral surrogate modeling	Moderate	Reduced training-sample requirement	Requires careful domain-confinement setup	[16], [20]
Consensus / Ensemble DNN	Robust design and optimization	Moderate-high	Improved robustness over single DNN	Higher training cost (multiple networks)	[26]
FDTD-Equivalent RCNN	General EM modeling	Moderate-high	Tightly integrates DL with numerical method	Tied to FDTD-equivalent formulation	[34]
Deep Learning (radiation pattern synthesis)	Array antenna pattern synthesis	Moderate	Synthesizes pattern directly	Generalization beyond training patterns untested	[37]

The comparison indicates a gradual shift from conventional machine learning algorithms toward deep learning and surrogate modeling approaches. Recent studies increasingly focus on reducing computational time while improving prediction accuracy and optimization efficiency.

A comparative evaluation of the reviewed AI techniques is presented based on important performance factors, including computational complexity, prediction accuracy, training data requirements, optimization capability, and overall suitability for antenna design applications.

Table V. Comparison of Surrogate Modeling Strategies

Surrogate Strategy	Core Idea	Reported Benefit	References
Deep learning surrogate (horn antenna)	DL model trained on simulated horn antenna data	~80% computational cost reduction; validated by 3D-printed prototype	[9]
Knowledge-based domain-constrained DL	Constrain DL training with structural priors	Lower training-data cost at comparable accuracy	[16], [20]
Multistage collaborative ML	Sequential, staged learning pipeline	Reduced sample requirement	[36]
Nested / performance-based surrogates	Progressive refinement of a coarse global model	Fewer full-wave simulations to reach target accuracy	[40]
Parallel surrogate-assisted evolutionary algorithm	Parallelized surrogate evaluation within an EA	Improved global-search efficiency	[41]
Triangulation-based / multi-fidelity constrained surrogates	Constrain surrogate using triangulation or multiple fidelity levels	Lower simulation cost under design constraints	[43], [44]

Overall, surrogate modeling and deep learning demonstrate superior performance for complex antenna design problems, whereas conventional machine learning techniques remain attractive for simpler applications with limited datasets. Hybrid optimization methods further improve design efficiency by combining the strengths of AI prediction models and optimization algorithms.

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Table VI. Comparison of Optimization Techniques Used With AI-Assisted Antenna Design.

Technique	Optimizer Type	Typical Design Variables	References
ML-assisted geometry optimization	Learned surrogate guiding direct search	Continuous geometric parameters	[8]
ANN + Simulated Annealing (hybrid)	Hybrid learned model / stochastic search	Continuous, wideband patch geometry	[12]
ML-optimized multiband filtering design	Learned model guiding multiband tuning	Multiband notch/filter parameters	[13]
ML-assisted swarm intelligence (PSO-type)	Hybrid learned model / swarm search	Mixed continuous and binary variables	[14]
ANN-assisted substrate selection	Learned model guiding material choice	Categorical (substrate) and continuous parameters	[22]
Multilayer ML-assisted robust design	Learned model with tolerance-aware objective	Continuous parameters under manufacturing uncertainty	[33]
Parallel surrogate-assisted evolutionary algorithm	Evolutionary algorithm with parallel surrogate evaluation	Continuous geometric parameters	[41]
Improved BPNN surrogate-based optimization	Neural-network surrogate guiding multiobjective search	Multi-parameter antenna structures	[38]

Table VII summarizes representative studies published between 2018 and 2026 on AI-assisted antenna design. The selected papers cover a wide range of antenna types and artificial intelligence techniques, highlighting the recent progress in antenna modeling, surrogate modeling, inverse design, and optimization. This comparison provides a concise overview of how AI methods have evolved to improve antenna design efficiency and prediction accuracy.

Table VII. Comparative Summary of Representative Reviewed Papers

Ref.	Year	AI Technique	Antenna Type	Reported Contribution
[1]	2026	Verifiable CNN + evolutionary optimizer	5G MIMO antenna	Verifiable CNN tuned by a novel evolutionary algorithm
[2]	2025	Physics-aware GAN	Sparse antenna array	Unsupervised joint synthesis of feeding, spacing, element count
[9]	2024	Deep learning surrogate	Horn antenna	~80% cost reduction; validated by 3D-printed prototype
[15]	2023	Review (ML/DL, multiple)	Multiple (survey)	Comprehensive review of ML/DL in antenna design and selection
[16]	2023	Domain-constrained DL surrogate	General antenna structures	Low-cost, knowledge-based behavioral surrogate
[20]	2022	Pyramidal domain-confined DNN	General antenna structures	Domain confinement improves DNN surrogate accuracy
[25]	2022	ML-based synthesis	General antennas	Automatic antenna-type selection and geometry synthesis
[27]	2021	Conditional GAN	Multilayer metasurfaces	Generative inverse design framework
[36]	2020	Multistage collaborative ML	General antennas	Staged ML reduces sample requirement
[39]	2019	Adaptive ANN, inverse design	Graphene-based metamaterials	Adaptive sampling improves inverse-ANN accuracy
[45]	2018	Tolerance-aware surrogate + GA	General/parametric antennas	Fabrication-tolerance-aware multiobjective optimization

