

Broad-Range Inverse Design of Antennas Using Deep Neural Networks with Material Parameter Embedding and Rapid Fine-Tuning

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Abstract— Contemporary antenna design increasingly depends on numerical optimization to manage multiple design variables, objectives, and constraints. In many applications, such as metasurfaces, antenna arrays, or redesign over wide operating ranges, global optimization is no longer optional but essential. However, conventional bio-inspired algorithms are notoriously inefficient, while machine-learning-based methods struggle to construct sufficiently accurate metamodels. This paper presents a new broad-range optimization strategy based on inverse data-driven surrogates implemented with deep convolutional neural networks (CNNs). A custom embedding process is applied to allow constructing models covering diverse materials properties (e.g., substrate permittivity). The surrogate maps antenna frequency responses to geometry parameters. Training data are generated in a dimensionally reduced space that captures the most influential directions in the design space, enabling accurate model construction with a limited number of samples. In the first phase, the inverse model produces an initial design directly from the performance specifications (e.g., desired operating bandwidth) mapped into a target frequency response, which is subsequently refined using an accelerated gradient-based optimizer. The presented approach is verified with two planar antennas optimized for the best reflection response and gain. The outcomes indicate that the inverse surrogate can be applied across a broad spectrum of frequencies, geometries, and substrate materials at low cost of fewer than 30 EM analyses on average. Benchmarking demonstrates the benefits of our method and its practical edge over a broad spectrum of bio-inspired, machine learning, and surrogate-assisted population-based approaches.

Index Terms— Antenna engineering, antenna optimization, inverse design, CNN, material-oriented embedding, fine-tuning.

I. INTRODUCTION

Modern antenna design is a challenging endeavor because of growing performance requirements imposed by diverse applications (5G/6G technology, implantable devices, Internet of Things) [1]–[3]. To secure optimal operation, topologically sophisticated structures must be meticulously tuned [4], [5], and their reliable assessment necessitates electromagnetic (EM) simulation [6]. To efficiently handle multiple decision variables and objectives, the utilization of rigorous numerical methods became imperative [7]. While most widely used techniques are local (e.g., gradient-based) procedures [8], global optimization is imperative in many situations, such as the development of metasurfaces [9], antenna arrays [10], and system redesign within broad operating condition ranges [11].

Global search is mainly executed by means of bio-inspired procedures [12], [13]. However, these techniques exhibit dramatically poor computational efficiency, making them unsuitable for straightforward EM-based design. A workaround has been offered by surrogate-assisted methods, either incorporated into population-based algorithms [14], [15], or arranged as machine learning (ML) frameworks [16], [17].

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The major bottleneck, both in the context of offline (build model first, then optimize) and online methods (iterative prediction-correction strategies with model refined using accumulated EM data), is construction a sufficiently reliable metamodel, which requires considerable amounts of training data, and is only possible over relatively narrow ranges of design variables. These problems can be partly mitigated by feature-based techniques [18], or multi-fidelity approaches [19].

An alternative approach to facilitate EM-driven optimization, including global search, is inverse modeling [20], [21]. Therein, the surrogate is configured to directly predict design parameters from the target input data. Inverse modeling allows for alleviating some fundamental issues of behavioral modeling such as the curse of dimensionality. While research on inverse modeling is sparse in antenna engineering, some interesting applications were reported, e.g., inverse design of antenna superstrate for stable beam pattern [22], time-domain S -parameter-based inverse neural network (NN) model for antenna design [23], inverse design of horn antennas using physics-informed NNs [24], or multi-objective antenna design using K-means NNs with data augmentation [25]. Generic global-optimization methods leveraging inverse models were proposed as well for antennas, sensors, and microwave passives [26], along with uncertainty quantification techniques [29]. Some recent works also employ generative artificial intelligence for inverse antenna design [30] or integrate inverse NNs with bio-inspired algorithms [31]. Notwithstanding, most available works are related to metasurface design [32]–[37]. The likely reason is that metasurface unit-cell design is easier to handle than generic antenna development, owing to more straightforward parameterization and clearly defined targets (e.g., transmission responses). Unfortunately, most papers are vague regarding the setup of the input and output spaces, computational costs, method generality, or the applicable operating condition ranges. A few works provide information on input parameter ranges (e.g., [20], [25], [34]), which are typically narrow, casting doubt on the adequacy of the reported methods for global search.

