
Adaptive Online Surrogate-Assisted Multi-Objective Optimization for Analog Circuit Design Using Active Learning and NGSpice Feedback

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Abstract.

This work proposes an online surrogate-assisted TSMCOA sizing framework using constrained parameterization, Random Forest surrogates, uncertainty-guided NGSpice feedback, and NSGA-II. With 500 initial samples and 600 evaluations, adaptive optimization reduces NGSpice calls from 600 to 190 (68.3%) while retaining competitive Pareto quality.

Keywords. Analog circuit optimization; surrogate modeling; active learning; NGSpice; NSGA-II; machine learning assisted EDA.

1. INTRODUCTION

Analog sizing requires repeated SPICE evaluation under nonlinear constraints [1]–[4]. Surrogate methods reduce cost [5], [6], but fixed offline models can fail in localized feasible regions. The proposed method therefore invokes NGSpice only for uncertain candidates and retrains online.

2. LITERATURE REVIEW AND RELATED WORK

Prior work covers evolutionary and surrogate-assisted sizing [7]–[11]. Offline models depend on initial coverage, while online and feasibility-aware approaches use new high-fidelity samples [12]–[16]. This work combines uncertainty-guided simulation with constrained multi-objective search.

3. PROBLEM FORMULATION

The TSMCOA is optimized in open-loop NGSpice with a constrained decision vector that preserves device relationships and minimizes power and area subject to gain, phase-margin, UGB, slew-rate, and saturation constraints.

$$x = [W_1, W_5, r_m, r_{s2}, r_{sink}, I_{bias}, C_c]^T \quad (3.1)$$

$$W_2 = W_1, \quad W_3 = W_4 = W_1 r_m, \quad W_6 = W_1 r_{s2}, \quad W_7 = W_5 r_{sink} \quad (3.2)$$

$$F(x) = [P(x), A(x)]^T \quad (3.3)$$

$$A(x) = L_{ch} \sum_{k=1}^7 W_k, \quad P(x) \quad (3.4)$$

$$g(x) = \begin{bmatrix} 75 - G \\ 60 - PM \\ 85 \times 10^6 - UGB \\ 7.5 \times 10^6 - SR \\ \mathbb{I}[\text{sat} = \text{False}] \end{bmatrix} \leq 0 \quad (3.5)$$

RANGES: W1,W5 11–13 μm ; MIRROR RATIO 1.9–2.1; STAGE-2 RATIO 2.2–2.6; SINK RATIO 0.55–0.72; IBIAS 14–18 μA ; C_C 0.60–0.85 pF .

CONSTRAINTS: GAIN ≥ 75 dB, PHASE MARGIN $\geq 60^\circ$, $UGB \geq 85$ MHz, SLEW RATE $\geq 7.5 \times 10^6$ V/s, AND SATURATION.

4. PROPOSED METHODOLOGY

4.1. Circuit Benchmark Description

The benchmark uses 1.8 V, $L=0.18 \mu\text{m}$, $V_{CM}=0.9$ V, generic 180 nm MOS models, and optimized device widths, bias current, and Miller capacitance.

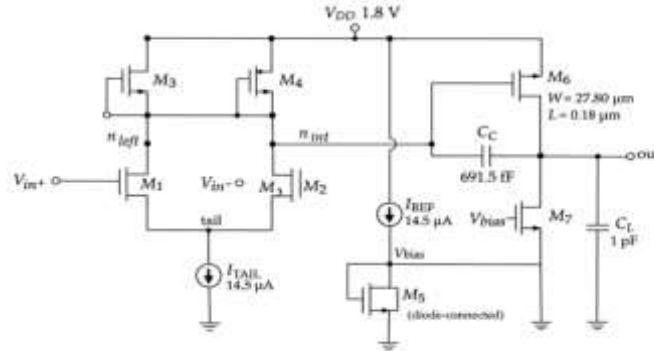


Figure 4.1. Implemented TSMCOA benchmark schematic.

4.2. Surrogate Modeling

Random Forest regressors predict six performance targets; a classifier predicts saturation feasibility.

$$\text{sat}_{\text{status}} = \prod_{k=1}^7 \mathbb{I}(m_k \in \text{saturation}) \quad (4.1)$$

4.3. Active Learning Strategy

Maximum normalized uncertainty triggers NGSpice evaluation and periodic retraining; otherwise the surrogate prediction is accepted.

$$u_j = \frac{\sigma_j}{\max(|\mu_j|, 1)} \quad (4.2)$$

4.4. NSGA-II Optimization Framework

NSGA-II uses population 30 and 20 generations with active-learning evaluation, non-domination ranking, and crowding distance.

5. EXPERIMENTAL SETUP

5.1. Dataset Generation

5.2. Simulation Configuration

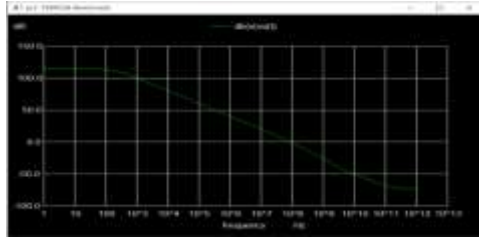


Figure 5.1. Open-loop gain response for gain and UGB extraction.

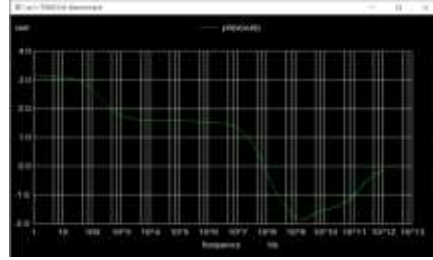


Figure 5.2. Open-loop phase response for phase-margin evaluation.

