Deep-Learning-Based Inverse Design of Multilayer RF Transformers

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***Abstract*—This project develops a deep-learning-based inverse design framework for multilayer radio-frequency (RF) transformers and passive circuit topologies, addressing the inefficiency of manual, simulation-heavy workflows. A dataset was assembled of 3,398 multilayer layouts encoded as 40x40×3 pixel grids paired with scattering-parameter (S-parameter) responses sampled at 301 frequency points. A convolutional neural network (CNN) in an autoencoder configuration was trained with Huber loss to associate desired electrical behavior with pixel-level geometry. On test data, the model achieved strong predictive performance (average R-squared roughly equal to 0.95) and produced layouts that, when validated in a High-Frequency Structure Simulator (HFSS), exhibited the expected resonance, bandwidth, and insertion/return loss behavior. These results indicate that inverse design with deep learning can substantially accelerate RF co-design for multilayer transformers without sacrificing electromagnetic fidelity.**

I. Introduction

Designing compact, high-performance RF transformers typically requires expert intuition and repeated parameter sweeps in full-wave solvers, which imposes long iteration cycles and limits exploration of large design spaces. Inverse design re-frames the problem: rather than tuning predefined unit components, it maps target S-parameter behavior directly to geometry, enabling rapid generation of novel layouts—an idea that has been demonstrated at scale in adjacent domains of wave-based design [1] and shown effective for RF passives and even power amplifiers [2]. This work focuses on multilayer on-chip transformer structures, which introduce additional electromagnetic coupling and parasitic interactions—but also a richer topology space than single-layer approaches. Note related work from Dr. Sensen Li's group—PulseRF: Physics-Augmented ML Modeling and Synthesis for High-Frequency RFIC Design—which presents a physics-augmented machine-learning framework to model and synthesize high-frequency RFICs [3]. The objective of this project was to build and validate a machine-learning tool that ingests representative multilayer transformer data and returns candidate pixel layouts whose electromagnetic responses meet desired specifications, thereby reducing design turnaround time while maintaining agreement with trusted simulation results.

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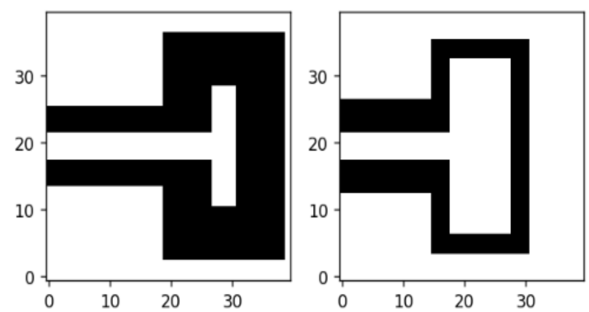

Fig. 1. Figure 1. Sample Coil Designs

II. Approach

A. Dataset and Representation

Two aligned arrays were curated: (i) input multilayer layouts of shape (3398, 3, 40, 40), where the three channels encode a bottom ground plane and two symmetric coil layers; and (ii) output S-parameters of shape (3398, 12, 301), capturing twelve unique S-parameter traces over 301 frequencies (as shown in Figure 1). This pixel-based encoding gives the model direct access to spatial features that drive electromagnetic behavior. Data were split into training/validation/test subsets using a randomized procedure with a fixed seed to ensure reproducibility and balanced coverage of the design space.

B. Model and Training

A CNN autoencoder was implemented that compresses input layouts into a latent representation (encoder) and reconstructs candidate geometries via learned upsampling and 2D transpositions (decoder) (as shown in Figure 2). Huber loss was selected for robustness: it behaves quadratically for small errors and linearly for outliers, which helps stabilize learning around resonant regions where S-parameter magnitudes and phases can change rapidly. Models were evaluated using Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and R^2 on held-out data to capture absolute deviation, relative accuracy across frequency, and variance explained, respectively. Model capacity (e.g., number of convolutional blocks) and optimization hyperparameters were tuned against validation performance to balance generalization with computational cost.

