

Common-Centroid Layouts for Analog Circuits: Advantages and Limitations

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Abstract—Common-centroid (CC) layouts are widely used in analog design to make circuits resilient to variations by matching device characteristics. However, CC layout may involve increased routing complexity and higher parasitics than other alternative layout schemes. This paper critically analyzes the fundamental assumptions behind the use of common-centroid layouts, incorporating considerations related to systematic and random variations as well as the performance impact of common-centroid layout. Based on this study, conclusions are drawn on when CC layout styles can reduce variation, improve performance (even if they do not reduce variation), and when non-CC layouts are preferable.

I. INTRODUCTION

Over the years, analog designers have developed a set of widely-followed best practices to make designs less sensitive to absolute variability (which is hard to control), and more sensitive to differential variability (which is easier to limit). An essential ingredient of these practices is the use of layout techniques [1] to reduce the process-induced differential mismatch between elements in a layout. Structures with both active (e.g., differential pairs, current mirrors) and passive (e.g., resistor or capacitor arrays) devices are matched for this reason.

For transistor arrays, we examine the technique of common-centroid (CC) layout, with a focus on FinFET technologies. We gauge the effectiveness of CC in combating process variations in transistor arrays, and examine the tradeoffs involved in using CC. We overview the nature of on-chip variations, along with a set of variation models. We examine the impact of CC and other layout styles on layout-dependent effects (LDEs), which have become increasingly important in recent technology generations [2]. We study the circuit-level impact on nominal performance and on performance variations, identifying scenarios where CC can be beneficial or suboptimal. We show that larger layouts can benefit from the use of CC. For smaller layouts, we demonstrate that while some designs may not need CC layout, in other cases, CC may result in improved performance compared to other layout patterns. Finally, we present an algorithm for selecting an optimized layout pattern from a given set of layout patterns.

II. COMMON-CENTROID LAYOUT

A CC layout of k devices places the s_i segments of each device i so that their centroids coincide. For example, the layout of the differential pair (DP) shown in Fig. 1 could be organized

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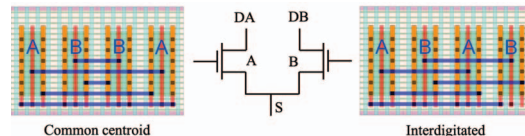


Fig. 1: CC and ID FinFET layout of a $2 \times$ differential pair. into an array of two devices, A and B (i.e., $k = 2$), with $s_A = s_B = 2$ segments,¹ each built as a unit cell with multiple FinFETs. The CC technique lays out devices in a 1-D or 2-D array such that the centroids match in each dimension. We denote the location of segment i of device j as (x_i^j, y_i^j) . This is met using the “ABBA” sequence. Similarly, a 2-D CC layout pattern is symmetric around both the X- and Y-axes.

Interdigitated (ID) layouts alternate the placement of unit cells of each device, as shown in the 1-D “ABAB” layout in Fig. 1. Interdigitated schemes do not have a common centroid for the devices: in the figure, the centroid for the A cells lies to the left of that for the B cells. CC layouts are widely used and are considered to be better for matching process-induced variations than alternatives such as ID patterns.

The rationale for using CC layouts is that they cancel out linear systematic variations due to first-order process gradients. A variation Δp in process parameter p induces a small perturbation, ΔP , in the circuit performance parameter P . This can be modeled using a linear Taylor series expansion, $\Delta P = S_p \Delta p$, where $S_p = \partial P / \partial p$ is the sensitivity at the nominal point. Using the centroid as the origin, the variations are modeled by a plane $\Delta p = \alpha \cdot x$, for an unknown α , since the precise slope of the variation during manufacturing is unknown. It is easily seen that where x is the horizontal dimension with the origin at the center of the layout,

$$\Delta P = \alpha S_p \cdot x \quad (1)$$

i.e., for linear variations, i.e., constant α , the performance P is a linear function of x , the location of each device.

