Automated Design of Antennas Using AI Techniques: A Review of Contemporary Methods and Applications

Mobayode O. Akinsolu*, Qiang Hua†, Bo Liu‡
*Faculty of Arts, Computing and Engineering, Wrexham University, U.K., m.o.akinsolu@ieee.org
†School of Computing and Engineering, University of Huddersfield, U.K., q.hua@hud.ac.uk
‡James Watt School of Engineering, University of Glasgow, U.K., bo.liu@glasgow.ac.uk

***Abstract*—The automated design of antennas made possible through the use of artificial intelligence (AI) techniques is attracting much attention. This development can be mainly attributed to the reduced design time and the higher quality of design solutions that AI-driven antenna optimization methods provide in comparison to their more traditional counterparts. Due to the growing need to fulfill more stringent design specifications and functional requirements for both present-day and future wireless communication systems, the design and development of antennas and antenna systems have increased both in scope and complexity, such that conventional methodologies are often not fit for an efficient practical implementation. In this paper, a brief overview of some of the latest AI-based techniques for the design and optimization of contemporary antennas is provided with the goal of providing information on recent research to researchers in this growing area of interest.**

***Index Terms*—AI, Antenna Optimization.**

I. Introduction

The design of contemporary antennas is often fraught with a number of challenges such as dealing with complex topological profiles and material compositions, and the need to meet stringent performance requirements for present-day applications such as 5G and 6G [1]. To overcome these challenges, antenna engineers often tend to combine their experience with parametric studies (the sweeping of a few critical design parameters in discrete step-sizes to understand their influence on the performance of the antenna) until a sufficiently good design can be found [2]. In many cases, as is often the case with contemporary antenna structures having quite a few interrelated design parameters and specifications, this process tends to be exhaustive without any guarantee of successful outcomes [3], [4]. Hence, an automated approach (design automation via optimization) is preferred for a more effective design exploration of modern antenna structures [5].

The automated design of antennas via optimization offers numerous advantages that include, but are not limited to, consideration of more than a few design parameters concurrently and obtaining a high-quality design solution for the given antenna structure. In spite of the many advantages offered by numerical optimization techniques that are compatible with antenna design, their inherent drawbacks also tend to make them unfit for many contemporary antenna design problems. For example, local optimization techniques tend to rely on a good initial design as a starting point or an anchor point to ensure their success [6], [7]. Global optimization methods, on the other hand, often require a large (sometimes not affordable) number of full-wave electromagnetic (EM) simulations (i.e., objective function evaluation) to obtain near-optimal designs [6], [8], [7]. Today, a good initial design is often unavailable for many practical antenna design cases and large computational efforts costing several weeks to months are also undesirable to ensure a low time-to-market for antenna products [9]. This is why standard local and global numerical optimization techniques are often not suitable for the automated design of a broad class of antennas.

In the last decade, researchers in the artificial intelligence (AI)-driven design field have proposed innovative ways of overcoming the limitations (discussed above) inherent in traditional numerical optimization techniques. A majority of these proposed methods are implemented by introducing AI techniques, specifically, machine learning (ML) into the kernel of conventional numerical optimization methods to make them more efficient and robust [9]. This approach often takes the form of surrogate modeling where predictions from metamodels or data-driven models are used to replace computationally expensive full-wave electromagnetic (EM) simulations in the optimization process [10]. In this paper, some of the state-of-the-art AI-driven design methods that employ surrogate modeling or predictive modeling for the expedited design of antennas for contemporary applications are briefly discussed.

II. AI-driven Antenna Design Optimization

In recent times, AI techniques have been used to enhance the efficiency and reliability of simulation-driven antenna design and optimization methodologies to make them better suitable for a broader class of contemporary antenna structures. Some of the most recent approaches are briefly discussed as follows to highlight their mode of operations and applications:

A. Evolutionary Algorithms

Evolutionary algorithms (EAs) such as genetic algorithms (GAs), differential evolution (DE), particle swarm optimization (PSO), and their state-of-the-art variants have been applied extensively to the automated design of antennas [11]. They mainly work by carrying out a nature-inspired global search of the given antenna's design space to find near-optimum antenna designs. The primary advantages of employing EAs in the antenna design process include their non-reliance on initial designs and the circumvention of the time and labor-intensive experience-driven manual tuning of antenna structures that is often required to get proposed antenna structures to meet desired specifications and requirements [12], [6], [11].

