An Efficient Optimization Framework for Material and Conductor Designs of Antennas

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Abstract **–Design optimization has become an inevitable task to accommodate for stringent performance requirements of wireless applications. Existing techniques are mainly restricted to parametric design of the size or more recently material of the device. However, to allow for global exploration of novel designs, large-scale design optimization problems need to be solved possibly via efficient reanalysis based on electromagnetic analysis tools. Needless to say, reanalysis is very time consuming, hence is the bottleneck of iterative synthesis problems.. In this paper, a simple but effective technique based on Bayesian trained rational functions is introduced to lower the number of reanalysis calls to a full wave analysis tool. It allows for robust interpolation of frequency based response data, i.e. return loss. The technique is also implemented on a design example.**

1 INTRODUCTION

Design Optimization has been a difficult, demanding but necessary task for the development of novel wireless applications. Among others, particular applications include miniaturized antennas without sacrifice in their bandwidth and radiation efficiency. The need for design, preferably design optimization is pertinent to the competing physics of these metrics, which has been the focus of researchers for the past two decades. It is reasonable to expect that designs resulting from global design optimization studies possibly allowing for full design space exploration including antenna shape, size, feed location and material will lead to novel configurations with enhanced performance. However, global synthesis via heuristic search techniques especially within the topology optimization framework allowing for such explorations is a challenging task due to the bottlenecks of fast and accurate reanalysis. Therefore, unless design studies are limited to only a few number of design variables, heuristic/ evolutionary search studies can become impractical. To address this issue, in this paper an approximation scheme suitable for frequency sampled Finite Element Analysis response of electromagnetic systems such as miniature broadband antennas is investigated. The goal is to develop an efficient and reliable scheme that will allow for fast reanalysis to be implemented in large scale global design optimization studies. Polynomials, multiquadrics [1], kriging [2] and artificial neural networks (ANNs) [3] are examples of interpolating techniques/surrogate models used so far. They all serve a common purpose to provide a 'virtual' objective function to be called by the optimization algorithm. Many Response Surface Methods [4], [5], space mapping techniques [6] or combinations thereof [7] are documented recently coupling especially the aforementioned approximation techniques with stochastic algorithms. The scheme in this paper is based on the Bayesian trained quadratic rational functions. Unlike other naïve techniques such as linear approximation that fails to predict resonance behavior, the proposed quadratic rational function effectively emulates resonance with an overall better accuracy than uniformly sampled data with twice as many frequency points. When compared with other known data training approaches, the Bayesian trained rational function proves to present a powerful yet simple approximation capability based on statistics and just a single controlling parameter, *coef*. An in-depth analysis of the proposed interpolation's efficiency and reliability follows its use in designing miniaturized broadband antennas via the dielectric and conductor topologies.

2 Approximation Method: Bayesian trained quadratic rational functions

The trained data in this paper relates to the return loss response of an antenna model that comprises a geometry discretized by 400 volumetric and 400 surface finite elements. Properties such as permittivity, permeability and conductivity of each cell could be assigned as design variables in a topology optimization problem. Conductors could attain discrete values of 0 or 1 representing the on/off feature of a conductor, hence a possibly conductor topology. The use of popular heuristic (global) based techniques to optimize the device and locate the global optimum will call for multiple reanalysis of the full-wave bandwidth response of a binary

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encoded large scale design problem. In order to predict the return loss response accurately, a frequency sampling of 10 MHz is needed (Fig. 1). The on/off nature of conductors is observed to result in high oscillations/multiple resonances within the frequency range of interest (1-2GHz) for various topologies. This makes accurate interpolation of the response an extremely challenging task. The optimization model with 101 frequency points and N individuals/function of a micro-GA, micro-Genetic Algorithm, would call the FEA model 101N times for each generation until convergence is achieved. Carefully reselecting design variables, speeding-up the simulation runs for the analysis and optimization are among remedies to reduce computation time. In this paper we focus on sampling with lower number of frequency points (21 vs. 101) and investigate the possibility of predicting the cost function reliably by interpolation using quadratic rational functions. The numerator and denominator of the chosen rational function are of second order, and are therefore named as 'quad-quad'. The minimum order is chosen to closely follow the behavior of the return loss curve. To ensure smooth continuity of successive intervals for highly oscillatory response, we impose boundary conditions for zeroth and first order derivatives at end points. Quad-quad equation (Eq. 1) is solved analytically for β_i coefficients satisfying these boundary conditions.