This paper introduces a broad-range design procedure that uses inverse behavioral surrogates constructed with deep convolutional neural networks (CNNs). The metamodel predicts antenna geometry parameters based on the input frequency responses. To reduce the computational overhead while ensuring model reliability, the training data are generated in a dimensionally reduced space that captures the most influential design space directions. In the first phase, the inverse model yields a high-quality initial design directly from the performance specifications (e.g., the desired operating bandwidth) mapped to a target frequency response. This design is further tuned using an accelerated gradient routine. Our method is verified based on two planar antennas developed to achieve the best impedance matching and gain. The mean design expenses are just about 30 EM analyses. The outcomes indicate that our approach identifies solutions across a broad spectrum of frequencies, geometries, and parameters. Furthermore, benchmarking demonstrates the benefits of our method and its practical benefits over nine nature-inspired, machine learning, and surrogate-assisted population-based approaches.

The technical input of this research is as follows: (i) the development of an inverse-model based antenna optimization strategy capable of handling broad ranges of geometrical and operating parameters (ii) the development of a material embedding framework which allows for building the inverse models that account for different substrate permittivity and thickness, (iii) the implementation of the complete optimization procedure combining inverse-model-based rendition of the initial design and rapid fine-tuning using accelerated trust-region routine, (iv) demonstrating the advantages of our technique over a broad range of benchmark methods including nature-inspired and machine learning approaches.

II. ANTENNA OPTIMIZATION USING INVERSE DEEP CNN SURROGATES AND RAPID FINE-TUNING

This section provides details of the proposed optimization strategy, which involves a deep convolutional neural network (CNN) and expedited gradient-based fine-tuning. Numerical and experimental verification is postponed until Section III.

A. Optimization Task

Given the vector of design variables $\mathbf{x} = [x_1 \dots x_n]^T$ (typically, antenna dimensions) and aggregated responses $\mathbf{R}(\mathbf{x})$ of the EM simulation model (e.g., $|S_{11}|$, gain, etc.), the aim is to diminish a scalar function U , established to be monotonic regarding design quality (i.e., so that better-quality designs are associated with lower U). Formally, we have

$$\mathbf{x}^* = \arg \min_{\mathbf{x} \in X} U(\mathbf{x}) \quad (1)$$

In (1), X is a optimization domain defined using lower and upper parameter bounds, whereas $\mathbf{x}^*$ is the optimum design. For example, if F is the target bandwidth, $S_{11}(\mathbf{x}, f)$ and $G(\mathbf{x}, f)$ are reflection and gain as functions of $\mathbf{x}$ and frequency f , and the goal is to maximize mean gain and maintaining $|S_{11}| \leq -10$ dB over the band F , the merit function takes the form

$$U(\mathbf{x}) = -\frac{1}{|F|} \int_{f \in F} G(\mathbf{x}, f) df + \beta \left[\frac{\max \{ \max \{ f \in F : |S_{11}(\mathbf{x}, f)| \} + 10 \}}{10} \right]^2 \quad (2)$$

where the second term enforces the impedance matching condition with $\beta > 0$ being a penalty coefficient [7].

B. Inverse Surrogate

The key component of the proposed optimization approach is a deep convolutional neural network (CNN) [38] surrogate that maps antenna frequency characteristics to corresponding geometric parameters. CNN is perhaps the most appropriate network architecture for processing sequences of antenna frequency characteristics, as it can extract characteristic features, e.g., the locations of resonances, and effectively encode their relationships with the design parameters (i.e., antenna dimensions). The model architecture is shown in Fig. 1, and it is trained using ADAM algorithm [38] (the learning rate is 10^{-5} , and the maximum number of epochs is 1000). The inputs (here, reflection and gain responses) are concatenated before entering the first CNN block. Four blocks are employed, using 512, 256, 128, and 64 filters. The size of the kernel is 3×1 , and padding is applied along with ReLU activation. To allow building models valid for different parameters of the antenna substrate, the material embedding is applied as follows:

