Design and Optimization of 3D RF Modules, Microsystems and Packages Using Electromagnetic, Statistical and Genetic Tools

N. Bushyager [1], D. Staiculescu[1], L. Martin[2], J.-H. Lee[1], N. Vasiloglou[1], M. M. Tentzeris[1]
(1) Georgia Electronic Design Center, School of ECE, Georgia Tech, Atlanta, GA 30332-0250, U.S.A.
(2) Motorola, 8000 Sunrise Blvd., Plantation, FL, 33322, U.S.A.

Abstract

The successful use of the Design of Experiments (DOE) and Response Surface Modeling (RSM) approaches in an optimization study for a multilayer interdigitated passband filter is presented. The medium of interest is Liquid Crystal Polymer (LCP) and the frequency band is in the 60 GHz range. The two figures of merit chosen are the resonating frequency f_o and the quality factor Q with the optimization goals of f_o = 60 GHz and maximum Q. The electromagnetic performance of the filter is determined with a Method of Moments commercial simulator. The results of these simulations are incorporated into DOE and RSM techniques, statistical models are developed for the two output variables, and then applied to optimize the filter. The effectiveness of the method is compared to that of the Genetic Algorithm (GA) optimization.

I. Introduction

Modern RF 3D modules and packages [1] demand a high level of compactness and functionality. As the problems associated with the integration involve more and more factors to be considered, the optimization of such systems requires more comprehensive and sophisticated tools. The current optimization methods incorporated in commercial simulators like High Frequency Structure Simulator (HFSS) [2] and IE3D [3] do not take into account the specific effect of each of the factors involved in the design process, the degree these factors are interacting with each other and their ranges of values. Only this type of thorough understanding of the entire system can enable the optimization and synthesis of any module or microsystem under different given conditions. The combination of Design of Experiments (DOE) and Response Surface Modeling (RSM) to be presented in this paper allows all these goals to be achieved. The presented methodology integrates simulation, measurements and statistical tools and is applied for the optimization of a benchmarking geometry of interdigitated filters in LCP technology.

The optimization is performed with respect to the geometrical parameters that affect the performance of the filter in terms of resonant frequency and bandwidth. These are identified to be the length of the coupled lines and the gaps between them. The effect of each of these parameters can be determined by comparing the performance of configurations for different values of these parameters. The number of cases required by varying them can be very large and their fabrication time consuming and expensive, so the analysis has been made using IE3D, a very accurate Method of Moments commercial simulator. This way, the parameter variation can be carried out numerically in a significantly quicker and inexpensive way.

The hybrid design procedure begins with identifying the parameters and the ranges of variation. The ranges, i.e. the design space, have to be chosen to include the fabrication value range while providing sufficient variation in performance. The optimization variables are the resonating frequency and the quality factor of the bandpass filter. The results of the simulations are incorporated in DOE [4] and RSM [5] statistical topologies. First, the effect of each factor on the output variables is understood and the insignificant variables are eliminated from further analysis. Then, explicit statistical models are developed for each of the figures of merit and the optimization is done using these models.

The nonlinearity of the system, combined with the lack of analytical input-output description suggest the use of soft computing algorithms also. Genetic algorithms (GA) [6] can be utilized as an optimization method of this kind. GA search the parameter space stochastically generating solutions that are close to the optimal. They also turn out to be very efficient for problems where small perturbations in the optimal solution lead to abrupt increase of the error. Although the requirement of more iterations makes GA more computationally heavy and time consuming, it is used for a comparative evaluation and validation of the DOE/RSM method.

The proposed technique can be applied to any type of designs, especially in complex RF microsystems and packages, where the number of factors increases and it is extremely difficult to optimize using only electromagnetic simulators. It gives a thorough understanding of the system behavior and integrates geometrical, material and functional parameters altogether. The presented approach is generic and independent of the choice of the electromagnetic simulator and statistical analysis software.

II. Benchmarking Structure

The benchmarking structure analyzed in this paper is presented in Figure 1. The interdigitated filter is located on the top of a LCP substrate and consists of quarter wavelength parallel coupled lines, which alternate between the short- and open-circuited ends. All lengths and spacings are determined by self capacitances and mutual capacitances respectively, taking into consideration the inevitable fringing capacitances. This interdigitated filter is symmetrical for better phase and delay characteristics. The desired operation is around the center frequency of 60 GHz with minimum bandwidth (desired values between 6 and 7%).

