A Study of Optimized Algorithm Based on EDA Virtual Laboratory

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Abstract

This paper describes a practical algorithm applied in optimizing the parameters of virtual laboratory. The yield maximization problem is first reformulated into a deterministic design-centering problem. Macromodeling is then applied to solve the efficient design-centering problem. The effectiveness of this methodology is illustrated through a simulation example about virtual laboratory.

1. Introduction

With the development of new computer technologies, the interactive multimedia programming language, and the WorldWideWeb, now, it is possible to simulate engineering and science laboratory projects on computers. Internet resources offer students "virtual laboratories".

The Virtual Laboratory is a part of a process aimed at promoting education, particularly in higher education. It takes good advantage of the available new information and communication technology. In this respect, the project provides students with mobility that enables them to be initiative in learning and follow high-quality electrical courses through their computer monitors. The principal concrete aim of the project is to develop accessible teaching modules through the Internet for fundamental and specialized study projects, particularly for subjects that attract large numbers of students.

However, there are some main difficulties in the project. One of them is prohibitive to high cost of the simulations, which involve the solution of a set of nonlinear partial and/or ordinary differential equations having hundreds or thousands of variables. The high simulation cost propels people to find new efficient methodologies. Two traditional ways to solve the difficulties are as follows: The first is to improve the quality of the programme and the precision of the processing equipment. The second is to design the process (including devices and circuits). The nominal process control parameters (e.g., oxidation time and temperature), device geometries(i.e., layout), or circuit topologies can be optimized.

This paper mainly discusses the design optimization of virtual laboratory. Here, Virtual Laboratory is only referred to the Electronic Design Automatic (EDA). The WorkBench is the same software as our virtual laboratory programme, but it only can optimize 8 parameters. Just as the followed description, the number of the parameters is not limited by the method. This paper focuses on the problem of adjusting nominal process control parameters so as to maximize parametric yield. Meanwhile, modeling is interested because the variable screening is that not all of the input variables exert the same influencing level on each response. The Macromodeling is efficient enough to improve capability so as not to be limited to low dimensional problem.

2. Problem Description of Design-Centering

For the purpose of this discussion, the parametric process yield of EDA circuit is defined

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to possess characters that satisfy a set of acceptability constraints specified by the user. The process yield, Y, can be expressed as follows:

$$Y = \int_{a_y} f_y(y)\,dy \qquad (1)$$

here: y represents vector of device characteristics or responses of interest.

$f_y(.)$ represents joint probability density function(JPDF) of y.

a_y represents output acceptability region in the y-space defined by the acceptability constraints, $y^L \le y \le y^U$，则 $a_y = \{y \mid y^L \le y \le y^U\}$.

In general, the vectory is composed of implicit functions of process variables, and the evaluation of y requires the execution of a process and device simulator.

It is convenient to divide the set of process variables, X, into two groups: the set of designable process control parameters, and the set of nondesignable physical parameters. To emulate the random nature of the fabrication line, each of the process variables is modeled as a random variable and is assumed to be normally distributed and statistically independent from the others. More specifically, the process variables are expressed as

$$x = \begin{bmatrix} x_c \\ x_d \end{bmatrix} + \begin{bmatrix} \zeta_c \\ \zeta_d \end{bmatrix} \qquad (2)$$

here: x_c represents the vector of nominal (deterministic) process control parameter values that are designable.

x_d represents the vector of nominal physical parameter values that are nondesignable.

ζ_c, ζ_d represent vectors of independent Gaussian random variables whose statistical characteristics are assumed to be known a prior[2] and are invariant with respect to their respective nominal parameter values.

The goal of the yield maximization problem (YMP) is to optimize the process yield defined in (1) by the judicious choice of the nominal parameters x_c, that is

$$\max_{x_c} \; Y(x) \qquad \text{subjected to } \; x_c \in D \qquad (3)$$

The methods for solving yield maximization problem (YMP) can generally be categorized as either Monte Carlo or geometric. The Monte Carlo methods tackle the problem through direct evaluation of the process yield using some forms of Monte Carlo yield estimations. Inversely, the geometric methods address the problem indirectly through the construction of an approximation to the acceptability region in the input space. Although each class of methods has its advantages as well as disadvantages, both of them have the following two common difficulties:

1>Accurate yield estimation is prohibitive through computer, primarily due to high simulation cost.

