Ordinary Kriging Metamodel-Assisted Ant Colony Algorithm for Fast Analog Design Optimization

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Presented By
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Outline of the talk

- Background and Motivation
- Related Prior Research
- Fundamentals of Ordinary Kriging
- Proposed Design Optimization Flow Methodology
- Case Study Circuit: 45nm Sense Amplifier
- 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

Novel Contributions

- Design flow methodology incorporating Kriging metamodeling and ant colony based optimization.
- Ordinary Kriging metamodeling techniques that account for correlating effect of process parameters.

Prior Related Research

- Polynomial regression techniques
- Neural Networks
- Kriging Based Techniques
  - G.Yu --- re-iterative pareto fronts
  - H.You -- Metamodeling

Fundametals of Kriging

- Originally used in geostatistics fields for mining purposes.

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

- Each point is predicted based on a set of unique weights (λ_j).

Fundametals of Kriging…

- Ordinary kriging weights are biased

$$\sum_{j=1}^{n} \lambda_j = 1. \tag{3}$$

- Weighting

$$\begin{pmatrix} \lambda_1 \\ \vdots \\ \lambda_n \\ \mu \end{pmatrix} = \Gamma^{-1} \begin{pmatrix} \gamma(e_1, e_0) \\ \vdots \\ \gamma(e_n, e_0) \\ 1 \end{pmatrix}, \tag{4}$$

$$\Gamma = \begin{pmatrix} \gamma(e_1, e_1) & \cdots & \gamma(e_1, e_n) & 1 \\ \vdots & \ddots & \vdots & 1 \\ \gamma(e_n, e_1) & \cdots & \gamma(e_n, e_n) & 1 \\ 1 & 1 & 1 & 0 \end{pmatrix}, \tag{5}$$

Proposed Design Flow Algorithm

Algorithm 1 The Proposed Design Flow.

```
1:  Create baseline design.
2:  Identify Figures of Merit (FoMs) (verify functionality).
3:  Create physical layout.
4:  Perform DRC/LVS and RLCK extraction.
5:  Identify design parameters and parameterize netlist.
6:  Metamodel Generation.
7:  Perform Latin HyperCube Sampling to generate design
    points for metamodel.
8:  Generate Kriging metamodels using mGStat tool.
9:  Optimization.
10: while (Optimization objective not met ) do
11:     Perform ACO based algorithm.
12: end while
13: return Optimized Design.
```

