

Statistical Construction of a Representative CAD Model from a Measured Population for RF Design Applications

William Leiker and Krishna Naishadham

RF Engineering R&D, Philips Broadband Networks, Manlius, NY, 13104, USA

Abstract: Component models available in CAD software do not consider statistical variation and layout or package parasitic effects of components. Because of the complexity of device packages, EM simulation can only be used to analyze relatively simple circuits. In this paper, we present a methodology to statistically construct a representative SMD component model from a *measured* population, and show how such a model can be used in a circuit simulator for effective *first-pass* design, which incorporates all the parasitic effects through measurements. Using measured component data in optimization and yield analysis is expected to enable CAD packages to reduce considerably the number of design cycles.

I. INTRODUCTION

Computer Aided Design (CAD) is crucial to reducing RF product development cycle time. CAD packages have improved so that they not only allow for simulation and modeling, but also for optimization and yield analysis of RF and microwave circuits. These features become even more powerful when coupled with the ability to use measured data for the components, which incorporates all the layout and device package parasitic effects. Implementing these features together can truly reduce the number of prototype cycles and increase speed to market.

RF circuits designed in CAD packages using components measured and modeled without consideration of the environment in which they will be used (layout, package, loss), do not correlate closely with actual prototype unit responses [1] – [2]. For example, the parasitic effects caused by a different layout may result in different resonant frequencies for the same capacitor or inductor [3]. Therefore, CAD optimization and yield analysis are limited in accuracy by the quality of the component models available in the software library. Inevitably, these library models do not include the layout and package effects. This may actually result in additional design iterations and prototype builds by focusing on why the model does not correlate with the prototype unit.

With the increase in speed and memory of computers, the technological capability of CAD packages is quickly expanding. The ability to now incorporate measured component data into the simulation and analyze the results using advanced numerical methods has opened the door for improving the correlation between a simulation and the prototype build. However, to be effective in reducing the number of design cycles, the measurements must include the process and material-related statistical variation of the components and consider their extrinsic (functional) design environment. This enables us to evaluate *apriori* the long-term performance variation of the circuit.

Another important enabling factor of the measured data models is the ability to perform optimization and yield analysis in CAD packages using realistic data. This paper discusses a methodology to statistically construct a representative component model from a *measured* population and shows how such a model can be used in a circuit simulator for effective *first-pass* design incorporating the relevant parasitic effects through measurements. This work is expected to lay the foundation for using measured data properly in CAD simulators to achieve first-pass design success.

II. REPRESENTATIVE SAMPLE

For any simulation using a component's data, it is paramount that the data properly represent the component population. There are two key factors to consider. First, for optimization with component data files in RF CAD simulators, the optimizer considers one set of values (usually a set of S-parameters) across the frequency band. Therefore, the entire component population must be represented by one set of values. The second factor is that the yield analysis portion of the simulation requires multiple measured files from which the simulator makes random selections. These files are then included in the circuit simulation and the output of the circuit is compared to the specification for pass/fail analysis.

A given component has multiple sources of variation: within lot, lot-to-lot and supplier-to-supplier. The process used for selecting a representative S-parameter set of values must account for these variation sources in a statistical sense. The process should sample multiple units from each supplier over multiple lots. This sampling yields information about all the major sources of variation that a production circuit will encounter. Since it is impractical to consider the entire population, appropriate sampling techniques need to be employed to reach a manageable sample size. As an example, suppose that there are C lots of a resistor to choose from, and we need to estimate the number of samples, R , from each lot. Using ANalysis of VAriance (ANOVA), for a given power of hypothesis test, denoted as $p = 1 - b$, and confidence level $1 - a$, we can use the power tables to estimate R from the statistic

$$\Phi = \frac{1}{S_s} \sqrt{\frac{R \sum_{j=1}^C (\bar{m}_j - \bar{m})^2}{C}} \quad (1)$$

where \bar{m}_j is the mean within a lot, \bar{m} is the overall mean, and S_s is the standard deviation of the sample [4]. The power is tabulated in terms of a , Φ and the degrees of freedom $n_1 = C - 1$ and $n_2 = (R - 1)C$. Normally, we choose $p = 0.9$, $a = 0.05$ (95% confidence), calculate Φ from the Tables, and estimate the sample size iteratively using eq. (1). This approach suggests data collection for each supplier from four randomly sampled lots spanning a year and five units sampled from each lot. This results in twenty samples per supplier.