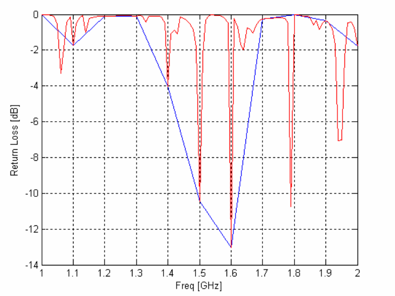

Figure 1: Representative return loss response of multi-resonant patch antenna: Sampled with 10 MHz interval (blue) and 100 MHz interval (red).

$$y = \frac{\beta_1 + \beta_2 x + \beta_3 x^2}{1 + \beta_4 x + \beta_5 x^2} \qquad (1)$$

In addition to the 4 boundary conditions, a constraint is imposed on the denominator to attain complex roots inside the frequency interval of interest, the imaginary part of which is required to be small enough (by 0.5 determined empirically) in order to emulate poles of the return loss response. This constraint is enforced via a tuning coefficient, *coef that* relates β_4 to β_5. The boundary conditions in a non-dimensional frequency interval $x \in [0\ 1]$ are given by $y(0)=y_0$, $y'(0)=y'_0$, $y(1)=y_1$, $y'(1)=y'_1$.

$$\beta_1 = y_0$$
$$\beta_4 = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a} \qquad \begin{cases} a = -(coef/4)y'_1 \\ b = y_1 - y_0 - y'_1 \\ c = 2(y_1 - y_0) - (y'_1 + y'_0) \end{cases} \qquad (2)$$
$$\beta_2 = y'_0 + y_0 \beta_4$$
$$\beta_3 = y_1\left(1 + \beta_4 + (coef/4)\beta_4^2\right) - \beta_1 - \beta_2$$

Complex roots of the of quadratic function denominator are calculated via Eq. 3. Roots are enforced to be complex in intervals where a pole is desired. Moreover, their real part has to fall within [0 1], i.e. the desired interval and the imaginary component has to fall within the interval [0.1 0.5] to ensure a good pole prediction in that interval. To ensure satisfaction of these conditions, piecewise defined equations are solved for various feasible coef ranges. Complex roots of the denominator and/or possible complex solutions of β's still ensure boundary condition satisfaction at the interval endpoints since the possible imaginary component of quad-quad vanishes at the boundaries (i.e. BCs are real).

$$r_{1,2} = \frac{\dfrac{b}{coef.c} - \dfrac{\mathrm{sgn}_1 \mathrm{sgn}_2 \sqrt{1-coef}\sqrt{b^2 + coef.y'.c_2}}{coef.c} + \dfrac{\mathrm{sgn}_1 \sqrt{b^2 + coef.y'.c_2}}{coef.c} - \dfrac{b.\mathrm{sgn}_2 \sqrt{1-coef}}{coef.c}}{} \qquad (3)$$

In order to predict the optimum *coef* of a specific interval, the use of Bayesian classifier [8] seems to be appropriate since it recognizes the probabilistic nature of the training set and assigns classes to the test sets accordingly. The goal is to classify the intervals' BCs so as to minimize the probability of *coef* misclassification. In *d*-dimensions the general multivariate normal probability density function is written as:

$$p(\mathbf{x}) = \frac{1}{(2\pi)^{d/2}|\boldsymbol{\Sigma}|^{1/2}} \exp\left\{-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1}(\mathbf{x}-\boldsymbol{\mu})\right\} \qquad (4)$$

where $\mathbf{x}$ is the variable vector (i.e. BC), $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$ are, the mean vector and *covariance* matrix of the training set and *d* refers to the dimension of the problem (i.e. number of BC). *coef* for each interval is assigned to the class with maximum probability.

