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# AI-Driven Metamaterial Antenna Design: A Review

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**Abstract—** The emergence of artificial intelligence (AI) has accelerated the design of microwave devices, including antennas, enhancing throughput and reducing time-to-market. This is mostly due to the fact that design automation via optimization has replaced labor-intensive manual design methods that rely on trial and error without assurance of effective results. Surrogate model-based optimization (SMBO) approaches are leading the way in the quick design of antennas via optimization, mostly owing to their enhancement of efficiency regarding computing costs.

The Surrogate Model Assisted Differential Evolution for Antenna Synthesis (SADEA) algorithm family is a category of cutting-edge Sequential Model-Based Optimization (SMBO) techniques. This study illustrates the use and benefits of the SADEA algorithm family via two case studies of actual antenna design challenges. The antenna design challenges include optimizing a multi-layered small multiple-input multiple-output (MIMO) antenna array for wireless communications and a microwave imaging antenna for ultra-wideband (UWB) body-centric applications. In both instances, the SADEA algorithm family achieved excellent design solutions in a reasonable timeframe, and the quality of these solutions is corroborated by the close alignment between the simulated and measured results of the fabricated, operational prototypes of the antennas. In both instances, the efficacy of the SADEA algorithm family is juxtaposed with the 2019 Computer Simulation Technology - Microwave Studio (CSTMWS) optimizers, namely the trust region framework (TRF) and particle swarm optimization (PSO). Comparative results indicate that the SADEA algorithm family consistently achieves highly satisfactory design solutions across all iterations, utilizing a reasonable optimization duration, whereas the alternative optimizers consistently fail to meet design specifications and/or produce designs with geometric inconsistencies.

***Index Terms****—Antenna optimization; Artificial intelligence; Evolutionary methods; PSADEA; SADEA; SADEA-II; Surrogate model-based optimization.*

## INTRODUCTION

Artificial intelligence (AI) increasingly assumes a pivotal role in microwave engineering. on recent decades, the design and development of microwave devices, including antennas, have been significantly accelerated by advanced machine learning and computational approaches grounded on AI paradigms [1]–[4]. Traditionally, microwave devices, particularly antennas, may be developed by adhering to established heuristics that are often corroborated by design experience. Although these criteria effectively function as practical guidelines for antenna designers and engineers, their careful implementation often results in suboptimal antenna designs [4], [5]. This situation usually arises when the design requirements and performance parameters are very rigorous and heavily dependent on the geometric profiles and/or material composition of the antennas [4]. Consequently, antenna designers and engineers often adjust the parameters of sub-optimal antenna designs produced by manual methods to enhance performance. This method is very arduous, and effective solutions are not certain, since it often relies on trial and error. To overcome the aforementioned obstacles, antenna design automation via optimization is essential for producing near-optimal antenna designs and configurations.

Local optimization and global optimization are the two primary methods for conducting antenna optimization. Local optimization approaches need an exceptional starting design, which is seldom attainable in reality, to get satisfactory or acceptable design solutions. since a result, global optimization techniques are preferable because of their resilience and optimization capabilities, since they do not need a starting design.

AI methodologies, particularly evolutionary computing, have primarily influenced the development of global optimization strategies, especially evolutionary algorithms (EAs). Evolutionary algorithms, including differential evolution (DE) [6] and particle swarm optimization

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(PSO) [7], are prominent global optimization techniques used in antenna synthesis. Nonetheless, global optimization techniques like evolutionary algorithms sometimes need several full-wave electromagnetic (EM) simulations to get satisfactory or acceptable design solutions [8].

Accurate characterization of antennas for performance estimate and assessment necessitates computationally intensive numerical method-based electromagnetic simulations, such as time domain analysis using the finite integration technique (FIT) [5], [9]. Consequently, the optimization duration becomes unnecessarily prolonged (or even prohibitive in some instances) when evolutionary algorithms are used for antenna synthesis [4]. To tackle the issue of prolonged optimization duration, it is essential to use efficiency enhancement techniques that significantly reduce the total computational expense of the optimization while minimally compromising the quality of the design solutions produced by the optimization process. Surrogate model-based optimization (SMBO) is a very promising strategy for enhancing optimization efficiency.

Artificial intelligence methodologies, including machine learning and statistical modeling, are the fundamental attributes of SMBO.

