Geostatistics Inspired Fast Layout Optimization of Nanoscale CMOS Phase Locked Loop

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Presented By
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Outline of the talk

- Background and Motivation
- Related Prior Research
- Geostatistics Based Metamodeling
- Proposed Design Flow and GSA Optimization
- Case Study Circuit and Experimental Setup
- Results
- Conclusions

Background and Motivation

- Computer simulations are expensive
- Pronounced effects of process variations in deep nanometer regions
  - Increase in number of design parameters
  - Current modeling techniques not effective at capturing effects of process variation
- Complex and high density designs
- Designs for low power consumption

Novel Contributions

- Exploring Kriging for high dimensional metamodeling
- Design flow methodology
  - Kriging metamodeling and gravitational search algorithm optimization.

Prior Related Research

- Exploration of optimization algorithms for NanoCMOS designs
- Kriging Based Techniques
  - O. Okobiah --- simple and ordinary kriging metamodels
  - G.Yu --- re-iterative Pareto fronts
  - H. You --- kriging metamodeling

Fundamentals of Kriging

- Originally used in geostatistics 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).

$$\sum_{j=1}^{n} \lambda_j = 1. \qquad (3)$$

Fundametals of Kriging…

$$\begin{pmatrix} \lambda_1 \\ \vdots \\ \lambda_n \\ \mu \end{pmatrix} = \Gamma^{-1} \begin{pmatrix} \gamma(x_1, x_0) \\ \vdots \\ \gamma(x_n, x_0) \\ 1 \end{pmatrix}, \qquad (3)$$

$$\Gamma = \begin{pmatrix} \gamma(x_1, x_1) & \cdots & \gamma(x_1, x_n) & 1 \\ \vdots & \ddots & \vdots & 1 \\ \gamma(x_n, x_1) & \cdots & \gamma(x_n, x_n) & 1 \\ 1 & 1 & 1 & 0 \end{pmatrix}, \qquad (4)$$

$$\widehat{P_{PLL}}(\mathbf{Wn_0}) = \sum_{j=1}^{L} \lambda_j B_j(\mathbf{wn}) + z(\mathbf{wn}), \qquad (7)$$

