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Intelligent Optimization of Antenna Parameters Using Machine Learning Algorithms

R.Ananthakrishnan[1], Dr.Aarthi @ Ananthakirupa V P M B[2]

[1](Research Scholar
Electronics and Communication Engineering
Kalasalingam Academy of Research and Education
ak.ananth27@gmail.com)

[2](Associate Professor
Electronics and Communication Engineering
Kalasalingam Academy of Research and Education (KARE)
vpmb2aarthi@gmail.com)

Abstract- Parameter optimization of antennas is an extremely resource-intensive task in contemporary wireless systems design, especially considering the increasing complexity of antenna geometry and tightening constraints in terms of performance at millimeter-wave and terahertz frequencies. In this paper, we consider a systematic study of the application of machine learning algorithms in antenna parameter optimization with a particular focus on surrogate modeling and regression-based ensemble approaches. Our approach involves development of a closed-loop methodology based on generation of electromagnetic simulation data, feature engineering, model selection, and iterative training of a machine learning-based optimizer. We evaluate three algorithm families: tree-based ensembles, neural network surrogates, and kernel methods as possible candidates for predicting antenna metrics based on its geometry. The analysis of optimization process reveals that ensemble algorithms, such as random forest regressor, have very promising prospects for significantly lowering the number of simulations needed during optimization while preserving design accuracy within given parameter spaces. The comparison of algorithms is carried out by means of evaluating their performance according to several criteria: convergence rate, efficiency of data use, robustness to variations in parameters.

Keywords- Antenna Optimization, Machine Learning, Surrogate Modeling, Random Forest, Electromagnetic Simulation, Parameter Prediction

I. INTRODUCTION

Design of contemporary antennas for wireless communication applications is a process that entails the fine-tuning of multiple geometric and physical properties to meet certain design specifications in regard to frequency band width, antenna gain, radiation pattern, and impedance matching. The conventional method of antenna optimization makes extensive use of fully three-dimensional electromagnetic simulations, such as those provided by CST Microwave Studio or ANSYS HFSS, which offer high precision but are extremely computationally intensive [3], [5], [8]. If the optimization process needs many function evaluations, such as when using global optimization techniques including genetic algorithm and particle swarm optimization, simulation times may become impractical for complex geometries like gap waveguide slot arrays, multi-layer patch antennas, and terahertz devices [1], [7], [9].

Machine learning represents a potentially powerful technique for overcoming this bottleneck [3], [5]. Instead of considering the electromagnetic solver as the only source of design information, machine-learning-aided optimization employs the creation of data-driven surrogate models, which estimate the input-output mapping between the antenna structure and its performance characteristics [2], [4], [6]. These models are trained using a relatively small number of simulations and are then able to analyze candidate structures in fractions of a second, thus

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allowing a fast exploration of the design space [2], [6]. The surrogate model can be used in conjunction with some optimization techniques—evolutionary, gradient-based, or Bayesian—to find promising candidates for further verification [2], [4], [9].

The attraction of such an approach is in the possibility of shifting antenna design from the trial-and-error loop of simulation to a more knowledge-based one [2], [5]. Some recent investigations have shown that machine learning surrogates may help decrease the amount of full-wave calculations needed to achieve a certain design quality level; moreover, the use of ensembles may ensure the robustness of the process in situations where there is insufficient data to train the models and avoid overfitting [1], [4], [6]. The success of the process relies heavily on several aspects, including algorithms, training data generation, parameter space dimension, and smoothness of the response [5], [8].

This paper focuses on the problem of parameter optimization of intelligent antennas by means of a machine learning approach. The three contributions are described as follows. Firstly, a methodology that involves simulation-driven data collection, surrogate models creation and subsequent optimization is introduced, which is general enough for various types of antenna geometries. Secondly, a comparison of different families of algorithms – tree ensembles, neural networks, and kernel-based algorithms – in terms of their applicability to antenna parameters prediction is carried out.