2>The dimension of x is high, typically on the order of hundreds, which further complicates the task of performing optimization.

This paper is proposed a geometrical-based methodology that overcomes these difficulties. Macromodeling helps to reduce the cost of function evaluation during optimization by replacing the complex functional relationships between y and x with a set of simplified analytic functions substantially.

3.Design-Centering Formulation

The deterministic design-centering problem (DCP) is an approximation to YMP that is derived through geometric interpretation. Methods for solving DCP usually have a better rate of convergence than Monte Carlo methods. DCP is derived from YMP through the following geometric reasoning. First, the input acceptability region, a_x, is defined in the x-space which represents the set of process variable values that yield an acceptable process. $\alpha_x = \{x \mid y^L \le y(x) \le y^U\}$, write the lower and upper acceptability constraints separately

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to give as follow:

$$\alpha_x = \{x \mid y_i^L - y_i(x) = \theta_i(x) \le 0, and\ , y_i(x) - y_i^U = \theta_{m+i}(x) \le 0, i = 1,2,\Lambda\ ,m\}$$

here m is the dimension of y. then an equivalent definition of process yield is given in the input space $Y = \int f_x(x)dx$ (4)

here $f_x(.)$ is the JPDF of x. Assuming that $f_x(.)$ is Gaussian and that a_x is convex, YMP can be approximated by the geometric problem of inscribing the largest JPDF-norm-body[3] in a_x through the proper placement of the norm-body's center. This geometrical-based approach to yield enhancement is illustrated in Fig 1, where the placement of x_c on the right hand diagram x_c^*, results in a higher process yield.

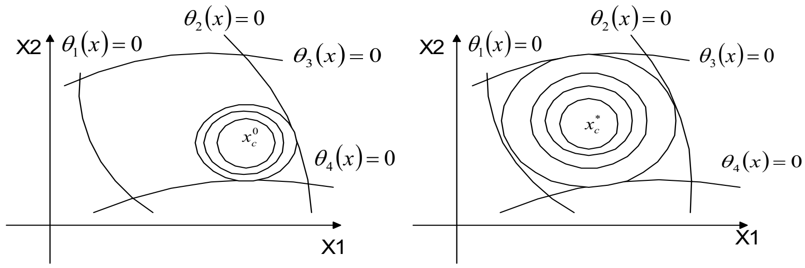

Figure 1. Deterministic design-centering for a two-dimensional example

Mathematically, DCP can be written as follows:

$$\max_{x_c} \min_{i \in Q} r_i(x_c) \quad \text{subjected to} \quad x_c \in \{x_c \mid \theta_i(x_c) \le 0 . i \in Q\} \cap D \tag{5}$$

here: Q represents the set of indexes of the nonredundant acceptability constraints.

r_i represents the absolute minimum distance from x_c to the ith constraint, that is

$$r_i(x_c) = \min \|x - x_c\|_2 \quad \text{subjected to} \quad \begin{array}{l} \theta_i(x) = 0 \\ \theta_j(x) \le 0,\ for\ ,\ j \ne i,\ j \in Q \end{array} \tag{6}$$

The main advantage of the above formulation is that it is a deterministic optimization problem, which is usually much easier to solve than the original statistical optimization problem. However, the cost of constructing an approximation to a_x increases rapidly with the dimension of x. Furthermore, even if all the acceptability contraint functions are smooth, (5) belong to the class of minimax optimization problems. So marcomodeling must be used to gain the approximate y.

4. Macromodeling

The macromodeling problem can be formally stated as follows: given a set of d responses (or outputs) of interest, y1,y2,…,yd, and a set of n input variables, x1,x2,……xn, a set of simplified empirical formulas should be detemined:

$$\hat{y}_1 = \hat{h}_1(x_{11}, x_{12}, ..., x_{1n1})$$
$$\hat{y}_2 = \hat{h}_2(x_{21}, x_{22}, ..., x_{2n2})$$
$$\Lambda \qquad\qquad \Lambda$$
$$\hat{y}_d = \hat{h}_d(x_{d1}, x_{d2}, ..., x_{2nd})$$

here: $\hat{y}_i$ represents the ith approximated response . $\hat{h}_i$ represents the ith macromodel.

x_{ij} represents the jth input variable of $\hat{h}_i$. n_i represents the number of input

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variables for the ith macromodel.