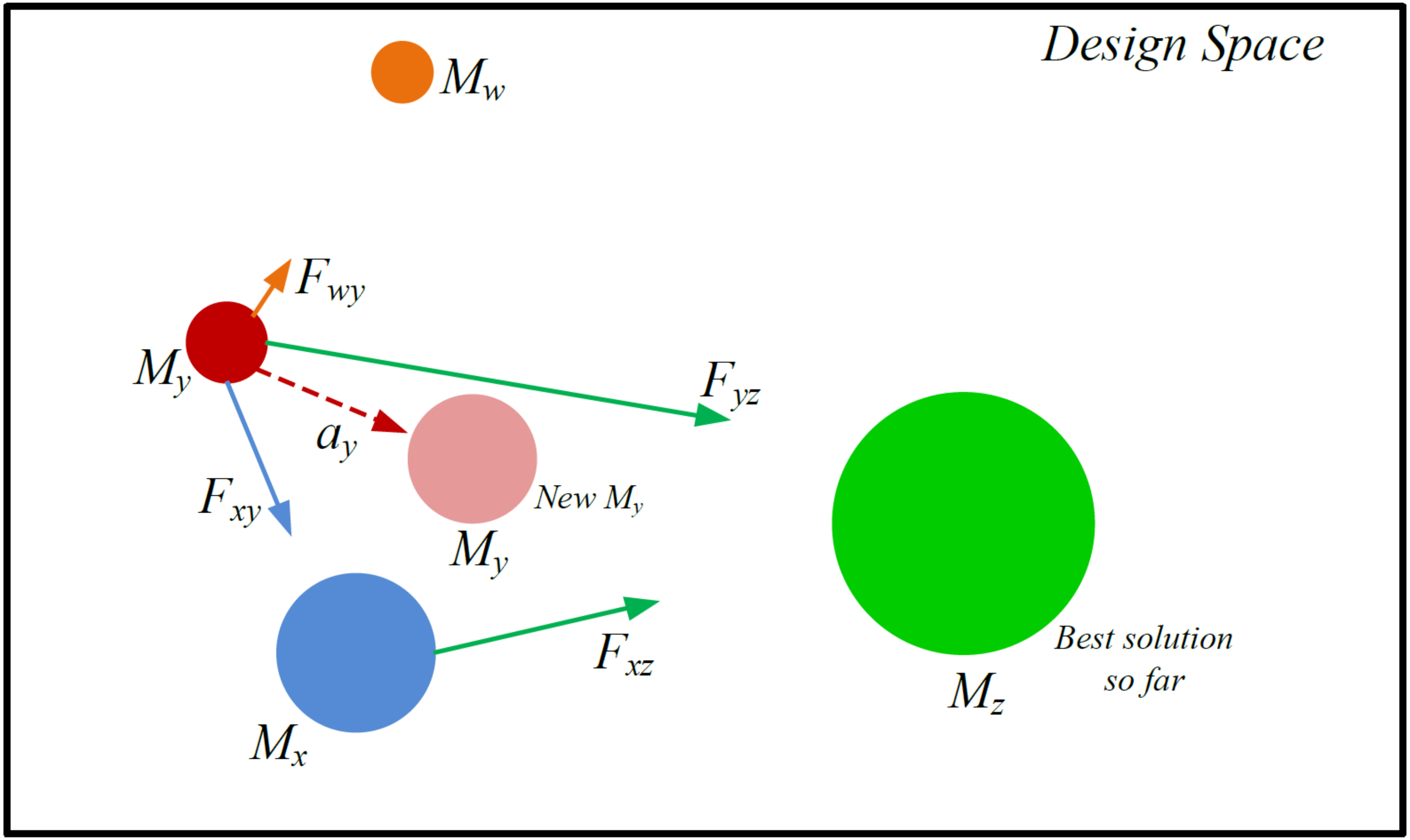
Gravitational Search Algorithm

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