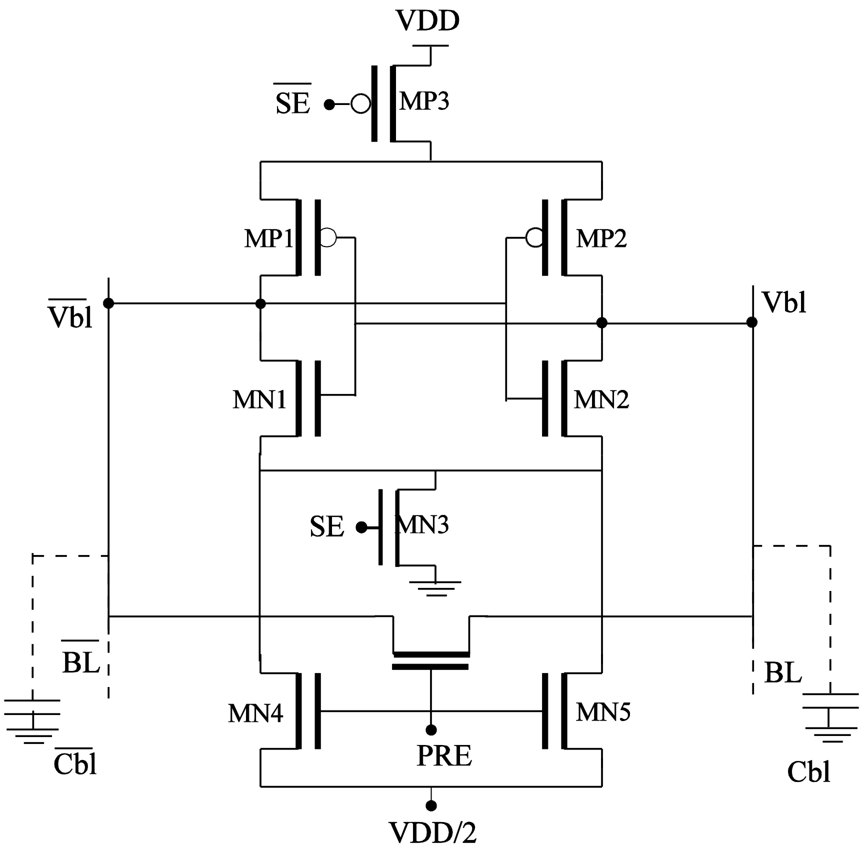
Design Flow Components

- Design and Netlist Optimization
  - Baseline design (schematic and layout)
  - Parameterize extracted parasitic netlist
  - Identify performance objectives to be optimized.
- Sampling Technique (with LHS)
  - Divides design space into equal number of n sample points.
  - L, W used as sampling corners and process parameters are varied
  - Captures better representation of design space

Design Flow Components

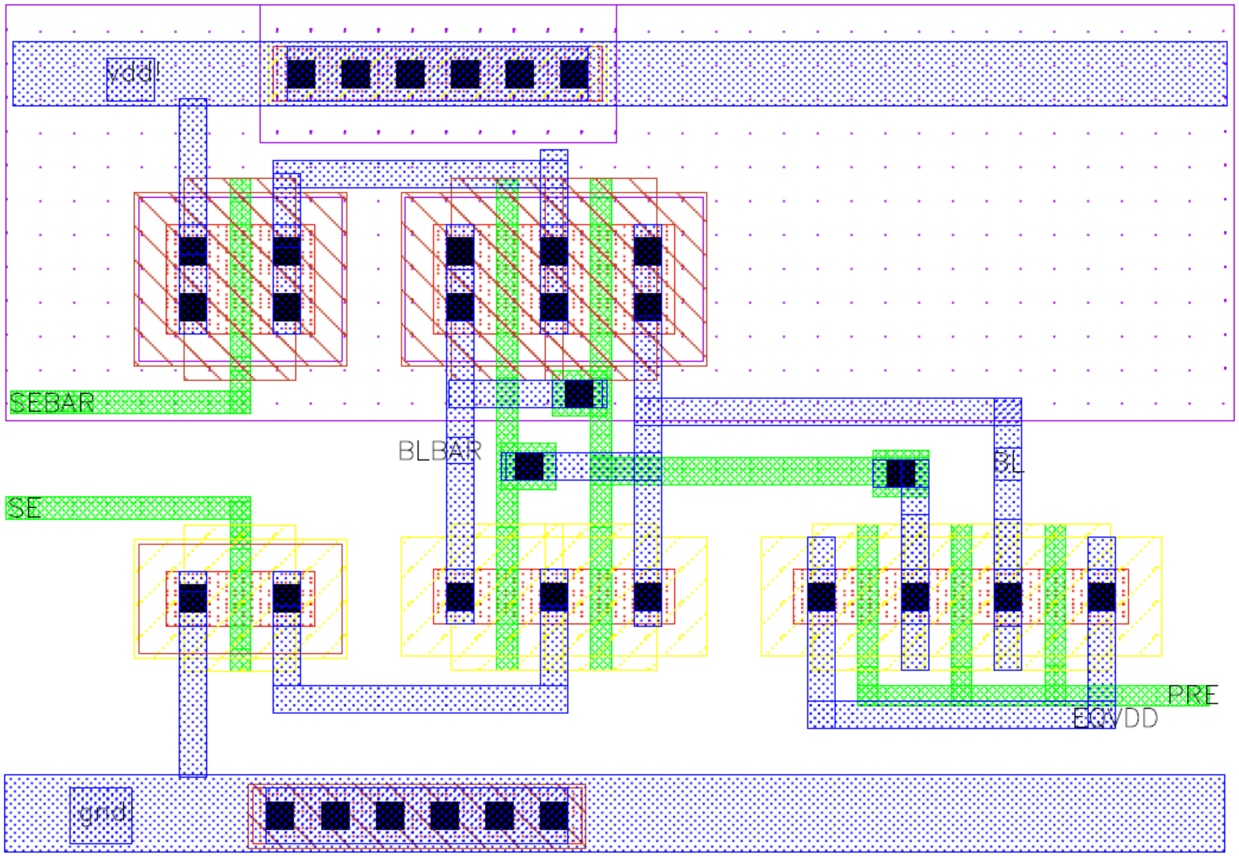
- Kriging assisted metamodels
  - Metamodel for each design objective is generated
    - using mGstat (MATLAB Kriging tool)
  - Design objectives are functions of design parameters
    - e.g. $$\widehat{Y}_{pr}\left(W_n^*\right) = \sum_{i=1}^{N} \lambda\left(W_n^*\right)_i Y_{pr}\left(W_{n_i}\right), \qquad (7)$$
- Conflicting design objectives used as optimization goal and constraint.
  - Kriging based metamodels optimized with SA algorithm
  - Conflicting design objectives used as optimization goal and constraint.

