Fast and Intelligent Antenna Design Optimization using Machine Learning

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***Abstract*—Traditional antenna optimization solves the modified version of the original antenna design for each iteration. Thus, the total time required to optimize a given antenna design is highly dependent on the convergence criteria of the selected algorithm and the time taken for each iteration. The use of machine learning enables the antenna designer to generate trained mathematical model that replicates the original antenna design and then apply optimization on the trained model. Use of trained model allows to run thousands of optimization iterations in a span of few seconds.**

***Keywords*—antenna optimization, design of experiments, machine learning, regression.**

I. Introduction

In recent times, industries working with large amount of data have recognized the value of machine learning (ML) technology. Thus, it is widely used in financial services to prevent fraud, in health care to assess a patient's health in real time, in oil and gas to find new energy sources, in government services to minimize identity theft, in retail industry to personalize shopping experience, in transportation to make routes more efficient, and many more such applications. However, machine learning has not gained much attention in computer aided antenna design. With the advent of clever design exploration methods such as space filling Design of Experiments (DOE) approaches, machine learning can be used to speed up the antenna design optimization process tremendously. In addition, machine learning can also accelerate other related simulations such as tolerance studies using stochastic methods.

This paper presents how to use DOE and machine learning for fast and intelligent antenna design optimization with an example. Trained Mathematical model is generated using the multi-disciplinary design exploration and optimization software Altair HyperStudy [1] and numerical electromagnetic field simulations are done with Altair Feko [2].

II. Machine Learning

Machine learning is a method of data analysis that automates analytical model building. The machine learning algorithms on a broader scale can be classified into *unsupervised learning* and *supervised learning*.

A. Unsupervised Learning

To understand unsupervised learning, one should first understand what a dataset is: a collection of examples without a specific desired outcome or correct answer – just data. The machine learning algorithm attempts to automatically find structure in the data by extracting useful features and analyzing its structure.

B. Supervised Learning

Supervised learning is best suited to problems where there is a set of available reference points a.k.a. data with labels with which to train the algorithm. The data is generated by extensible sampling or by running simulations in our case of computer-aided antenna design. The two main types of supervised learning are *classification* and *regression.* This paper is focused on the regression method.

Regression models allow us to predict a continuous output variable Y based on the value of one or multiple predictor variables x,

$$Y = f\,(x_1, x_2, x_3, x_4, x_5, \ldots). \tag{1}$$

The goal of the regression model is to build a trained mathematical model a.k.a. machine learning model that defines Y as a function of the x variables. As such, (1) can be used to predict the outcome Y based on new values of the predictor variables x. Though there are several approaches to build the machine learning model Y, some of the typical methods are Least Square Regression (LSR), Moving Least Square Method (MLSM) and Radial Basis Functions (RBF). Regression methods are extremely useful to speed up the optimization process as the evaluation on the trained machine learning model is tremendously faster than the numerical solution of a physical simulation model. Data required to generate the trained model via regression can done by DOE methods as explained in the next section.

III. Design of Experiments [1]

DOE is a series of tests in which purposeful changes are made to input design variables to investigate their effect on the output responses and to get an understanding of the global behavior of a design problem. There are two types of DOE methods:

A. Screening Methods

These methods are mainly used to determine which input design variables and which variable interactions are most influential on the output responses of a given design. Some examples of the screening methods are, fractional factorial, full factorial, Plackett Burman and Taguchi.

Submitted On: August 28, 2020
Accepted On: September 5, 2020

https://doi.org/10.47037/2020.ACES.J.351144

B. *Space Filling Methods*

These methods can do screening to determine which factors are most influential on the output response and generate data that can be used by a machine learning algorithm to come up with a trained mathematical model that can be used as a surrogate in place of the original design. Box Behnken, Central Composite Design, Hammersley, Latin HyperCube and Modified Extensible Lattice Sequence (MELS) are the examples of some of the space filling methods.

IV. Antenna Optimization Using Machine Learning

Machine learning approaches presented in this paper can be applied to any type of antenna design with any number of design variables. The complete workflow of the machine learning approach for antenna design optimization is detailed in the below steps:

- Generate training and test data with an appropriate DOE study and numerical simulation.
- Build a machine learning model based on the generated training data.
- Validate the machine learning model using the generated test data.
- If the validation is not successful, generate additional training data or use a more appropriate machine learning approach.