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As shown in Table VII, recent research has increasingly focused on deep learning, surrogate modeling, and hybrid AI techniques for antenna design. These approaches have consistently demonstrated improvements in prediction accuracy, computational efficiency, and optimization performance across various antenna applications, indicating a clear shift toward intelligent data-driven antenna design methodologies.

10. BIBLIOMETRIC ANALYSIS

Bibliometric analysis provides a quantitative overview of research trends in AI-assisted antenna design by examining publication patterns, keyword relationships, collaboration networks, and citation trends. Unlike conventional literature reviews, bibliometric analysis helps identify emerging research directions and the evolution of artificial intelligence techniques applied to antenna design. The analysis presented in this review is based on representative studies published between 2018 and 2026.

10.1 Publication Distribution by Year

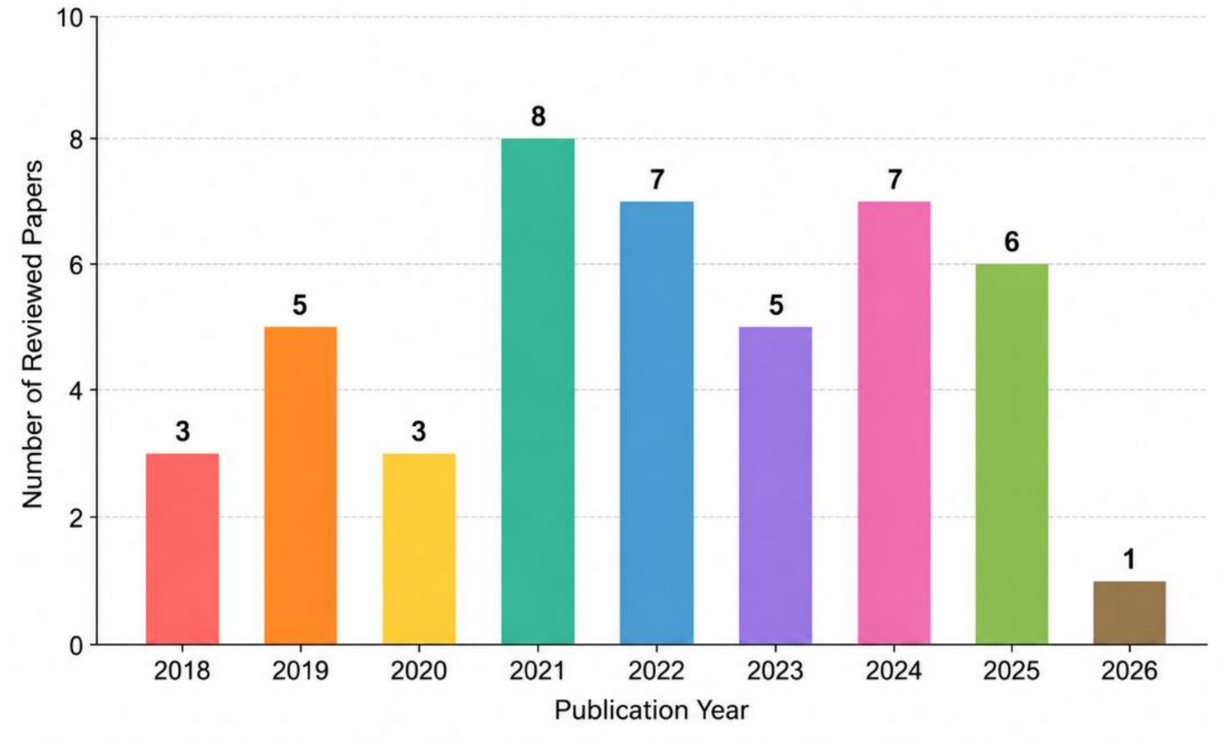

Figure 5. Publication Distribution of AI-Based Antenna Design Research (2018-2026)

Figure 5 illustrates the annual publication trend of AI-assisted antenna design research. The number of publications remained relatively low between 2018 and 2020 but increased steadily from 2021 onward. A significant rise is observed during 2023-2026, reflecting the growing adoption of machine learning, deep learning, surrogate modeling, and inverse design techniques in antenna engineering.