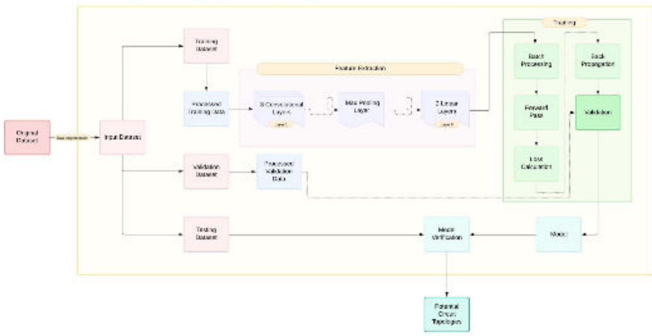

Fig. 2. Figure 2. Block Diagram for CNN and Model

C. Simulation-Based Validation

Beyond statistical metrics, representative model outputs were validated with HFSS to confirm that predicted layouts manifest the intended electromagnetic behavior under full-wave analysis. A Python workflow using scikit-rf automated S4P parsing and visualization of magnitude/phase responses, enabling quick checks of resonance placement, bandwidth trends, and port-to-port coupling characteristics before deeper analysis. This loop anchored the ML results to physically meaningful behavior and guided incremental refinements to training and selection criteria.

III. Results

A. Predictive Accuracy

On validation data, the model achieved high fidelity across S-parameters, with average R^2 values around 0.95. For a representative sample, R^2 for imaginary/real parts included:

$$S11 \approx 0.971/0.985$$
$$S12 \approx 0.941/0.909$$
$$S13 \approx 0.951/0.963$$
$$S14 \approx 0.944/0.959$$
$$S33 \approx 0.988/0.942$$
$$S34 \approx 0.942/0.912$$

MAE remained low across the band, indicating small absolute deviations, while MAPE highlighted the expected sensitivity near resonances and nulls where target magnitudes approach zero and percentage errors inflate. These complementary views—MAE for stability, MAPE for relative fidelity, and R^2 for variance capture—show that the learned mapping generalizes well over the frequency grid.

B. Layout Quality and Symmetry

Qualitatively, generated layouts preserved the expected transformer symmetries and winding-like features across layers. Side-by-side comparisons demonstrated close visual agreement between outputs and targets drawn from the validation set, suggesting that the latent representation captures the spatial regularities that matter for coupling and impedance transformation in multilayer contexts.

C. HFSS Verification

Full-wave simulations of selected outputs confirmed practical viability. Magnitude and phase plots showed resonance and bandwidth characteristics aligned with targets, with insertion and return-loss trends tracking the desired behavior over most of the band. Deviations were most pronounced at higher frequencies, where small geometric perturbations produce larger electromagnetic differences due to stronger parasitic and coupling effects—an expected limitation that points toward data and loss-function refinements. This outcome is consistent with the broader direction of ML-enabled inverse design seen in PulseRF, while this contribution centers on multilayer pixel representations and transformer-specific targets.

Efficiency and scalability. Compared with manual trial-and-error sweeps, the workflow produced ranked design candidates quickly, reducing solver-in-the-loop iterations to targeted verification runs. This reallocation—from broad manual exploration to focused simulation checks—shortens end-to-end design time and opens the door to broader topology exploration for multilayer components.

IV. Conclusion and Career Plans

This work demonstrates that a CNN-based inverse design pipeline can generate multilayer transformer layouts whose simulated responses closely match desired S-parameter targets, validating deep learning as a practical accelerator for RF co-design. Near-term improvements include increasing dataset diversity, refining the treatment of high-sensitivity frequency regions, and exploring loss formulations that weight resonant features more explicitly. Although I am currently pursuing opportunities in industry, the scholarship experience motivated me to apply for graduate school and reinforced my plan to return to research-oriented work. The MTT-S Scholarship—and the opportunity to engage with the community at IMS—shaped my technical direction, broadened my perspective on RF/microwave design, and strengthened my commitment to advancing this line of work

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