UDC 621.3.049.77-047.56

ADAPTIVE OPTIMIZATION OF RING OSCILLATORS BASED ON PROCESS-CIRCUIT CO-DESIGN

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Abstract: as CMOS technology approaches its physical and economic limits, Design-Technology Co-Optimization (DTCO) has become a critical approach to tapping circuit potential within a constrained process window. Targeting ring oscillators (ROs), this paper proposes an adaptive process-circuit co-optimization scheme. A parameter-exploration framework is established using a multi-objective composite reward function and an improved greedy genetic algorithm. Source/drain extension (EXT) doping is adopted as a low-risk tuning knob, and a staged quantitative-loss-function-driven BSIM4 model extraction strategy is employed to achieve high-fidelity mapping from TCAD to SPICE. Simulation results show that an approximately 6% increase in EXT doping yields a 10.76% rise in RO frequency and an around 11% improvement in the energy-delay product (EDP). The proposed method can substantially enhance circuit performance under a controllable power budget and is applicable to other advanced process nodes.

Keywords: DTCO; Ring Oscillator; Genetic Algorithm; BSIM4 Model.

I. INTRODUCTION

As CMOS technology continues to scale down, device non-ideal effects and process variations exert growing impacts on circuit performance. The conventional sequential design paradigm, which fixes process parameters prior to circuit optimization, suffers from limitations including narrow optimization headroom and non-reproducible performance-power-reliability trade-offs. By introducing design feedback at the early stage of process development to realize joint optimization of devices, processes and circuits, Design-Technology Co-Optimization (DTCO) has emerged as a core solution to address these challenges [1].

Ring oscillators (ROs) are highly sensitive to process parameters. Their key metrics such as frequency, delay and power consumption are directly determined by physical quantities including drive current and parasitic resistance-capacitance [2]. Unlike digital circuits, analog circuits have little structural redundancy, making it difficult to compensate for performance degradation induced by process non-idealities through circuit-level design [3]. Consequently, ROs are widely adopted as benchmark circuits for process-performance evaluation and can readily reveal bottlenecks in conventional design flows.

This paper presents an adaptive design-space-exploration framework integrating process tuning, model fitting and circuit optimization. A closed-loop optimization flow for process parameters guided by circuit performance is established, and a staged high-precision model-fitting algorithm is adopted to improve accuracy in critical steps. Simulation validation on a 55 nm-process RO demonstrates that EXT doping optimization delivers prominent performance gains, and the proposed method can be migrated to advanced nodes such as FinFET.

The main contributions of this work are summarized as follows:A process-circuit adaptive closed-loop optimization method for ROs, with EXT doping as the core tuning knob, is constructed as illustrated in Figure 1;A genetic-algorithm search scheme guided by a composite reward function is proposed to achieve fast convergence of performance metrics;A staged parameter-fitting method is developed, which matches IV/CV characteristics sequentially following physical hierarchies to realize high-accuracy model calibration.

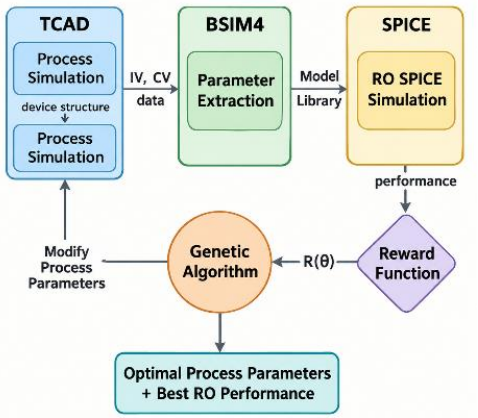


Figure 1. DTCO optimization framework

II. PROBLEM DEFINITION AND CORE ALGORITHM

A. Delay Model of the Ring Oscillator

A ring oscillator (RO) is formed by closing a loop with an odd number of inverter stages. Its oscillation frequency provides a direct measure of transistor switching speed. Given an RO with N inverter stages, its oscillation period and frequency are expressed as (1) and (2):

$$T \approx 2N \cdot t_{delay}, \tag{1}$$

$$f = \frac{1}{T} \approx \frac{1}{2N \cdot t_{delay}}. \tag{2}$$

The single-stage delay t_{delay} can be further modeled as (3):

$$t_{delay} \propto \frac{C_{eff} \cdot \Delta V}{I_{d,eff}}, \tag{3}$$

whereC_{eff} is the effective load capacitance and $I_{d,eff}$ is the effective drive current.