The scope of the current research lies in parameter-level optimization where the topology of the antenna is known and the objective is to find out geometric parameters and material properties for achieving desired performance. This scope aligns with most of the existing research papers where the antenna topology is taken as the parameterized geometry and learning the function from parameters to results is the objective [2], [5], [6]. Although topology optimization and generative design are some frontier areas of research but they lie beyond the scope of current research.

Rest of the paper is organized in the following manner. Literature Survey section provides an overview of recent advances in ML based antenna optimization with special focus on algorithm selection and workflow design. Proposed Methodology section contains details of the procedure followed in terms of data generation, modeling, and optimization. Analysis section contains comparative analysis of algorithms' performance.

II. LITERATURE SURVEY

The application of machine learning to antenna design and optimization has accelerated substantially over the past five years, driven by the growing complexity of wireless systems and the maturation of accessible ML tooling [3], [5], [8]. Early work in this domain focused primarily on neural network surrogates trained to approximate the scattering parameters or radiation patterns of parameterized antenna geometries [2], [8]. More recent investigations have expanded the algorithmic repertoire to include ensemble methods, Gaussian processes, and deep learning architectures, while also refining the methodologies for integrating surrogates into optimization loops [4], [5], [6].

Another major line of research revolves around applying the techniques of tree-based ensembles for the prediction of antenna parameters. In one comparison of ML algorithms for gap waveguide slot array antennas, a number of regression techniques were compared, such as K-nearest neighbors, decision trees, support vector regression, XGBoost, and random forests [1]. It was found that the random forest algorithm performed the best on the considered dataset because of its feature of ensemble averaging and ability to tolerate irrelevant features in the parameters [1]. This is not surprising as random forests are well known to be applicable to tabular regression problems of medium size in the ML literature [5].

The neural network methods have also been concurrently considered especially for those problems in which there exist non-linearities in the parameter performance relationship that are not

easily captured using the tree methods [2], [7]. The optimization using neural networks (ONN) method proposed by Papathanasopoulos et al. utilizes a neural network model as a surrogate model using a sequential optimization method such that the ONN approach needs fewer objective function evaluations compared to the particle swarm optimization or genetic algorithm for the design of six-element Yagi-Uda antenna and dual band slotted patch antenna [2]. It is important to note that the ONN technique specifically concentrates on reducing the number of simulations [2].

Higher-dimensional problems have also been considered using deep learning-based extensions. The combination of convolutional neural networks and MLP models were proposed as a surrogate model in order to solve multi-objective antenna decoupling problems by means of exploiting the convolutional layer to obtain spatial features from geometric representations and mapping the features to performance criteria using the fully connected layers [7], [8]. Within the terahertz band, the use of a surrogate model-assisted differential evolution (SADEA-I) algorithm for solving the antenna synthesis problem has been completed within thirty hours without providing an initial design [9].

The methodological reviews of this field have revealed certain repeating trends. In particular, the survey conducted by Sarker et al. has classified the uses of ML and DL for antenna design as design, optimization, and selection, stating that surrogate-based optimization is currently the prevailing methodology for parameter-level problems [5]. Another methodology revealed is reinforcement learning as a promising methodology to solve sequential decision problems within antenna selection and beamforming [5]. Additionally, there is another review of optimization methodologies in the context of ML and DL algorithms that can be applied to such fields as reconfigurable antennas and MIMO [3], [8].

Nevertheless, some shortcomings are still present in the literature. Comparing algorithms in the context of a particular antenna and parameter space reduces the generalizability of research results about the choice of algorithms [5], [8]. The connection between the properties of training sets (e.g., sampling density and space coverage) and the performance of surrogate models is usually not adequately explored, although such an issue is quite important from the point of view of resource allocation for simulation [4], [6]. Additionally, using machine learning-based surrogates in commercial antenna designs has not attracted as much engineering attention as the algorithms development [5], [8]. In the current study, these gaps have been considered in the course of performance evaluation of different algorithms and in the methodology setup.

III. PROPOSED METHODOLOGY

The described method is a closed-loop approach to optimizing antenna parameters via machine learning surrogates. The process includes four sequentially linked steps – definition of the parameter space and its sampling, electromagnetic data production, creation and validation of surrogate models, and surrogate optimization of antenna parameters with full-wave validation. The architecture of the whole process is shown in Figure 1.

