Machine Learning Assisted Optimization Methods for Automated Antenna Design

Lauren Linkous and Erdem Topsakal
Electrical and Computer Engineering, Virginia Commonwealth University, Richmond, VA, USA
linkouslc@vcu.edu

***Abstract*—This paper presents the basis of defining data-driven, machine learning assisted optimization models for automating the adjustment of physical parameters in EM software simulations controlled by AntennaCAT. Data from over 60,000 simulations have been collected for a rectangular patch antenna case study and used to design boundaries for rule-based models, and for increasing the reliability of machine learning based optimization models fed with unbalanced classes, or with sparse data. The data collection methodology, some early empirical results, and implications for automated tuning and design are discussed.**

***Keywords*— antenna design; machine learning; optimization; rule engine; simulation**

I. Introduction

Machine Learning Assisted Optimization (MLAO) combines the ability to learn non-obvious and non-analytic solutions to a given problem with the stability of a mathematical model or otherwise bounded system. This approach reduces the number of potential invalid states and has an impact beyond training more effective machine learning (ML) models capable of evolutionary optimization. Rather than training classification-focused models on static networks, MLAO utilizes hyperparameter tuning and intelligent search algorithms to handle a broader range of input variation and adaptation. For antenna design, this means focusing on training models to recognize the impact of interactions between physical parameter changes rather than only correct feature classification. This paper treats MLAO, and any algorithms spawning from it, as a singular component to the optimization approach used by AntennaCAT (Antenna Calculating and Autotuning Tool) [1-3] for automating the tuning of physical features in parameterized designs. AntennaCAT takes a modular approach to antenna design optimization by applying different optimizers based on the number of controllable parameters in a simulated design, and thus the estimated maximum size of the state space. Designs with few controllable parameters utilize rule-based systems with user-set design limitations, such as a maximum deviation from the numerical solution in the rectangular patch design used in this case study, rather than complex ML models. When using a topology known to the solver, boundaries and system behavior based on patterns from empirical data are used to decrease the time to an optimized solution. For designs with many controllable parameters and known topologies, ML models trained on the collected data are implemented. In cases where designs with many parameters and an unknown topology are being optimized, several simulation iterations are run to collect an initial data sample, and then either a rule-based approach or ML method is used depending on results and proximity to an acceptable solution.

II. Data Collection and Evaluation

AntennaCAT is built on Python 3.9, and uses common libraries for data collection, processing, and machine learning [3]. A major feature of AntennaCAT is its Batch data collection process, which has been used here to create a collection of more than 60,000 simulation results organized into 15 datasets by frequency and feed type. Each dataset contains the raw output for parameter values, gain, directivity, and reflection for the individual steps in a simulation sweep. Summarized, extracted values for multiple resonance information, first null beamwidth (FNBW), half power beamwidth (HPBW), efficiency, and other characteristics for each simulation step are provided in addition. The summarized data for each set is preformatted for ML, and contains some pre-evaluated metrics used in AntennaCAT for deciding the empirical boundaries in the rule-based optimization models, and for verifying ML optimizer outputs as valid simulation decisions. These boundaries include metrics for filtering for valid designs, but also using known patterns, such as the gain data patterns shown in Fig. 1 to classify probable frequency.

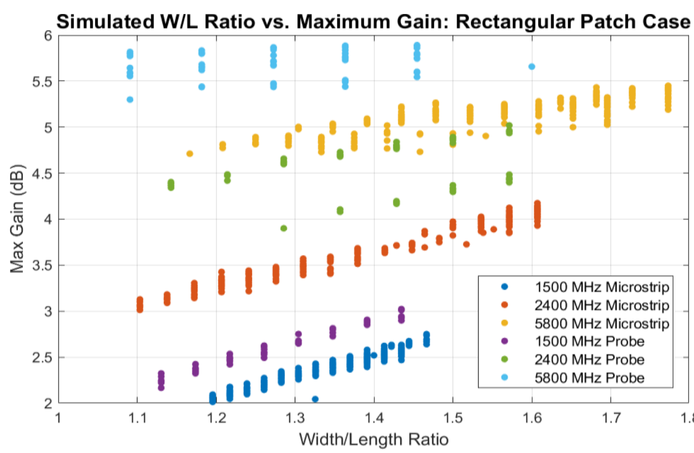

Figure 1. Linearly Separable Gain Data Patterns for a Classification Filter for 5 Frequencies of 2 Designs.

A. Parameter Variation

The database is split into sets based on frequency and feed type. In this case study, both microstrip and probe fed rectangular patch antennas were simulated. The probe fed patch varied length and width of the patch, feed location, and substrate thickness, while the microstrip fed patch varied those parameters and the strip length, thickness, and the gap distance between the microstrip and the patch. Initial values for each parameter were found using AntennaCAT's internal calculator, and then a maximum and minimum deviation range of at least ± 15% was used for initial data collection. For completeness of the set, ranges were expanded or contracted depending on impact on simulation results. That is, if valid designs were occurring at the edge of the ± 15% for some variable configurations, the range was expanded.