$$|S_{11}(f)| \leftarrow |S_{11}(f)| + \varepsilon_r + h(f - f_L) / (f_H - f_L) \quad (3)$$

where f_L and f_H determine the simulation frequency range, whereas ε_r and h are the relative substrate permittivity and thickness (both normalized to the unity range). For example, if the permittivity range of interest is from 2.0 to 5.0, normalization is implemented as $\varepsilon_r \leftarrow (\varepsilon_r - 2.0)/3$.

The network architecture was established through ablation studies, in which the number of CNN blocks varied from 2 to 4, and different filter arrangements were tested. The architecture shown in Fig. 1 represents the most reliable setup assuming a medium-sized training dataset of about 1000 samples.

C. Training Data Acquisition

The standard search space X is delimited by the parameter bounds. To facilitate addressing the curse of dimensionality, training samples are distributed in a reduced space X_d , established using global sensitivity analysis (GSA) [39]. GSA employs fifty random points and identifies directions having the greatest effect on the system's frequency responses. A subset of N_d of the most influential directions $\mathbf{e}_j$, $j = 1, \dots, N_d$ (collectively accounting for $\geq 90\%$ of the overall variability), is used to determine a confined domain. The latter is an intersection of the conventional search region and the affine subspace defined by $\mathbf{e}_j$. For the sake of brevity, the details are omitted here. The in-depth formulation and discussion of GSA are presented in [39]. The above arrangement effectively addresses the curse of dimensionality without compromising the surrogate's design readiness, as the reduced domain covers the most important parameter space while neglecting those with minor effects on frequency characteristics.

In this work, the training pairs, $\{\mathbf{x}_B^{(j)}, \mathbf{R}(\mathbf{x}_B^{(j)})\}$, $j = 1, \dots, N_B$, are acquired within X_d . The EM solver of choice is CST Microwave Studio. In the verification experiments, $N_B = 1000$.

D. Target Frequency Response from Design Specifications

To use the inverse model for optimization purposes, design specifications are transformed into synthetic target frequency characteristics using appropriately shaped transfer functions. In the case of reflection responses, assuming K center frequencies $f_{0,k}$, $k = 1, \dots, K$, the target response takes the form of

$$H_{S_{11}}(f) = \prod_{k=1}^K (f_{0,k}^2 + f_{0,k}^2 / Q_{b,k} + s^2) / (f_{0,k}^2 + f_{0,k}^2 / Q_{d,k} + s^2) \quad (4)$$

where $Q_{b,k}$ and $Q_{d,k}$ are determined to achieve required bandwidths and resonance depths, respectively. For gain, a bandpass transfer function is employed

$$H_{G_{11}}(f) = \sum_{k=1}^K K_k s f_{0,k} / (f_{0,k}^2 + f_{0,k}^2 / Q_{w,k} + s^2) \quad (5)$$

where K_k and $Q_{w,k}$ are determined to achieve the required in-band gain and bandwidth, respectively. Figure 2 shows exemplary target responses generated for a dualband antenna and a quasi-Yagi structure with target end-fire gain responses.

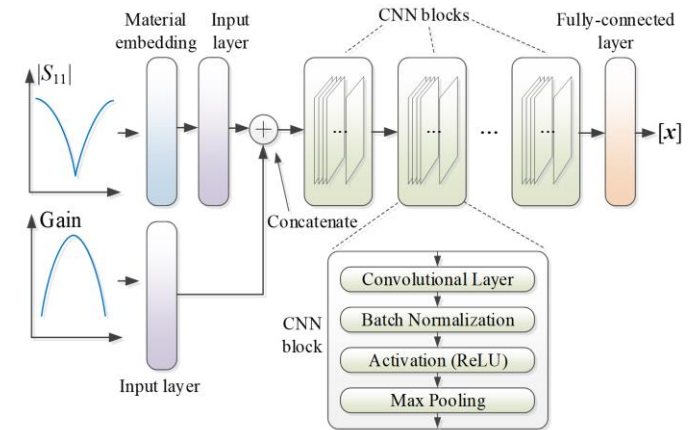


Fig. 1. Inverse model using deep CNN with material-based embedding. Each CNN block encapsulates a convolutional layer, batch normalization, a ReLU activation, and a max pooling layer. Four CNN blocks are employed, using 64, 128, 256, and 512 filters.