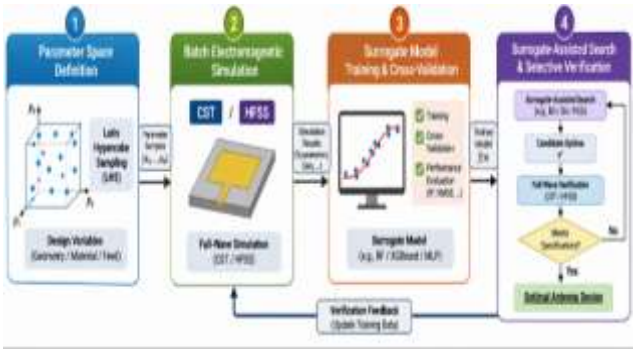


Figure 1: Overall architecture of the ML-assisted antenna optimization framework

The four stages in the pipeline are as follows:

- Definition of Parameter Space by Latin Hypercube Sampling
- Batch Electromagnetic Simulations Using CST/HFSS
- Training and Cross-Validation of Surrogate Model
- Surrogate-Assisted Optimization and Verification of Selected Optima

In the initial step, the design parameterization of the antenna is specified and the sampling strategy is devised. In this context, a vector of the design parameters is defined: $x = [x_1, x_2, \dots, x_n]$, where each x_i denotes a geometric dimension or a material property to be optimized. Upper and lower bounds for each of the parameters are defined considering the physical limitations of the fabrication process and the electromagnetic characteristics of the design. In order to construct a representative training set without clustering, the Latin hypercube sampling approach is utilized. According to this stratified sampling method, each dimension of the parameter space is divided into N equally likely segments, and a sample is placed such that each segment occurs exactly once. This produces N samples that have better coverage than the samples generated using the random sampling approach.

In the second step, electromagnetic simulations are performed for each parameter combination using the full-wave solver. The solver performs calculation of the desired parameters for each design vector x_i, which can be reflection coefficient s_{11} over a frequency range, gain at certain angles, radiation efficiency, and bandwidth. They are combined into a vector y_i. Simulation results form a training dataset for the construction of the surrogate model. Appropriate mesh settings and convergence conditions are used in simulations, and those that do not converge are ignored. Thus, a dataset $D = \{(x_i, y_i)\}_{i=1}^{N}$ is created.

This stage entails fitting the surrogate model. Three families of algorithms are proposed for this purpose:

- Tree-based ensembles such as random forest regression, where an ensemble of decision trees is fitted to bootstrap samples of the training data and averaged
- Neural networks surrogates such as multilayer perceptrons having one or two hidden layers
- Kernel methods such as support vector regression with radial basis function kernels

The models will be used to learn the function $x \rightarrow y$ from the dataset D. Hyperparameters are tuned using k-fold cross-validation, where the value of k is chosen to be five for the trade-off between reducing variance and increasing the computational complexity. Model evaluation will be done using holdout validation data not seen during training.

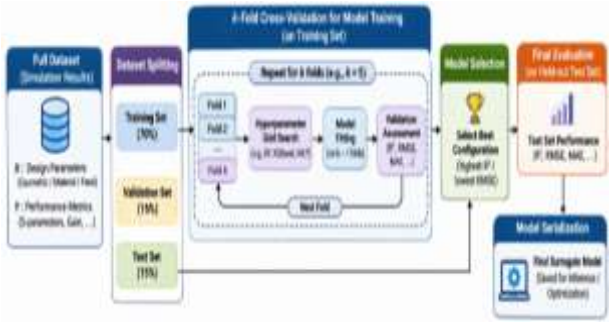


Figure 2: Surrogate model training and validation pipeline

The fourth phase involves the incorporation of the trained surrogate into an optimization loop. A search scheme (population-based schemes like differential evolution or model-based sequential schemes) queries the surrogate in order to find candidates of parameter vectors, which are expected to perform better. Since surrogates give approximate predictions, the K best candidates (with K being a small value from 3 to 10) are chosen for full-wave verification. In case the verification results in a candidate satisfying the design criterion, the procedure stops. Otherwise, the new data sample is included in the training data set, and the surrogate is updated. The strategy of iterative improvement, called often active learning or sequential sampling, focuses computation on the promising yet uncertain areas of the parameter space.