B. Simulation and Data Collection

AntennaCAT's batch data collection is based on the closed-loop control system that automates the CAD design and creation, simulation setup, analysis, and report export of a compatible EM simulation software (currently, HFSS, Feko, CST, COMSOL, and EMPIRE XPU). All datasets were collected using this process with Ansys HFSS 2021 and 2022. Rectangular patch antennas have been simulated for 100 MHz, 500 MHz, 900 MHz, 1500 MHz, 2400 MHz, 5800 MHz, 6000 MHz, 8160 MHz, and 12000 MHz. External processing converted raw data into the summarized and ML sets for investigation. Other frequencies of interest will be simulated as initial processing progresses.

C. Evaluation and Interpretation

The evaluation of the data collection as a dataset and evaluation for valid antenna design have been treated as separate metrics. Valid datasets are those that produce a mix of valid and invalid antenna designs while generating designs that are physically possible to create. The 100 MHz, 500 MHz, and 900 MHz designs are physically possible, but not the most effective design choice for those frequencies. Configurations that create potentially valid antenna designs are filtered by a minimum gain of 3dB, efficiency at or above 40%, and simulated S_{11} of -10dB or lower. Combining these metrics, with physical relations between parameters yield trends such as those in Fig. 2, where the best simulated S_{11} values occurred with width/length ratios between 1.2 and 1.6. When filtering for more effective designs, increasing the efficiency or gain minimums retains the same spread, but with less dramatic visualization.

III. Empirical Boundaries, Rule-Based Models, and MLAO Combinations

For analytical or semi-analytical models, there are relatively known, and bounded state space for design parameters in the system. Within this state space are parameter combinations that perform well, and others that produce invalid solutions. Empirical boundaries from numerical solutions to analytical or semi-analytical designs complement these models, and are the basis for rule-based systems. Rule-based systems merge the modeled relation with information about behavior for optimization. This information can be human provided, or collected from contextualized data, but has an exponential increase in complexity for systems with many controllable parameters. However, for systems with few parameters, using a rule-based optimizer instead of machine learning may reduce computation time.

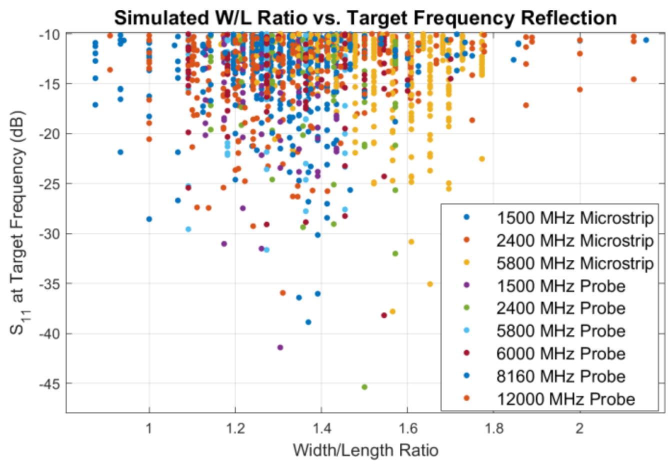

Figure 2. The Characteristic 'V' Shape of Width/Length Ratio Variation on S_{11} at Collective Target Resonance Frequencies.

Complex semi-analytical, or non-analytical models cannot be characterized with rule-based models, but in many cases can be represented with ML models. However, pure ML techniques in this context will suffer from sparse data and classification issues. Additionally, if optimization systems are not carefully executed, it is possible to implement parameter variation commands that are not physically possible within a system, increasing time for optimization through unnecessary simulations. However, MLAO combines the adaptability of ML and the stability of rule-based approaches. In AntennaCAT, this is accomplished by extracting trends from the same datasets that the ML models are trained on to create empirical boundaries in the system. These boundaries are used to estimate initial conditions for prediction, potential next valid states, and automated simulation adjustments, while the ML network is used to decide the next design parameter adjustments.

IV. Results

Early analysis of the 60,000 simulations in the database suggests several observable relations between physical parameters are a predictor for potentially valid antenna designs. These empirical relations can be implemented in rule-based optimizers, as input for ML models, and in MLAO methods for reducing the number of simulations needed for optimizing antenna designs for known topologies. A comparison of implemented rule-based, ML, and MLAO tuning method results, and empirical trends, will be presented.

References

[1] L. Linkous, E. Karincic, J. Lundquist and E. Topsakal, "Automated Antenna Calculation, Design and Tuning Tool for HFSS," *2023 United States National Committee of URSI National Radio Science Meeting (USNC-URSI NRSM)*, Boulder, CO, USA, 2023, pp. 229-230, doi: 10.23919/USNC-URSINRSM57470.2023.10043119.

[2] L. Linkous, J. Lundquist and E. Topsakal, "AntennaCAT: Automated Antenna Design and Tuning Tool," *2023 IEEE International Symposium on Antennas and Propagation and USNC-URSI Radio Science Meeting (AP-S/URSI)*, Portland, OR, USA, 2023

[3] L. Linkous, (LC-Linkous) (2022) AntennaCAT (Version 2.0) [Source code] https://github.com/LC-Linkous/AntennaCalculationAutotuningTool