Geostatistical-Inspired Metamodeling and Optimization of Nano-CMOS Circuits

O. Okobiah¹, S. P. Mohanty², and E. Kougianos³ NanoSystem Design Laboratory (NSDL, http://nsdl.cse.unt.edu) University of North Texas, Denton, TX 76203, USA.^{1,2,3,} Email: oo0032@unt.edu¹, saraju.mohanty@unt.edu², and eliask@unt.edu³.

> Presented By Oghenekarho Okobiah University of North Texas Email: oo0032@unt.edu

Acknowledgment: This research is supported in part by NSF awards CNS-0854182 and DUE-0942629 and SRC award P10883.









Outline of the talk

- Background and Motivation
- Related Prior Research
- Thermal Sensors
- Proposed Design Optimization Flow Methodology
- Experimental Results
- Conclusions and Future Research Directions









Issues in NanoCMOS Design

- Expensive Computer Simulations
- Pronounced effects of process variations in deep nanometer regions
 - Increase in design parameters
 - Current modeling techniques unable to capture effects of process variation







Background and Motivation

- Complex and High density designs
- Design for low power consumption
- Reliability issues
 - Thermal monitoring







Novel Contributions

- Design flow methodology with geostatistical based metamodeling (kriging) and Gravitational Search algorithms (GSA) for nano-CMOS design optimization
- Implementation of GSA for nano-CMOS designs
- 45nm Thermal sensor designs







Prior Related Research

- Exploration of optimization algorithms for NanoCMOS designs
 - Simulated annealing, swarm intelligence
- Efficient designs for thermal sensors
- Kriging based metamodels
 - O. Okobiah --- Ordinary and Simple kriging metamodels
 - G. Yu ---- Re-iterative pareto fronts
 - H. You --- Kriging metamodels







Proposed Design Flow Diagram









Kriging Fundamentals

Kriging Fundamentals

 Originally used in geostatics fields for mining purposes

$$y(\mathbf{x_0}) = \sum_{j=1}^{-1} \lambda_j B_j(\mathbf{x}) + z(\mathbf{x})$$

Each point is predicted with a set of unique weights (λ_j)



Kriging Fundamentals: Ordinary Versus Simple

- Simple kriging assumes a known and local mean while ordinary kriging assumes a constant but unknown mean
- Ordinary kriging weights are biased,

$$\sum_{j=1}^{n} \lambda j = 1$$

I S V





Simple Kriging Metamodel Generation





Gravitational Search Algorithm ...

- Part of Swarm Intelligence family
 - population based heuristic algorithms
- Based on gravitational laws of attraction and motion

$$F_{ij}^d(t) = G(t) \left(\frac{M_{pi}(t) \times M_{aj}(t)}{R_{ij}(t) + \epsilon}\right) \left(x_j^d(t) - x_i^d(t)\right)$$

Where F^d_{ij}(t) is design objective, M is the quality of solution at search location i or j, x_i is the set of design parameters at location i









Gravitational Search Algorithm

- Basic principles...
 - Heavier masses which correspond to better solutions attract search agents with poor solutions
 - Lighter masses move faster randomly -exploring the search space
 - Heavier masses move slowly exploiting possible optimal locations







Gravitational Search Algorithm

Algorithm 1 Proposed Gravitational Search.

- 1: Initialize iteration counter: $counter \leftarrow 0$.
- 2: Initialize max iteration Max_{iter} .
- 3: Initialize number of search agents η gravity constant G, and velocity ν .
- 4: Generate η random search nodes (design parameter sets).
- 5: Consider the objective of interest $Power_{TS_i}$.
- 6: $counter \leftarrow max_Iteration$.
- 7: while $(counter < Max_{iter})$ do
- 8: Evaluate objective of interest (Power $_{TS_i}$) for each search node.
- 9: Update best and worst solution per function objective.
- 10: Update the gravity constant G.
- 11: Calculate M and a for each search node.
- 12: Update ν for each search node.
- 13: Update search nodes by applying velocity on M.
- 14: $counter \leftarrow counter + 1$.
- 15: end while
- 16: return bestsolution.







Experimental Results: 45nm Thermal Sensor



- Ring Oscillators for sensing
- Binary Counter
- **Register**









45nm thermal sensor physical design









Experimental Results

Accuracy Analysis of Simple Kriging Metamodel

Metric	Value	
MSE	4.36 x 10 ⁻¹⁸	
RMSE	2.09 x 10 ⁻⁰⁹	
R_2	0.9934	



Optimal Design Results

Design	Average Power	Sensitivity	Area
Schematic	293.1µW	16.88MHz/°C	-
Layout	379.4µW	9.42MHz/°C	1221.37µm²
Final	+29%	9.42MHz/°C	1770.98µm²*
% Change	36.9%	44.2%	45%*



Conclusions

- A novel design flow methodology incorporating simple kriging and GSA was presented.
- Average power consumption was reduced by 36.9%
- Reduced design space exploration by 90%
- Current techniques will be explored for process variation effects and statistical optimization.







Thank you !!!