CBSA: Case Study Circuit



- ❑ MP_1, MP_2, MN_1 and MN_2 form cross-coupled inverters.
- ❑ MN3 , MN4 and MN5 form the precharge circuit

CBSA:Case Study Circuit

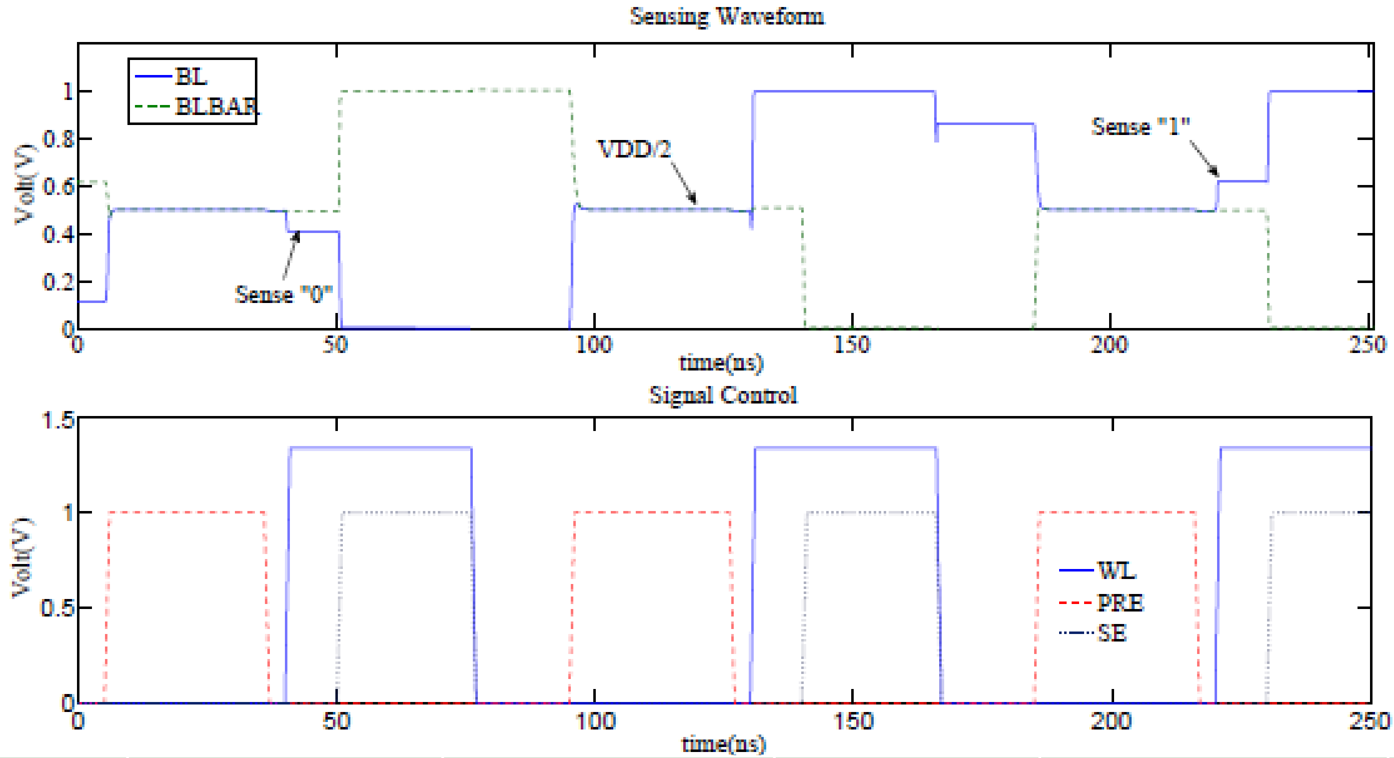


- L_n ,L_p= 45nm
- W_n = 120nm
- W_p = 240nm

Sense Amplifier: Figure of Merits

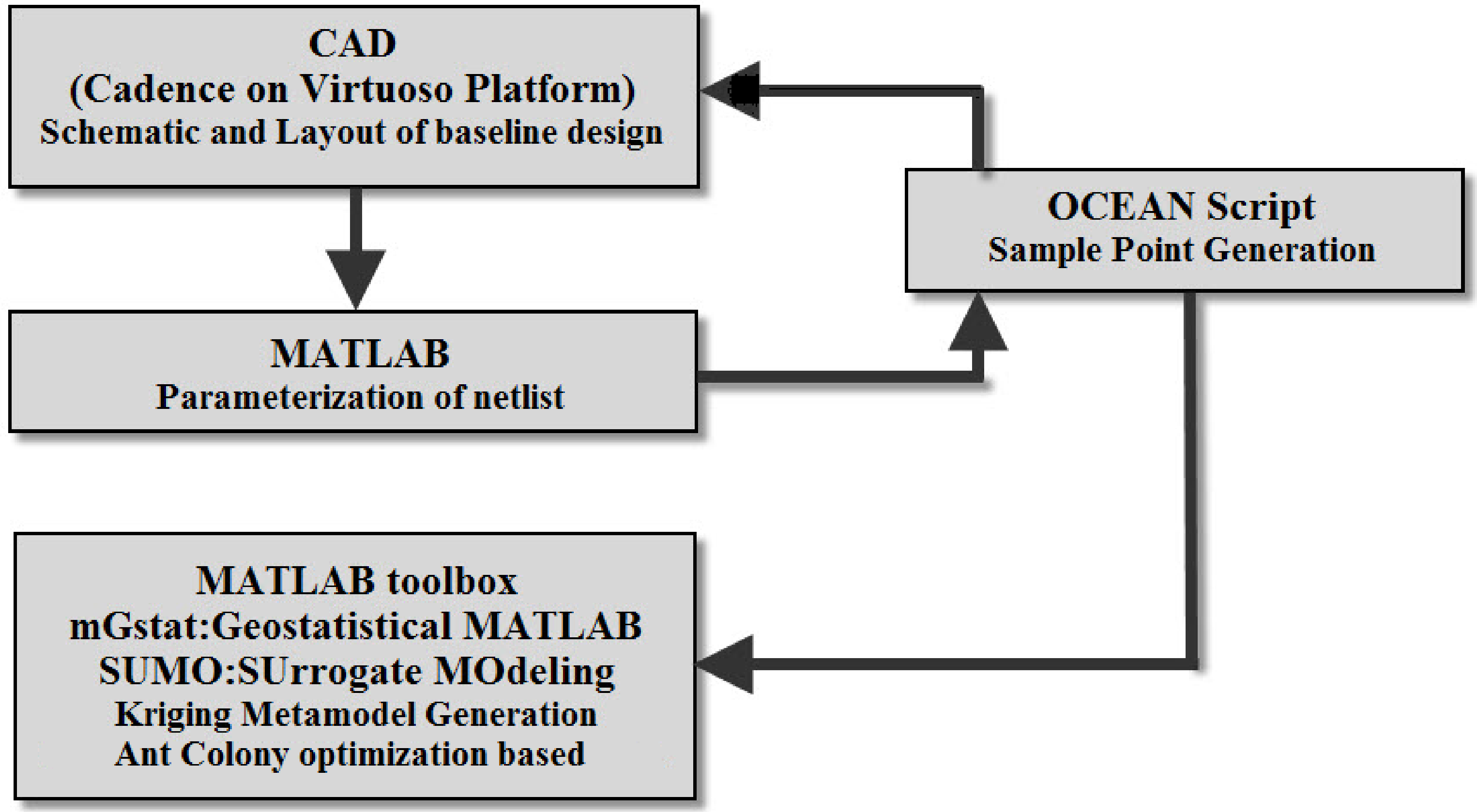
- Precharge time
  - Time required to setup bitlines
- Sense Delay
  - Time required for sufficient voltage to appear on bitlines
- Power Consumption
  - Average power consumption (including dynamic, subthreshold and leakage power)
- Sense Margin
  - Amount of sufficient voltage required for correct read or write