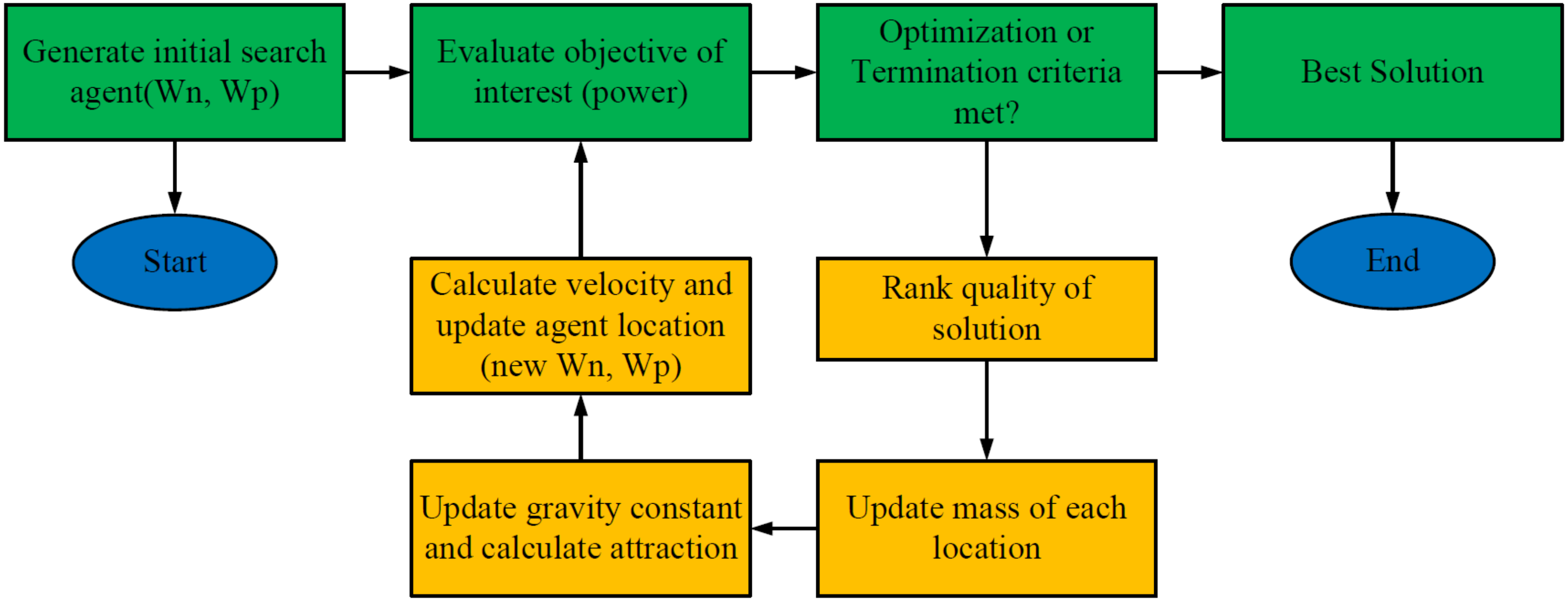
$$F_{ij}^{d}(t) \quad = \quad G(t)\frac{M_{pi}(t) \times M_{aj}(t)}{R_{ij}(t) + \epsilon}(x_j^d(t) - x_i^d(t)),$$