In addition, to evaluate the combined performance–power metric of the ring oscillator, the energy-delay product (EDP) is defined as (4):

$$EDP = \frac{P_{total}}{f^2}. \tag{4}$$

B. Key Physical Quantities Dominating RO Performance

The performance of an RO is mainly governed by the drive current I_d and effective capacitance C_{eff}. I_d directly determines the charge-discharge rate and represents the most effective means to boost frequency, whereas C_{eff} is constrained by device architecture and offers limited room for optimization.

At fixed supply voltage and device dimensions, reducing the source/drain series resistance R_s/R_d can directly increase I_d and improve the RO frequency [4]. This effect outperforms merely optimizing carrier mobility or threshold voltage. According to the MOSFET current model, R_s limits the current by reducing the effective gate overdrive voltage [5]:

$$V_{gs,eff} = V_{gs} - I_d \cdot R_s. \tag{5}$$

Parasitic resistance decomposition reveals that the source/drain extension (EXT) region accounts for the major portion of Rs/Rd owing to its low doping concentration. Increasing the EXT doping dosage reduces the resistivity of the extension region and selectively lowers Rs/Rd. It introduces little perturbation to thermal budget, short-channel effects and leakage current, and therefore serves as a low-risk tuning knob [6,7]. For this reason, EXT doping is selected as the core optimization parameter in this work.

C. Adaptive Optimization Strategy Based on Improved Greedy Genetic Algorithm

EXT doping adjustment is constrained by manufacturing feasibility and reliability. Excessively high doping aggravates short-channel effects, increases leakage current, and degrades performance trade-offs. In this work, the safe window for EXT doping is set to 10 % of the baseline value, where risks remain controllable.

To perform optimization within this limited window, a composite reward function R(θ) is introduced, where θ covers the arsenic dosage of NMOS and boron dosage of PMOS, to integrate multiple objectives and process constraints into a single scalar quantity:

$$R(\theta) = w_1 * \left(\frac{f_\theta}{f_{base}} - 1\right) - w_2 * \left(\frac{P_\theta}{P_{base}} - 1\right) - w_3 * \left(\frac{EDP_\theta}{EDP_{base}} - 1\right) - w_4 * \left(\frac{I_{off,\theta}}{I_{off,base}} - 1\right) - \lambda * C(\theta), \tag{6}$$

where w_1,w_2,w_3,$w_4$denote the respective weighting coefficients. This composite reward function explicitly integrates multiple objectives (frequency improvement, power and EDP control, leakage suppression) and process constraints into a single scalar metric, providing clear “good/bad” feedback for the genetic algorithm.

λ acts as a trade-off coefficient to balance performance gain and penalty strength. $C(\theta)$ denotes the penalty term for process constraints, which is described by the following formula:

$$C(\theta) = max(0, \Delta dose - 10\%)^2, \tag{7}$$

where Δdose is the relative dose change in percentage (%). The quadratic penalty form ensures mild deduction just beyond 10% and sharply increasing penalties for severe overruns, thereby keeping the search consistently within the low-risk region.

To achieve efficient search under this reward function, we adopt a variant of the greedy genetic algorithm as the intelligent decision-making mechanism for the DTCO closed-loop. This algorithm continuously generates new solutions around the current optimal individual and strictly preserves elite candidates, realizing targeted and adaptive optimization with minimized computational cost. Its detailed workflow is illustrated in Figure 2:

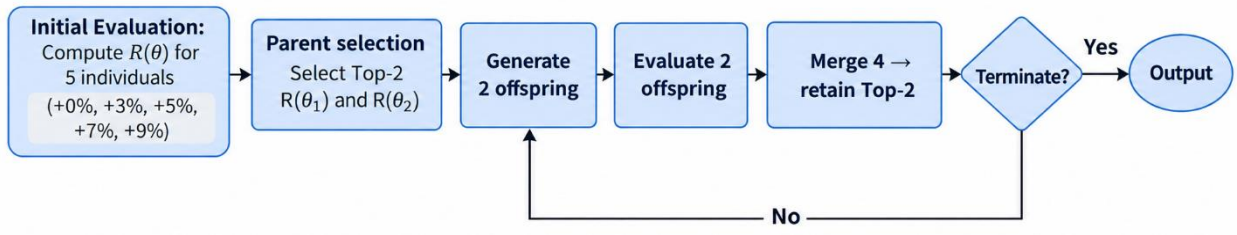


Figure 2. Flowchart of the genetic algorithm

Reward function values are first calculated for five sets of gradient-based initial doping ratios, and the top-two candidates are selected as parents. After generating and evaluating two offspring, parents and offspring are combined, and only the top-two elite individuals are retained. If the termination condition is satisfied, the optimal solution is output; otherwise, the iteration continues. Adopting a small-population elite strategy, this algorithm fits well with high-cost simulation scenarios and enables efficient convergence within the limited process window.

