

Parasitic-Aware GP-Based Many-Objective Sizing Methodology for Analog and RF Integrated Circuits

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- Problem definition
- Previous works
- Our work:
 - Synthesis flow
 - Parasitic-awareness
 - The geometrical programming (GP)
 - The theta-dominance-based evolutionary algorithm
 (θ-DEA)
- Experimental results and conclusions

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Circuit Sizing Problem

Given: A circuit topology

Find: Device sizes and bias information that make the performance meet the specification.

- The biggest problem in the sizing task:
 - Performance not converge between pre- and post-layout (Due to layout effects)
 - Unexpected design cycles
 - Parasitic effects: primary and inevitable

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Recent Works on Automatic Sizing

Synthesis approaches categorization:[1]

How parasitics considered:

- Analytic modelling (our approach)
- Heuristic exploration
- From extraction and simulation tools

[1]T. Liao and L. Zhang, "Analog integrated circuit sizing and layout dependent effects: A review," *Microelectronics and Solid State Electronics*, 3(1A), pp. 17-29, 2014.

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Synthesis Flow



Fig. 1. The GP-many-objective two-phase hybrid sizing flow

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Parasitic-awareness

Interconnect parasitic models [2][3]

New models firstly being applied to GP platform

Device parasitics from foundry provided (PDK)

- GP phase (technology files)
- EA phase (model in netlist, called in simulation)

[2] G. Shomalnasab and L. Zhang, "New analytic model of coupling and substrate capacitance in nanometer technologies," *IEEE Trans. on Very Large Scale Integration* (*VLSI*) *Systems*, vol. 23, no. 7, pp. 1268-1280, 2015.

[3] L. Zhang, N. Jangkrajarng, S. Bhattacharya, and R. Shi, "Parasitic-aware optimization and retargeting of analog layouts: a symbolic template approach," *IEEE Trans. on Computer-Aided Design of Integrated Circuits and Systems*, vol. 27, no. 5, pp. 791-802, 2008.

Interconnect Parasitics

Interconnect length:

Int._length = f(w, l, nf, interconnect relationship)

Express parasitic R and C in symbolic way:

Para._R,C = g(Int._length, Int._width, parameters)

Merits:

- Models reusable in GP and EA
- Parasitic-awareness throughout the two phases

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Geometrical Programming

 A GP is a type of mathematical optimization problem characterized by objective and constraint functions that have a special form (posynomial and monomial). It is a class of nonlinear optimization.

GP Pros & Cons

Pros:

Quickly determine a first-level optimum global solution

- Cons:
 - Requires in a convex form (GP-compatible)
 - Controversy of accuracy
- Contribution:
 - Two actions to address the cons

Action to the 1st Cons

Transfer non-posynomial to be GP compatible:

$$f_i(x) = \frac{ax^b + cx^d + \dots}{pq^r + lm^n + \dots}$$

$$\begin{array}{ll} ax^{b} + cx^{d} + \cdots \leq temp_{1}, & (\text{posynomial}) \\ pq^{r} + lm^{n} + \cdots \leq temp_{2}, & (\text{posynomial}) \\ temp_{1}/temp_{2} = f_{i}(x). & (\text{monomial}) \end{array}$$

Action to the 2nd Cons

- Idea of two-phase sizing process:
 - GP solution => Cadence verification => elite
 - Improve the elite: 2nd-phase optimizer with numerical simulation (fix the accuracy issue!)
- New problem:
 - Large EA search space + simulation => slow
- Solution:
 - Benefits of GP-elite:

Imply information => shrink variable ranges/trimmed space => decreases search configuration and time

In order to be efficient: GP and EA cannot be isolated!

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A many-OEA: θ-DEA

- Multi-objective EA (MOEA):
 - Weak in handling problems with more than 3 objectives
- Analog circuit design:
 - > 3 objectives
- Many-OEA:
 - Good for >3 objectives
 - *θ*-DEA:
 - Structural strength of NSGA-III (H. Jain and K. Deb, 2014)
 - Aggregation function as the selection scheme from MOEA/D (Q, Zhang, 2007)
 - First practice in sizing domain

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Experimental Circuits



Fig. 2. Circuit diagrams for a): two-stage OpAmp and b): Cascode common source LNA with source degeneration

Experiment Setups

Schemes:



One solution: best cost, performance One set: average cost, SR

Sch-0 and Sch-1 to 4: GP elite? large or small EA setting?

Cost function:

- minimize $\sum_{i=1}^{n} \alpha_i \cdot \frac{S_i}{P_i} + \sum_{j=n+1}^{m} \beta_j \cdot \frac{P_j}{S_j}$
- Performance vector → single cost as a representative

Experimental Results: Op-Amp

Table I. Settings and performance of the Two-Stage OpAmp

OpAmp	GP	Many-objective improved θ-DEA Methods							
0.18um: Schemes	0:	1: GP- Small	2: GP- Large	3: NoGP- Small	4: NoGP- Large				
Best cost	0.593	0.460	0.458	0.478	0.450				
Average cost	-	0.569	0.528	0.552	0.519				
Successful rate	-	21.88%	5.36%	25.00%	30.36%				
Run Time(hrs)	1.31s	2.25	8.25	2.25	8.25				
Specification	Performance								
Gain > 60dB	88.93 (0.675)	80.75 (0.743)	73.26 (0.819)	72.46 (0.828)	85.97 (0.698)				
UGF > 1M	1.50 (0.667)	5.52 (0.181)	20.83 (0.048)	4.32 (0.231)	4.06 (0.246)				
PM > 60°	80.13 (0.749)	87.59 (0.685)	91.32 (0.657)	131.35 (0.457)	124.41 (0.482)				
GM > 10dB	35.33 (0.283)	43.48 (0.230)	32.26 (0.310)	25.34 (0.395)	26.82 (0.373)				

Experimental Results: LNA

Table II. Settings and performance of the Low Noise Amplifier

LNA 90nm: Schemes	GP	Many-objective improved θ-DEA Methods						
	0:	1: GP-	2: GP-	3: NoGP-	4: NoGP-			
		Small	Large	Small	Large			
Best cost	0.866	0.709	0.753	0.766	0.766			
Average cost	-	0.765	0.782	0.766	0.766			
Successful rate	-	15.63%	8.93%	3.13%	1.79%			
Run Time(hrs)	1.76s	2.50	8.50	2.50	8.50			
Specification	Performance							
Gain > 15dB	20.32	19.34	19.16	16.47	21.00			
	(0.738)	(0.776)	(0.783)	(0.911)	(0.714)			
NF < 2.5dB	1.87	2.01	2.022	2.20	2.12			
	(0.748)	(0.804)	(0.809)	(0.878)	(0.847)			
S11 < -15dB	-15.16	-19.41	-23.67	-29.13	-22.17			
	(0.989)	(0.773)	(0.634)	(0.515)	(0.677)			
S22 < -15dB	-15.16	-30.94	-19.05	-19.79	-18.14			
	(0.989)	(0.485)	(0.787)	(0.758)	(0.827)			

Conclusion

Two-phase hybrid sizing flow

- Floorplan optimization
- Parasitic-awareness:
 - intrinsic parasitics
 - interconnect parasitics
- GP
- θ -DEA with numerical simulation
- Experimental analysis
 - Methodology efficacy: easy and hard problems

Thank You for Your Attention!