A slotted patch antenna designed for the GPS application is chosen to demonstrate the above workflow. Fig. 1 shows the design of the square patch whose initial reflection coefficient is illustrated in Fig. 2. The reflection coefficient data clearly illustrates that the initial design has a resonance around the GPS operating frequency of 1575 MHz, but there is ample scope to improve the matching of this antenna by further optimizing this design.

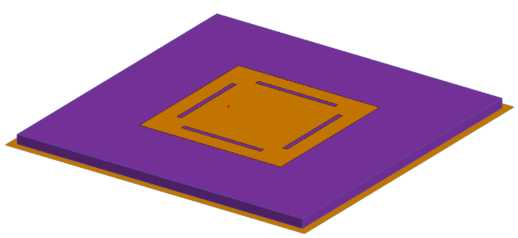

Fig. 1. Slotted patch antenna designed for GPS applications.

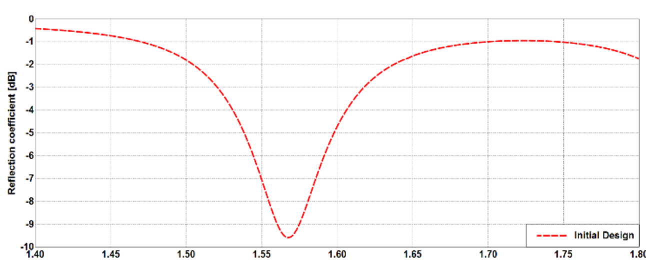

Fig. 2. Reflection coefficient of the initial patch antenna design.

The patch antenna is fully parametric with respect to the patch size, slot length, slot width, slot to edge length and the feed position. To understand the benefits of optimization using machine learning, this approach is compared with the traditional optimization using numerical field simulations. For a fair comparison between the two approaches, the Global Response Search Method (GRSM) optimization algorithm is used in both the optimization approaches. The traditional optimization ran for 250 iterations for a total of 810 seconds.

The first step in the machine learning approach is generating the test data and the space filling MELS method is used for this design exploration. This DOE study will also give a pareto chart illustrating the influence of each design variable on the output response, as shown in Fig. 3.

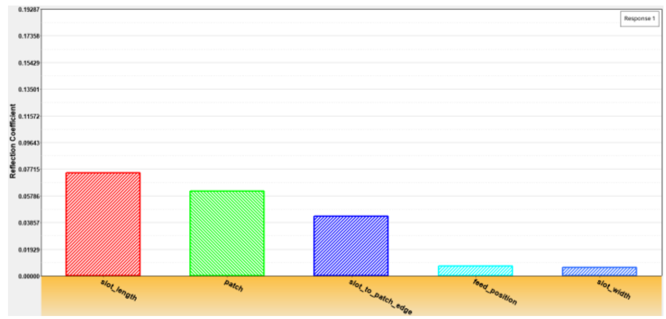

Fig. 3. Pareto chart illstrating the influence of each design variable on the output response.

The test data from the DOE study is then used by the Altair proprietary regression algorithm Fit Automatically Selected by Training (FAST) to generate a trained machine learning model. Optimization is then performed on the trained model rather than using the physical antenna design. Fig. 4 shows the comparison of the optimum reflection coefficient obtained using the traditional optimization and machine learning. The overall time required for the machine learning approach is 168 seconds (as compared to 810 secs) of which a total of 162 seconds is spent in DOE study. This clearly is orders of magnitude faster than traditional optimization.

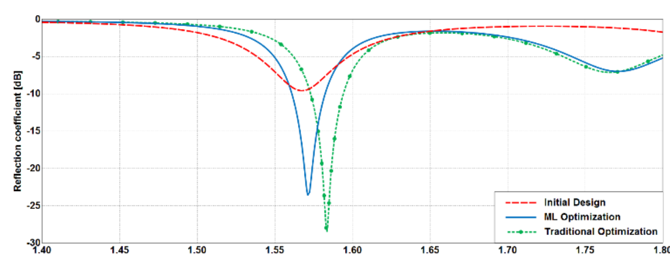

Fig. 4. Comparing the optimum design achieved via machine learning approach to the optimum from traditional optimization.

References

[1] Altair HyperStudy, Altair Engineering, Inc., www.altairhyperworks.com/product/HyperStudy

[2] Altair Feko, Altair Engineering, Inc., www.altairhyperworks.com/product/Feko