IV. ANALYSIS

Evaluation of the suggested approach relies on a quantitative assessment of surrogate models' performance and efficiency of the optimization process. This assessment takes into account three criteria: accuracy of the trained surrogates, efficiency of the process in terms of the connection between the size of the training set and model performance, and reduction in full-wave simulation evaluations owing to the use of surrogate-based search. Table 1 summarizes the comparative features of the families of algorithms considered in the work, based on their

operating peculiarities and application to antenna optimization tasks.

Table 1: Comparative analysis of ML algorithm families for antenna parameter optimization

Criterion	Random Forest	Neural Network (MLP)	Support Vector Regression
Training data requirement	Moderate; robust to small samples	High; benefits from larger datasets	Moderate; sensitive to kernel choice
Hyperparameter sensitivity	Low to moderate (number of trees, depth)	High (architecture, learning rate, regularization)	Moderate (C, γ, kernel width)
Handling of nonlinearity	Good via recursive partitioning	Excellent with sufficient depth	Good with RBF kernel
Interpretability	Moderate (feature importance available)	Low (black-box)	Low to moderate
Risk of overfitting	Low (ensemble averaging)	Moderate to high without regularization	Moderate (controlled by C)
Computational cost (training)	Low to moderate	Moderate to high (GPU beneficial)	Moderate
Computational cost (inference)	Low	Very low	Moderate (support vector expansion)
Suitability for low-dimensional parameter spaces	High	High	High
Suitability for high-dimensional spaces	Moderate	High	Moderate

From the comparative study, it is evident that the random forest technique represents a favorable combination of prediction accuracy, training speed, and robustness given the parameter space characteristic of the antenna design problem. Being an ensemble algorithm helps in solving the issue of increased variance experienced in decision tree algorithms, and having the measure of feature importance assists the designer in understanding the parameters that have the greatest impact on performance. The neural networks can represent more complex functions but will need more training data in addition to proper regularization since there is the danger of overfitting.

Figure 3 shows the trend of error as a function of training data for each family of algorithms. These curves demonstrate the anticipated decreasing-returns effect whereby gains in prediction accuracy become smaller as the number of data samples increases. It is evident that the random forest model produces very low errors on small training sets, whereas the neural network demands a larger data set to obtain similar results. There are practical consequences of this observation when considering simulation budgets: on design projects in which simulations are costly and budget is limited, tree-based models might prove to be a better bargain in the beginning phases.

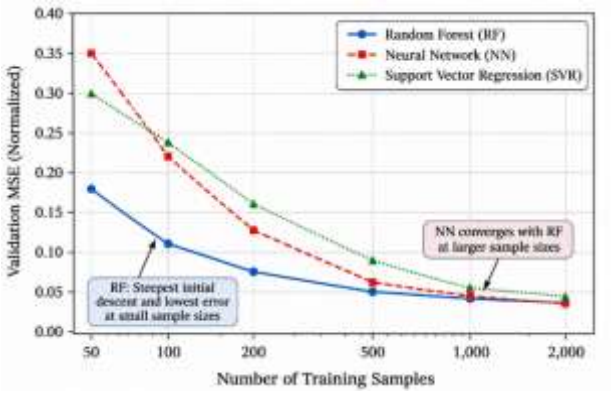


Figure 3: Surrogate prediction error as a function of training set size for three algorithm families

The effectiveness of the loop optimization is illustrated in Figure 4, where the evolution of the optimal solution design quality in relation to the total number of full-wave simulations performed by the three approaches, evolutionary optimization (all simulation calls are used for candidate evaluation), surrogate-assisted optimization using random forest and neural network, is presented. It should be noted that the two surrogate-assisted optimization lines demonstrate a typical behavior, characterized by slow progress at the beginning, when the training set is being formed, and fast evolution later on, as soon as the surrogate is sufficiently accurate to be used for guiding search.