Functional simulation of CBSA



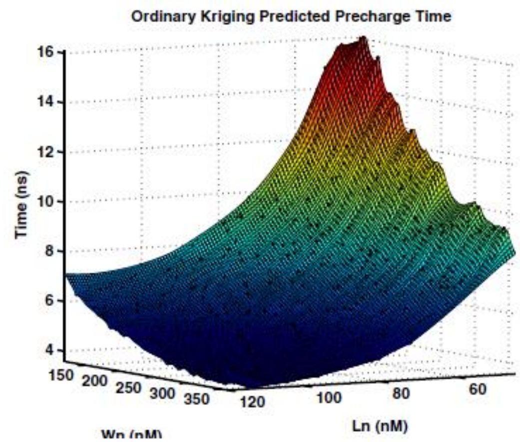
Design	Precharge time, T_{PC} (ns)	Sense delay, T_{SD} (ns)	Power, P_{SA} (µW)	Sense Margin, V_{SM} (mV)	Area (µm2)
Schematic	18.02	7.46	1.16	29.933	-
Layout	18.20	7.45	1.17	26.86	4.294

Setup and Tools Interaction

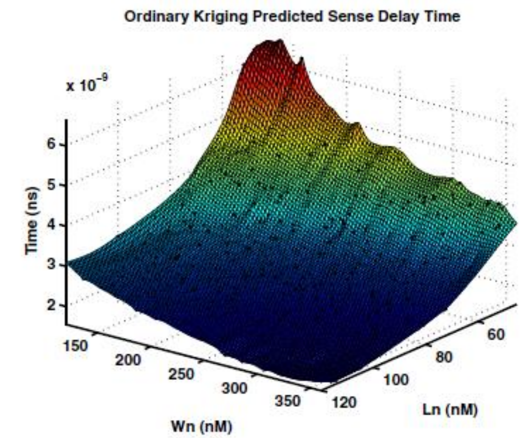


Steps and Tool Interaction

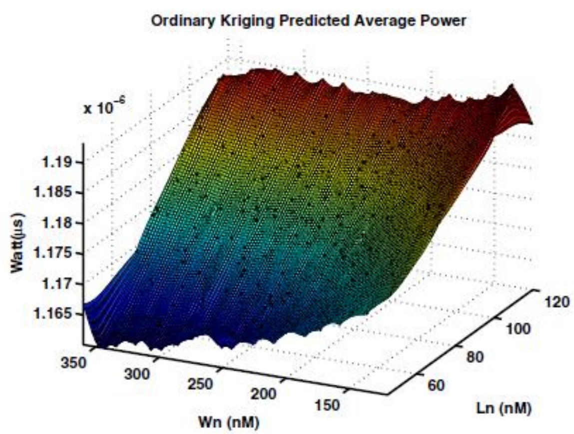
Kriging predicted metamodels (ordinary)