Under this linear assumption, the CC criterion ensures that the sum of variations over all devices cancel each other out. In Fig. 1, let us say that p represents the threshold voltage and P the drain current. Since $\Delta p = \alpha \cdot x$, the parameter p of device A is shifted by -2α for the leftmost device and $+2\alpha$ for the rightmost device with respect to the value at the centroid. From Eq. (1), the drain current shift by $-2\alpha S_{p,A}$

¹In analog design, devices are divided into segments called fingers [1]. For FinFET technologies, transistors may be split into *unit cells* of multiple FinFETs.

and $+2\alpha\mathcal{S}_{p,A}$, adding up to a net shift of zero. Using similar notation, currents in the devices of B shift by currents shift by $-\alpha\mathcal{S}_{p,B}$ and $\alpha\mathcal{S}_{p,B}$, also creating a net shift of zero. A similar argument justifies CC in 2D layouts.

III. MODELING ON-CHIP VARIATIONS

A. A Taxonomy of Process Variations

Process-induced variations can be categorized as either *systematic* variations, which can be modeled predictably, or *random* variations, which can only be represented statistically. These variations can also be classified according to their provenance: **Across-die** (or global) variations affect all devices on a chip similarly, and do not cause mismatch between devices on a die. These are well modeled using process corners.

Within-die variations affect devices differently based on their location on a chip and result in differential mismatch. Within-die systematic variations are often modeled by linear gradients [3], while random variations are modeled with distributions. Random variations have uncorrelated and spatially correlated components characterized by a correlation distance [4]–[7]. Uncorrelated variations, e.g., due to dopant fluctuations or line edge roughness, can be reduced using larger devices [8].

B. Variation in Nanometer-Scale Technologies

Analog circuit performance is predicated on reducing the differential variability, or *mismatch* between devices. Pelgrom's model [8] quantifies the mismatch in a parameter P of two devices as the sum of random variables corresponding to the uncorrelated component, u , and a spatially correlated component, s . The variance of the mismatch is given by

$$\sigma_{\Delta P}^2 = \sigma_u^2 + \sigma_s^2 \text{ where } \sigma_u^2 = A_P^2/(WL) ; \sigma_s^2 = S_P^2 r^2 \quad (2)$$

where A_P and S_P are technology-dependent proportionality constants, W and L are the device width and length, respectively, r is the distance between the devices, and σ^2 denotes a variance. The first component depends on the transistor area and its impact can be reduced using large-sized transistors; the second can be mitigated by reducing the distance between devices.

We use a variation model [4], [5] for nanometer technologies, modeling a process parameter P as a sum of global (g), uncorrelated (u), and spatially-correlated (s) components.

$$\Delta P = g + u + s \quad (3)$$

The mean of ΔP is zero, and its variance is $\sigma_P^2 = \sigma_g^2 + \sigma_u^2 + \sigma_s^2$. At a distance r , the correlation functions are:

$$\rho_g(r) = 1; \quad \rho_u(r) = 0; \quad \rho_s(r) = e^{-(r/R_L)^2} \quad (4)$$

where R_L is the **correlation distance** for the process, formally defined as the distance at which the correlation $\rho_s(r)$ goes down to a factor of $1/e$, or 37%, of $\rho_s(0)$. For devices i and j separated by a distance r [4], $\text{cov}(P_i, P_j) = \sigma_g^2 + \rho_s(r)\sigma_s^2$. The correlation coefficient $\rho(r)$ between P_i and P_j is:

$$\rho(r) = \frac{\text{cov}(P_i, P_j)}{\sigma_{P_i}\sigma_{P_j}} = \frac{\sigma_g^2 + \rho_s(r)\sigma_s^2}{\sigma_P^2} \quad (5)$$

Thus, the global component, g , is fully correlated, regardless of distance, while the uncorrelated component, u , limits the maximum correlation at $r = 0$ to $(\sigma_g^2 + \sigma_s^2(0))/\sigma_P^2$. As r increases, $\rho_s(r)$ decreases, and for large r , spatial correlations vanish and the correlation coefficient saturates at σ_g^2/σ_P^2 . A plot of $\rho(r)$, similar to industry data [4], is shown in Fig. 2(a).

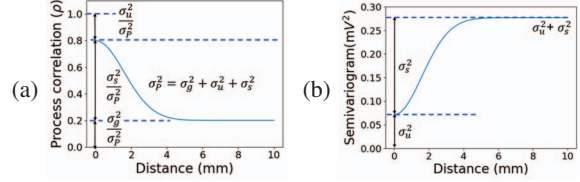


Fig. 2: (a) Process correlation as a function of distance and (b) its corresponding semivariogram (adapted from [4]).