III. COMPONENT SELECTION

After the S-parameter data is taken from all the samples, the focus becomes how to pick a representative sample for use in the CAD optimizer. Using statistical methods for choosing the mean response of all the data has a couple of problems. First, there is a chance that the laws of physics do not hold with the mean data. For example, all the measured samples' S-parameters satisfy the energy conservation principle for a lossless passive circuit,

$$|S_{11}|^2 + |S_{21}|^2 = 1 \quad (2)$$

and yet, this relation may not hold for the mean. Another problem with using the mean is that any errant or outlier data set from one single component measurement will shift the mean in its direction [5] – [6]. A better technique is to first find the median data set from all the measurements, and then find the *one set of measured component data that best “matches” the median data set*. Finding the

median value is a simple calculation available in any spreadsheet package and may also be coded easily.

The median is not subject to any anomalies in data collection or outlier data. However, if only the median values are used for all the S-parameters in the simulation, physics may again be violated. Hence, we propose that the particular component whose measured S-parameters are closest to the median trace for all the samples be used in the design. This representative, being part of the measured data, does not violate any physical principles.

Fig. 1 illustrates the median data set for one of the four S-parameters, S11 magnitude. Twenty capacitors from different lots of one supplier, spanning one year, were measured. The median at each frequency point is plotted to show the “median data set.” This median data set is required for a “trace matching” algorithm described in Sec. IV, which finds the *measured* trace in the sample closest to the median.

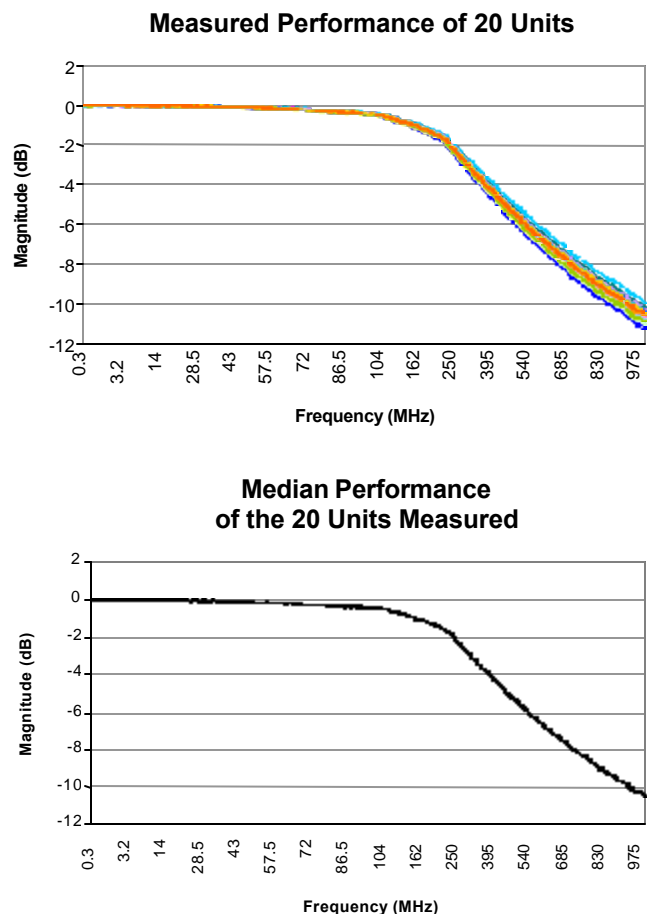


Fig. 1. Twenty measurements of parameter S11, a 3.3 pF capacitor, and the corresponding median trace.

IV. TRACE MATCHING ALGORITHM

One common problem with using Design of Experiments or statistics in RF design is the multiple frequency points in the measurement. Many designers simply use their eyes to try to estimate which trace is “best” or which traces “match” each other the closest. The following discussion focuses on an algorithm that ranks the traces from best to worst, based on their match to the median trace. Thus, the median trace gives a quantitative figure of merit to compare the various measurements.