This will adequately approximate the input/output relationship of the EDA circuit while the corresponding sets of model input variables as small as possible.

The proposed approach begins with a variable screening phase in order to determine a set of significant input variables used as the independent variables in the macromodel. This step can substantially reduce the number of indispensable variables for the model, so do the complexity of the analysis. The variable screening can be accomplished by using an efficient experimental design procedure described in the next section. Next a piecewise-regression model, in terms of the significant variables. Each of the model pieces is of at most quadratic order. That is, each model piece is of the form:

$$\hat{y} = \hat{\beta}_0 + \sum_{i=1}^{m} \hat{\beta}_i x_i + \sum_{i=1}^{m} \sum_{j=i}^{n} \hat{\beta}_{ij} x_i x_j \tag{7}$$

here: x_i represents the ith significant input variable. $\hat{y}$ represents the approximated response.

$\hat{\beta} x$ represents the estimated regression coefficients. 'm' represents the number of significant input variables.

Then, the key of the experimental design technique is to minimizing the simulation cost for variable screening and regression analysis. In a two-level factorial experimental design plan, each factor is taken two values respectively: -1 and +1. Thus a full two-level factorial plan with n factors requires 2^n experimental runs and the case of three factors, x1, x2, x3, where the response value observed for the kth run is denoted by y_k, k=1,⋯, n ($n=2^3=8$ for this example).

The selection of the q basic factors in a "saturated" plan can be made random since both the basic and nonbasic factors are disordered. If n+1 is not an integral power of 2, q can be chosen as $q = [\log_2(n+1)]$.

Having identified the set of significant input variables for each response, a macromodel of the response is constructed in term of these input variables. The macromodel is composed of a number of quadratic least square model pieces. Each of the model pieces has a general form given as:

$$\hat{y} = \hat{\beta}_0 + \sum_{i=1}^{m} \hat{\beta}_i x_i + \sum_{i=1}^{m} \sum_{j=i}^{m} \hat{\beta}_{ij} x_i x_j \tag{8}$$

The actual response given by the simulator is assumed to be $y = \hat{y} + \in$. Where $\in$ is a random error resulted from the effects of the set of random input variables, which have not been included in the macromodel.

5. Experimental Results

We will choose remote-control circuit as an example to illustrate the proposed design-centering methodology. The remote-control circuit as follows:

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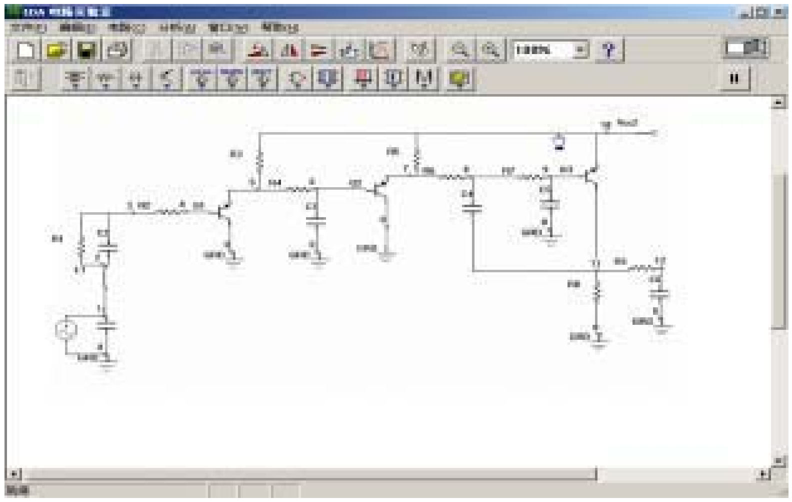

In this circuit, there are 16 components: {R1, R2, R3, R4, R5, R6, R7, R8, R9, C1, C2, C3, C4, C5, C6, L1, Q1, Q2, Q3}, $q = \lceil \log_2 (16+1) \rceil = 5$. The variables out of the original 16 variables (except Q1, Q2, Q3) were found to be significant and were incorporated into the macromodels as input variables. This automatic variable screening technique substantially reduced the dimension of the problem space.

