Statistical Circuit Optimization Considering Device and Interconnect Process Variations

I-Jye Lin, Tsui-Yee Ling, and Yao-Wen Chang

The Electronic Design Automation Laboratory Department of Electrical Engineering National Taiwan University March 17, 2007



Outline

Introduction Deterministic Algorithm Statistical Algorithm Experimental Results Conclusions

Outline

Introduction

Deterministic Algorithm Statistical Algorithm Experimental Results Conclusions

Interconnect Process Variation

Interconnect delay and reliability highly affect VLSI performance.

The variability of interconnect parameters will raise up to 35%.

- Sirvastava et al., Springer, 2005.

The worst-case corner models cannot capture the worst-case variations in interconnect delay.

_ Liu et al., DAC 2000

The interconnect optimization guided by statistical analysis techniques has become an inevitable trend.

- Visweswariah, SLIP 2006

Previous Work in Statistical Optimization

Statistical gate sizing with timing constraints using Lagrangian Relaxation.

- Choi et al.," DAC 2005.

Statistical power minimization by delay budgeting using second order conic programming.

– Orshansky et al., DAC 2005.

Statistical gate sizing using geometric programming

– Patil et al., ISQED 2005.

No statistical optimization work consider both interconnect and device sizing.

Comparison with Previous Work

	Orshansky's work	Our work		
	(DAC 2005)			
Sizing variable	Gate only	Gate and wire		
Delay Model	Linear model	Elmore delay model		
	(linear term)	(nonlinear term)		
Objective	Power	Area		
Constraint	Timing	Power, timing, thermal		

Due to the nonlinear term introduce by the Elmore delay model, the optimization using both gate and wire sizing will be much harder to solve.



Delay model and timing constraint used in previous work in DAC 2005: $a_i \ge a_j + d_i^0 + d_i$ linear terms!

 $- d_i^0$ = delay due to the sizing for maximum slack

 $- d_i$ = slack added to node i due to the loading

Statistical Circuit Optimization with SOCP

0.5

Second-order conic programming (SOCP)



- Convex optimization
- Theoretical runtime O(N^{1.3})
- Orshansky (DAC 2005), Davoodi (DAC 2006)

Second-order conic constraint:

 $\|\underline{A}_{i}x + \underline{b}_{i}\|_{2} \leq c_{i}^{T}x + d_{i}$ ApproximationLinear terms!
Nonlinear (quadratic) terms are not applicable!

 x_1

Approximation Method

Fix the gate size in the timing constraint.

 Reduce the timing constraint from quadratic order to linear order.

Approximate the gate sizes by a two-stage flow.

- Iteratively reduce the approximation errors.
- The flow is similar to Sequential Linear Program (SLP).



Our Contributions

The first work of statistical optimization on circuit interconnect and devices

- Previous work considers only circuit devices (gates).
- Statistical optimization for considering both interconnect and devices is much harder.

The first work that statistically optimizes the area with *thermal-* and *timing-constrained* parametric yields

Most existing statistical optimization considers only timing.

The first work capable of analytically transforming the statistical RC model into an SOCP

Previous work uses linear delay model

Outline

Introduction

Deterministic Algorithm

Statistical Algorithm Experimental Results Conclusions

Timing Constraint



of paths may grow exponentially to the circuit size. To reduce problem size, we distribute the timing information to each node.

$$\begin{array}{ll} D_i \leq a_i & i=1,...,s \ /* \ primary \ inputs * / \\ \\ a_j + D_i \leq a_i & i=s+1,...,n+s \ and \ \forall j \in input(i) \\ \\ \\ a_j \leq D^B & j \in input(m) \ /* \ primary \ outputs * / \end{array}$$

Electron Migration (EM) lifetime reliability of metal interconnects is governed by the well-known Black's equation: TTF: time-to-fail period

A* : a constant

: average current density

specific metal temperature

: activation energy KB : Boltzmann's constant.

Tm: metal temperature

$$TTF = A^{\star} \cdot j^{-n} \cdot exp(\frac{Q}{k_B T_m}),$$

The design is reliable when

$$\frac{j_{avg}^2}{exp\left(\frac{Q}{k_BT_m}\right)} \leq \frac{j_0^2}{exp\left(\frac{Q}{k_BT_{ref}}\right)}.$$

$$\begin{bmatrix} j_0: \text{ specific current density} \\ T_{ref}: \text{ specific metal temper} \\ T_{ref}: \text{ specific metal temper} \\ \hline T_{ref}: \text{ specific metal temper} \\ \hline T_m \leq \frac{Q \cdot T_{ref}}{Q - 2K_BT_{ref}(\ln j_0 - \ln j_{avg})} = T^{B'}.$$

$$T_m = \Delta T_{self-heating} + T_{environment}$$

Average Temperature of the Chip

The average temperature of the chip, T_{avg} , can be estimated by:

$$T_{avg} = T_{air} + R_n(\underbrace{P_{tot}}_{A})$$
 Power



– Banerjee et al., ISPD 2001.