E. Fine Tuning

The first optimization phase is carried out across broad parameter ranges using the inverse CNN model is followed by fine-tuning arranged using an accelerated gradient-based routine. This step is carried out in the original parameter space to account for potential coverage deficiencies of the metamodel built in the reduced domain. The optimization engine is a trust-region (TR) procedure [40]. The Jacobian matrix is computed using finite differences (FD) [41]. The TR process generates approximations $\mathbf{x}^{(i)}$, $i = 0, 1, \dots$, to $\mathbf{x}^*$ as $\mathbf{x}^{(i+1)} = \text{argmin}\{\mathbf{x}, \|\mathbf{x} - \mathbf{x}^{(i)}\| \leq d^{(i)} : U_L(\mathbf{x})\}$, where the local cost function U_L is assessed with the help of a linear model of antenna characteristics. The search radius $d^{(i)}$ is controlled by the conventional TR arrangements [40]. The TR task is handled with the sequential quadratic programming procedure [42] of Matlab Optimization Toolbox [43]. The stopping criterion is convergence in argument ($\|\mathbf{x}^{(i+1)} - \mathbf{x}^{(i)}\| < \varepsilon$; here, $\varepsilon = 10^{-3}$). For acceleration, the Jacobian is calculated by FD only throughout the first two iterations. Afterwards, it is refined using the Broyden formula [44], thereby greatly reducing the computational cost.

F. Optimization Procedure

The operating flow of the complete framework is illustrated in Fig. 3. Given the specifications, a target response is generated (cf. Section II.D), which is used to produce a rough solution $\mathbf{x}^{(0)}$; therefore, no explicit specification of the initial starting point is required. The latter undergoes fine-tuning to obtain the ultimate optimized vector $\mathbf{x}^*$.

III. RESULTS

The suggested design framework is showcased here using two planar antennas. The structures are optimized for diverse performance requirements regarding operating frequencies and substrate materials. The test cases are introduced in Section III.A. Section III.B encapsulates the setup the results. Benchmarking is covered in Section III.C. Finally, Section III.D discusses prototyping and measurements of selected designs.

A. Test Cases

Figure 4 visualizes the geometries of the verification antennas, named Antenna I and Antenna II. The EM models are prepared in CST Microwave Studio. Antenna I is designed for best $|S_{11}|$ at the target frequencies $f_{1.1}$ and $f_{1.2}$. The cost function takes the form of $U(\mathbf{x}) = \max\{|S_{11}(\mathbf{x}, f_{1.1})|, |S_{11}(\mathbf{x}, f_{1.2})|\}$. Antenna II is designed for maximum average in-band gain within the operating bandwidth F centered at the frequency f_0 , with a constraint $\max\{f \in F : |S_{11}(\mathbf{x}, f)|\} \leq -10$ dB. The merit function is defined as in (2). The latter example has been included, as in practical antenna design, impedance matching alone might not suffice, and other characteristics, such as gain, need to be considered.

B. Setup and Results

The inverse CNN models were constructed for each test antenna using $N_B = 1000$ samples uniformly distributed in the domain X_d , meaning that the one-time cost of our procedure equals 1000 EM simulations. The relative root-mean-squared errors of the models are 1.5% (Antenna I) and 5.3% (Antenna II), evaluated using 100 test points. The dimensionality of X_d , established using GSA (cf. Section II.C), is $N_d = 3$ for Antenna I, and $N_d = 4$ for Antenna II. Table I collects the assumed design specs (four cases per structure). Note that both problems are demanding because of wide ranges of geometric parameters and simulation frequency (cf. Fig. 5), as well as a broad spectrum of design specifications, especially for Antenna II, which is optimized for different center frequencies, bandwidths, and substrate permittivities.