In order to optimize this structure, the range of the filter parameters' values has to be determined. The four design parameters that dramatically affect the filter performance are shown in Figure 1: L is the length of the quarter wave resonator, and G_1, G_2 and G_3 are the gaps between the resonators. The filter is symmetric, so G_1 and G_2 are the same for the other half of the structure. The widths of the 3 lines are kept constant at W_1=193, W_2=146.5 and W_3=146 µm and the structure is symmetrical.. These values of the widths were calculated from the self capacitance of the lines, chosen to satisfy the ripple specifications.

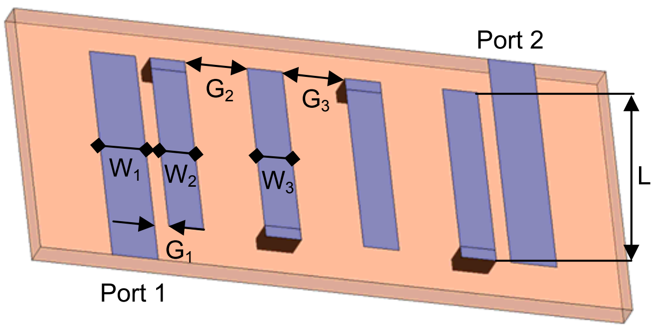

Figure 1. 3D schematic of the interdigitated passband filter.

The chosen technology is the Liquid Crystal Polymer (LCP), with a 2.9 dielectric constant and a 0.002 loss tangent. The substrate is 100 µm thick, enough for small variations of thickness to have no significant effect on the field penetration.

First, a preliminary design of the filter has been simulated. Then, the design space for the four parameters has been chosen such that it represents physically realizable values without severely affecting the filter performance. The three gaps between the coupled lines were determined from the mutual capacitance condition, chosen to satisfy the bandwidth specification. The ranges for the four input variables are presented in Table 1.The center frequency f_0 and the quality factor Q are the responses for the statistical models.

Table 1. Ranges for the input variables

Variable	Min (µm)	Max (µm)	Nominal (µm)
L	750	800	775
G_1	54	66	60
G_2	225	285	260
G_3	225	285	260

Since the statistical model is based on deterministic simulations, the variation of all parameters was statistically simulated based on a ± 2.5 µm tolerance and a 3σ process. Specifically, the values of the parameters were randomly generated assuming means equal to the nominal target and standard deviations equal to 0.8333 µm for the center points of the DOE and RSM experimental designs.

The procedure used in the development of the statistical models is presented in Figure 2.

The experimentation method chosen for the DOE is a full factorial design with center points. The factorial designs are used in experiments involving several factors where the goal is the study of the joint effects of the factors on a response. Prior knowledge of the analyzed system is required for choosing the factors and their studied ranges. The 2^k factorial design is the simplest one, with k factors at 2 levels each. It provides the smallest number of runs for studying k factors and is widely used in factor screening experiments [4]. The design used was a 2^k factorial design with center points to increase capability of investigating model fit, including curvature in the response. The statistical analysis of the first order model shows which parameters are significant for each of the two figures of merit and the ones that are not significant are eliminated from further analysis. Then, the model is checked for ultimate lack of fit, that is, lack of fit that can not be resolved with transformation. If an ultimate lack of fit is found, curvature in the output response can be investigated. If curvature in the response is detected, RSM can account for curvature through second-order model development. Usually, these second-order models are reasonable approximations of the true functional relationship over relatively small regions. Once validated, the models are approximately equivalent to the actual system within the defined design space.

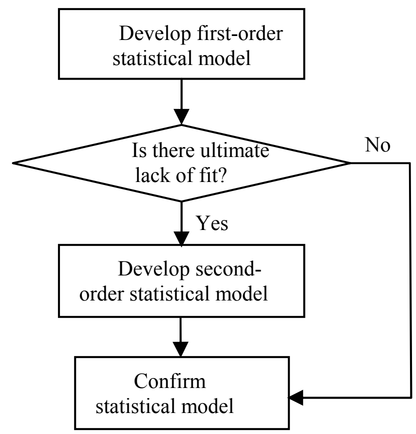

Figure 2. Procedure for statistical model development

In this case, a 2^4 full factorial DOE was performed for the first-order statistical model and a rotatable CCD (central composite design) [5] for the second-order statistical model. Once the first- and second-order models were validated for the model assumptions, the final statistical models were confirmed for prediction of the output variables and an optimization of the tested filter performed. The optimized values have been compared to the Genetic Algorithm results for the validation of the method.