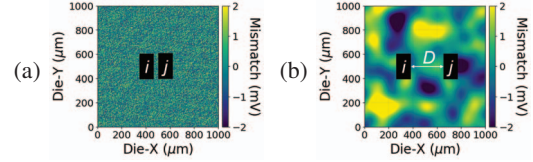


Fig. 3: Threshold voltage mismatch between devices i and j due to (a) uncorrelated and (b) spatially correlated variations.

We visualize the mismatch between two devices, i and j , due to variations. The random component, u , (Fig. 3(a)) is the first component of Pelgrom's model and shows no spatial pattern. Spatially correlated variations, s , (Fig. 3(b)) corresponding to the second term of Pelgrom's model, affect devices differently based on their location on the die. These maps are consistent with published industry data [5]. We discuss our approach to generate these maps in the next sub-section.

C. Random Fields and Semivariograms

Based on the distributions of Section III-B, we analyze the impact of variations on analog layouts using Monte Carlo methods. Each instance of the Monte Carlo simulation is based on a sample of the distribution, and corresponds to a two-dimensional random field. We borrow ideas from geostatistics to use Kriging methods [9] to build random fields based on a correlation map similar to Fig. 3. For a spatial function $F(\mathbf{p})$ with mean zero and constant variance σ^2 over the region, a *semivariogram* γ is defined as half the average squared difference of two samples. For points at a distance r in a stationary spatial random variable in an isotropic region:

$$\gamma(r) = \frac{1}{2} E [(F(r) - F(0))^2] \quad (6)$$

For an ergodic spatial field F , it is easy to see that $\gamma(r) \geq 0 \forall r$, and $\gamma(r=0) = 0$. A semivariogram is described by its:

- *sill*, or its limiting value, $\lim_{r \rightarrow \infty} \gamma(r)$, which equals σ^2 .
- *nugget*, the value at $r = 0^+$, i.e., $\gamma(r = 0^+) = \frac{1}{2} (E(F(0^+) - F(0)))$. If F has a spatially independent component, this value is nonzero.

The plot of $\rho(r)$ in Fig. 2(a) is referred to as a correlogram, and can be related to the semivariogram as follows:

$$\gamma(r) = (1 - \rho(r))\sigma^2 \quad (7)$$

R_L and $A_{V_{th}}$, and a set of N candidate layout patterns (e.g., clustered, CC, ID) for placing M devices.

The core idea of the algorithm is to first sort the patterns according to the level of deterministic mismatch in Step 1; then to use the small-signal current through R_s as a tie-breaker in Step 2. This orders patterns from the most- to the least-preferred for deterministic mismatch. Finally, in Step 3, we traverse this list till we reach the first pattern where spatial variations s are a small fraction of random variations u : this is chosen as the optimal pattern. Next, we detail each step.

Algorithm 1 Selection of an optimized pattern

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1: Input:  $R_L$ ;  $A_{V_{th}}$ ; Threshold voltage gradient  $\alpha_{V_{th}}$ ;  $M$  devices to be matched
   (sizes  $(W_1, L_1), \dots, (W_M, L_M)$ );  $N$  layout patterns  $P = (P_1, P_2, \dots, P_N)$ 
2: Output: Optimal pattern in  $P$ 
3: // Step1: Sort the layout patterns based on mismatch
4: for  $i = 1$  to  $N$  do
5:    $S = \text{NULL}$ ;  $Z = \text{NULL}$ 
6:   for  $j = 1$  to  $M$  do // Over all devices
7:      $(C_X, C_Y) = \text{CC point for the device } j \text{ in } P_i$ 
8:      $S.add(C_X, C_Y)$ 
9:      $Q = \text{LOD for the device } j \text{ in } P_i \text{ using (8)}$ 
10:     $Z.add(Q)$ 
11:   end for
12:    $\Delta = \max(Z) - \min(Z)$  // Deterministic mismatch
13:    $D_{max} = \max(\text{Distance between the CC points stored in } S)$ 
14:    $U.add(P_i, \Delta, D_{max})$ 
15: end for
16: Sort  $U$  in ascending order of  $\Delta$ 
17: // Step2: Sort  $U$  for effective small-signal current
18: Calculate the effective small-signal current through  $R_s$  for patterns in  $U$ 
19: Sort patterns in  $U$  with same  $\Delta$  in ascending order of effective small-signal current
20: // Step3: Compare random and spatial variations
21:  $\sigma_u^2 = \sum_{i=1}^M A_{V_{th}}^2 / (W_i L_i)$  // Calculate random variations
22: for  $T$  in sorted patterns  $U$  do
23:   Calculate spatial variations  $\sigma_s(r = D_{max})$  using (10)
24:   if  $\sigma_s(r = D_{max}) \leq \epsilon * \sigma_u$  then
25:     Pattern  $T$  is the best among the layout patterns in  $P$ 
26:     break
27:   end if
28: end for

