Geostatistical-Inspired Metamodeling and Optimization of Nano-CMOS Circuits

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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 geostatistics fields for mining purposes
    \[ y(x_0) = \sum_{j=1}^{L} \lambda_j B_j(x) + z(x) \]
  - Each point is predicted with a set of unique weights (\( \lambda_j \))
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, 
\[ \sum_{j=1}^{n} \lambda_j = 1 \]
Simple Kriging Metamodel Generation
Gravitational Search Algorithm ...

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

\[ F_{i,j}^d(t) = G(t) \left( \frac{M_{p_i}(t) \times M_{a_j}(t)}{R_{i,j}(t) + \epsilon} \right) (x_j^d(t) - x_i^d(t)) \]

- Where \( F_{i,j}^d(t) \) 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: \( \text{counter} \leftarrow 0 \).
2: Initialize max iteration \( \text{Max}_\text{iter} \).
3: Initialize number of search agents \( \eta \) gravity constant \( G \), and velocity \( \nu \).
4: Generate \( \eta \) random search nodes (design parameter sets).
5: Consider the objective of interest \( \text{Power}_{TS_i} \).
6: \( \text{counter} \leftarrow \text{max}_\text{Iteration} \).
7: \textbf{while} (\( \text{counter} < \text{Max}_\text{iter} \)) \textbf{do}
8: \hspace{1em} Evaluate objective of interest (\( \text{Power}_{TS_i} \)) for each search node.
9: \hspace{1em} Update best and worst solution per function objective.
10: \hspace{1em} Update the gravity constant \( G \).
11: \hspace{1em} Calculate \( M \) and \( a \) for each search node.
12: \hspace{1em} Update \( \nu \) for each search node.
13: \hspace{1em} Update search nodes by applying velocity on \( M \).
14: \hspace{1em} \( \text{counter} \leftarrow \text{counter} + 1 \).
15: \textbf{end while}
16: \textbf{return} bestsolution.
Experimental Results: 45nm Thermal Sensor

- Ring Oscillators for sensing
- Binary Counter
- Register
45nm Thermal Sensor

Frequency response vs temperature for 45nm thermal sensor

<table>
<thead>
<tr>
<th>Design</th>
<th>Avg Pwr</th>
<th>Sensitivity</th>
<th>Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>Schematic</td>
<td>293.1µW</td>
<td>16.88MHz/°C</td>
<td>-</td>
</tr>
<tr>
<td>Layout</td>
<td>379.4µW</td>
<td>9.42MHz/°C</td>
<td>1221.37µm²</td>
</tr>
<tr>
<td>% Change</td>
<td>+29%</td>
<td>-44%</td>
<td></td>
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</tbody>
</table>
Experimental Results

Accuracy Analysis of Simple Kriging Metamodel

<table>
<thead>
<tr>
<th>Metric</th>
<th>Value</th>
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<tbody>
<tr>
<td>MSE</td>
<td>4.36 x 10^{-18}</td>
</tr>
<tr>
<td>RMSE</td>
<td>2.09 x 10^{-09}</td>
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<tr>
<td>R₂</td>
<td>0.9934</td>
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</tbody>
</table>

Optimization using GSA
# Optimal Design Results

<table>
<thead>
<tr>
<th>Design</th>
<th>Average Power</th>
<th>Sensitivity</th>
<th>Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>Schematic</td>
<td>293.1µW</td>
<td>16.88MHz/°C</td>
<td>-</td>
</tr>
<tr>
<td>Layout</td>
<td>379.4µW</td>
<td>9.42MHz/°C</td>
<td>1221.37µm²</td>
</tr>
<tr>
<td>Final</td>
<td>+29%</td>
<td>9.42MHz/°C</td>
<td>1770.98µm²*</td>
</tr>
<tr>
<td>% Change</td>
<td>36.9%</td>
<td>44.2%</td>
<td>45%*</td>
</tr>
</tbody>
</table>
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 !!!