III. Statistical model development

The DOE first revealed the significant parameters for both figures of merit and then first-order prediction models were developed based on them. At the 95% confidence level, it was found that all four parameters are statistically significant for both figures of merit. It was also found that there is ultimate lack of fit for the first-order model to the quality factor Q, and it was detected, by inspection of the model validation diagnostics, that this was due to the curvature in the response.

The following step was a second-order model development for the figures of merit using RSM. The analysis of the second-order RSM data agreed with the results found for the DOE that, at the 95% confidence level, all four parameters are statistically significant for both figures of merit. The curvature was alleviated by L^2 and G_2^2 terms. Additionally, the model for resonating frequency f_o was validated for model assumptions of normality and equal variance of the residuals. The model for quality factor Q was validated for normality assumption, but there appeared to be a slight funnel of residuals, increasing with increasing response, when the equal variance assumption was investigated. This is due to the fact that, for these values of the quality factor, the overall filter performance starts degrading and therefore, higher Q's than these are not attainable. These models were taken as the final models and are given by the (1)-(2).

$$f_0 = 60.811 - 1.845\left(\frac{L-775}{25}\right) - 0.057\left(\frac{G_1-60}{6}\right) + 0.164\left(\frac{G_2-260}{25}\right) - 0.1\left(\frac{G_3-260}{25}\right) + 0.07\left(\frac{L-775}{25}\right)^2 - 0.094\left(\frac{G_2-260}{25}\right)^2 \quad (1)$$

$$Q = 15.42 - 0.345\left(\frac{L-775}{25}\right) + 0.292\left(\frac{G_1-60}{6}\right) + 1.104\left(\frac{G_2-260}{25}\right) + 0.474\left(\frac{G_3-260}{25}\right) - 0.104\left(\frac{L-775}{25}\right)^2 - 0.349\left(\frac{G_2-260}{25}\right)^2 \quad (2)$$

IV. Model interpretation and optimization

Because the models are based on the identical model parameters, the models give the possibility to optimize the filter performance with respect to either figure of merit or both simultaneously. They can also be used to predict the performance of the system for a specific configuration.

Before proceeding to the actual optimization, the models had to be confirmed. The confirmation of the models were performed for the following combination of parameters: L = 780 µm, G_1 = 58 µm, G_2 = 250 µm, G_3 = 265 µm. This configuration was simulated in the electromagnetic simulator and was also predicted with the developed models. The results of the simulation, compared to the RSM 95% confidence intervals defined by the lower and upper bounds for the predicted resonant frequency and quality factor, are shown in Table 2.

Table 2. Resonant frequency and quality factor from electromagnetic simulation compared to the RSM 95% confidence intervals

	f_0	Q
Simulation	60.37	14.99
RSM lower bound	60.28	13.96
RSM upper bound	60.45	15.73

Because the simulation values fall into the 95% confidence intervals from the RSM, the RSM models were confirmed.

The next step was the actual optimization of the structure. The optimization goals chosen in this case were a resonant frequency f_0 of 60 GHz and a maximum quality factor Q, i.e. maximum selectivity of the filter. For this optimization, the most significant variables, L and G_2, were varied within the ranges defined for the parameters in Table 1, while G_1 and G_3 were kept at the nominal values of 60 and 260 µm respectively. The surfaces for the two figures of merit as a function of the optimizing parameters are presented in Figure 3. The optimization is done based on the plot in Figure 4. The values that satisfied the two optimization conditions within the ranges presented in Table 1 were L = 786.11 µm and G_2 = 285 µm, leading to the optimized values of the two figures of merit of f_0 = 60 GHz and Q = 16. The RSM optimized structure were simulated in the electromagnetic simulator and the values obtained for the output variables are f_0 = 60.1 GHz and Q = 16.78. These results were further compared to the RSM models by confirming that they fall within the 95% confidence intervals for the RSM at the given set of conditions.

