Kriging Bootstrapped Neural Network Training for Fast and Accurate Process Variation Analysis

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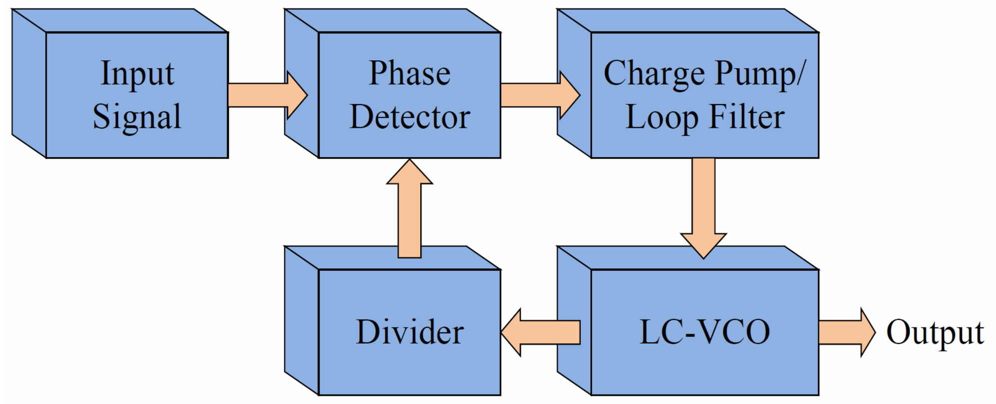
Abstract

Speeding up the design optimization process of Analog/Mixed-Signal circuits has been a subject of active research. Metamodeling assisted techniques provide promising and accurate results. However, the effects of process variation on design space exploration still persist. This paper presents a novel technique for fast and accurate process variation analysis of nanoscale circuits. The technique combines traditional Kriging with an Artificial Neural Network (ANN) to achieve this objective. Kriging captures correlated process variations and accurately trains the ANN to generate the metamodels. The proposed technique uses Kriging to bootstrap target samples used for the ANN training. This introduces Kriging characteristics, which account for correlation effects between design parameters, to the ANN. The proposed Kriging bootstrapped trained ANN metamodels are presented for an 180 nm Phase-Locked Loop (PLL) circuit design.