10.2 Publisher Distribution of Reviewed Papers

The reviewed literature was also analyzed based on the publishers in which the selected studies were published. This analysis helps identify the major publication sources that have contributed to the advancement of AI-assisted antenna design research over recent years.

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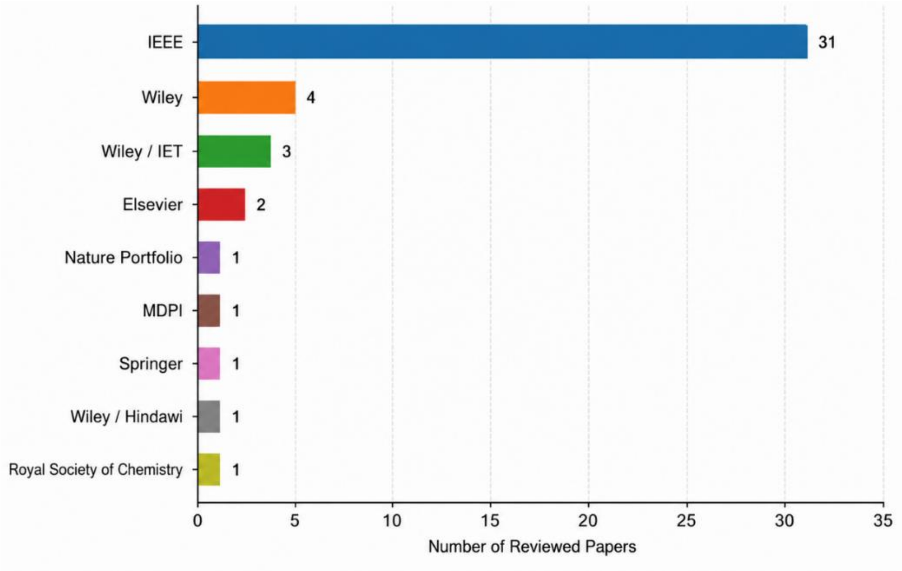

Figure 6. Publisher distribution of the reviewed papers included in this study.

Figure 6 illustrates the distribution of the selected papers based on their publishers. IEEE contributes the largest share of publications, demonstrating its dominant role in disseminating research on AI-assisted antenna design. Other publishers, including Wiley, Elsevier, Springer, MDPI, Nature Portfolio, and the Royal Society of Chemistry, also contribute to this research area, although with comparatively fewer publications. This distribution indicates that IEEE journals remain the primary source for recent developments in intelligent antenna design.

10.3 Research Category Distribution

To better understand the current research focus, the reviewed papers were classified into different research categories based on their primary objectives. The categories include classical machine learning, deep learning, surrogate modeling, generative or inverse design, optimization with hybrid AI techniques, and review studies. This classification provides an overview of the major research directions in AI-assisted antenna design.

