Explainable Planar Multiband Antenna Designer with Wasserstein Generative Adversarial Network

Hoin Jung, Vinicius C. do Nascimento, Hongyang Liu, Xiaoqian Wang, Cheng-Kok Koh, and Dan Jiao
School of Electrical and Computer Engineering, Purdue University, West Lafayette, IN 47907, USA

***Abstract*—In the antenna design process, predicting return loss via electromagnetic (EM) simulation is crucial for understanding the antenna's behavior. As EM simulation can be time-intensive, its role is often confined to simulating the response, and not extended to proposing alternative designs. To address this, we propose a novel artificial intelligence (AI) framework for antenna design. It comprises a regressor for accurate and fast response prediction, a generative designer for proposing a vast number of new designs that meet users' requirements, and an explainer for analyzing the impact of design parameters. Application of the proposed AI framework to the design of planar multiband antennas has demonstrated its accuracy and capability.**

I. Introduction

The adoption of neural network as surrogate models for numerical simulations and inverse design of electromagnetic (EM) devices has gained popularity [1], [2]. However, artificial intelligence (AI) methodologies in EM device simulation and design are explored separately but are yet to be comprehensively integrated. In [1], for example, a sparsely connected neural network is trained as a surrogate model for antenna performance within a general multi-objective evolutionary design optimization algorithm. However, this framework relies solely on an optimization space search approach on random design without utilizing existing designs. The randomness in design parameters potentially leads to less realistic results and a more time-intensive process in generating diverse designs. In [2], a Wasserstein Generative Adversarial Network (WGAN) [3] is trained for inverse design, proposing new candidate solutions. However, the class labels indicating antenna quality are embedded as inputs, making their impact on the output less clear through the neural network. Moreover, since the model does not generate predictive labels, it is not explicitly controlled by class labels, making it challenging to evaluate the performance of the generated data.

To this end, we introduce a novel approach to the antenna design process, employing WGAN to automate the generation of new antenna design parameters by training with human-designed antennas. The generative designer meets specific multiband frequency requirements, regulated by a classifier. The classifier with a regressor assesses the performance of geometries produced by the generator, enhancing the reliability of the generative model. Moreover, we analyze how each design parameter influences the antenna's performance using the SHapley Additive exPlanations (SHAP) values [4]. The proposed approach more comprehensively integrates into the antenna design process the AI-enabled abilities of predicting the response of the antenna, generating reliable designs, and explaining the contribution of each design parameter.

This work was supported by Rapid-HI (Heterogeneous Integration) Design Institute (an Elmore ECE Emerging Frontiers Center) and an NSF Future of Semiconductors (FuSe) grant under award No. 10002201.

II. Generative Antenna Designer

A. Regressor

Prior to initiating the design process, we first pre-train a neural network regressor to substitute EM simulations for the antenna design. This regressor, denoted as F, is employed to predict the S_{11} curves of newly generated designs; see Section II-B for their generation. We employ the antenna's complex input impedance as a prediction target, thus accounting for both the magnitude and phase of return loss. This approach diverges notably from some of the existing methods [1], [5] that focus solely on the magnitude, leading to a more comprehensive impedance characterization of the antenna and offering precise regression result.

B. Designer

The designer's objective is to generate new design parameters illustrated in Fig. 1(a). The generated designs have an adequate bandwidth at resonant frequencies, demonstrating feasibility comparable to the actual data, while also displaying a necessary level of diversity. We propose a WGAN-based designer consisting of *critic* and *generator* as demonstrated in Fig. 1(b). In the design step, the critic and generator adversarially train the real antenna design samples, optimized by gradient descent. Upon training completion, the generator provides a feasible antenna design tailored to user requirements, offering a vast number of design suggestions.