- 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



Gravitational Search Algorithm



Case Study Circuit: 180nm PLL

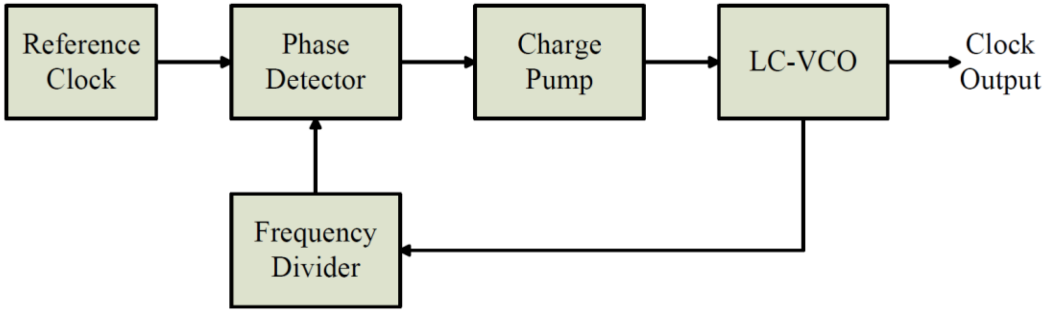


Fig. 3. System level diagram of the PLL

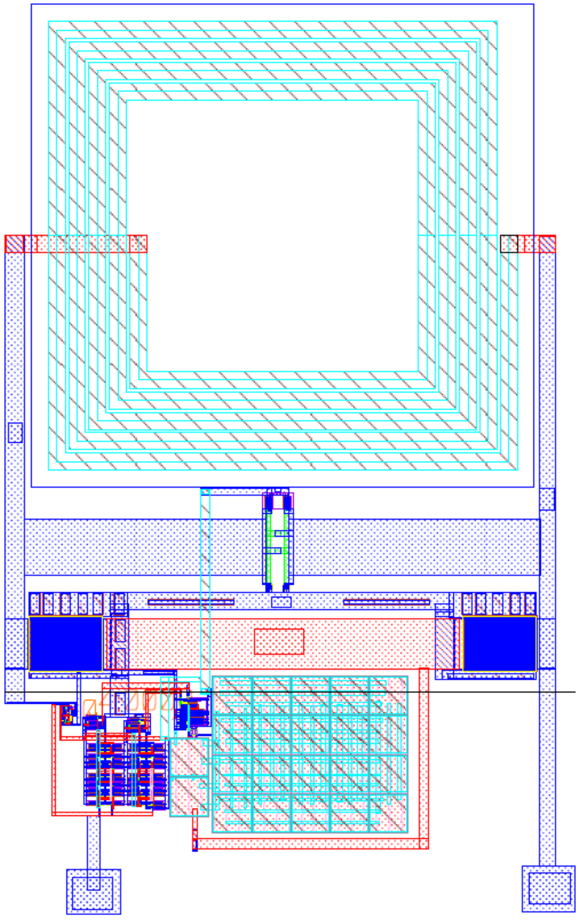
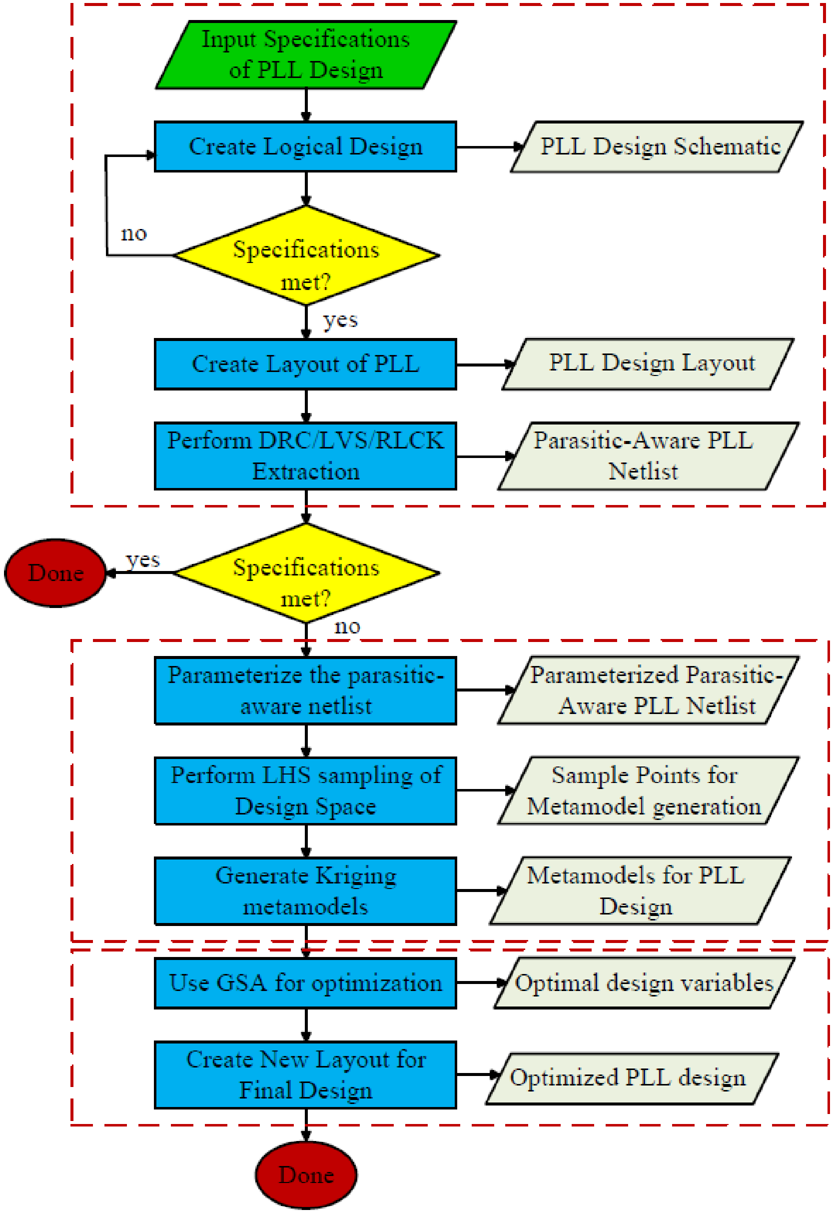