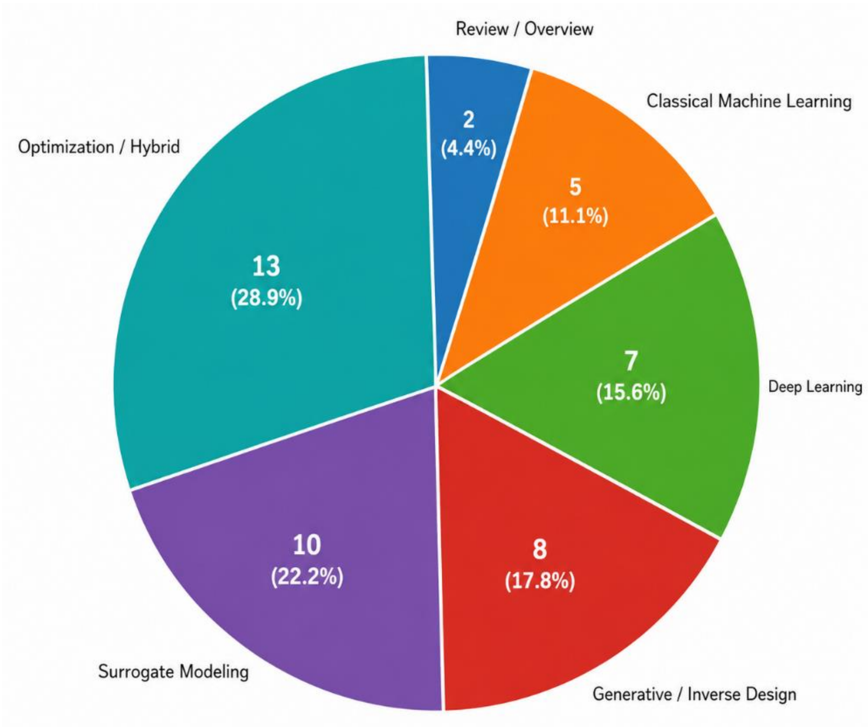

Figure 7. Research Category Distribution of Reviewed Papers

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Figure 7 shows that optimization and hybrid AI techniques represent the largest research category, followed by surrogate modeling, generative or inverse design, and deep learning. Classical machine learning methods continue to contribute significantly to antenna design research, while review papers account for a relatively smaller proportion. Overall, the distribution reflects the growing interest in advanced AI-based methodologies for improving antenna performance, reducing computational cost, and accelerating the antenna design process.

11. RESEARCH GAPS

Although significant progress has been achieved in applying artificial intelligence to antenna design, several research challenges remain. The reviewed studies demonstrate that AI techniques can effectively improve prediction accuracy and reduce computational time. However, issues related to computational cost evaluation, experimental validation, benchmark datasets, and early-stage antenna design still require further investigation. Addressing these limitations will improve the reliability, reproducibility, and practical adoption of AI-assisted antenna design methodologies.

Table VIII. Summary of Identified Research Gaps.

Research Gap	Description	Illustrative References
Inconsistent cost reporting	Few papers quantify computational cost relative to full-wave EM simulation using a common baseline	[9]
Limited physical validation	Most surrogate/inverse-design work validates only in simulation, not via fabrication and measurement	[9]
Under-studied early-stage design	Topology selection prior to geometry parameterization is rarely addressed compared to late-stage tuning	[7], [15], [17]
Absence of standardized benchmarks	No widely adopted public benchmark dataset exists for antenna ML research	[15], [17]

Table VIII highlights the major research gaps identified from the reviewed literature. Most existing studies primarily emphasize improving prediction accuracy and optimization performance, while comparatively less attention is given to standardized evaluation methods and experimental validation. Future research should focus on developing publicly available benchmark datasets, establishing common performance evaluation metrics, and validating AI models through fabricated antenna prototypes. These improvements will enhance the credibility, reproducibility, and real-world applicability of AI-assisted antenna design.

12. CHALLENGES

Although artificial intelligence has significantly improved antenna design and optimization, several practical challenges still limit its widespread adoption. One of the primary challenges is the availability of high-quality training data. Developing reliable AI models requires a large number of electromagnetic simulation results or measured datasets, which are often expensive and time-consuming to generate [15], [17].

Another important challenge is the computational cost associated with training complex deep learning models. While AI-based prediction is generally faster than repeated electromagnetic simulations, the initial dataset generation and model training process may require considerable computational resources, particularly for complex antenna structures and multi-objective optimization problems [16], [20].

The generalization capability of AI models also remains a concern. Many models perform well only within the range of the training data and may produce inaccurate predictions for unseen antenna geometries or operating conditions. Consequently, careful dataset preparation, model validation, and performance evaluation are essential to ensure reliable antenna design [9], [16].

Furthermore, most reported studies validate their proposed methods using simulation data, whereas experimental validation through fabricated antenna prototypes is relatively limited [9]. Bridging the gap between simulation and real-world measurements will improve confidence in AI-assisted antenna design and encourage its practical adoption in wireless communication systems. Despite these challenges, continuous advancements in machine learning algorithms, computational resources, and electromagnetic simulation techniques are expected to further enhance the efficiency, reliability, and practical applicability of AI-driven antenna design in future communication technologies.

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13. FUTURE RESEARCH DIRECTIONS

Artificial intelligence continues to transform antenna design by enabling faster prediction, efficient optimization, and intelligent design automation. Although significant progress has been achieved in recent years, several emerging technologies are expected to further enhance the capabilities of AI-assisted antenna engineering. Future research is likely to focus on developing more accurate, explainable, and computationally efficient AI models that can support practical antenna design for next-generation wireless communication systems.