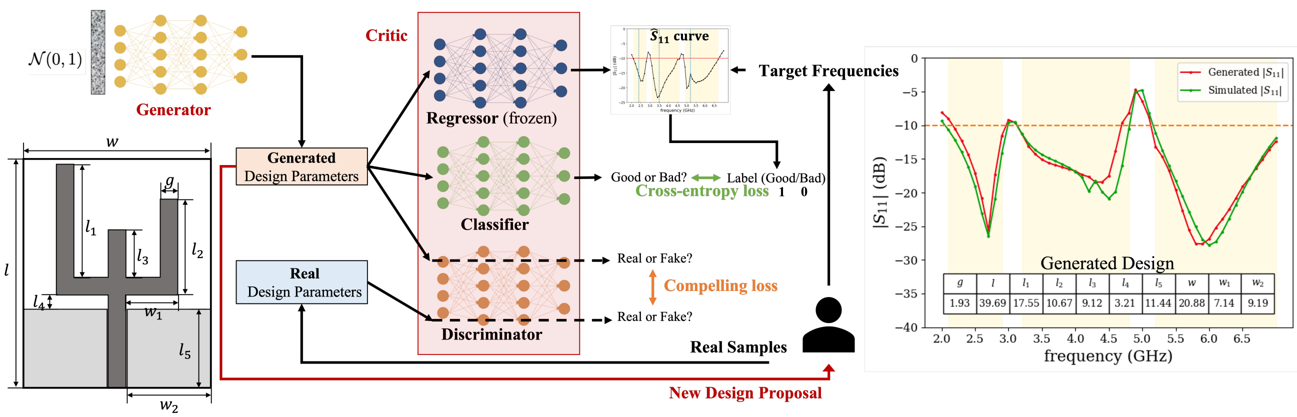
1) Critic: The critic is composed of three different neural networks, a discriminator (D), a classifier (H), and a frozen regressor (F). The discriminator distinguishes between real and artificially generated design parameters. It is trained by minimizing the objective function

$$\mathcal{L}_D = -\frac{1}{N}\Big(\sum_{i=1}^{N} D\left(x_i\right) - \sum_{i=1}^{N} D\left(\hat{x}_i\right)\Big),$$

where x_i and $\hat{x}_i$ are the real and generated design parameters respectively, D is a discriminator network, and N is the mini-batch size denoting the number of real and generated samples provided during training. The higher the discriminator's output, the more likely it predicts the data to be real.

The classifier H aims to assess whether the response from the generated design parameters achieves the desired bandwidth by minimizing the following binary cross-entropy loss

$$\mathcal{L}_H = -\frac{1}{N}\sum_{i=1}^{N}\left(y_i' \log \hat{y}_i + \left(1 - y_i'\right)\log \hat{y}_i\right),$$



g	l	l_1	l_2	l_3	l_4	l_5	w	w_1	w_2
1.93	39.69	17.55	10.67	9.12	3.21	11.44	20.88	7.14	9.19

(a) Planar multiband antenna from [1] and its design parameter (b) Architecture of Generative Antenna Designer (c) S_{11} curve from the generated design

Fig. 1. Framework and validation of the proposed generative antenna designer.

where y_i' is the binary label obtained with the predicted $\hat{S}_{11}$ curve from the regressor F, $\hat{y}_i = \sigma\left(H\left(\hat{x}_i\right)\right)$, and σ is the sigmoid function. Specifically, given a user-specified resonant frequency set ω and $\hat{S}_{11} = F\left(\hat{x}_i\right)$, y_i' is obtained by

$$y_i' = \begin{cases} 1 & \text{if } \max_f\left(\left\{\left|\hat{S}_{11}\right|_{f\in\omega}\right\}\right) \leq -10 \text{ dB}, \\ 0 & \text{otherwise.} \end{cases}$$

2) Generator: Generator G, taking Gaussian noise $\{z_i\}_{i=1}^{N} \sim \mathcal{N}(0,1)$ as inputs, aims to generate design parameter combinations $\hat{x}_i = G(z_i)$ that are realistic, bandwidth-optimized, and diverse. The objective function of G is structured to align with these three goals through three components.