Through machine learning and statistical modeling, SMBO approaches construct and use surrogate models that serve as cost-effective approximations of precise evaluations, substituting for computationally intensive exact function evaluations (e.g., EM simulations). Surrogate model-assisted evolutionary algorithms (SAEAs) are developed when evolutionary algorithms serve as the search mechanism in surrogate model-based optimization approaches [10], [11]. A crucial trade-off arises between the quality of the surrogate model and the efficiency, based on the required number of precise assessments, in SAEAs. Consequently, a surrogate model management approach is necessary to identify an optimal trade-off in SAEAs. Owing to a plethora of surrogate model management methodologies, there exists a variety of SAEAs. The surrogate model-aware evolutionary search (SMAS) framework is a cutting-edge SAEA framework, with its efficiency and optimization quality well proven and validated.

## AI-DRIVEN ANTENNA DESIGN OPTIMIZATION

Recently, AI approaches have been used to improve the efficiency and reliability of simulation-driven antenna design and optimization methods, making them more applicable to a wider range of modern antenna structures. The following is a quick discussion of some of the most current techniques, emphasizing their operational mechanisms and applications:

### Metamaterials

The characteristics of metamaterials depend on their architectural design, and hence, their qualities are not only determined by the attributes of the component materials. characteristics may be regulated and altered by modifying the topology of metamaterial 'unit cells.' Although the bulk characteristics of the component materials exert effect, they are often not the primary variable considered in metamaterial design. In topology design, the characteristics of metamaterials may be tailored within an extensive design space, contributing to the exponential expansion of metamaterials research and development across contemporary engineering disciplines. Metamaterials may be classified into four primary objective-based categories: mechanical, acoustic, optical, and electromagnetic [1]. The mechanical characteristics of metamaterials are noteworthy, since the alteration of designs has been shown to provide a broad spectrum of features and behaviors. Computational design can enhance the consistency of metamaterial functionality, enabling fundamentally desirable attributes such as increased material durability, superior mechanical energy absorption, and distinctive modes of load-controlled deformation, achieved by initially calculating the results of architectural iterations on the metamaterial structure. The technique is dual in nature, since both structure and composition are most effectively optimized together, usually with a defined design purpose. This bilateral technique facilitates the production of deliberately different mechanical characteristics and behaviors, which are significant in several general and specialized applications [2–5].