The results, shown in Figs. 6 and 7, indicate that our methodology enables reliable optimization across broad parameter ranges for all design specifications considered. By reusing the inverse model, the total design cost is small.

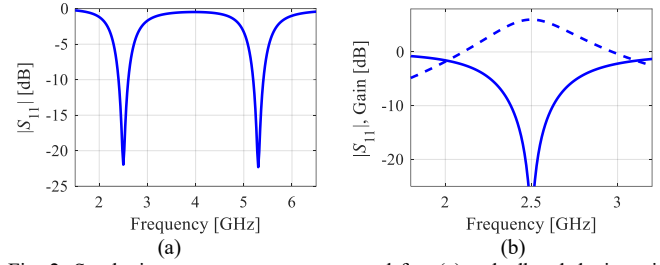


Fig. 2. Synthetic target responses generated for: (a) a dualband device with center frequencies of 2.45 and 5.3 GHz and bandwidths of 0.2 GHz, (b) a quasi-Yagi antenna with the intended center frequency of 2.5 GHz, bandwidth of 0.25 GHz, and maximum gain of 6 dB.

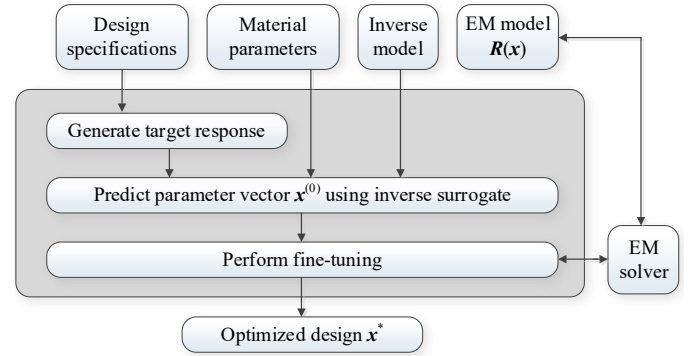


Fig. 3. Complete optimization process using inverse CNN surrogate and gradient-based fine-tuning.

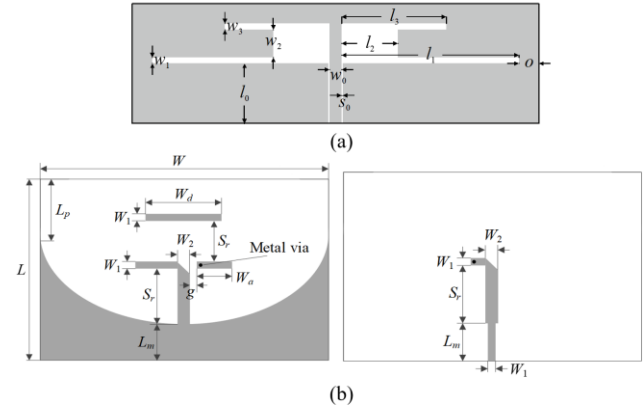


TABLE I. OPTIMIZATION SETUP FOR ANTENNAS I AND II

Case	Antenna I		Antenna II		
	$f_{i,1}$	$f_{i,2}$	f_0	F	ε_r
1	2.5	5.3	2.6	0.4	4.4
2	3.0	5.5	3.5	0.5	3.0
3	2.7	4.0	4.8	0.8	4.4
4	2.5	4.0	3.6	0.8	2.5