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Performance shift due to mismatch For each layout pattern, the maximum distance between the common-centroid points of the devices (line 7) and the total LOD mismatch (Eq. (8)) for each device (line 9) are computed. The largest deterministic mismatch, Δ , for a pattern (line 12), and the largest distance, D_{max} , between the common-centroid points (line 13) are then determined. The LOD matching criteria also ensure the parasitic matching at the source/drain terminals of the devices in a layout pattern. In principle, the mismatch due to process gradient (Eq. (1)) for the layout can also be incorporated into this shift, but in practice it is much smaller than the LOD effect.

Thereafter, the patterns are sorted (line 16) in increasing order of mismatch, Δ . For the DP in the previous subsection, the clustered and ID patterns P3 do not have LOD mismatch, but the CC pattern P2 does. After sorting, the clustered and ID patterns come before CC at the end of Step 1.

Small-signal current through R_s Next, as a tie-breaker, the layout patterns with the same mismatch are sorted based on the small-signal current through R_s in the pattern (line 18–19).

Comparing variations Next, we compute the variance, σ_u , of random variations using Pelgrom’s model (line 21), and for the sorted layout patterns in Step 2, the spatial variations σ_s are calculated using (10) (line 23). We traverse the sorted patterns list (line 16) to pick the first pattern for which spatial variations

are small compared to random variations, i.e., they are within the allowable percentage (ϵ) of the random variations (e.g., 1%), the pattern is chosen as the best in P (line 25).

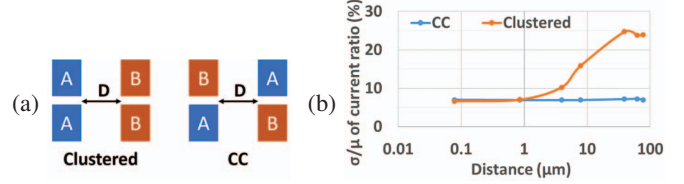


Fig. 5: (a) A CM layout in two different patterns. (b) Copying current mismatch as a function of D ($R_L = 10\mu\text{m}$).

Fig. 5(a) shows two layout patterns for a CM with two devices ($W/L = 2.3\mu\text{m}/14\text{nm}$) A and B. Both patterns show no LOD mismatch between A and B. The centroids for devices A and B coincide for the CC pattern (Fig. 5(a)), irrespective of spacing D , but not for the clustered pattern. For $R_L = 10\mu\text{m}$, Fig. 5(b) shows the trend of copying current variance with D . For $D < 1\mu\text{m} = 0.1R_L$, a clustered pattern is preferred as it has lower parasitics and the same variance as CC. For $D > 1\mu\text{m}$, CC layout is necessary to cancel spatial variations.

V. RESULTS AND DISCUSSION

A. Spatial Field Generation

We use public-domain models to model process variations and analyze the impact of layout patterns on performance. All circuit simulations use HSPICE and commercial 12nm FinFET device models. We use spatial random fields [10] for V_{th} variations to generate the V_{th} semivariogram as follows:

Variations of the components of ΔP : We use data from [14] to obtain σ_u . From [4], $\sigma_s/\sigma_u = 1.7$ at $r \gg R_L$. Thus,

$$\sigma_s^2(r) = 2.9 \sigma_u^2 (1 - e^{-(r/R_L)^2}) \quad (10)$$

Correlation length: Data on the correlation length is inconsistent in the literature. Therefore, we show results using two values from commercial processes: $1000\mu\text{m}$ [5], and $10\mu\text{m}$ [6].

Die-to-die variations: Global variations g affect all devices on a die uniformly, and therefore do not affect mismatch.

We also model gradient-based variations, representing the gradient in the V_{th} across the chip, based on [15].