3 Design optimization example

The proposed approximation scheme is adopted in this section to a design example. The goal is to identify in some automatic process the conductor composition and material permittivity of a probe fed antenna subject to maximum bandwidth performance. By definition this is a large scale conductor topology optimization problem. The design optimization procedure is based on the integration of an analysis module (via the hybrid Finite-Element Boundary-Integral method) with the on/off design approach to be solved via a heuristic optimization tool, the micro-GA. By virtue of the Finite Element Modeling, the simulator is suitable for complex structures such as those involving inhomogeneous dielectrics and resistive or conducting patches, etc. The optimization process systematically and iteratively eliminates and re-distributes conductor topologies throughout the design domain, comprised of surface conductor cells and varies the dielectric constant to obtain a concept structure.

The antenna volume is 0.3173x2.5x2.5 cm and the conductor patch area comprises top surface on the dielectric substrate and the feed is located as shown in Fig. 2. The substrate is discretized into 20x20=400 volumetric FE cells (see Fig. 2), the pemittivities of which are the same as the layer permittivity in the chosen design problem but could also be assigned as design variables.

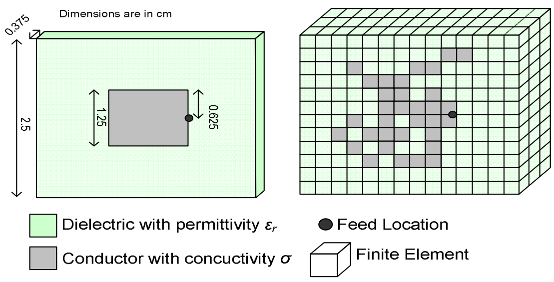

Figure 2: Schematic of patch antenna on homogeneous substrate (left) and discretized model with arbitrary metallic patch cells (right)

In this design case, the conductor is a random arrangement that can occupy 40x20=800 triangular FE cells. To allow for more practical geometries, a single design variable is assigned to two adjacent triangular cells, resulting in various conductor topologies via on/off nature of 400 cells. Also, permittivity of the supporting homogeneous substrate is an additional design variable. We will refer to this case as MPE, multi-patch epsilon problem. The return loss response is calculated at 10 MHz and 50 MHz frequency samples with both a linear and the proposed quad-quad interpolation schemes within a frequency range of operation of 1-2 GHz. The initial design of the MPE problem is shown in Fig. 3. It corresponds to an arbitrary initial conductor distribution provided by GA on a dielectric substrate with relative permittivity ε_r = 13.07. The results of the optimization study are provided in the next section

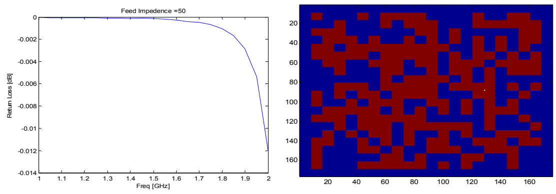

Figure 3: MPE Initial design return loss performance (left) and conductor (red patches) distribution (right) on εr = 13.07 substrate.