In recent years, examples of EAs applied to the automated design of antennas include (but are not limited to) the use of invasive weed optimization (IWO) and ant colony optimization (ACO) to the design of aperiodic subarrayed phased arrays and millimeter wave (mmWave) microstrip antennas, respectively [13], [14]. For both problems, IWO and ACO generated acceptable design solutions with better performance than the reference designs. However, the computational budget for EAs could easily become cumbersome or even unaffordable due to the large number of full-wave EM simulations required to find near-optimum designs for several antenna design problems [15], [6]. EAs also tend to have slow convergence speeds for some antenna design problems [6].

B. ML-Assisted Evolutionary Algorithms

To lower the computational cost of EAs and enhance their efficiencies, surrogate models built using ML techniques are often used to replace full-wave EM simulations in their optimization kernels. This class of EAs also called SAEAs (surrogate model-assisted EAs) tend to be more efficient (typically, in terms of optimization speed) and offer design solutions of higher quality in comparison to their pure EA counterparts [16], [17]. The SADEA (surrogate model-assisted differential evolution for antenna synthesis) family of algorithms fall into this category. They primarily focus on the harmonious working of evolutionary computation and supervised learning techniques considering antenna design landscape characteristics [18], [19], [20], [21], [22], [23]. SADEA methods are non-reliant on initial designs and ad-hoc processes in their optimization frameworks, making them more robust and better suited for the optimization of a broad class of antenna design problems [24], [25]. SADEA methods show several times to up to 20 times speed improvement compared to standard numerical optimization methods when employed for the design automation of the same antenna structures, while obtaining design solutions of higher quality [18], [6], [21].

In SAEAs, the curse of dimensionality has been a major bottleneck [18], [22]. This is often linked to an exponential increase in the training or learning time of ML techniques as the dimensional space of their training data points increases [18], [22]. As a result, the efficiency of traditional SAEAs is often lowered for the optimization of antenna structures having a relatively large dimensional space [22]. In recent times, SADEA methods have also been demonstrated to be fit for the optimization of complex and high-dimensional (up to and over 100-D) antenna structures [22], [23]. In [22], radial basis function (RBF)-assisted local optimization and self-adaptive Gaussian process (GP) surrogate modeling are employed to have a reduced training cost for the surrogate modeling stage of the optimization process, while maintaining the efficiency of the SAEA-based optimization. To further lower the computational cost of the surrogate modeling stage of the ML-assisted optimization of high-dimensional antenna structures, whilst keeping the efficiency, the harmonious working of Bayesian neural network (BNN)-based surrogate modeling and self-adaptive lower confidence bound (LCB) prescreening of predictions is employed in [23], the latest installment of the SADEA series of algorithms.

Another recent approach is the improved PSO that employs the co-use of a global radial RBF model and a kriging model to replace computationally expensive full-wave EM simulations and to guide the PSO updating mechanism [9]. This approach allowed for the use of mixed prescreening in a coadjutant manner, where swarm particles with the minimum predicted objective function and maximum expected improvements are co-selected in the improved ML-guided PSO. The improved PSO has been verified using antenna problems that include a substrate-integrated waveguide (SIW) cavity-backed slot antenna, a linear array, and a sequential-rotation feeding network for wireless communication applications [9]. In all cases, good design solutions were obtained.

C. Multifidelity Optimization

The general idea behind multifidelity optimization of antennas is to filter out non-promising design solutions using low-fidelity models that are inexpensive to simulate but less accurate, and to search around "promising" solutions discovered by the low-fidelity model using more accurate and expensive high-fidelity models. The models could be surrogate and/or EM models [26], [27], [28]. Multifidelity optimization methods have been applied to several antenna design problems. For example in [28], an ultrawide band monopole antenna, a dual-band monopole antenna, a triband patch antenna, and a series-fed microstrip array antenna have been designed using this approach. The method in [28] improves the conventional Gaussian process regression (GPR)-based ML-assisted optimization of antennas via a multi-branch approach involving the use of multiple fidelity models to generate multifidelity GPR models and multiple constants or thresholds for the lower LCB prescreening. Such that during the optimization process, the accuracy of the low-fidelity models of the antennas is established and validated using corresponding high-fidelity simulations, and the search space for the LCB constant that is largely responsible for balancing exploration and exploitation assumes predefined discrete values (i.e., $\{0, 1, 2\}$).