Case Study Circuit: PLL

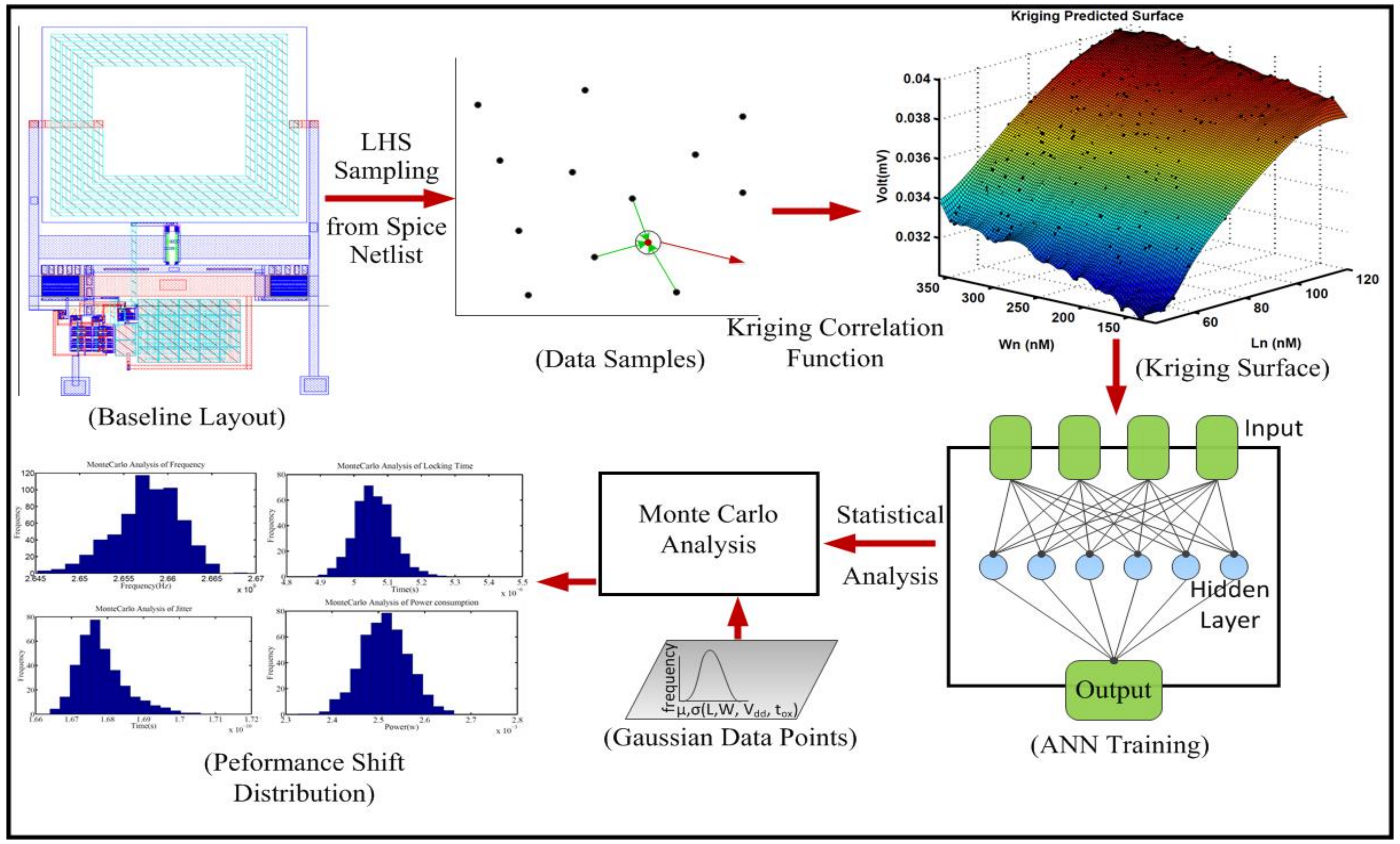
- The design process of a Phase Locked Loop (PLL) is used to illustrate the efficiency of the proposed technique.
- The design objective was to minimize power dissipation using locking time as a constraint.
- The physical design of the PLL was implemented using 180nm technology.
- The parasitic netlist is extracted and parameterized for 21 design variables.



Characterization of PLL for Figures-of-Merit (FOM)

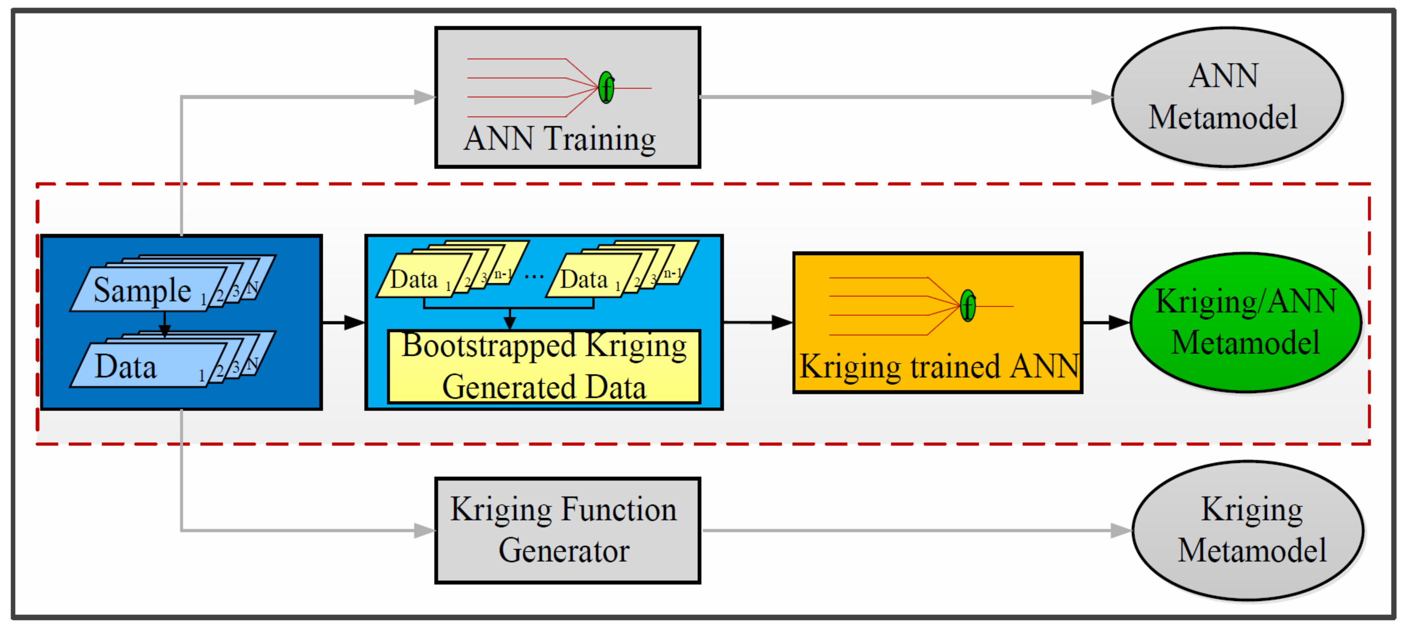
Circuit	P_{PLL}	F_{PLL}	Lck_{PLL}	J_{PLL}
PLL	2.48 mW	2.66 GHz	5.51 μs	16.80 ns