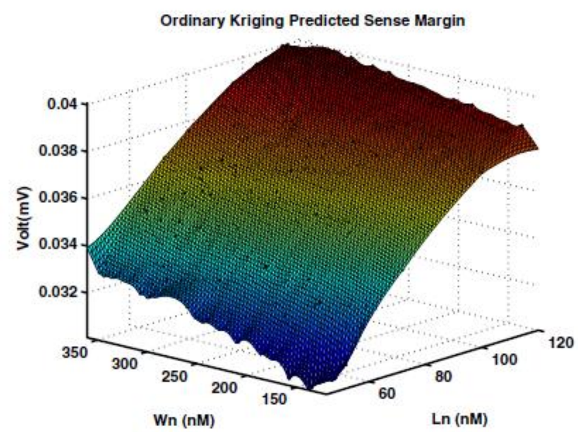
(a) Response for precharge time



(b) Response for sense delay



(c) Response for average power



(d) Response for sense margin

Accuracy and Validation

STATISTICAL ANALYSIS OF THE KRIGING PREDICTED RESPONSES

FoMs	Ordinary Kriging		
Samples	100	200	500
Precharge			
MSE	2.20×10^{-19}	5.23×10^{-20}	1.84×10^{-20}
$RMSE$	4.69×10^{-10}	2.29×10^{-10}	1.36×10^{-10}
R^2	0.9650	0.9917	0.9971
STD	4.32×10^{-10}	2.03×10^{-10}	1.27×10^{-10}
Sense Delay			
MSE	4.22×10^{-20}	1.16×10^{-20}	4.75×10^{-21}
$RMSE$	2.05×10^{-10}	1.08×10^{-10}	6.89×10^{-11}
R^2	0.9529	0.9871	0.9947
STD	1.89×10^{-10}	9.39×10^{-11}	6.26×10^{-11}
Power			
MSE	1.84×10^{-17}	1.08×10^{-17}	1.02×10^{-11}
$RMSE$	3.44×10^{-09}	3.29×10^{-09}	3.20×10^{-09}
R^2	0.8384	0.8525	0.8606
STD	1.19×10^{-09}	9.47×10^{-10}	6.06×10^{-10}
Sense Margin			
MSE	1.12×10^{-07}	3.41×10^{-08}	9.47×10^{-09}
$RMSE$	3.35×10^{-04}	1.85×10^{-04}	9.73×10^{-05}
R^2	0.9804	0.9940	0.9983
STD	2.98×10^{-04}	1.62×10^{-04}	9.05×10^{-05}

Design Optimization

Algorithm 3 ACO Heuristic Algorithm for Sense Amplifier.

Initialize $number\ of\ ants\ (solutionset)$
Initialize iteration counter: $counter \leftarrow 0$
Start with initial baseline solution $\widehat{(SA_i)}$
Generate metamodel functions for each FoM of $\widehat{(SA_i)}$ with Ordinary Kriging.
Consider the objective of interest T_{PC_i}
Generate random ant nodes AL, W_i, where i = 1,2,...,N_{ant}.
Assign initial pheromone, τ_i
$counter \leftarrow max\_Iteration$
while $(counter > 0)$ **do**
    Generate ant solutions T_{PC_i}
    Rank solutions $\widehat{(SA_i)}$ in set from best to worst.
    Update pheromone, increase pheromone for best solution and evaporate pheromone for all others
    $result \leftarrow T_{PC_i}$
    Generate new ant nodes AL, W_i,
    $counter \leftarrow counter - 1$
end while
return $result$

Optimal Simulation Results

Design	Precharge time, T_{PC} (ns)	Sense delay, T_{SD} (ns)	Power, P_{SA} (µW)	Sense Margin, V_{SM} (mV)	Area (µm2)
Schematic	18.02	7.46	1.16	29.33	-
Layout	18.20	7.45	1.17	26.86	4.294
Optimized	6.23	2.58	1.18	35.56	5.286
Change	65.77%	65.37%	-0.85%	21.57%	23.10%

Conclusions

- A novel design flow methodology incorporating Kriging metamodeling and Ant Colony optimization algorithm based was presented
- Optimized FoM (T_{PC}) by 65.77%
- Current techniques will be extended to high dimension parameters and multi objective optimization.

Thank you !!!