It is assumed that the S-parameters are measured at N frequency points. Let Γ_{TM} be the S11 magnitude corresponding to the computed trace median, and Γ_{ij} be the i -th frequency point of the j -th component trace. Calculate two ratios from these reflection coefficients

$$P_{ij} = \frac{\Gamma_{ij}}{\Gamma_{TM}} \quad (3)$$

$$Q_{ij} = \frac{\Gamma_{TM}}{\Gamma_{ij}} \quad (4)$$

For further calculation, take the larger of the two ratios

$$R_{ij} = \begin{cases} P_{ij}, & \text{if } P_{ij} > Q_{ij} \\ Q_{ij}, & \text{if } P_{ij} < Q_{ij} \\ 1, & \text{if } P_{ij} = Q_{ij} \end{cases} \quad (5)$$

Note that a perfect match creates a ratio of unity, and therefore, the ratio $R_{ij} \geq 1$. Performing the same for all N frequency points and taking the square root of the sum of the squares, we obtain for the j -th measured component

$$S11_j = \sqrt{\sum_{i=1}^N R_{ij}^2} \quad (6)$$

This metric compares the median trace to measured component traces. The lower the number, the better the measured S11 trace matches the median trace. The larger the number, the worse the match to the median trace.

V. SELECTING BEST OVERALL MEDIAN MATCH

The algorithm above is useful for single trace matching; however, there are four S-parameters. The component that best matches the median for S_{11} may be different than the component that best matches the median for S_{21} . Since the trace comparison metrics for the four S-parameter magnitudes are independent variables, we can find the best overall match from the square root of the sums of the squares for each metric

$$d_j = \sqrt{S11_j^2 + S12_j^2 + S21_j^2 + S22_j^2}, j = 1 \text{ to } N_s \quad (7)$$

where N_s is the number of samples. The result, d_j , can be used for trace comparison. The smallest d_j gives the closest overall match to the median S-parameter data set.

VI. SAMPLE RESULTS

We have designed a simple LC-filter with SMD components, appropriate pad footprints, and transmission line sections. Twenty samples of each component were measured for the S-parameters, and the trace-matching algorithm described in Sec. IV was used to find the best representative of the population. The filter was fabricated on FR-4 substrate using a grounded CoPlanar Wave guide (CPW) architecture and the “best match” components. The filter’s S-parameters as well as the phase delay of the transmission lines were measured on the network analyzer.

Fig. 2 compares the S11 magnitude and phase of the measured filter response, the cascaded model of the filter constructed from measured “best match” components, and

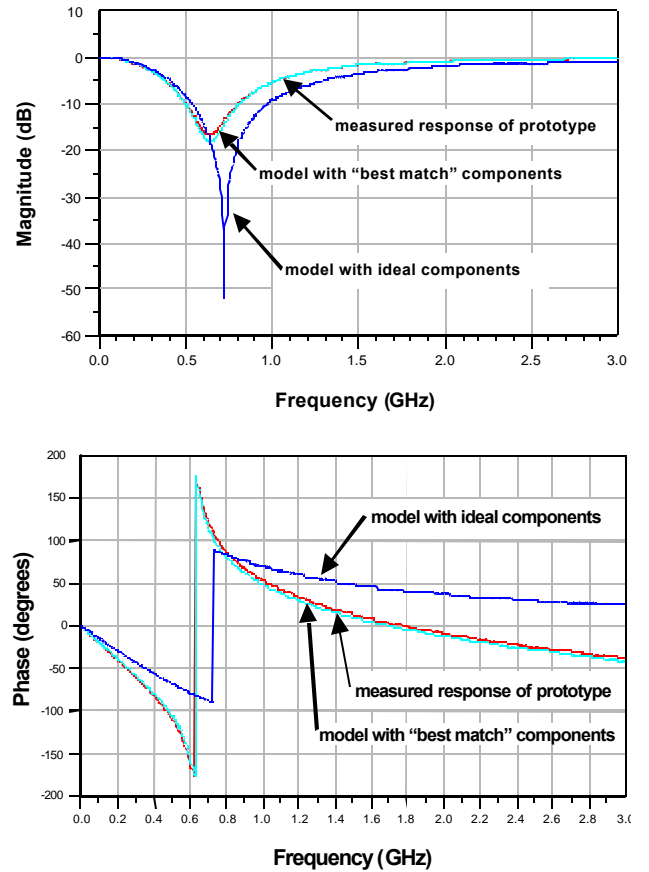


Fig. 2. Magnitude and phase comparison of S11.

the cascaded circuit using resident commercially available lumped element component models. The former two are observed to be in excellent agreement, whereas the ideal circuit model departs significantly because it neglects the pad layout and SMD parasitic effects. Fig. 3 depicts similar agreement in S21 between the same three cases.