B. SPICE Simulations using Spatial Fields

We first apply our methodology to analyze DPs, CMs, and CM banks (CMBs). Device matching in these blocks is critical for performance and they have conventionally employed CC layouts. We analyze the performance of these building blocks with different layout patterns, and then move to larger circuits that use these building blocks: a five-transistor operational transconductance amplifier (OTA) and StrongARM comparator. Layouts for these circuits are generated using ALIGN [16]. To ensure that we accurately capture the impact of mismatch on performance, all simulations are based on post-layout RC-extracted netlists. For each layout, using these extracted RC parameters, we perform 1000 Monte Carlo simulations and show the mean μ and standard deviation σ of circuit performance parameters over these trials.

1) *Basic Analog Blocks*: Fig. 6(a) shows a schematic of a DP, CM, and current mirror bank (CMB), sized as follows:

DP and CM: Transistors in the DP have $W/L = 46\mu\text{m}/14\text{nm}$ and in the CM, $W/L = 18.4\mu\text{m}/14\text{nm}$, respectively. The overall layout areas $3.1\mu\text{m} \times 5.2\mu\text{m}$ for the DP and $1.6\mu\text{m} \times 5.2\mu\text{m}$ for the CM: these sizes are based on the sizing of the OTA that they will be inserted into in Section V-C.

CMB: The structure has 256 transistors: 16 devices (M1-M16), each with 16 unit cells. Each transistor has $W/L = 18.4\mu\text{m}/112\text{nm}$, and the layout size is $20\mu\text{m} \times 21.5\mu\text{m}$.

Three layout patterns – a clustered (non-CC) layout, CC, and ID – are used. The layouts for DP and CM are shown in Fig. 6(b), where the unit cells/fingers of M1 and M2 are labeled A and B, respectively. The clustered pattern resembles P1 and the ID patterns interleaves 16 devices (M1 – M16), similar to P3. The CC layout scheme is taken from [17].

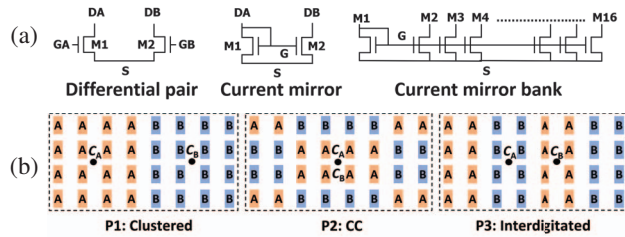


Fig. 6: (a) Schematics and (b) layout patterns of DP/CM/CMB.

2) *Performance Drift due to On-Chip Variations*: We simulate the performance of the DP, CM, and CMB layouts for each random trial. As representative performance metrics, for the DP we use the *input-referred offset* (i.e., ΔV_{gs} when $\Delta I = 0$) and the change in *copying current ratio* for the CM/CMB (for the CMB, taking the largest change over all devices).

TABLE I: Variability performance of the DP, CM, and CMB for three layout patterns (P1: Clustered, P2: CC and P3: ID).

	DP: Input referred offset			CM: Copying current ratio			CMB: Copying current ratio		
	$g + u + s; R_L = 1000\mu\text{m}$	$10\mu\text{m}$	u only	$g + u + s; R_L = 1000\mu\text{m}$	$10\mu\text{m}$	u only	$g + u + s; R_L = 1000\mu\text{m}$	$10\mu\text{m}$	u only
P1	1.4mV	3.2mV	1.3mV	4.6%	5.3%	4.5%	1.6%	31.5%	1.5%
P2	1.3mV	1.3mV	1.4mV	4.6%	4.6%	4.5%	1.5%	3.1%	1.5%
P3	1.4mV	1.4mV	1.4mV	4.5%	4.6%	4.6%	1.5%	15.2%	1.6%

Table I shows the variation of these metrics for the two process correlation distances discussed above. Based on the the confidence interval for 1000 Monte Carlo simulations, the data is rounded to one decimal place. For $R_L = 1000\mu\text{m}$, the CC, ID, and clustered layouts have similar stdev for the input-referred offset and copying current ratio when all components of variation ($g + u + s$) are considered. Examining each component of variation: *global die-to-die variations*, g , do not affect mismatch on a die. For this R_L , *spatially correlated variations*, s affect all unit cells to the same degree because the layout size is well below R_L . Over the small layout size, *gradient-based variation* is also minimal [15]. Random *uncorrelated variations*, u thus dominate all other components, and variations for the large R_L match a separate Monte Carlo simulation considering u only, shown in the table.