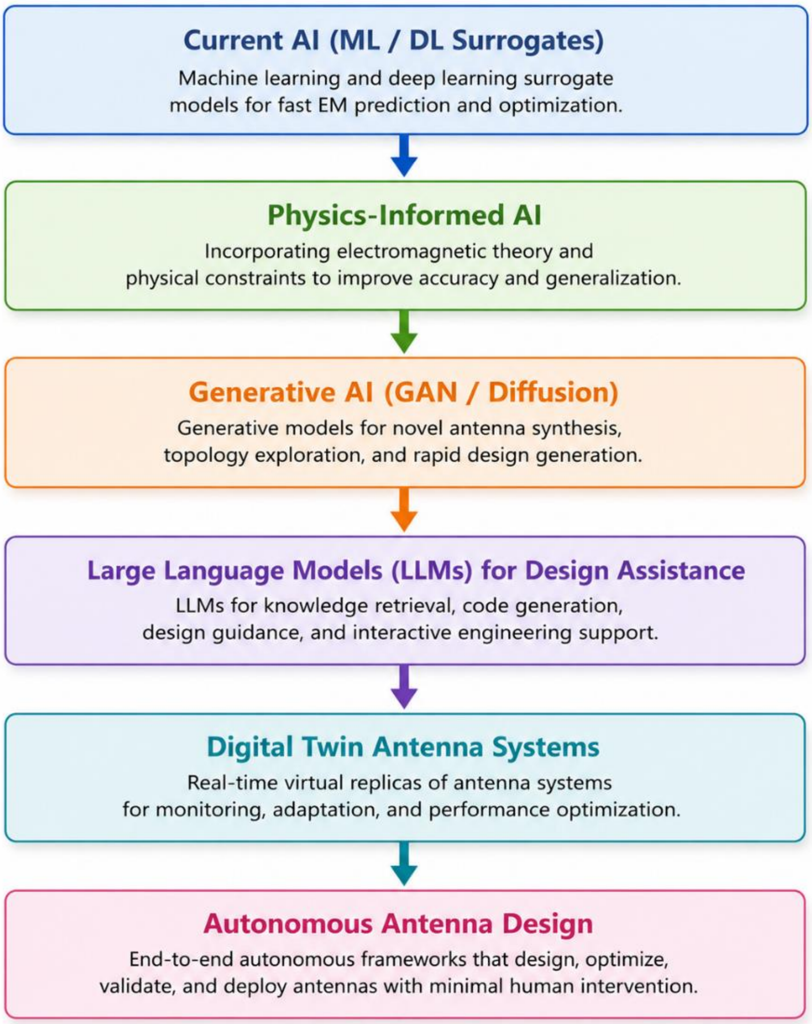

Figure 8. Evolution of future AI technologies for intelligent antenna design.

Figure 8 illustrates the expected evolution of artificial intelligence in antenna engineering. Current machine learning and deep learning surrogate models are gradually advancing toward physics-informed AI, which incorporates electromagnetic knowledge into the learning process. Emerging technologies such as generative AI and large language models (LLMs) are expected to support automated antenna synthesis, design assistance, and optimization. In the long term, the integration of digital twin technology and autonomous antenna design frameworks may enable intelligent systems capable of designing, optimizing, and validating antenna structures with minimal human intervention.

Artificial intelligence is also expected to play an important role in future communication technologies, including 6G, reconfigurable intelligent surfaces (RIS), massive MIMO, terahertz communication, and intelligent wireless networks. The integration of AI with these advanced communication systems has the potential to reduce design complexity, improve antenna performance, and accelerate the development of next-generation wireless devices. Continued collaboration between antenna engineers, electromagnetic researchers, and AI specialists will be essential for realizing these future research opportunities.

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14. CONCLUSION

Artificial intelligence has significantly transformed antenna design by improving prediction accuracy, reducing computational complexity, and accelerating the overall design process. This review presented a comprehensive overview of AI techniques applied to antenna engineering, including machine learning, deep learning, surrogate modeling, inverse design, and AI-based optimization methods. A comparative analysis of recent studies published between 2018 and 2026 highlighted the rapid evolution of intelligent antenna design methodologies and their growing importance in modern wireless communication systems.

The reviewed literature demonstrates that surrogate modeling and deep learning have become key technologies for reducing dependence on computationally expensive electromagnetic simulations while maintaining reliable prediction accuracy. Similarly, inverse design and hybrid optimization techniques have enabled faster exploration of antenna design parameters, making antenna development more efficient and practical for complex communication applications.

Despite these advancements, several challenges remain, including the availability of high-quality datasets, limited experimental validation, and the absence of standardized benchmark datasets for evaluating AI models. Addressing these issues will improve the reliability and practical applicability of AI-assisted antenna design.

Overall, artificial intelligence is expected to play an increasingly important role in future antenna engineering. Emerging technologies such as physics-informed AI, generative AI, large language models, digital twin systems, and autonomous antenna design are likely to further enhance the efficiency, accuracy, and automation of next-generation antenna development. This review provides a consolidated reference for researchers and engineers seeking to understand recent advancements and future opportunities in AI-assisted antenna design.

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