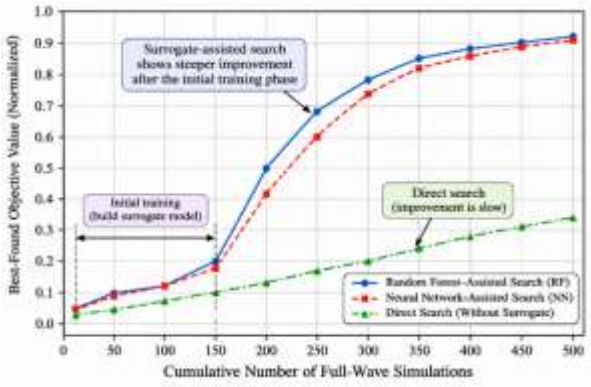


Figure 4: Optimization progress versus cumulative full-wave simulations

Another factor of importance is the robustness of predictions obtained by surrogate models to perturbations in the values of parameters. Variability in antenna construction implies that the actual performance of such structures will deviate from the optimal value at least within some tolerance range. If a surrogate model is highly accurate only in the vicinity of training data points, it may deliver erroneous advice when tolerance ranges of parameters are taken into account. Figure 5 shows how different algorithms perform in terms of robustness to perturbations of input parameters, measured in terms of standard deviation of predictions made under small random perturbations. Random forest algorithm yields smaller prediction variance due to the averaging effect inherent in ensembles.

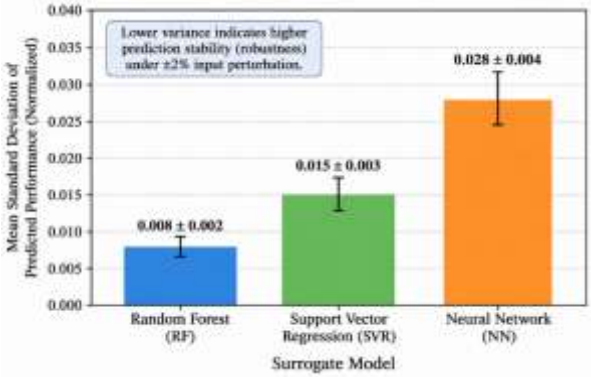


Figure 5: Prediction stability under input perturbation for three surrogate models

The quantitative results together imply that there is no algorithm that rules over all the criteria. However, the selection of a surrogate would depend upon the

context of design. In case of small simulation budgets with moderate input dimensions, random forest appears to be a sensible choice. In case of highly nonlinear problems and large simulation budget, the neural network algorithm could yield better ultimate accuracy. A reasonable approach would be to start with random forest and then switch to a more sophisticated model as more data is obtained.

V. CONCLUSION

In this paper, an optimization framework based on machine learning techniques for antenna optimization has been developed. The idea behind the use of data-driven surrogate models in antenna parameter optimization, which significantly cuts down the computation cost of the simulation process, is backed up by the comparison of different algorithm families and loop optimization behavior analysis. This methodology offers a general optimization scheme applicable to various antennas with different purposes ranging from microwave patch antennas to millimeter-wave arrays and terahertz antennas.

The comparison results in a number of useful conclusions for the purposes of design. First, tree-based ensembles, especially the random forest regressor, have attractive properties for antenna parameter tuning with a restricted number of simulations and moderate-dimensional parameter spaces. The fact that they are not sensitive to small training samples, are less sensitive to hyperparameters than other models, and allow estimation of the importance of features makes them a reasonable first option for numerous practical tasks. Second, neural network surrogates have greater representation power but need more data for training and regularization; they should be used if the simulation budget allows sufficient data generation and there is initial indication of the nonlinearity of parameter-performance dependencies. Third, the use of surrogates in an iterative refinement cycle is more efficient in terms of simulation data usage than one-off training on a static dataset.