Another ML-assisted antenna optimization method employing the use of multifidelity or variable-fidelity models of the given antenna structure in the optimization process to further improve the efficiency of surrogate modeling and the overall optimization process has been proposed [29]. In [29], variable-fidelity EM models are used for both the surrogate domain definition and the final rendering of the surrogate model employed in the optimization process. Co-kriging is then employed to blend the low-fidelity and high-fidelity simulation data to better manage model discrepancies. This approach eliminates the need to correct the low-fidelity model which is a norm in multifidelity-based optimization approaches where model discrepancies must be handled reliably. The surrogate-model-assisted combined global and local search stage for efficient high-fidelity simulation model-based optimization is another method for the multifidelity optimization of antennas that handles model discrepancies efficiently [18]. It is the second installment in the SADEA series of algorithms [19]. It works as a multi-stage optimization framework that features data mining and local search to efficiently and reliably handle model discrepancies while ensuring high efficiency and good convergence speed [19].

D. Domain Knowledge-Assisted Antenna Optimization

To reduce the computational cost of antenna array design, a methodology that employs knowledge of the active base elements (ABEs) of antenna arrays and their patterns, and the use of GPR to predict and model ABE geometries and the corresponding excitations of the sub-arrays (in instances where it will not be possible for analytical methods to build accurate models) is proposed in [30]. This approach is more efficient compared to related approaches (such as [31]) because it lowers both the dimension space and computational complexity of design and surrogate modeling via virtual sub-array approximation. Domain knowledge such as the division of the space around the ABE of interest into several sections using a fixed coupling area radius and further segmentation of the coupling area into a fixed number of sections using the azimuth angle are employed to guarantee the efficiency of the optimization process [30].

To have a low-cost robust design of antennas and arrays, ML-assisted optimization algorithms have also been introduced into a conventional design framework to effectively reduce the computational cost of simulation-driven global optimization and tolerance analysis in [32]. Specifically, worst-case analysis (WCA), maximum input tolerance hypervolume (MITH) search mechanism, and robust optimization are employed to expedite the robust design process. The proposed method in [32] was successfully applied to the multi-objective optimization of an antenna array and a microstrip patch antenna, respectively. To ensure an effective implementation of the method, a surrogate model mapping between the design parameters and performance via a GA-based WCA is first performed, followed by an MITH-based search to obtain the MITH of the design point of interest. These processes are reliant on domain knowledge about the design space for the design point, the output tolerance region and the model [32]. Correlations between the design parameters and the MITH are then established using the training set resulting from the MITH-based search before the primary online GPR-based surrogate modeling can take place.

E. Other Recent ML-Assisted Antenna Optimization Methods

The co-working of a novel generative algorithm (inspired by generative adversarial networks (GANs)) and support vector classifier (SVC) in a unified evolutionary approach framework has been proposed in [33] for the automation of antenna design using dual resonance and broadband antennas as examples. The proposed method primarily works by training the discriminator, the generator, and the SVC to predict the performances of antenna models, create new candidate designs, and classify the candidate designs before simulating the created designs, respectively. This approach shows noticeable improvement (in terms of optimization time) compared to traditional antenna optimization methods and allows for the generation of multiple geometric designs that meet the same performance requirements in terms of reflection coefficient specifications.

Recently, an expedited way of optimizing the parameters of antenna structures has been proposed through the co-use of accelerated gradient-based antenna optimization with numerical derivatives and response feature methodology in [4]. For the proposed method in [4], the response feature methodology allowed for the enhancement of the predictive power of the surrogate models used to replace computationally expensive EM simulations in the optimization process, and a sparse Jacobian matrix update for the trust region-based search is enacted by limiting the finite differentiation-based sensitivity updates to subspaces where a majority of response variability is restricted to. The proposed method in [4] has been applied to optimize dual-band and tri-band microstrip patch antennas having less than 12 design parameters and good design solutions were obtained.