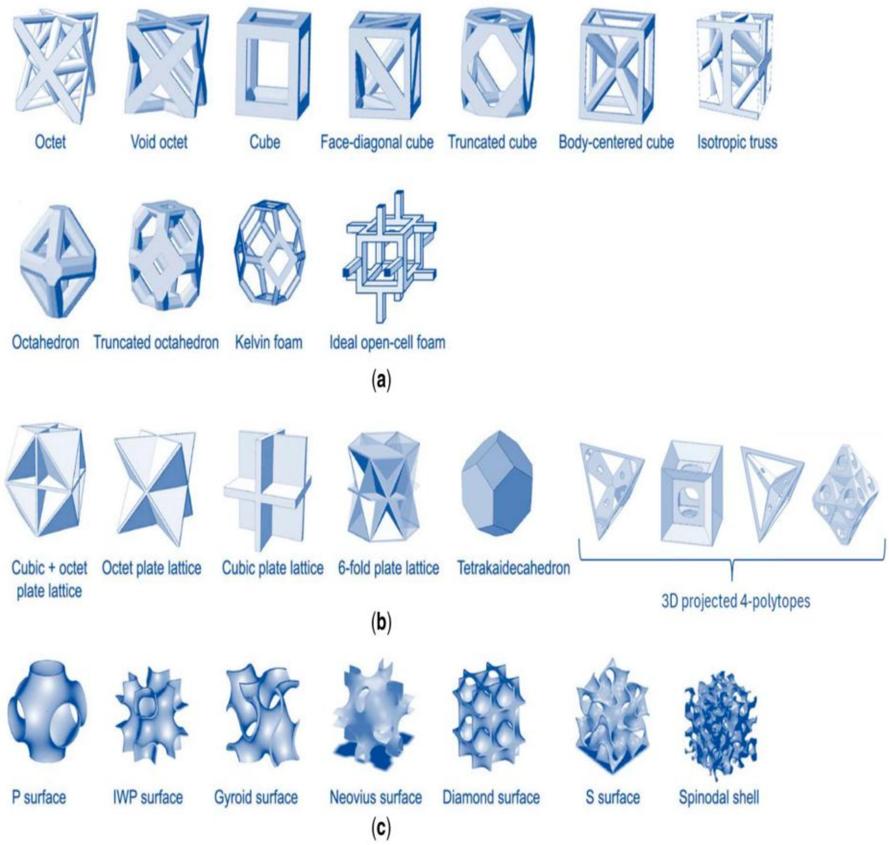


**Figure 1. Examples of mechanical metamaterials based on geometry type.**

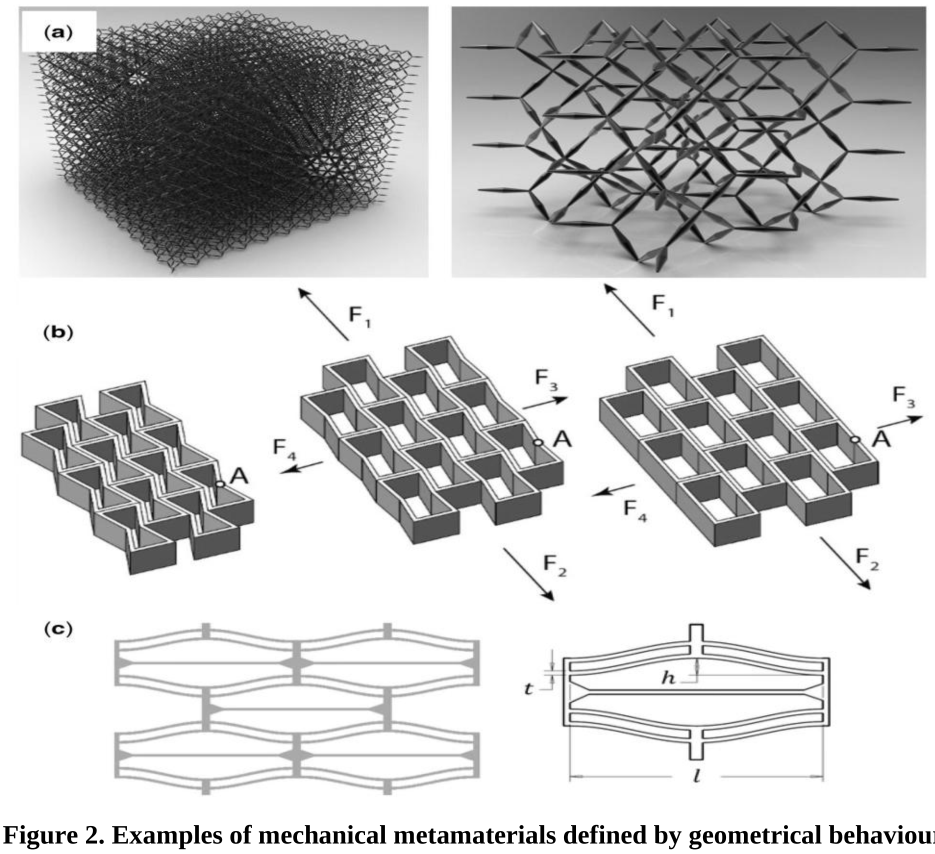


**Figure 2. Examples of mechanical metamaterials defined by geometrical behaviour**

## A. Evolutionary Algorithms

Evolutionary algorithms (EAs), including genetic algorithms (GAs), differential evolution (DE), and particle swarm optimization (PSO), together with their advanced variations, have been widely used in the automated design of antennas. They primarily operate by conducting a nature-inspired global search inside the specified antenna's design space to identify near-optimal antenna configurations. The principal benefits of utilizing evolutionary algorithms (EAs) in antenna design encompass their independence from preliminary designs and the avoidance of the time-consuming and labor-intensive manual tuning of antenna structures typically necessary to achieve specified criteria and requirements [12], [6], [11].

Recent applications of evolutionary algorithms (EAs) in the automated design of antennas encompass, but are not limited to, the utilization of invasive weed optimization (IWO) for aperiodic subarrayed phased arrays and ant colony optimization (ACO) for millimeter wave (mmWave) microstrip antennas, respectively [13], [14]. Both IWO and ACO produced satisfactory design solutions that outperformed the reference designs. Nonetheless, the computational expenditure for evolutionary algorithms may become burdensome or prohibitively expensive owing to the extensive amount of full-wave electromagnetic simulations necessary to identify near-optimal solutions for various antenna design challenges [15], [6]. Evolutionary algorithms sometimes exhibit sluggish convergence rates for certain antenna design challenges [6].