III. STAGED GOAL-ORIENTED BSIM4 MODEL EXTRACTION FRAMEWORK

High-fidelity TCAD-to-SPICE model transfer constitutes the essential foundation for iterative DTCO closed-loop operation. Following each adjustment of process parameters, accurate BSIM4 models must be rapidly generated to guarantee the credibility of circuit-level simulation. To address the drawbacks of conventional manual extraction, including abundant strongly-coupled BSIM4 parameters, low efficiency and unsatisfactory precision, this chapter proposes a staged goal-oriented quantitative extraction strategy to provide efficient and high-accuracy model support for the DTCO closed loop.

A. Staged Quantitative Extraction Framework

This paper performs step-by-step fitting following the device-physics hierarchy: threshold region → current-transport region → parasitic-capacitance region. Upon the completion of each stage, the converged parameters of the current stage are frozen, and only the corresponding parameter subset for the next stage is optimized. Such operation realizes parameter decoupling and balances fitting accuracy and convergence efficiency. Target data for extraction are derived from TCAD-simulated I_d-V_g,I_d-V_d and C-V curves, which fully cover both DC and AC device characteristics. Only the parameter subsets relevant to the dominant physical quantities at the current stage are optimized, with weighted root-mean-square error (RMSE) adopted as the unified loss function:

$$L = \Sigma w_i * RMSE\left(y_{i,model} - y_{i,target}\right). \quad (8)$$

The Levenberg-Marquardt algorithm is selected as the optimization algorithm to minimize the loss function in each stage. The loss function takes the form of weighted RMSE, where weights are configured according to the precision tolerance of each SPEC.

B. Model Extraction Results and Validation

To verify the effectiveness of the staged tuning strategy, precision evaluation was performed on the BSIM4 models for both NMOS and PMOS using RMS error as the quantitative metric. The evaluation covers threshold voltage, current characteristics, and capacitance characteristics. All SPEC values are based on TCAD simulation or target data.

Tables 1 and 2 present the SPEC accuracy results for the NMOS and PMOS models, respectively. All key metrics exhibit RMS errors controlled at low levels, meeting industrial-grade model accuracy requirements.

Table 1. NMOS model SPEC Accuracy

SPEC	Vtgm	Vtlin	Vtsat	Idlin	Idsat	Ioff	Id1	Id2	Id3	Cgg	Cgg0	Cgginv
RMS	1.4mV	8.9mV	0.03mV	0.13%	2.69%	7.31%	1.35%	3%	4.77%	2.22%	0.25%	0.1%

Table 2. PMOS Model SPEC Accuracy

SPEC	Vtgm	Vtlin	Vtsat	Idlin	Idsat	Ioff	Id1	Id2	Id3	Cgg	Cgg0	Cgginv
RMS	14.4mV	1.8mV	16.5mV	1%	2.81%	3.2%	4.81%	6.82%	4.05%	1.26%	2.83%	2.27%

To further visually validate the model extraction accuracy, Fig. 3 shows the Id-Vgs curve matching results for a typical NMOS device (W = 1.000 μm, L = 0.0550 μm, T = 27.0 °C) in the linear region (Vds = 0.05 V) and saturation region (Vds = 1.4 V).