Need to constrain chip's temperature under a reasonable bound during the optimization:

$$\alpha_i c_i \le P_i^{B'}, \quad P_i^{B'} = P_i^B / V_{DD}^2 f$$

- For simplicity, consider the dynamic power consumption only.
- $P_i^{B:}$ the power bound of the gate i
- $-c_i$: the downstream capacitance of the gate I
- $-\alpha_i$: switching activity of component *I*

Deterministic Formulation



f: working frequency; α_i : switching activity of component *I*; C_i : load capacitance of component *I*; ω : path in the path set Ω .

Outline

Introduction Deterministic Algorithm Statistical Algorithm Experimental Results Conclusions Introduce two process parameters as the variation sources: Inter-layer dielectric (ILD) thickness (H), and metal thickness (T).

R and C can be approximated by the first-order Taylor expression:

$$R = R_{nom} + a_1 \Delta T,$$

$$C = C_{nom} + b_1 \Delta T + b_2 \Delta H$$

 R_{nom}/C_{nom} : nominal value of R/C $\Delta T/\Delta H$: random deviation of metal thickness/ILD thickness

 a1, b1, b2 are sensitivities calculated by the differential differentiation of:

$$R = \frac{\rho}{WT},$$

$$\frac{C_{gnd}}{\epsilon} = \frac{W}{H} + 3.28 \left(\frac{T}{T+2H}\right)^{0.023} + \left(\frac{S}{S+2H}\right)^{1.16}$$

– Srivastava et al., Springer 2005.

Assume T and H are Gaussian, the variability magnitude of R and C can easily be calculated by:

$$\sigma_R^2 = \boldsymbol{a}_1^2 \sigma_T^2$$
$$\sigma_C^2 = \boldsymbol{b}_1^2 \sigma_T^2 + \boldsymbol{b}_2^2 \sigma_H^2$$

Apply the *interconnect delay variation metric* to calculate the variability of the product of R and C.

- Well captured by a normal distribution with 1.2% average error of the mean delay and 3.8% average error of the standard deviation.
- Blaauw et al., DAC 2004.

Statistical Formulation



 $-\delta/\zeta/\eta$: Thermal/Timing/Power yield constraint

Transformation into SOCP

Theorem: Given independent Gaussian random vectors a_i and bound vectors b_i , the parametric yield (η) problem is as follows:

Minimize

$$\sum x_i$$

subject to $Prob(a_i^T x_i \le b_i) \ge \eta$, the problem can be reformulated as an SOCP:

Minimize

$$\sum x_i$$

subject to

$$\left(\bar{a}_{i}^{T}x_{i}\right) + \Phi^{-1}\left(\eta\right)\left(x^{T}\Sigma_{i}x\right)^{1/2} \leq b_{i}.$$

 $- \Phi^{-1}$: the cumulative density inverse function Boyd and Vandenberghe, Cambridge, 2004. The EDA Laboratory

Transformation Flow



Thermal & Power Constraints in SOCP Form

Thermal constraint:

$$\mathcal{P}(T_{mi} \leq T_i^B) \geq \delta$$

$$\bar{T}_{mi} + \phi^{-1}(\delta) \sqrt{\sigma_1^2 x_w^2 + \sigma_2^2 \frac{1}{x_w^2} + \sigma_3^2 + \sigma_4^2} \leq T_i^B$$
Power (Thermal distribution) constraint:
$$\mathcal{P}(\alpha_i c_i \leq P^{B'}) \geq \eta$$

 $\alpha_i \bar{c_i} + \phi^{-1}(\eta) \sqrt{\sigma_5^2 \sum_{i=s+1}^{n+s} (x_i^2)} \le P^{B'},$