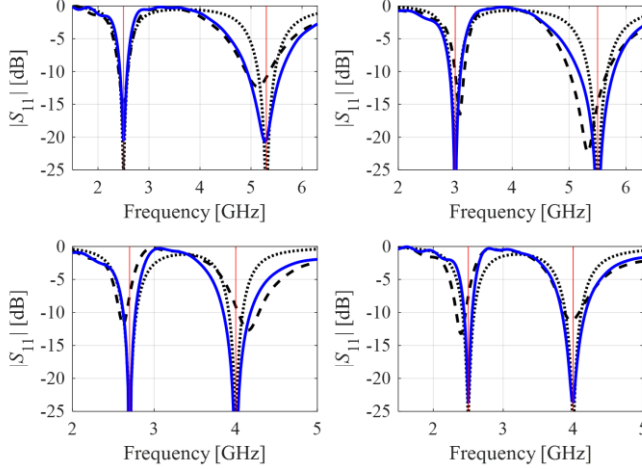


Fig. 6. Optimization of Antenna I using the suggested inverse-model-based procedure. Cases 1 through 4 of Table I are arranged from top left to bottom right: (····) synthetic target response (4), (---) EM simulated characteristic at the starting point produced by the inverse model, (—) final design obtained through fine-tuning. Vertical lines mark the target center frequencies.

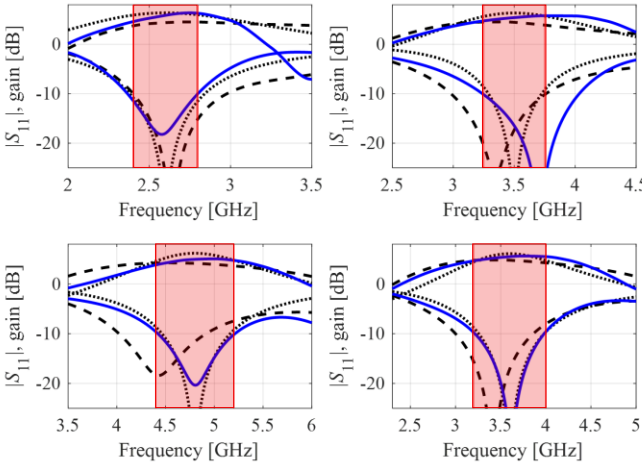


Fig. 7. Optimization of Antenna II using the suggested inverse-model-based procedure. Cases 1 through 4 of Table I are arranged from top left to bottom right: (····) synthetic target response (4), (---) EM simulated characteristic at the starting point produced by the inverse model, (—) final design obtained through fine-tuning. Vertical lines mark the target bandwidth.

C. Benchmarking

The proposed optimization procedure has been juxtaposed against a broad range of benchmark methods outlined in Table II. The comparison pool includes random-start gradient-based optimization, several bio-inspired methods (PSO, DE, GWO), multi-fidelity PSO, and four machine learning procedures. The first two (Algorithms VI and VII) utilize kriging and DNN surrogates constructed to represent antenna frequency characteristics. The metamodells are iteratively producing candidate designs by optimizing the surrogate across broad parameter ranges, which corresponds to predicted cost function enhancement as an infill criterion. The surrogates are then refined using the accumulated EM data. The last two methods are surrogate-assisted PSO and DE, respectively, also using kriging and

DNN metamodells. Because the benchmark methods are stochastic, ten independent runs of each algorithm were performed.

Tables III and IV collect the results obtained for Antennas I and II. Due to significant computational expenses, optimization was only carried out for Cases 1 and 3 of Table I. The reported data includes the mean value of the merit function, its standard deviation, and the CPU cost expressed in the number of EM simulations. The surrogate model training cost is negligible compared to the expenses associated with EM simulations. Recall that for Antenna I, the merit function measures the maximum $|S_{11}|$ at the intended center frequencies, whereas for Antenna II, the cost function quantifies the (negative) average inband end-fire gain.

The analysis of data in Tables III and IV allows us to make several observations:

- The reliability of the presented approach is significantly better than benchmark concerning the merit function. The primary reason is that the combination of inverse modeling and gradient-based fine-tuning allows generating good-quality initial solution and more precise allocation of the optimum, compared to bio-inspired and machine learning methods.