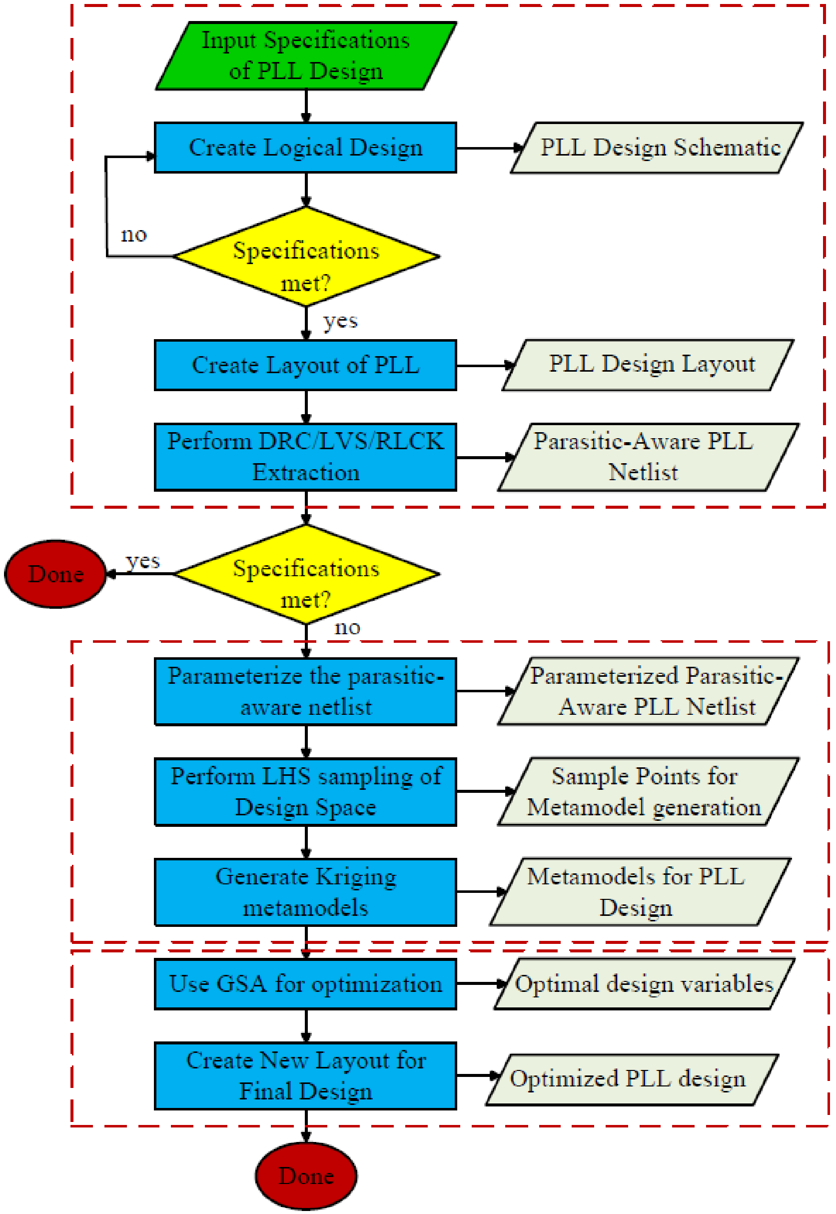
Fig. 4. 180nm layout of the PLL

Proposed Design Flow



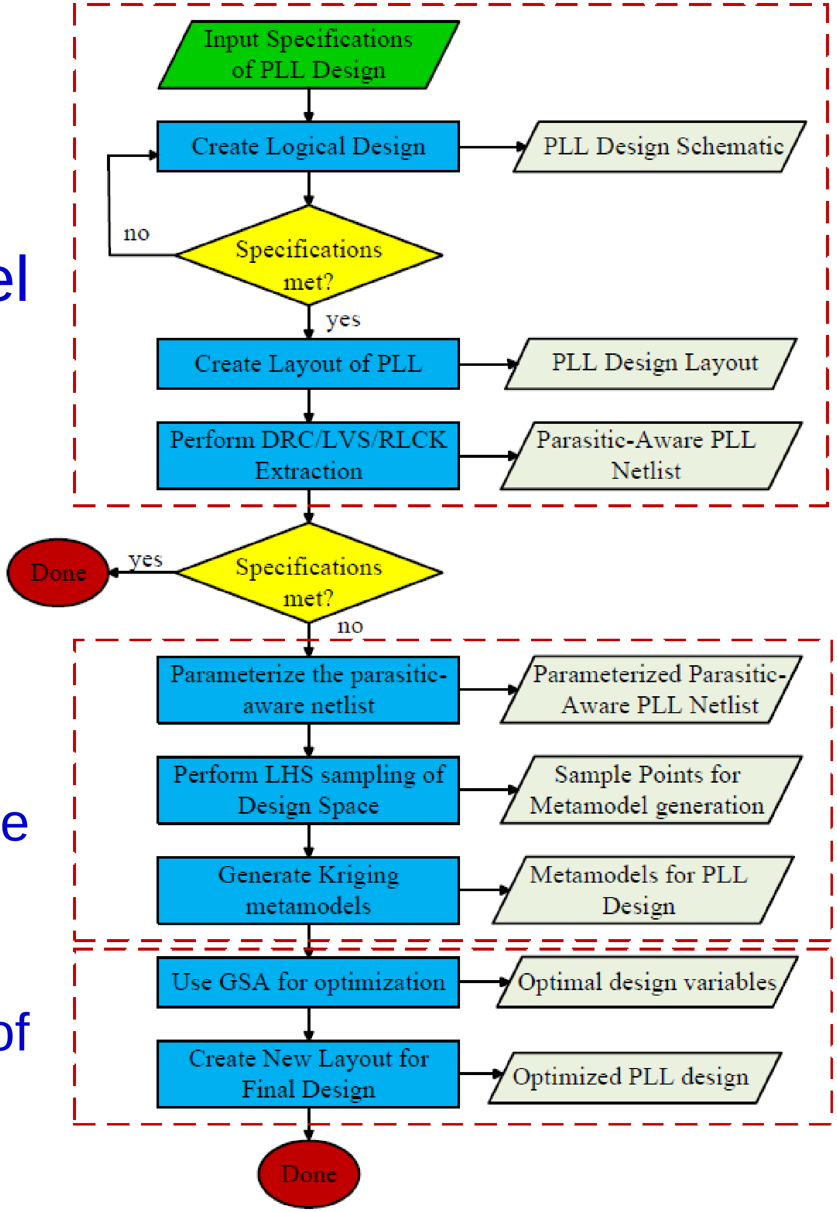
Design Flow Components

- Design and netlist optimization
  - Baseline design
    - (schematic and layout)
  - Extract parasitic netlist