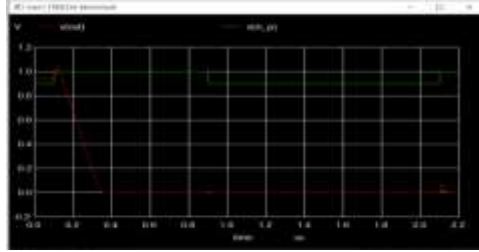


Figure 5.3. Large-signal transient response for slew-rate measurement



Figure 5.4. Derivative waveform for maximum slew-rate extraction.

5.3. Training Setup

Dataset: 500 samples split 350/75/75 (seed 42); 600 evaluations/method; uncertainty threshold 0.35; retraining batch 10.

6. RESULTS AND DISCUSSION

6.1. Surrogate Training Results

Test R^2 : power 0.991, area 0.953, phase margin 0.931, slew rate 0.696, gain 0.684, UGB 0.452.

6.2. Benchmark Comparison

Benchmark: NGSpice calls 600/0/190, constraint satisfaction 62.8/71.3/69.2%, and hypervolume $2.213/1.716/2.020 \times 10^{-4}$ for traditional/offline/adaptive methods.

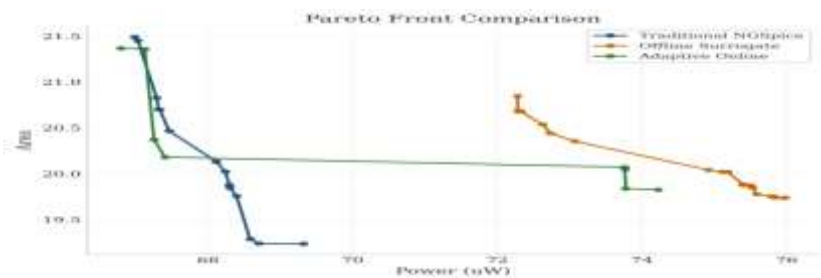


Figure 6.1. Feasible Pareto-front comparison in the power-area plane.

6.3. Pareto and Hypervolume Analysis

Adaptive hypervolume is 8.7% below traditional versus 22.4% offline; best feasible power is 66.791 μ W.

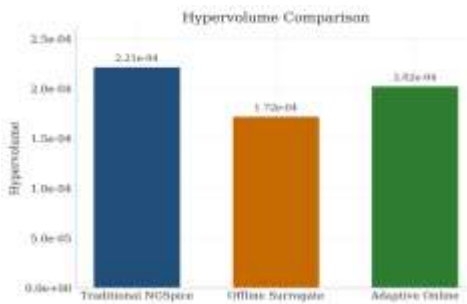


Figure 6.2. Hypervolume comparison of the three benchmark methods.

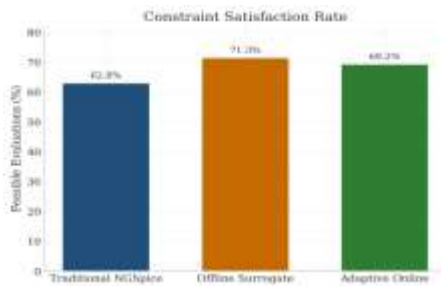


Figure 6.3. Constraint-satisfaction rate of the three methods.

6.4. NGSpice Reduction and Runtime Trade-offs

Adaptive reduces NGSpice calls 68.3% (600 $\rightarrow$ 190); runtime is 377.12 s versus 65.37 s traditional and 67.07 s offline.

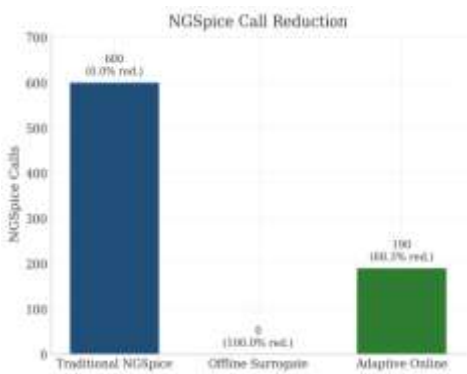


Figure 6.4. NGSpice call reduction across benchmark methods.

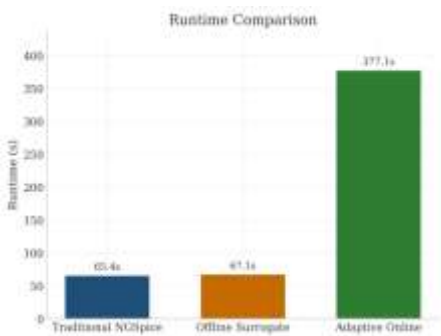


Figure 6.5. Runtime comparison of the benchmark methods.

7. CONCLUSION

Adaptive online optimization reduces simulator calls while preserving better Pareto quality than the offline surrogate; constrained sampling and selective high-fidelity correction are critical.

8. FUTURE WORK

Future work: foundry models, larger analog blocks, improved uncertainty estimation, efficient retraining, explainability, and transfer learning.

9. REFERENCES

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Biographies



Umesh Balkishan Phiske received the B.E. degree in Electronics and Telecommunication Engineering in 2011 and the M.E. degree in 2017. He is currently pursuing a Ph.D. at ALARD University, Pune. His research interests include artificial intelligence, machine learning, analog circuit optimization, FPGA-based systems, MATLAB, and NGSpice.



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