TABLE II. BENCHMARK ALGORITHMS

Algorithm	Algorithm type	Setup
I	Trust-region gradient based optimizer [40]	Random initial design, response gradients estimated using finite differentiation, termination based on convergence in argument; termination threshold is $\varepsilon = 10^{-3}$.
II	Particle swarm optimizer (PSO) [47]	Swarm size $N = 20$, standard control parameters ($\chi = 0.73$, $c_1 = c_2 = 2.05$); number of iterations set to 100.
III	Differential evolution (DE) [48]	Population size $N = 20$, number of iterations set to 100; conventional parameter setting ($CR = 0.5$, $F = 1$).
IV	Grey-wolf optimizer [49]	Pack size $N = 20$, standard algorithm setup; number of iterations set to 100.
V	Multi-fidelity PSO [50]	Swarm size $N = 20$, standard control parameters ($\chi = 0.73$, $c_1 = c_2 = 2.05$); number of iterations set to 100, EM simulation resolution adjusted during the algorithm run starting from low-fidelity (coarse-discretization) model; model fidelity L , controlled using the lines-per-wavelength (LPW) parameter of CST Microwave Studio, gradually increases as $L(k) = L_{\min} + (L_{\max} - L_{\min})[k/k_{\max}]^p$, where k is the iteration index, $k_{\max} = 100$, and $p = 2$.
VI	Machine learning (ML) procedure I	• Surrogate model: kriging interpolation. • Initial surrogate set up to ensure relative RMS error not higher than 20% with the maximum number of training samples equal to 400. • Infill criterion: minimization of the predicted objective function.
VII	Machine learning (ML) procedure II	• Surrogate model: deep neural network, DNN (multi-layer perceptron with three hidden layers, 256-128-64 neurons, ReLU activation, trained using the ADAM algorithm, maximum number of learning epochs 1000). • Initial surrogate set up to ensure relative RMS error not higher than 20% with the maximum number of training samples equal to 400. • Infill criterion: minimization of the predicted objective function.
VIII	Surrogate-assisted PSO	• Primary surrogate: forward kriging interpolation surrogate constructed to represent complete frequency characteristics. • Population size $N = 20$, maximum number of iterations 100. • Initial dataset: 100 random samples. $N_{EM} = 4$ best candidate solutions predicted by the surrogate are subject to EM analysis and incorporated into the overall training dataset. • Surrogate model refined after each iteration.
IX	Surrogate-assisted DE	• Primary surrogate: DNN (multi-layer perceptron with three hidden layers, 256-128-64 neurons, ReLU activation, trained using the ADAM algorithm, maximum number of learning epochs 1000). • Population size $N = 20$, maximum number of iterations 100. • Initial dataset: 100 random samples, • $N_{EM} = 3$ best candidate solutions predicted by the surrogate are subject to EM analysis and incorporated into the overall training dataset, • Surrogate model refined after each iteration.

TABLE III. OPTIMIZATION RESULTS FOR ANTENNA I: PROPOSED VS. BENCHMARK

Algorithm		Case 1			Case 3		
		$U(\mathbf{x}^*)^{\delta}$ [dB]	Std(U) ^{η} [dB]	Cost [%]	$U(\mathbf{x}^*)^{\delta}$ [dB]	Std(U) ^{η} [dB]	Cost [%]
Benchmark	I	-13.5	4.8	84.2	-15.2	6.1	79.1
	II	-19.8	3.5	2000	-25.2	4.1	2000
	III	-21.3	3.8	2000	-23.8	4.4	2000
	IV	-18.9	4.2	2000	-22.1	3.8	2000
	V	-19.5	4.0	895.5	-23.8	4.3	907.2
	VI	-20.7	3.0	457.8	-28.3	2.7	444.2
	VII	-20.5	2.7	468.2	-18.2	3.2	457.9
	VIII	-18.7	3.0	500	-24.2	4.6	500
	IX	-18.5	3.2	500	-16.7	3.9	500
This work		-20.5	0.0	31	-43.2	0.0	24 [§]

^a Average objective function value at the final design

^b Standard deviation of the objective function value for 10 runs.

^c Average optimization cost in the number of EM simulations.

^d Per-design cost of fine tuning of the initial design yielded by inverse model.