The Proposed Kriging-ANN Metamodel based Fast Analysis Method



Kriging Bootstrapped ANN Concept

- Kriging techniques take into account the correlation effects between design parameters and can thus better capture the effects of process variation during the design process.
- Kriging weighting calculations are potentially time consuming for high dimensional designs.



- ANN techniques produce accurate models but do not model process variation effects.
- The proposed technique combines Kriging and ANN by using intermediate sample (bootstrapped) data points to train the ANN model.

Metamodel Accuracy and Comparison

Statistical Analysis for Accuracy of Generated Metamodels for PLL

		Circuit	Kriging-ANN		Kriging		ANN	
		Value	Value	error (%)	Value	error (%)	Value	error (%)
P_{PLL}	Mean	2.48 mW	2.40 mW	3.22	2.50 mW	0.81	2.50 mW	0.81
	STD	0.42 mW	0.34 mW	19.05	0.51 mW	21.43	0.69 mW	64.28
F_{PLL}	Mean	2.66 GHz	2.51 GHz	5.64	2.66 GHz	0.11	2.74 GHz	5.38
	STD	10.95 MHz	41.93 MHz	282.92	3.72 MHz	66.03	51.9 MHz	373.97
Lck_{PLL}	Mean	5.51 μs	5.11μs	7.26	5.51 μs	0.07	5.20 μs	5.63
	STD	0.72 μs	0.44 μs	38.88	.58 ns	10.25	1.01 μs	40.27
J_{PLL}	Mean	16.80 ns	14.69ns	10.25	16.78ns	0.12	17.91 ns	6.61
	STD	1.32 ps	4.50 ps	240.91	0.68ps	48.48	19.17 ps	1352.22

Comparison with Related Metamodel Designs

Research	Metamodel	Test Circuit	Accuracy
Garitselov [28]	Polynomial	PLL	0.157
Yu [9]	Kriging	RO	0.5325 (MSE)
		LC-VCO	0.5325 (MSE)
Kuo [7]	Polynomial	PLL	2.0×10^{-4}
This Paper	Kriging-ANN	PLL	2.51×10^{-6}

Model	Kriging-ANN	Kriging	ANN
Time	19 s	468 s	19 s
Speedup	24.63×	1	24.63×

Monte-Carlo Time Analysis

Conclusion

- A metamodeling technique combining Kriging and Artificial Neural Networks to create process aware metamodels is presented.
- The proposed technique shows improved process awareness over conventional ANN models and achieves Monte Carlo analysis time speed up of 25x over Kriging models.
- Future work could explore techniques for increasing nominal accuracy.