III. Conclusion

In this paper, present-day AI-based antenna design optimization methods are briefly discussed to highlight their key features and applications. The following observations can be noted summarily for present-day ML-assisted antenna optimization methods: (1) They are typically more efficient than their more traditional counterparts while providing designs with higher quality. (2) Some of them are more suitable for specific antenna problems (e.g., antenna problems where relatively good initial designs are available as starting or anchor points), showing excellent results. (3) In some methods, domain knowledge for implementing ad-hoc processes plays an important role in guiding the optimization process to yield excellent results. (3) The SADEA series, which is non-reliant on initial designs and ad-hoc processes, is more general and applicable to a broader class of antenna design problems, including those with many design variables.

References

[1] Y. J. Guo *et al.*, “Quasi-optical multi-beam antenna technologies for b5g and 6g mmwave and thz networks: A review,” *IEEE Open Journal of Antennas and Propagation*, vol. 2, pp. 807–830, 2021.

[2] M. Ikram *et al.*, “Sub-6 ghz and mm-wave 5g vehicle-to-everything (5g-v2x) mimo antenna array,” *IEEE Access*, vol. 10, pp. 49 688–49 695, 2022.

[3] J. Zhang *et al.*, “Design of zero clearance siw endfire antenna array using machine learning-assisted optimization,” *IEEE Transactions on Antennas and Propagation*, vol. 70, no. 5, pp. 3858–3863, 2022.

[4] A. Pietrenko-Dabrowska and S. Koziel, "Accelerated parameter tuning of antenna structures by means of response features and principal directions," *IEEE Transactions on Antennas and Propagation (Early Access)*, 2023.

[5] B. A. F. Esmail and S. Koziel, "Design and optimization of metamaterial-based dual-band 28/38 ghz 5g mimo antenna with modified ground for isolation and bandwidth improvement," *IEEE Antennas and Wireless Propagation Letters*, vol. 22, no. 5, pp. 1069–1073, 2023.

[6] V. Grout *et al.*, "Software solutions for antenna design exploration: A comparison of packages, tools, techniques, and algorithms for various design challenges," *IEEE Antennas and Propagation Magazine*, vol. 61, no. 3, pp. 48–59, 2019.

[7] M. O. Akinsolu, K. K. Mistry *et al.*, "Machine learning-assisted antenna design optimization: A review and the state-of-the-art," in *2020 14th European Conference on Antennas and Propagation (EuCAP)*, 2020, pp. 1–5.

[8] X. Li and K. M. Luk, "The grey wolf optimizer and its applications in electromagnetics," *IEEE Transactions on Antennas and Propagation*, vol. 68, no. 3, pp. 2186–2197, 2020.

[9] K. Fu *et al.*, "An efficient surrogate assisted particle swarm optimization for antenna synthesis," *IEEE Transactions on Antennas and Propagation*, vol. 70, no. 7, pp. 4977–4984, 2022.

[10] A. Pietrenko-Dabrowska and S. Koziel, *Knowledge-Based Globalized Optimization of High-Frequency Structures Using Inverse Surrogates*, 2023, pp. 409–433.

[11] S. K. Goudos, *Emerging Evolutionary Algorithms for Antennas and Wireless Communications*. London: SciTechPublishing, The IET, 2021.

[12] S. K. Goudos, C. Kalialakis, R. Mittra *et al.*, "Evolutionary algorithms applied to antennas and propagation: A review of state of the art," *International Journal of Antennas and Propagation*, vol. 2016, no. 1010459, pp. 1–12, 2016.

[13] L. W. Mou and Y. J. Cheng, "Design of aperiodic subarrayed phased arrays with structural repetitiveness," *IEEE Transactions on Antennas and Propagation*, vol. 70, no. 12, pp. 11 697–11 706, 2022.

[14] R. Jian, Y. Chen, and T. Chen, "Multi-parameters unified-optimization for millimeter wave microstrip antenna based on icaco," *IEEE Access*, vol. 7, pp. 53 012–53 017, 2019.

[15] P. I. Lazaridis, E. N. Tziris, Z. D. Zaharis, T. D. Xenos, J. P. Cosmas, P. B. Gallion, V. Holmes, and I. A. Glover, "Comparison of evolutionary algorithms for lpda antenna optimization," *Radio Science*, vol. 51, no. 8, pp. 1377–1384, 2016.