TABLE IV. OPTIMIZATION RESULTS FOR ANTENNA II: PROPOSED VS. BENCHMARK

Algorithm		Case 1			Case 3		
		$U(\mathbf{x}^*)^{\text{a}}$ [dB]	Std(U) [#] [dB]	Cost [%]	$U(\mathbf{x}^*)^{\text{a}}$ [dB]	Std(U) [#] [dB]	Cost [%]
Benchmark	I	-2.1	2.8	148.1	-1.7	3.2	125.7
	II	-5.1	1.0	2000	-4.7	0.9	2000
	III	-5.3	0.9	2000	-4.7	0.7	2000
	IV	-5.2	1.1	2000	-4.8	1.0	2000
	V	-5.1	1.2	912.7	-4.6	1.4	938.2
	VI	-4.8	1.7	528.3	-4.4	1.5	592.1
	VII	-4.5	2.0	505.4	-4.3	1.9	638.2
	VIII	-5.2	1.1	500	-4.6	0.8	500
	IX	-5.4	0.9	500	-4.8	0.4	500
This work		-5.7	0.0	31	-4.9	0.0	35 ^S

^a Average objective function value at the final design

^b Standard deviation of the objective function value for 10 runs.

^c Average optimization cost in the number of EM simulations.

^d Per-design cost of fine tuning of the initial design yielded by inverse model.

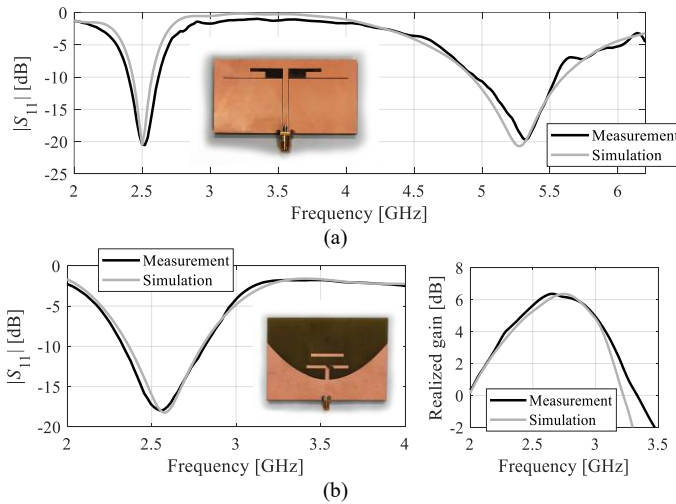


Fig. 8. Experimental validation of designs corresponding to Case 1 of Table I: (a) Antenna I, (b) Antenna II.

- The proposed approach is essentially deterministic. Once the inverse model has been constructed, the entire optimization process leads to the same final outcome, which is only determined by the input data (here, the target response). Consequently, the standard deviation of the cost function for multiple runs is zero in contrast to the benchmark. Therein, it is always positive, i.e., each algorithm run produces different outcome.
- The computational complexity of the proposed algorithm is considerably lower than the benchmark. Of course, one needs to remember about a relatively high initial cost associated with

building the inverse model. However, this model is reusable and can be applied to different optimization scenarios (such as Cases 1–4 of Table I) without any extra computational overhead. The only added expenses are those incurred by fine-tuning.

D. Experimental Validation

The designs corresponding to Case 1 (cf. Table I) were experimentally validated. Figure 8 illustrates the prototypes and compares EM-simulated and measured $|S_{11}|$ and gain responses. The characteristics are in good agreement. Small discrepancies can be attributed to manufacturing imperfections and measurement errors (cable effects, imperfect VNA calibration, etc.).

IV. CONCLUSION

This paper proposed an alternative strategy for efficiently optimizing antenna structures across broad spectrum of frequencies, geometries, and parameters. Our approach employs an inverse deep learning surrogate, dimensionality reduction, and synthetic target responses generated based on the assumed design specifications. A custom embedding procedure allows the construction of the metamodel to represent antennas implemented on different dielectric substrates. As demonstrated with two planar devices, our approach enables reliable, low-cost antenna optimization across a broad spectrum of operating conditions, including center frequencies, bandwidths, and material parameters. Extensive benchmarking underscores the practical benefits of our method over a several distinct state-of-the-art routines including nature-inspired, surrogate-assisted and machine learning procedures, also employing deep learning metamodels. Future research will emphasize expanding the applicability of the framework for multi-band structures and microwave passives.

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