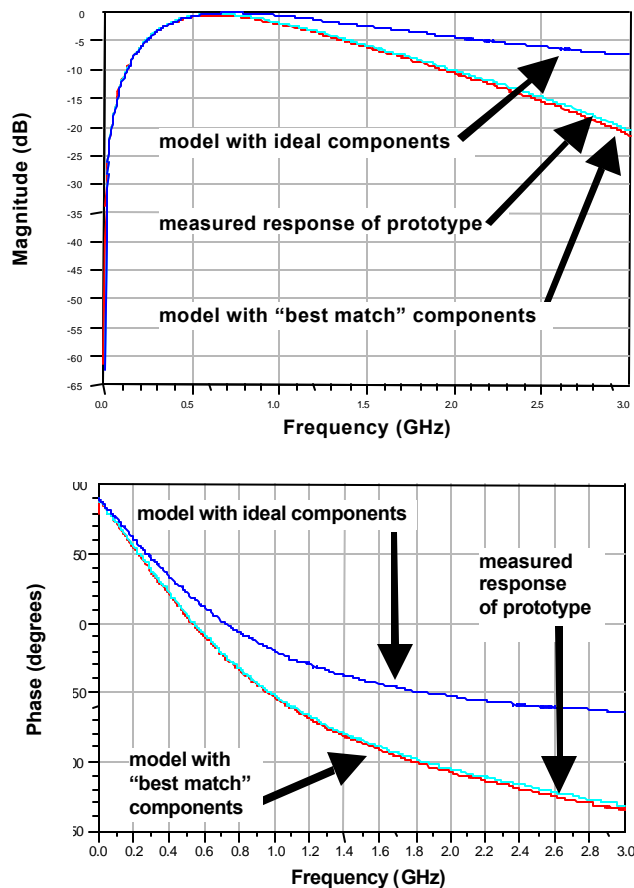


Fig. 3. Magnitude and phase comparison of S21.

The excellent corroboration between measured and modeled performance is achieved *in one design cycle* without any optimization or additional prototype builds. Thus, we have demonstrated first-pass design success for the circuit by utilizing measured component data files of a statistically constructed sample.

VII. CONCLUSION

As computer speed and memory continually increase, CAD simulation packages are getting more and more advanced. These packages may now be used as more than an ideal starting point for designers. The key in reducing the number of design cycles is measuring the circuit components in the actual design environment and using these measurements to construct a component circuit

model that includes package and layout parasitic effects. This paper shows how to construct a representative statistical sample that accounts for within lot, lot-to-lot, and supplier-to-supplier variation of electrical parameters from the component population. A representative component's measured data is used to demonstrate first-pass design success of an LC-filter made from SMD components with appropriate layout footprint and transmission line segments in a CPW environment.

Ranking component traces according to their match to the median trace enables two important facets of CAD simulation packages: optimization and yield analysis. The component's data that closely matches the median value from all the measurements can be used for optimization of the circuit. The component's data that is the farthest match to the median value can be used along with other data, randomly selected from the overall sample, for yield analysis. Thus, using the approach presented, CAD simulators can now optimize circuits based on measured data for components, which accounts for variations due to component tolerances, layout, and package parasitic effects. Designers may then more effectively correlate CAD simulation with prototype builds, resulting in a reduction in the number of design cycles.

ACKNOWLEDGEMENT

The authors wish to acknowledge the support of Senior Engineering Managers Paul Romanowski and Dave Thibado at various phases of this work. Dave Grucza and Tahsin Durak meticulously performed the measurements.

REFERENCES

- [1] D.D. Jatkari and B. Becker, "Effects of package parasitics on the performance of SAW filters," *IEEE Trans. Ultrasonics, Ferroelectrics and Freq. Control*, vol. 43, no. 6, pp. 1187 - 1194, 1996.
- [2] G.A. Hjellen, "Including dielectric loss in printed circuit models for improved EMI/EMC predictions," *IEEE Trans. Electromag. Compat.*, vol. 39, pp. 236-246, 1999.
- [3] K. Naishadham, "Closed-Form Synthesis of Equivalent Circuits for SMD Inductors Incorporating Package-Induced Parasitics," *IEEE Trans. Electromag. Compat.*, vol. 41, 2001 (accepted).
- [4] G. Keppel, *Design and Analysis - A Researcher's Handbook*, Third Edition, Prentice Hall, Upper Saddle River, NJ, 1991, pp.71-86.
- [5] J.R. Juroshek, C.M. Wang and G.P. McCabe, "Statistical Analysis of Network Analyzer Measurements," *Cal Lab, International Journal of Metrology*, pp. 26-31, May 1998.
- [6] N.A. Weiss and M.J. Hassett, *Introductory Statistics*, Second Edition, Addison-Wesley, pp. 56-61, 1987.