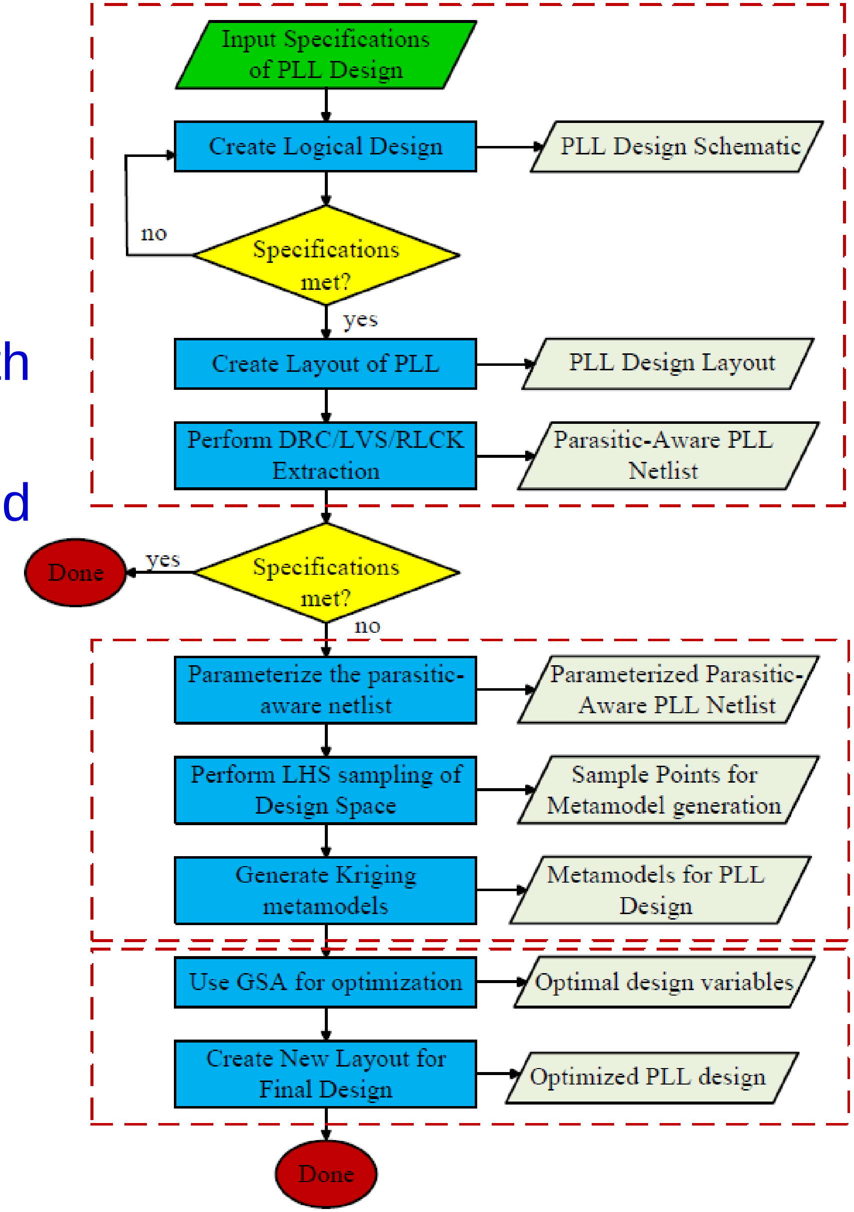
Design Flow Components

- Sampling and Metamodel Generation
  - Parameterize parasitic netlist
    - Identify performance objectives
  - LHS sampling
    - L, W as sampling corners
    - process variation
  - Metamodel for each design objective is generated
    - using mGstat (MATLAB Kriging tool)
  - Design objectives are functions of design parameters
    - e.g. $$\widehat{P_{PLL}}(\mathbf{Wn_0}) = \sum_{j=1}^{L} \lambda_j B_j(\mathbf{wn}) + z(\mathbf{wn}), \qquad (7)$$



Design Flow Components

- Design Optimization
  - Kriging metamodels optimized with GSA algorithm
  - Conflicting design objectives used as goal and constraint
  - Final physical design is drawn



Experimental Results

TABLE III
OPTIMIZED PARAMETER VARIABLES

PLL Components	Parameter	Min (m)	Max (m)	Optimal (m)
Phase Detector	W_{pPD1}	400n	2μ	1.53μ
	W_{pPD1}	400n	2μ	0.95μ
	W_{pPD1}	400n	2μ	1.00μ
	W_{nPD1}	400n	2μ	1.16μ
	W_{nPD1}	400n	2μ	0.52μ
	W_{nPD1}	400n	2μ	1.58μ
Charge Pump	W_{nCP1}	400n	2μ	1.12μ
	W_{pCP1}	400n	2μ	1.32μ
	W_{nCP2}	2μ	4μ	2.07μ
	W_{pCP2}	4μ	4μ	4.72μ
LC-VCO	W_{nLC}	3μ	20μ	12.22μ
	W_{pLC}	6μ	40μ	14.83μ
Divider	W_{pDIV1}	400n	2μ	1.06μ
	W_{pDIV2}	400n	2μ	1.11μ
	W_{pDIV3}	400n	2μ	0.75μ
	W_{pDIV4}	400n	2μ	1.78μ
	W_{nDIV1}	400n	2μ	1.35μ
	W_{nDIV1}	400n	2μ	1.86μ
	W_{nDIV1}	400n	2μ	1.65μ
	W_{nDIV1}	400n	2μ	1.96μ
	W_{nDIV1}	400n	2μ	0.43μ

Metric	Value
RMSE	6.46×10^{-10}
R^2	0.9959

Metric	Power (mW)	Locking Time (ns)	Area (μm^2)
Baseline Design	8.27	2.74	525 x 326
Optimal Design	1.67	2.63	525 x 326
Reduction	79 %	4 %	0 %