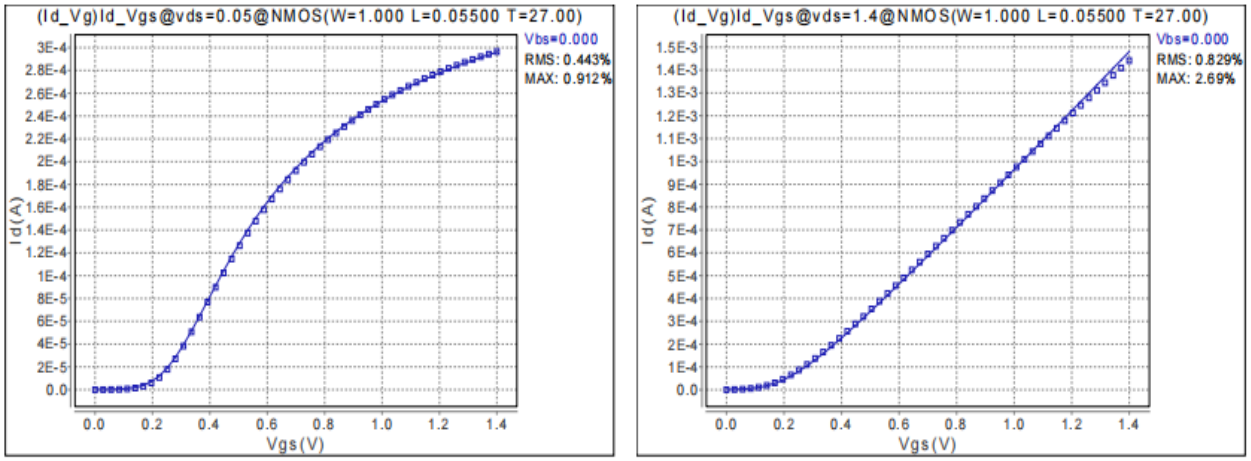


Figure 3. NMOS device Id-Vgs curve model matching results. (Left: linear region, Vds = 0.05 V; Right: saturation region, Vds = 1.4 V). Blue points represent TCAD target data; solid red lines represent BSIM4 model simulation results

IV. CONCLUSION

The DTCO closed-loop framework constructed in this paper uses the composite reward function R(θ) and the genetic algorithm as its core, performing parameter search within a 10% safe EXT doping window. The optimization process starts from selected initial parameter combinations and, through multiple generations of genetic algorithm evolution, progressively discovers better solutions in the surrounding parameter space, ultimately converging to an EXT doping increase of approximately 6%.

TCAD simulation results show that after an approximately 6% increase in EXT doping concentration, the linear drive current I_{dlin} and saturation drive current I_{dsat} of PMOS increase by 3.17% and 3.91%, respectively. For NMOS, I_{dlin} and I_{dsat} rise by 0.94% and 0.55%.

Based on the high-precision BSIM4 model, we evaluate the impact of EXT doping optimization on RO performance. The comparison between the pre-optimization and post-optimization results is shown in the table 3 below:

Table 3. Optimization Results

Metric	Before Optimization	After Optimization	Change
Frequency (GHz)	1.117	1.237	+10.76%
Total Power (W)	0.001	0.001091	+9.10%
EDP(J·s)	8.014×10^{-22}	7.130×10^{-22}	−11.04%

With the EXT doping variation kept within the process safety window, the proposed method reduces the parasitic resistance of source/drain extension regions to boost device drive current and RO oscillation frequency. After optimization, the RO frequency increases by 10.76%, the total power consumption rises by 9.10%, and the EDP decreases by approximately 11.04%. This demonstrates that the proposed process-model-circuit closed-loop optimization method can achieve favorable overall performance gains under controlled power growth.

ACKNOWLEDGEMENT

This research was funded by the National Key R&D Program of China (Grant No. 2022YFB 4400400). The research was supported by the Higher Education and Science Committee of MESCS RA (Research project 25RG-2B002).

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Адаптивная оптимизация кольцевых генераторов на основе совместного проектирования технологического процесса и схемы

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Аннотация: по мере того как КМОП-технологии приближаются к физическим и экономическим пределам, совместная оптимизация проектирования и технологического процесса (DTCO) становится ключевым подходом для раскрытия потенциала схем в рамках ограниченного технологического окна. В настоящей работе предложена адаптивная схема совместной технологической и схемной оптимизации для кольцевого генератора (RO): создан фреймворк поиска параметров на основе многокритериальной составной функции вознаграждения и модифицированного жадного генетического алгоритма. В качестве малорискованного регулятора используется легирование области расширения истока-стока (EXT). Применяется стратегия извлечения модели BSIM4, управляемая поэтапной квантифицированной функцией потерь, что обеспечивает высокоточное согласование между TCAD и SPICE. Моделирование показывает, что при увеличении концентрации легирующей примеси EXT примерно на 6 % частота кольцевого генератора возрастает на 10,76 %, а произведение энергии на задержку (EDP) улучшается приблизительно на 11 %. Данный метод позволяет значительно повысить производительность схемы при контролируемом бюджете мощности и подходит для других перспективных технологических узлов.

Ключевые слова: DTCO; кольцевой генератор; генетический алгоритм; модель BSIM4.