Table 1. List of resistance responses

	R1	R2	R3	R4	R5	R6	R7	R8	R9
+1	3.191	3.193	3.194	3.061	3.195	3.181	3.045	3.196	3.193
-1	3.191	3.193	2.734	3.195	2.967	3.195	3.195	3.196	3.193
Vi	0	0	0.231	0.067	0.114	0.007	0.075	0	0
result	N	N	Y	Y	Y	Y	Y	N	N

Table 2. List of capacitor and inductance responses

	C1	C2	C3	C4	C5	C6	L1
+1	3.193	3.193	3.193	3.193	3.193	3.193	3.193
-1	3.193	3.193	3.193	3.193	3.193	3.193	3.193
Vi	0	0	0	0	0	0	0
result	N	N	N	N	N	N	N

$$\begin{aligned}\hat{y} = \sigma + y' = \sigma + (1.001\,E-3)x_3 - (6.713\,E-2)x_4 + (11.402\,E-2)x_5 - \\ (7.001\,E-3)x_6 - (7.501\,E-2)x_7 + (4.938\,E-2)x_4x_5 + \\ (3.008\,E-2)x_3x_5 - (1.379\,E-2)x_5x_6 + (1.056\,E-3)x_6x_7\end{aligned}$$

In the end, the values of the R3、R4、R5、R6、R7 are { 7.3K, 18.9K, 3.2K, 36.7K, 63K}. Part data of the design-centering shows as follows:

Table 3. Input/output statistics and analysis

Output variables					**Output result**
X3	X4	X5	X6	X7	y
0.5	0.5	0.25	0.125	0.25	3.189
0.5	0.25	0.25	0.25	0.25	3.191
0.5	0.25	0.125	0.25	0.25	3.190

0.5	0.25	0.125	0.125	0.125	3.192
0.5	0.25	0.25	0.125	0.125	3.193
0.5	**0.125**	**0.125**	**0.125**	**0.125**	**3.193**

6. Conclusion

In this paper, a new methodology is proposed for performing EDA optimization. The salient features of the approach include the use of macromodeling and macromodel-based deterministic design-centering formulation. The macromodelig scheme automatically selects a set of significant variables from all the process variables, thereby substantially decreasing the complexity of the modeling procedure. The design-centering methodology has been shown to be both robust and efficient through its successful application to EDA circuit design. These measures offer a relatively low expense for the virtual laboratory. The experiment has been applied in process yield optimization. So, it is desired for being applied in circuit yield optimization. In the future, it is necessary to pursue greater simulation speed and accuracy.

References

[1] S.R.Nassif. A.J. Strojwas, and S.W. Director, FABRICS:A statistical based integrated-circuit fabrication process simulator, IEEEE Trans. Computer-Aided Desgn, vol. CAD-3, Jan.1984, pp. 40-46.

[2]C.J.Spanos and S.W.Director, "Parameter extraction for statistical integrated-circuit process characterization, IEEE Trans, computer-Aided Design, vol. CAD-5, Jan.1986pp. 66-78.

[3]R.K.Brayton, G.D.Hachtel, and A.L.Sangiovani-Vincentelli, Asurvey of optimization techniques for integrated-circuit design, Proc,IEEE, vol69, Oct,1981,pp,1334-1362.

[4] A.J. Strojwas, Design for manufacturability and yield, in design Automation Conf, Proc. 1989,pp.454-459

[5] P.Cox,P.Yang,S.S. Manhant-Shetti, and P.Chatterjee, Statiscirucits modeling for efficient parametric yield estimate of MOS VLSI circuits, IEEE Trans. Electron Devices, vol. ED-32, Feb,1985.pp.477-478.

[6] R.L. Burden and J.D.Faires, Numerical Analysis, 3rd ed. Boston, MS:Prindle,Weber and Schmidt,1985.

[7] G.E.P. Box and N.R.Draper, Empirical Model-Building and Response Surfaces. New York: Wiley, 1987.

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