[16] S. Koziel and S. Ogurtsov, *Surrogate-Based Optimization*. Cham: Springer International Publishing, 2014, pp. 13–24.

[17] C. He *et al.*, "A review of surrogate-assisted evolutionary algorithms for expensive optimization problems," *Expert Systems with Applications*, p. 119495, 2023.

[18] B. Liu, H. Aliakbarian *et al.*, "An efficient method for antenna design optimization based on evolutionary computation and machine learning techniques," *IEEE Transactions on Antennas and Propagation*, vol. 62, no. 1, pp. 7–18, 2014.

[19] B. Liu, S. Koziel, and N. Ali, "Sadea-ii: A generalized method for efficient global optimization of antenna design," *Journal of Computational Design and Engineering*, vol. 4, no. 2, pp. 86–97, 2017.

[20] B. Liu, M. O. Akinsolu *et al.*, "Efficient global optimisation of microwave antennas based on a parallel surrogate model-assisted evolutionary algorithm," *IET Microwaves, Antennas & Propagation*, vol. 13, no. 2, pp. 149–155, 2019.

[21] M. O. Akinsolu *et al.*, "A parallel surrogate model assisted evolutionary algorithm for electromagnetic design optimization," *IEEE Transactions on Emerging Topics in Computational Intelligence*, vol. 3, no. 2, pp. 93–105, 2019.

[22] B. Liu *et al.*, "An efficient method for complex antenna design based on a self adaptive surrogate model-assisted optimization technique," *IEEE Transactions on Antennas and Propagation*, vol. 69, no. 4, pp. 2302–2315, 2021.

[23] Y. Liu *et al.*, "An efficient method for antenna design based on a self-adaptive bayesian neural network-assisted global optimization technique," *IEEE Transactions on Antennas and Propagation*, vol. 70, no. 12, pp. 11 375–11 388, 2022.

[24] M. A. B. Abbasi *et al.*, "Machine learning-assisted lens-loaded cavity response optimization for improved direction-of-arrival estimation," *Scientific Reports*, vol. 12, no. 1, p. 8511, 2022.

[25] M. Alibakhshikenari *et al.*, "Dual-polarized highly folded bowtie antenna with slotted self-grounded structure for sub-6 ghz 5g applications," *IEEE Transactions on Antennas and Propagation*, vol. 70, no. 4, pp. 3028–3033, 2022.

[26] S. Koziel and A. Bekasiewicz, "Fast em-driven optimization using variable-fidelity em models and adjoint sensitivities," *IEEE Microwave and Wireless Components Letters*, vol. 26, no. 2, pp. 80–82, 2016.

[27] Y. Song *et al.*, "Multi-fidelity local surrogate model for computationally efficient microwave component design optimization," *Sensors*, vol. 19, no. 13, p. 3023, 2019.

[28] W. Chen *et al.*, "Multibranch machine learning-assisted optimization and its application to antenna design," *IEEE Transactions on Antennas and Propagation*, vol. 70, no. 7, pp. 4985–4996, 2022.

[29] A. Pietrenko-Dabrowska, S. Koziel, and L. Golunski, "Two-stage variable-fidelity modeling of antennas with domain confinement," *Scientific Reports*, vol. 12, no. 1, p. 17275, 2022.

[30] Q. Wu *et al.*, "Knowledge-guided active-base-element modeling in machine-learning-assisted antenna-array design," *IEEE Transactions on Antennas and Propagation*, vol. 71, no. 2, pp. 1578–1589, 2023.

[31] Q. Wu, W. Chen *et al.*, "Machine learning-assisted array synthesis using active base element modeling," *IEEE Transactions on Antennas and Propagation*, vol. 70, no. 7, pp. 5054–5065, 2022.

[32] Q. Wu *et al.*, "Multilayer machine learning-assisted optimization-based robust design and its applications to antennas and array," *IEEE Transactions on Antennas and Propagation*, vol. 69, no. 9, pp. 6052–6057, 2021.

[33] Y. Zhong *et al.*, "A machine learning generative method for automating antenna design and optimization," *IEEE Journal on Multiscale and Multiphysics Computational Techniques*, vol. 7, pp. 285–295, 2022.