At $R_L = 10\mu\text{m}$, it is seen that the CC layouts have the

same performance as at $R_L = 1000\mu\text{m}$. However, the clustered layout shows a shift in the stdev of about $2.3\times$ in the input-referred offset, and $1.2\times$ and $20\times$ in the copying current for the CM and CMB, respectively. This is understandable as their dimensions are comparable to R_L , and the absence of any cancellation in the clustered layout, unlike the CC layouts, leads to a larger stdev in performance. The ID layouts for the DP and CM are close to the CC layouts (centroids of the devices are close), therefore, results in a similar performance at $R_L = 10\mu\text{m}$. However, for the CMB, the ID pattern results in a larger mismatch in centroids of the devices (due to 16 different devices) and shows a shift of about $10\times$ in the copying current.

3) *Performance Drift due to LDE and Parasitics*: We examine the impact of parasitics and LOD on circuit performance.

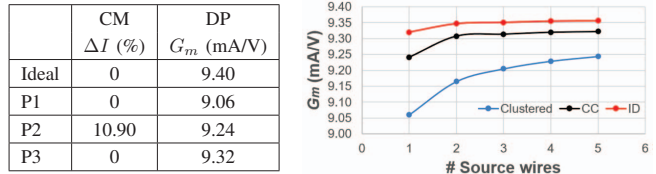


Fig. 7: (a) Impact of parasitics on DP and CM performance (b) Improvements in DP G_m using multiple parallel wires.

Current mirrors Fig. 7(a) shows the copying current mismatch of clustered, CC, and ID, layouts of a CM with four unit cells for each device and $W/L = 2.304\mu\text{m}/14\text{nm}$ (In Fig. 7(a), “Ideal” represents schematic simulation). It is helpful to view the layouts in Fig. 4 to understand these results.

For the clustered layout P1, placing all A and B unit cells together results in the lowest routing parasitics, with a symmetric route connecting the sources/drains (Fig. 4) that ensures a good V_{GS} match for the devices. For the ID layout P3, the unit cells of A and B are distributed uniformly, resulting in equal wire lengths/parasitics at source/drain. However, since the unit cells are spread over a larger area, wire length/parasitics are higher than P1. As stated earlier, the clustered and ID layouts result in equal LOD for A and B, providing good performance.

For the CC layout P2, the unit cells of A are farther apart than those of B. This results in a mismatch in wire parasitics between A and B at the source and drain, causing V_{GS} mismatch. As stated earlier, it is difficult to create matched routes in FinFET technologies where only unidirectional routes are permitted and via resistances are significant. Moreover, the LOD is also different for A and B. Consequently, there is a significant mismatch in the copying current ratio.

Differential pairs The last column of the table in Fig. 7(a) shows the impact of layout patterns on the performance of a DP with device $W/L = 46\mu\text{m}/14\text{nm}$. We evaluate the effective transconductance, G_m , defined in (9): as described qualitatively in Section IV-B, G_m is degraded to a greater extent in clustered layouts than ID or CC layouts due to the larger small-signal current through R_s , and the ID layout has the lowest small-signal current through R_s : this is quantitatively confirmed in the table, where the ID layout (P3) comes closest to the ideal G_m that assumes $R_s = 0$. Even when G_m is improved by using

multiple parallel wires at the source to reduce R_s , Fig. 7(b) shows that P3 is superior to P1 and P2.

C. Evaluation of Circuit Level Performance

We now examine two circuit structures in Fig. 8. The 5T-OTA uses the DP and NMOS CM from Section V-B1. and a PMOS CM, with transistors M_5 and M_6 [$W/L = 2.3\mu\text{m}/14\text{nm}$]. We evaluate its input-referred offset, which is sensitive to device mismatch [18]. The StrongARM comparator uses a DP (M_1, M_2) [$W/L = 6.1\mu\text{m}/14\text{nm}$], an NMOS cross-coupled pair (CCP) (M_3, M_4) [$W/L = 3.1\mu\text{m}/14\text{nm}$], a PMOS CCP (M_5, M_6) [$W/L = 1.6\mu\text{m}/14\text{nm}$], and switches. We evaluate its dynamic input offset, which is sensitive to the mismatch between X and Y [19].