## B. ML-Assisted Evolutionary Algorithms

To reduce the computing expense of evolutionary algorithms and improve their efficiency, surrogate models developed using machine learning methods are often used to substitute comprehensive electromagnetic simulations in their optimization processes. This category of evolutionary algorithms, referred to as surrogate model-assisted evolutionary algorithms (SAEAs), often exhibits more efficiency, particularly regarding optimization time, and provides superior design solutions compared to traditional evolutionary algorithms. The SADEA (surrogate model-assisted differential evolution for antenna synthesis) methods belong to this group. Their primary emphasis is on the synergistic integration of evolutionary computing and supervised learning approaches, taking into account the features of the antenna design landscape [18], [19], [20], [21], [22], [23]. SADEA approaches do not depend on initial designs and ad-hoc procedures inside their optimization frameworks, making them more resilient and more appropriate for optimizing a wide range of antenna design issues [24], [25]. SADEA approaches provide speed enhancements ranging from several times to 20 times compared to conventional numerical optimization techniques when used for the design automation of identical antenna structures, while achieving superior quality design solutions [18], [6], [21].

In SAEAs, the curse of dimensionality has been a significant impediment [18], [22]. This is often associated with an exponential escalation in the training or learning duration of machine learning approaches as the dimensionality of their training data points increases. Consequently, the efficacy of conventional SAEAs is often diminished when optimizing antenna configurations with a somewhat expansive dimensional space [22]. Recently, SADEA approaches have shown effective for optimizing complicated and high-dimensional antenna systems, exceeding 100 dimensions. In [22], radial basis function (RBF)-assisted local optimization and self-adaptive Gaussian process (GP) surrogate modeling are used to decrease the training costs associated with the surrogate modeling phase of the optimization process, while preserving the efficacy of the SAEA-based optimization. To reduce the computational expense of the surrogate modeling phase in the ML-assisted optimization of high-dimensional antenna structures while maintaining efficiency, the integration of Bayesian neural network (BNN)-based surrogate modeling with self-adaptive lower confidence bound (LCB) prescreening of predictions is utilized in [23], the most recent iteration of the SADEA algorithm series.

A recent advancement is the enhanced PSO that utilizes a combined global radial RBF model and a kriging model to substitute resource-intensive full-wave EM simulations and to direct the PSO updating process [9]. This methodology facilitated the implementation of mixed prescreening in a collaborative way, whereby swarm particles exhibiting the smallest anticipated objective function and highest expected enhancements are co-selected in the enhanced ML-guided PSO. The enhanced PSO has been validated via antenna challenges, including a substrate-integrated waveguide (SIW) cavity-backed slot antenna, a linear array, and a sequential-rotation feeding network for wireless communication applications [9]. In every instance, effective design solutions were achieved.

### C. Multifidelity Optimization

The fundamental concept of multifidelity optimization for antennas involves eliminating unpromising design solutions through the use of low-fidelity models, which are cost-effective to simulate but less precise, and subsequently exploring "promising" solutions identified by these low-fidelity models with more accurate and costly high-fidelity models. The models may be surrogate and/or EM models [26], [27], [28]. Multifidelity optimization techniques have been used in several antenna design challenges.

For instance, in [28], an ultrawideband monopole antenna, a dual-band monopole antenna, a triband patch antenna, and a series-fed microstrip array antenna have been developed with this methodology. The technique in [28] enhances traditional Gaussian process regression (GPR)-based machine learning optimization of antennas through a multi-branch strategy that employs various fidelity models to create multifidelity GPR models and multiple constants or thresholds for lower LCB prescreening. During the optimization process, the accuracy of the low-fidelity antenna models is established and validated through corresponding high-fidelity simulations, while the search space for the LCB constant, which primarily balances exploration and exploitation, is restricted to predefined discrete values (i.e., {0, 1, 2}).