,

Timing Constraint in SOCP Form



The EDA Laboratory

Statistical Problem Formulation using SOCP

$\mathtt{P}: Minimize$

	σ_1	σ_2	σ_3	σ_4		σ_5
$\sum n+s$ 1 m	$\sigma_{\rho_m}B_0^2A_1^2$	$\sigma_{\rho_m}B_1^2A_0^2$	$\sigma_{\rho_m}B_1^2A_1^2$	$\sigma_{\rho_m} B$	$R_0^2 A_0^2$	$\alpha_i^2 \sigma_{c_g}$
$\sum_{i=s+1} \iota_i x_i$	σ_6	σ_7	σ_8		σ_9	
	$\sigma_{\left(r_{j}\right)\left(c_{w}l_{w}\right)}$	$\sigma_{\left(r_{j}\right)\left(c_{i}\right)}$	$\sigma_{(r_w l_w)\left(\frac{\sigma_{c_w l_w}}{2}\right)}$		$\sigma_{(r_w l_w)(c_i)}$	

 $subject \, to$

$$\bar{T}_{mi} + \phi^{-1}(\delta) \sqrt{\sigma_1^2 x_{mi}^2 + \sigma_2^2 \frac{1}{x_{mi}^2} + \sigma_3^2 + \sigma_4^2} \le T_i^B,$$
Thermal constraint

$$a_j + \bar{D}_i + \phi^{-1}\left(\zeta\right) \sqrt{\sigma_6^2 x_w^2 + \sigma_7^2 + \sigma_8^2 + \frac{\sigma_9^2}{x_w^2}} \le a_i,$$
 Timing constraint

$$\alpha_i \bar{c}_i + \phi^{-1}(\eta) \sqrt{\sigma_5^2 \sum_{i=s+1}^{n+s} (x_i^2)} \le P^{B'},$$

Power constraint

$$L_i \le x_i \le U_i, \ \forall s+1 \le i \le n+s.$$

NTUEE

The EDA Laboratory

Program Flow



Outline

Introduction Deterministic Algorithm Statistical Algorithm Experimental Results Conclusions

Experimental Setup

Circuit	Circuit Size						
Name	#Gate	#Wire	#Total				
c17	11	12	23				
c432	122	230	352				
c499	c499 246		642				
c880	256	230	486				
c1355	297	555	852				
c1908	c1908 201		537				
c2670	c2670 499		1253				
c3540	c3540 429		1450				
c5315	c5315 927		2719				
c6288	1298	3596	4894				

Implemented in C++ & applied the MOSEK optimization tool to solve it.

Tested on the commonly used ISCAS85 benchmark circuits in this area.

Used Design Compiler & Astro with UMC 0.18¹m technology library to synthesize and place the circuits.

Experimental Results

Achieve 51%, 39%, and 26% area reductions for 70%, 84.1%, and 99.9% yield constraints, respectively.

Avg. / Max. # of the running iterations: 5.6 / 10

ſ	Circuit	Deterministic			70% yield				
	name	area (µm²)	Runtime / ite. (s)	Total runtime (s)	area (µm²)	Area improv.	Runtime / ite. (s)	Total runtime (s)	
ſ	c17	7160	0.06	0.6	2892	59.61%	0.09	0.36	
ſ	c432	47752	0.24	1.21	21543	54.89%	0.83	4.15	
ſ	c499	127103	0.41	2.07	56957	55.19%	2.41	9.62	
Ī	c880	152804	0.37	1.11	38346	74.91%	1.40	13.96	
ſ	c1355	174896	0.58	5.79	84076	51.93%	3.87	19.33	
ſ	c1908	96968	0.33	3.26	44350	54.26%	2.79	5.57	
I	c2670	275967	0.74	7.39	121065	56.13%	7.32	14.64	
ſ	c3540	362409	1.10	11.03	146519	59.57%	7.43	22.29	
ſ	c5315	913522	1.88	13.18	727853	20.30%	10.43	31.28	
I	c6288	1455730	5.23	15.69	1100120	24.43%	70.56	352.78	
N	Avg.					51.12%			

Timing constraint error bound: 2%

Experimental Results of 84.1% and 99.9% yield

The lower the yield constraints, the better the area optimization. All constraints (timing, power, thermal) are met.

Circuit		84.1%	yield		99.9% yield			
name	area (µm²)	Area improv.	Runtime / ite. (s)	Total runtime (s)	area (µm²)	Area improv.	Runtime / ite. (s)	Total runtime (s)
c17	3394	52.60%	0.09	0.6	3460	51.68%	0.09	0.47
c432	27860	41.66%	1.26	7.48	29179	38.89%	0.80	2.41
c499	57758	54.56%	2.11	8.43	89148	29.86%	1.54	4.61
c880	66420	56.53%	2.91	7.82	107349	29.75%	1.54	15.41
c1355	147397	15.72%	2.11	19.03	169347	3.17%	2.29	22.9
c1908	65020	32.95%	1.56	12.48	70830	26.96%	1.38	13.57
c2670	161426	41.51%	2.93	5.85	248474	9.96%	3.47	24.32
c3540	169331	53.28%	5.57	22.27	176715	51.24%	5.23	15.70
c5315	735838	19.45%	9.24	36.95	884514	3.18%	7.16	28.65
c6288	1109090	23.81%	69.74	348.71	1291240	11.30%	82.32	411.63
Avg.	(39.21%			(25.60%		

Delay, Power and Temperature Performance

Though the delay and the maximum metal temperature are increased, they all meet the given bounds.

