

Performance Optimization and Analysis of Blade Designs under Delay Variability

Dylan Hand*, Hsin-Ho Huang*, Benmao Chang[‡], Yang Zhang^{*}, Matheus Trevisan Moreira*[†], Melvin Breuer*, Ney Laert Vilar Calazans[†], and Peter A. Beerel*

May 5th, 2015

* University of Southern California, Los Angeles, CA
† Pontifícia Universidade Católica do Rio Grande do Sul, Porto Alegre, Brazil
‡ Dept. of Automation, Tsinghua University, Beijing, China





The Context: Delay Overheads



Traditional synchronous design suffers from increased margins

Worse at low and near-threshold regions



Potential of Average-Case Data





Delay variation due to data is rarely exploited in synchronous designs



Potential of Average-Case Data





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Potential of Average-Case Data





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Timing errors delay handshaking by the resiliency window Δ







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Resiliency Performance Benefit





Key Question: How do we set δ to optimize performance



Outline



Performance Optimization

- Delay models
- Impact of delay line quantization
- Impact of metastability
- Comparison to Bubble Razor
- Case Study
 - Analyze and optimize a 3-stage Blade CPU

Conclusions and Future Work





• Analyze the performance of Blade for a variety of delay models



Optimal Average-Case Performance







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Optimal Average-Case Performance



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- : Average delay of Blade stage Definitions
 - C : Clock Period / Cycle Time
 - EC : Effective Clock Period
 - p : Probability of error
- d : Average delay of Blade stage $C = \delta + \Delta$ $\overline{d} = \delta + p * \Delta$

Optimal performance achieved by minimizing d

Assumes backward latency is hidden via latch retiming



Optimal Probability of Error - popt





Higher Variance

 p_{opt} observations

- Varies between 20% and 35% for lognormal distributions
- Significantly higher than in sync resiliency
- Constant for normal distributions!



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Proof of constant popt



Assume worst case delay per stage is constant $K = \delta + \Delta$

Worst case delay is set by mean, variance, and SER $K = \mu + m * \sigma$

Systematic Error Rate (ξ) sets the worst-case delay per stage, K $\xi = 1 - [P_R \{d \le C\}]^N$ $m = f(\xi)$



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Proof of constant popt



Assume worst case delay per stage is constant $K = \delta + \Delta$

Worst case delay is set by mean, variance, and SER $K = \mu + m * \sigma$

Recall: $\overline{d} = \delta + p * \Delta = (1 - p) * \delta + p * K$

For Normal distribution: $(1-p) = \frac{1}{2} [1 + \operatorname{erf}\left(\frac{\delta-\mu}{\sqrt{2}\sigma}\right)]$ $(1-2p) = \operatorname{erf}\left(\frac{\delta-\mu}{\sqrt{2}\sigma}\right)$ Taking inverse error function of both sides: $\operatorname{erf}^{-1}(1-2p) = \frac{\delta-\mu}{\sqrt{2}\sigma}$ $\delta = \sqrt{2}\sigma[\operatorname{erf}^{-1}(1-2p)] + \mu$



Proof of constant popt



Assume worst case delay per stage is constant $K = \delta + \Delta$

Worst case delay is set by mean, variance, and SER $K = \mu + m * \sigma$

Recall:
$$\overline{d} = \delta + p * \Delta = (1 - p) * \delta + p * K$$

Rewrite: $\overline{d} = (1 - p)[\sqrt{2}\sigma[\operatorname{erf}^{-1}(1 - 2p)] + \mu] + p * K$
Minimize \overline{d} by taking derivative and setting it equal to zero :

$$\frac{\partial \bar{d}}{\partial p} = (1+y) \left[\sqrt{2} \frac{\partial \operatorname{erf}^{-1}(y)}{\partial y} \right] - \sqrt{2} \operatorname{erf}^{-1} y + m = 0$$
$$y = 1 - 2p$$

Note *y* and *p* are independent of σ and μ ! *m* depends only on ξ

Implication: Tuning of delay line may target fixed probability!





Blade supports maximum Δ of 50% of clock cycle Optimal Δ is larger for designs with high-variance!



Delay Line Quantification Effects



Quantification effects reduced due to inherent tradeoff between nominal delay δ and error penalty p * Δ



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Delay Line Quantification in BD





Linear relationship between delay line quantization and average stage delay in Bundled Data



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Metastability resolution times most often hidden!









$$P_R(met) = \int_{\delta - \frac{W_1}{2}}^{\delta + \frac{W_1}{2}} N(x, \mu, \sigma^2) dx$$

$$P_R(t_{MST} \ge T | met) = e^{-\lambda_C T}$$



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Performance Impact of Metastability



$$P_R(met) = \int_{\delta - \frac{W_1}{2}}^{\delta + \frac{W_1}{2}} N(x, \mu, \sigma^2) dx$$

$$P_R(t_{MST} \ge T | met) = e^{-\lambda_C T}$$

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Blade

• $EC = \delta + p_{opt} * \Delta$

Bubble Razor [Zhang, 2014]

• $EC = C[2 - (1 - p)^{2N}]$



Synchronous















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• $EC = \delta + p_{opt} * \Delta$

Synchronous

• EC set by systematic error rate

Bubble Razor [Zhang, 2014]

•
$$EC = C[2 - (1 - p)^{2N}]$$

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$$EC = C[2 - (1 - p)^{2N}]$$

Normal Distribution





Comparison to Sync Resiliency



Synchronous

• EC set by systematic error rate

Bubble Razor [Zhang, 2014]

• $EC = C[2 - (1 - p)^{2N}]$

Blade

• $EC = \delta + p_{opt} * \Delta$



Normal Distribution



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Plasma MIPS OpenCore

28nm FDSOI

Compare mathematical model of optimal resiliency window (Δ) with simulation results

[1] http://opencores.org/project,plasma



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	Distribution A		Distribution B		Distribution C	
	Model	Sim	Model	Sim	Model	Sim
Δ _{max}	27%		35%		43%	
Δ _{opt}	26%	27%	34%	35%	39%	37%
EC _{opt}	74.8%	75.1%	71.3%	71.9%	75.1%	74.8%

Model estimated optimal Δ within 5.4%

• Optimal EC within 99%



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	Distribution A		Distribution B		Distribution C	
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Δ _{max}	27%		35%		43%	
Δ_{opt}	26%	27%	34%	35%	39%	37%
EC _{opt}	74.8%	75.1%	71.3%	71.9%	75.1%	74.8%
Ideal Δ_{opt}	48%		53%		46%	
Ideal EC _{opt}	63.2%		67.8%		74.5%	

Model estimated optimal Δ within 5.4%

• Optimal EC within 99%

Model allows estimation of optimal Δ w/o limitations of simulated design



Summary and Conclusions



Performance model

- Use either analytical and real world delay distributions
- Predicts performance within 99% accuracy

Comparison to sync N-stage rings

- 23% better than Bubble Razor
- 35% better than traditional designs

Several interesting conclusions

- Optimal error rate is relatively high and may be constant
- Programmable delay line need not be fine-grained
- Metastability impact is negligible
- Supporting larger resiliency windows may be useful





Questions?



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