A novel ML-assisted antenna optimization technique using multifidelity or variable-fidelity models of the antenna structure has been developed to enhance the effectiveness of surrogate modeling and the entire optimization process [29]. In [29], variable fidelity EM models are used for both the definition of the surrogate domain and the final rendering of the surrogate model employed in the optimization phase. Co-kriging is used to integrate low-fidelity and high-fidelity simulation data to enhance the management of model inconsistencies. This method obviates the need of rectifying the low-fidelity model, a common practice in multifidelity-based optimization strategies that require dependable management of model inconsistencies. The surrogate model-assisted integrated global and local search phase for effective high-fidelity simulation model-based optimization is an additional approach for the multifidelity optimization of antennas, adeptly addressing model discrepancies. This is the second episode in the SADEA algorithm series [19]. It functions as a multi-stage optimization framework that incorporates data mining and local search to effectively and reliably address model differences while maintaining high efficiency and rapid convergence speed [19].

**D. Domain Knowledge-** Facilitated Antenna Optimization

A methodology is proposed in [30] to diminish the computational expense of antenna array design by utilizing knowledge of the active base elements (ABEs) and their patterns, alongside the application of GPR to predict and model ABE geometries and the corresponding excitations of sub-arrays, particularly in cases where analytical methods fail to produce accurate models. This method is more efficient than comparable techniques (such as [31]) since it reduces both the dimensional space and the computational cost of design and surrogate modeling using virtual subarray approximation. Domain expertise involves partitioning the spatial region surrounding the area of biological interest (ABE) into multiple sections utilizing a constant coupling area radius, followed by further segmentation of the coupling area into a predetermined number of sections based on the azimuth angle, to ensure the optimization process's efficiency [30].

To achieve a cost-effective and resilient design of antennas and arrays, machine learning-assisted optimization techniques have been integrated into a traditional design framework to significantly diminish the computing expenses associated with simulation-driven global optimization and tolerance analysis in [32]. Worst-case analysis (WCA), maximum input tolerance hypervolume (MITH) search mechanism, and robust optimization are used to accelerate the robust design process. The approach suggested in [32] was effectively used for the multi-objective optimization of both an antenna array and a microstrip patch antenna. To facilitate the successful execution of the procedure, a surrogate model correlating design parameters with performance using a GA-based WCA is first established, succeeded by an MITH-based search to determine the MITH of the design point of interest. These techniques depend on domain expertise on the design space for the design point, the output tolerance area, and the model [32].

Correlations between the design parameters and the MITH are created utilizing the training set derived from the MITH-based search prior to the implementation of the principal online GPR-based surrogate modeling.

**E. Other Recent ML-** Facilitated Antenna Optimization Techniques

A novel generative algorithm, influenced by generative adversarial networks (GANs), has been integrated with a support vector classifier (SVC) within a cohesive evolutionary approach framework, as proposed in [33], for the automation of antenna design, exemplified by dual resonance and broadband antennas.

The proposed technique largely involves training the discriminator, generator, and SVC to forecast antenna model performances, generate new candidate designs, and categorize these designs prior to simulation, respectively. This method demonstrates significant improvement in optimization time relative to conventional antenna optimization techniques and enables the creation of various geometric designs that satisfy identical performance criteria for reflection coefficient specifications.

A recent proposal outlines an expedited technique for improving antenna structural parameters using accelerated gradient-based optimization utilizing numerical derivatives and response feature methods as detailed in [4]. The methodology proposed in [4] improved the predictive capability of surrogate models that substitute computationally intensive electromagnetic simulations during optimization. A sparse Jacobian matrix update for the trust region-based search is implemented by confining finite differentiation-based sensitivity updates to subspaces where most response variability is concentrated. The approach provided in [4] has been used to optimize dual-band and tri-band microstrip patch antennas with less than 12 design parameters, yielding effective design solutions.

## CONCLUSION

This study succinctly examines contemporary AI-driven antenna design optimization techniques, emphasizing their principal characteristics and applications. The below points may be concisely highlighted about contemporary ML-assisted antenna optimization techniques: They are often more efficient than their conventional equivalents while delivering superior quality designs. Some methods are better appropriate for particular antenna issues (e.g., scenarios where reasonably effective early designs exist as beginning or anchor points), yielding outstanding outcomes. In some methodologies, domain expertise in executing ad-hoc procedures significantly influences the optimization process, leading to superior outcomes. The SADEA series, independent of preliminary designs and ad-hoc methodologies, is more universal and adaptable to a wider range of antenna design challenges, including those with many design variables.

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