Experimental Results

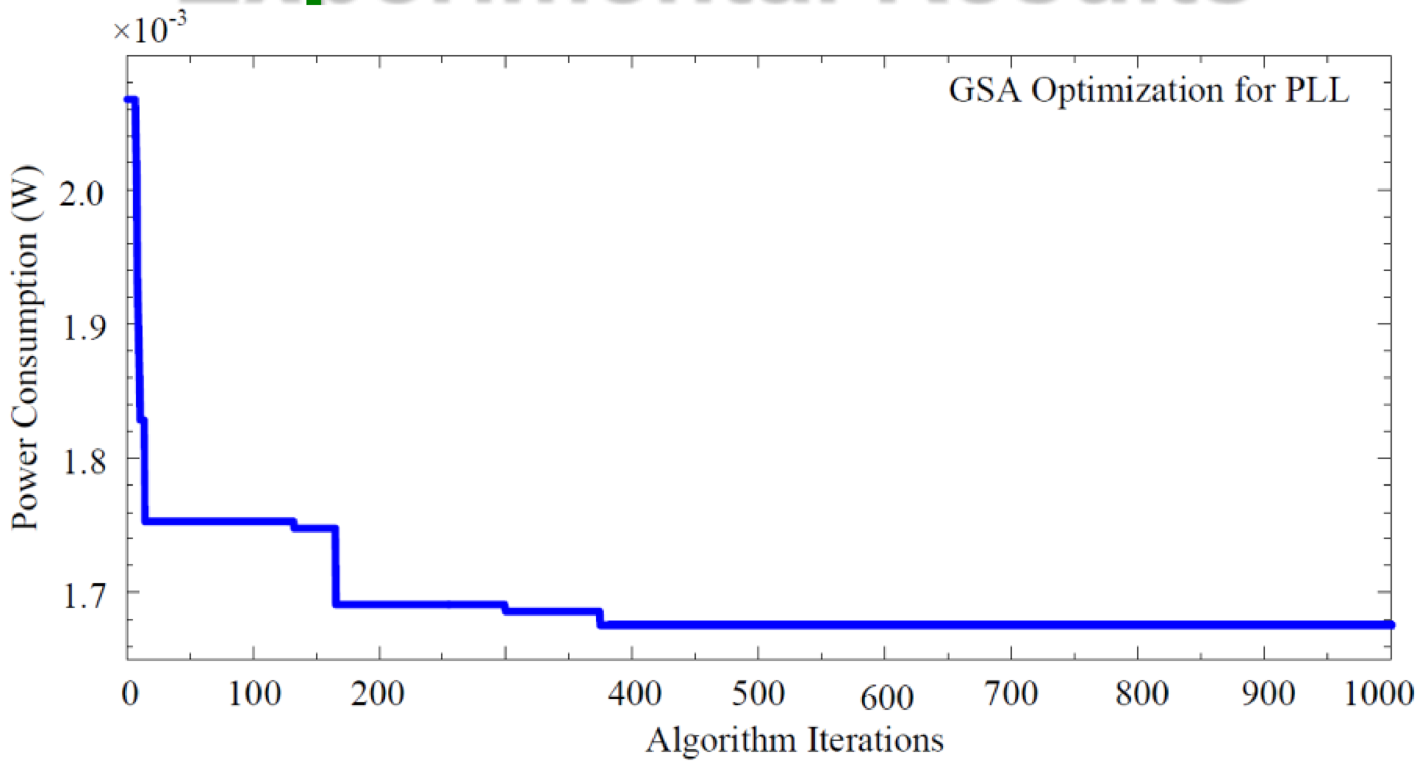


Fig. 5. Optimization Steps of the PLL

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Optimal Design	1.67	2.63	525 x 326
Reduction	79 %	4 %	0 %

Related Comparison

Research	Test Circuits	Metamodeling Technique	Accuracy	Optimization Technique
You	Integrated Op-Amp	Kriging	0.5658	-
Yu	Ring Oscillator	Kriging	0.5325% (MSE)	-
	LC-VCO		0.5563% (MSE)	-
Okobiah	Sense Amplifier	Kriging	3.2×10^{-9}	ACO
Garitselov	PLL	Polynomial	0.5658	ABC
		ANN	0.5658	
This work	PLL	Kriging	6.46×10^{-9}	GSA

Conclusions

- A novel design flow methodology was presented
  - Incorporating Kriging metamodeling
  - Demonstrating GSA algorithm based optimization
- Optimized PLL power by 79%

Thank you !!!