5 Results

The quad-quad response relies on first order derivatives computed numerically at 'close (~0.1%)' points via forward finite difference at sampled data points. The efficiency and accuracy of the quad-quad is compared with linear interpolation of exact same frequency points and with double number of frequency points (i.e. same number of analysis runs as the quad-quad). The first error measure is the square sum of error difference between predicted and original return loss curves at 550 intervals. Bayesian classifiers are used to predict the optimum *coef* of the fitted curves. The results indicate an overall error increase of the quad-quad vs. the double sampled linear fitting by 52% and a decrease by 11% vs. single sampled one, as shown in Fig. 5. However, better matched nulls with quad-quad prompt for reinvestigation of the error measure such as the bandwidth, where bandwidth is defined based on matched nulls in the original and fitted curves. Their difference is summed up over the entire frequency range to predict the overall error (see Fig.6). Results show that quad-quad predicts an error decrease by 25% and 54% with respect to double and single sampled linear fitting, respectively -a significant improvement over the previous case. The design cases with larger error are re-examined and displayed for a specific interval in Fig.7. Although the center plot is in favor of the double sampled linear interpolation, perturbing sampling points to the left or to the right (left and right plots, respectively) shows that double sampled linear approach is more viable to data change whereas the quad-quad consistently predicts the null and approximates bandwidth. This qualitatively shows that the quad-quad is more robust with respect to sample data but adaptive sampling for non-uniform frequency sampling might reduce computational efficiency. This is a topic for future work. The GA converged to the final result shown in Fig. 8 with a 27% bandwidth at -5dB. Considering no resonance initially the results attained with only 20 frequency point sampling of the quad-quad interpolation and a single homogeneous dielectric layer, the results motivate its use and further work. Moreover, an impossible design search (lasting about a week for a single trial) has become practical via proposed interpolation technique (about 90 generations in about 1.5 days on 3.4 GHz CPU processor). It is noted that variation of a multi-layer dielectric substrate could enhance matching of the attained -5dB return loss and will be explored next.

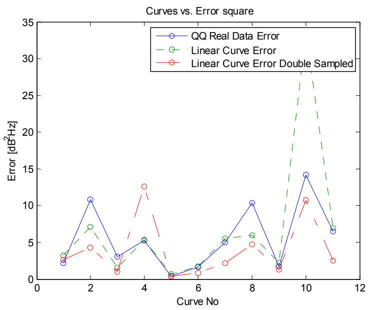

Fig. 5: Square of error vs. design number

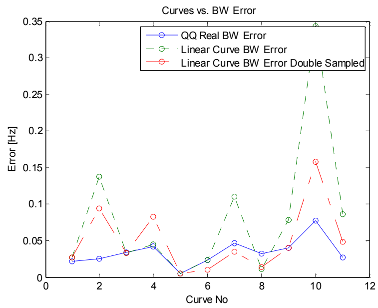

Fig. 6: Bandwidth error vs. design number

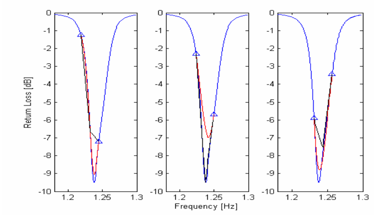

Fig. 7: Data point (triangle) perturbation effect on quad-quad (red) and linear double sampled (black)

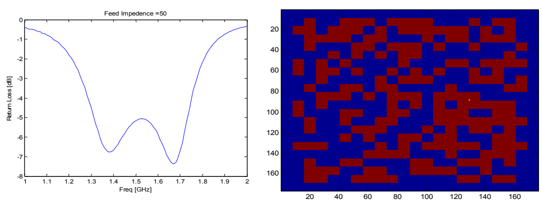

Fig. 8: Optimization results for MPE problem: Return loss (left) of conductor (red patch) distribution (right) on a dielectric substrate with $\varepsilon_r = 6.7515$

6 Conclusions

In this paper we proposed an interpolation scheme based on Bayesian trained quadratic rational functions for approximating frequency based electromagnetic functions, here the return loss. Results indicate that this scheme is able to predict poles and characterize resonance behavior efficiently. The method was demonstrated on a large scale design optimization problem. Future work includes adaptive selection of sample points and additional tuning on poles of quad-quad for better Bayesian classifier, hence a more efficient and reliable fitting scheme.

Acknowledgment

This work was supported in part by Yousef Jameel scholarship.

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