First, to generate realistic parameters, G seeks to maximize the discriminator score, thereby deceiving the discriminator. Second, the operative bandwidth of the design parameters is ensured by maximizing the classifier's score; this aligns with the bandwidth optimization goal. Third, to mitigate the risk of mode collapse, in which generative models like G converge to a few repetitive sets of outputs, a penalty term is introduced. Consequently, the objective function for G is to minimize

$$\mathcal{L}_G = -\frac{1}{N}\Big(\sum_{i=1}^{N} D(G(z_i)) + H(G(z_i)) + \frac{1}{N-1}\sum_{j=1, i\neq j}^{N} \max(0, 0.5 - \|G(z_i) - G(z_j)\|_2)\Big).$$

The generator is able to provide many new designs operating at user-specified resonant frequencies. An example is presented and validated by numerical simulations (see Fig. 1(c)), demonstrating the efficacy of the proposed design method.

III. Explaining the Impacts of Design Parameters

To gain further insights into the importance of each design parameter on antenna performance, we employ SHAP value analysis on the classifier H, a measure of how much each feature contributes, either positively or negatively to the classifier's outcome. The SHAP value is defined as:

$$SHAP_k(H) = \sum_{S\subseteq \boldsymbol{d}\setminus\{k\}} \left[\frac{|S|!(|\boldsymbol{d}|-|S|-1)!}{|\boldsymbol{d}|!} \cdot \left(\sigma(H(X_{S\cup\{k\}})) - \sigma(H(X_S))\right)\right],$$

where $\boldsymbol{d}$ is the set of all design parameters, S is all possible subsets of $\boldsymbol{d}$ without parameter $k \in \boldsymbol{d}$, and X_S denotes a dataset where only parameters in S are given.

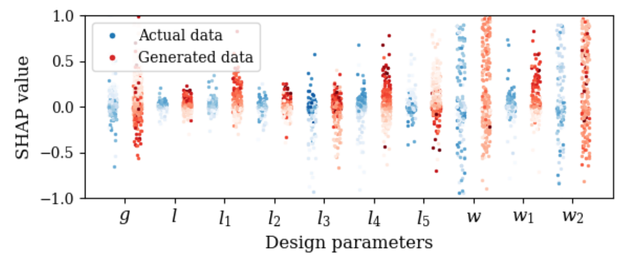


Fig. 2. SHAP value of design parameters. (Darker color indicates a larger value in length (mm). Dots with positive SHAP values signify positive contribution towards an effective antenna design in the classifier H. Conversely, dots with negative SHAP values indicate an opposite effect.)

A visualized SHAP value analysis for the generative antenna design is shown in Fig. 2. The similarity in SHAP values between the real and generated data indicates that the generated data possesses feature importance and properties akin to the actual data. Furthermore, the SHAP values of each dot signify the impact of each design parameter on achieving an effective antenna design. For example, a smaller g (a lighter dot) and a larger l_4 (a darker dot) exhibit positive SHAP values, signifying their contributions to the antenna's operative bandwidth at resonant frequencies. Additionally, a narrow range in the SHAP values for a parameter, such as l and l_2, indicates that it has minimal influence on the classifier's decision about the antenna's functionality at resonant frequencies, implying that it is less important in the overall antenna design.

References

[1] J. Dong, W. Qin, and M. Wang, "Fast multi-objective optimization of multi-parameter antenna structures based on improved bpnn surrogate model," *IEEE Access*, vol. 7, pp. 77 692–77 701, 2019.

[2] O. Noakoasteen, J. Vijayamohanan, A. Gupta, and C. Christodoulou, "Antenna design using a gan-based synthetic data generation approach," *IEEE Open Journal of Antennas and Propagation*, vol. 3, pp. 488–494, 2022.

[3] M. Arjovsky, S. Chintala, and L. Bottou, "Wasserstein generative adversarial networks," in *International conference on machine learning*. PMLR, 2017, pp. 214–223.

[4] S. M. Lundberg and S.-I. Lee, "A unified approach to interpreting model predictions," *Advances in neural information processing systems*, vol. 30, 2017.

[5] A. Patnaik, S. Sinha *et al.*, "Design of custom-made fractal multi-band antennas using ann-pso [antenna designer's notebook]," *IEEE Antennas and Propagation Magazine*, vol. 53, no. 4, pp. 94–101, 2011.