A more general importance of the current work is in contributing to the trend towards the evolution of the antenna design process from simulation-based approaches to hybrid ones based on a combination of physical modeling and data-driven methods. With the ever-improving performance of electromagnetic simulators, their use might become less advantageous than the use of surrogate models in simple problems. At the same time, the application of machine learning techniques to complicated optimization problems, including multi-objective and high-dimensional optimization of antennas in next-generation wireless networks, is likely to become indispensable. The task facing the scientific community is the development of algorithms which not only are technically advanced but also are deployable in practical design environments under the tight restrictions of available simulation capabilities, time to market, and technological constraints.

Further research can continue along a number of directions from the current study. The analysis of active learning algorithms capable of selecting informative simulation points can help enhance the efficiency of the approach. The inclusion of uncertainty quantification in the surrogate modeling can facilitate risk-averse optimization taking into account fabrication tolerance and modeling error. Lastly, the applicability of the proposed approach at higher frequencies, especially sub-terahertz and terahertz frequency ranges, where the cost of simulation is especially high, seems promising.

REFERENCES

1. A. Dwivedi, A. Dash, and P. Kaurav, "Optimization of 4X2 Slot Array Antenna Based on Gap Waveguide Using Machine Learning Techniques," in *2024 IEEE Microwaves, Antennas, and Propagation Conference (MAPCON)*, Hyderabad, India, Dec. 2024, pp. 1–5.
2. A. Papathanasopoulos, P. A. Apostolopoulos, and Y. Rahmat-Samii, "Optimization Assisted by Neural Network-Based Machine Learning in Electromagnetic Applications," *IEEE Transactions on Antennas and Propagation*, vol. 72, no. 1, pp. 160–173, Jan. 2024.

3. T. Gayatri, G. Srinivasu, D. M. K. Chaitanya, and V. K. Sharma, "A Review on Optimization Techniques of Antennas Using AI and ML/DL Algorithms," *International Journal of Advances in Microwave Technology*, vol. 7, no. 2, pp. 288–295, 2022.
4. Q. Wu, W. Chen, C. Yu, H. Wang, and W. Hong, "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, Sep. 2021.
5. N. Sarker, P. Podder, M. R. H. Mondal, S. S. Shafin, and J. Kamruzzaman, "Applications of Machine Learning and Deep Learning in Antenna Design, Optimization, and Selection: A Review," *IEEE Access*, vol. 11, pp. 103890–103915, 2023.
6. Y.-F. Li, Q. Wu, H.-M. Wang, and W. Yin, "An Efficient Antenna Design Method Based on Machine Learning–Assisted Hybrid Data Modeling," in *2024 IEEE 12th Asia-Pacific Conference on Antennas and Propagation (APCAP)*, Nanjing, China, Sep. 2024, pp. 1–2.
7. M. A. Tulum, A. Turk, and P. Mahouti, "Data Driven Surrogate Modeling of Phase Array Antennas Using Deep Learning for Millimetric Band Applications," *IEEE Access*, vol. 11, pp. 114415–114423, 2023.
8. M. M. Khan, S. Hossain, P. Mozumdar, S. Akter, and R. H. Ashique, "A Review on Machine Learning and Deep Learning for Various Antenna Design Applications," *Heliyon*, vol. 8, no. 4, e09317, Apr. 2022.
9. M. Zubair, M. O. Akinsolu, A. Abohmra, M. A. Imran, B. Liu, and Q. H. Abbasi, "Terahertz Antenna Design Using Machine Learning Assisted Global Optimization Techniques," in *2023 IEEE International Symposium on Antennas and Propagation and USNC-URSI Radio Science Meeting*, Portland, OR, USA, Jul. 2023, pp. 1007–1008.
10. A. Bediaf, R. Bedra, M. Bedra, S. Bedra, D. Arar, D. Benatia, and T. Fortaki, "Backward Design with Machine Learning: A Comparative Study for Predicting Electrical Width of Square Ring Microstrip Antennas," in *2024 International Conference on Telecommunications and Intelligent Systems (ICTIS)*, Djelfa, Algeria, Dec. 2024, pp. 1–4.