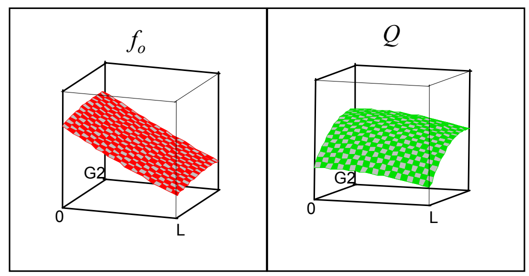

Figure 3. Surfaces of possible solutions for optimized f_0 and Q

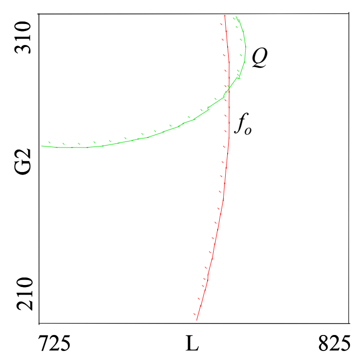

Figure 4. Intersection of the surfaces represent the possible values of L and G2 that satisfy the optimization conditions

V. Validation with a Genetic Algorithm

Genetic Algorithm (GA) optimization was also performed for validation purposes. The full-wave Finite Element Method (FEM) simulator HFSS was used to perform the simulations, controlled by a GA MATLAB script. Since the method is very complex and time consuming, and for simplification of the electromagnetic simulation, the length of the lines was kept constant at 775 µm and only the second figure of merit, Q, was optimized. The optimization goal is again maximum Q, i.e. maximum filter selectivity.

The optimization scheme was the following: constant L = 775 μm and the three gaps were varied with the constraint that they add up to 580 μm. The parameters of the GA algorithm were set to the following values: population size 5, generation gap between two offsprings 0.6. That means that only the 2 best designs generated each offspring population with the crossover and mutation procedures. The mutation probability was set to 0.7. In the first optimization scheme the algorithm converged very fast after 20 generations, giving an optimal Q=15.78. Figure 5 shows the convergence of the algorithm. The same optimization was performed with RSM and the comparison between the two optimizations is summarized in Table 3. Figure 6 shows good agreement for results from the two optimization approaches.

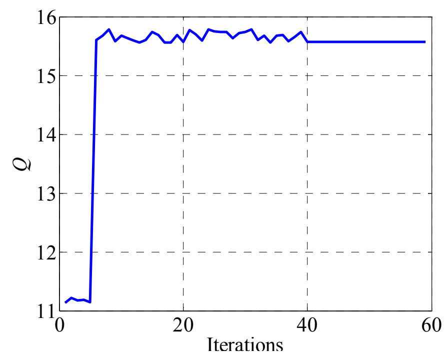

Figure 5. Convergence for two-factor GA optimization

Table 3. Comparison between the two optimization methods

	RSM	GA
Optimal *Q*	15.55	15.78
G_1 (μm)	55	55
G_2 (μm)	285	278
G_3 (μm)	240	247

The requirement of more iterations makes GA more computationally intensive and time-ccnsuming. On the other hand, it can provide better search in the range of the optimization variables. The DOE-RSM method is a fast, effectively instantaneous design tool, once the models are developed, but may odel sufficiently only small design spaces, where errors due to behavior in the response beyond second-order are sufficiently small .

VI. Conclusions

This paper presents a method in which deterministic electromagnetic simulation tools and statistical modeling methods can be used to optimize RF components and microsystems. To prove the concept, a benchmarking geometry of an interdigitated filter in LCP technology was chosen. The two optimized factors were the center frequency and the quality factor. Four physical parameters of the filter were chosen as optimization variables. The results of the hybrid electromagnetic-statistical analysis generated statistical models that could be used to predict the filter performance based on the geometry of the structure. These models could then be used to optimize the filter with respect to desired performance, enabling the system-level optimization of the geometry in quick and inexpensive way. In this case, the center frequency was chosen and the bandwidth was minimized to exemplify the possibilities of the method. The results were verified with the more complex GA optimization and good agreement has been observed.

The proposed approach can be easily extended to a larger number of design variables and optimized figures of merit. In this way, the behavior of a complex system, such as a 3D multilayer module, could be predicted and optimized at the beginning of the design process, leading to significant time savings and a much shorter design cycle of added functions, while achieving the design and optimization goals in a simple and elegant manner.

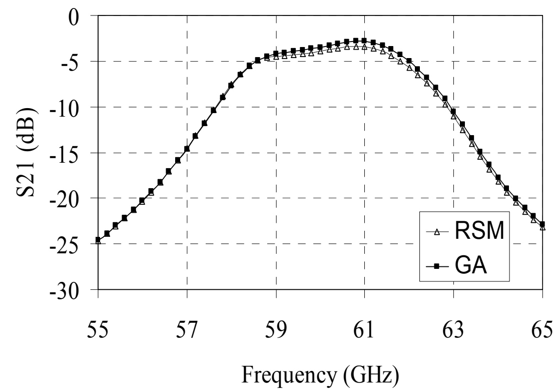

Figure 6. Comparison of the performance of the optimized filter using the two methods.

Acknowledgments

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