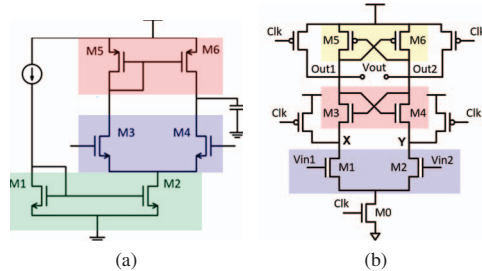


Fig. 8: Schematic of a (a) 5T-OTA (b) StrongARM comparator

We optimize primitive layouts for both circuits using Algorithm 1. The optimized OTA layout uses a CC pattern for the DP (due to high G_m , Section V-B3) and the NMOS CM (both layouts sizes are comparable to $R_L = 10\mu\text{m}$). A clustered pattern is used for the PMOS CM, which has a small area. All blocks in the comparator are small, and the optimized layout uses the clustered pattern. For these blocks, CC will result in capacitance mismatch between nodes X and Y, and ID incurs higher parasitics at X and Y. Table II shows the input-referred offset for the two circuits for $R_L = 10\mu\text{m}$ and $R_L = 1000\mu\text{m}$, laid out using three options: clustered, CC, and optimized.

TABLE II: Performance of 5T OTA, StrongARM comparator.

	5T-OTA: Input-referred offset (mV)			StrongARM: Dynamic offset (mV)		
	$g + u + s; R_L =$		u	$g + u + s; R_L =$		u
	$1000\mu\text{m}$	$10\mu\text{m}$	only	$1000\mu\text{m}$	$10\mu\text{m}$	only
Clustered (μ/σ)	0.9/3.1	1.0/4.0	1.1/2.9	3.1/2.4	4.5/3.4	3.2/2.4
CC (μ/σ)	3.1/3.1	3.1/3.1	3.0/3.0	4.6/3.2	4.9/3.4	4.8/3.2
Optimized (μ/σ)	1.1/3.0	1.2/3.0	1.1/2.8	3.1/2.4	4.5/3.4	3.2/2.4

5T-OTA: Input-referred offset: The mean of the offset is affected by layout parasitics and LDEs, and the CC layout is worse than the optimized layout. The main culprit in CC is the PMOS CM with four unit cells in each device, arranged in a single row: as discussed in Section V-B3 creates high parasitics and LOD mismatch in the CC configuration. The DP and NMOS current mirror have 80 and 40 unit cells for each device, respectively, and the CC patterns for these have four rows that can match both LOD and parasitics.

The offset stdev is affected by both u and s variations. For $R_L = 1000\mu\text{m}$, the total variations are dominated by u , irrespective of the layout pattern, as the block sizes are well below R_L , but for $R_L = 10\mu\text{m}$, the clustered pattern is clearly worse. The optimized layout has the best σ and good μ .

StrongARM comparator: Dynamic offset is a nonlinear function of V_{th} mismatch and parasitics [19]. Its mean is higher under CC due to parasitic mismatch and inherent LOD mismatch in the DP and CCP. Like the 5T-OTA, at $R_L = 1000\mu\text{m}$, μ and σ are similar to the u only case. At $R_L = 10\mu\text{m}$, for the clustered layout (= optimized layout), spatial variations greatly impact mismatch. Its nonlinear relationship with dynamic offset causes both μ and σ for the clustered case to degrade. For CC, spatial variations at both R_L values have modest effects: μ and σ are similar to u -only, but worse than the optimized case.

VI. CONCLUSION: IS CC IMPORTANT?

We have carefully analyzed common-centroid layout to question the conventional wisdom that CC layouts are always good. Small layouts, where the size is much less than the correlation distance, are dominated by random variations and do not require CC for matching, but as layouts become larger, CC is required to cancel spatial variations and process gradients. Deterministic shifts and parasitics are also important: clustered and ID layouts have lower LDE, and ID layouts have better parasitics. For differential structures, CC layouts may be useful even for small structures as they reduce the impact of parasitics. Our algorithm for optimized layout pattern generation shows improvements over CC layouts on several circuits.

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