Fully utilized the constraint bound to get the best optimization results.

Circuit		Delay (ns)		Power	r (mW)	Max T _{increase} ()	
Name	Bound	Before	After	Before	After	Before	After
c17	36.82	22.19	32.21	2.02	1.35	8.19	10.05
c432	247.65	154.59	136.62	22.96	12.59	6.97	23.46
c499	186.13	153.79	135.32	56.10	35.23	7.20	27.20
c880	253.43	208.84	170.15	64.03	43.44	7.26	19.69
c1355	274.55	203.45	241.45	78.56	67.24	7.37	27.47
c1908	222.91	161.09	136.11	43.32	28.36	7.09	31.78
c2670	290.84	176.66	229.94	103.81	98.69	8.88	22.72
c3540	507.80	308.59	245.85	143.14	72.65	8.25	14.03
c5315	445.58	313.52	421.54	365.65	355.45	7.78	19.55
c6288	1333.91	913.33	1148.41	661.62	513.14	7.35	11.62
Comparison		1	1.13	1	0.80	1	2.72

Outline

Introduction Deterministic Algorithm Statistical Algorithm Experimental Results Conclusions

Conclusions

Presented the first statistical work for area minimization under thermal and timing constraints by gate and wire sizing.

Obtained much better results than those of the deterministic method.

Formulated statistical RC model by SOCPs which can be solved efficiently and effectively.

- Used more accurate delay model (Elmore delay model)
- Solved the problem by a two-stage approximation flow
 - Nonlinear terms are not applicable to SOCP

Thank You

Backup Slides

Temperature Distribution

Applying the Finite Difference Method (FDM), we can divide the whole chip into *m* mesh nodes and calculate each node's temperature by

$$G_{2}T_{P} = \begin{bmatrix} g_{1,1} & g_{1,2} & \cdots & g_{1,m} \\ g_{2,1} & g_{2,2} & \cdots & g_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ g_{m,1} & g_{m,2} & \cdots & g_{m,m} \end{bmatrix} \begin{bmatrix} T_{1} \\ T_{2} \\ \vdots \\ T_{m} \end{bmatrix} = \begin{bmatrix} P_{1} \\ P_{2} \\ \vdots \\ P_{m} \end{bmatrix} = P_{P}$$



– Chapman, "Heat Transfer," New York: Macmillan, 1984 Vol., 4th Ed.,

Temperature Dependent Delay

An inseparable aspect of electrical power distribution and signal transmission through the interconnects Resistance is dependent of Temperature

$$r(x) = \rho_0 (1 + \beta \cdot T(x))$$

- ρ_0 : the resistance per unit length at reference temperature
- $-\beta$: the temperature coefficient of resistance (1/°C)

Interconnect Temperature Calculation

The interconnect temperature is given by

$$T_m = \Delta T_{self-heating} + T_{environment}$$

$$= I_{rms}^{2} \cdot R \cdot \theta_{int} + T_{environment}$$
$$= \frac{\sigma V_{cross}^{2} t_{ox} t_{m}}{K_{ox} l^{2} R_{m}} \cdot \frac{x_{i}}{x_{i} + \phi t_{ox}} + T_{environment}$$

 x_i : wire width

 θ_{int} : the thermal impedance of the interconnect line to the chip

 σ : duty cycle

 V_{cross} : cross voltage of wire

 t_{ox} : the total thickness of the underlying dielectric

 t_m : the thickness of the wire

 K_{ox} : the thermal conductivity

/: wire length

 R_m : the temperature dependent unit resistance

 $\boldsymbol{\psi}$: the heat spreading parameter

NTUEE

Not linear functions

Least Square Estimator

Least Square Estimator (LSE)

Least squares solves the problem by finding the line for which the sum of the square deviations (or residuals) in the d direction (the noisy variable direction) are minimized.

- Apply Cramer Rule to find the A₁ and A₀, which minimizes the square deviations



Approximation for Thermal Constraint

Let N = 5 and pick five sizes of xi, we can approximate the thermal constraint by Least Square Estimator (LSE).

– Banerjee et al., DAC 1999

