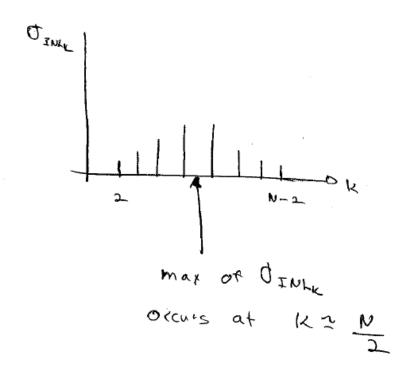
EE 505

Lecture 11

- Formalization of Statistical Models
- Offset Voltages

String DAC Statistical Performance

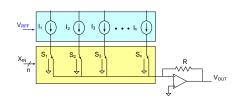
INL_k assumes a maximum variance at mid-code



$$\sigma_{INLk \max} = \sigma_{\frac{R_R}{R_{NOM}}} \frac{\sqrt{N}}{2}$$

Current Steering DAC Statistical Characterization Binary Weighted

$$\sigma_{INL_{b=<1000..0>}} = \sqrt{\frac{N}{2} \left[1 - \frac{N/2}{N-1} \right]^2 + \left(\frac{N}{2} - 1 \right) \left[\frac{N/2}{N-1} \right]^2} \bullet \sigma_{\frac{I_{RGk}}{I_{LSBX}}}$$



$$\sigma_{\textit{INL}_{MAX}} \cong \sigma_{\textit{INL}_{b=<1,0,...0>}} \cong \frac{\sqrt{N}}{2} \sigma_{\textit{I}_{LSBX}}^2$$

Note this is the same result as obtained for the unary DAC

But closed form expressions do not exist for the INL of this DAC since the INL is an order statistic

Statistical Modeling of Current Sources

$$\sigma_{\underline{I_{DR}}} = \sqrt{\sigma_{\underline{\mu_R}}^2 + \sigma_{\underline{C_{OXR}}}^2 + 4 \left(\frac{V_{THN}}{V_{GS} - V_{THN}}\right)^2 \sigma_{\underline{V_{THR}}}^2}$$

$$\sigma_{\frac{I_{DR}}{I_{DN}}} = \sqrt{\sigma_{\frac{\mu_R}{\mu_N}}^2 + \sigma_{\frac{C_{OXR}}{C_{OXN}}}^2 + 4\left(\frac{V_{THN}}{V_{GS} - V_{THN}}\right)^2 \sigma_{\frac{V_{THR}}{V_{THN}}}^2} \qquad \text{or} \qquad \sigma_{\frac{I_{DR}}{I_{DN}}} = \sqrt{\sigma_{\frac{\mu_R}{\mu_N}}^2 + \sigma_{\frac{C_{OXR}}{C_{OXN}}}^2 + \left(\frac{2}{V_{GS} - V_{THN}}\right)^2 \sigma_{\frac{V_{THR}}{V_{THN}}}^2}$$

It will be assumed that (will discuss assumption later)

$$\sigma_{\frac{\mu_R}{\mu_N}}^2 = \frac{A_\mu^2}{WL}$$

$$\sigma_{\frac{C_{OXR}}{C_{OXN}}}^2 = \frac{A_{Cox}^2}{WL}$$

$$\sigma_{V_{THR}}^2 = \frac{A_{VT0}^2}{WI}$$

where A_{μ} , A_{Cox} , A_{VT0} are Pelgrom process parameters

$$\sigma_{\frac{I_{DR}}{I_{DN}}} = \frac{1}{\sqrt{WL}} \sqrt{A_{\mu}^2 + A_{Cox}^2 + \frac{4}{V_{EB}^2} A_{VT0}^2}$$

Define

$$A_{\beta} = \sqrt{A_{\mu}^2 + A_{\text{Cox}}^2}$$

$$\sigma_{\frac{I_{DR}}{I_{DN}}} = \frac{1}{\sqrt{WL}} \sqrt{A_{\beta}^2 + \frac{4}{V_{EB}^2} A_{VT0}^2}$$

Often only A_{β} is available

Statistical Modeling of Current Sources

$$\sigma_{\frac{I_{DR}}{I_{DN}}} = \frac{1}{\sqrt{WL}} \sqrt{A_{\beta}^2 + \frac{4}{V_{EB}^2} A_{VT0}^2}$$

Gate area: A=WL

- Standard deviation decreases with \sqrt{A}
- Large V_{EB} reduces standard deviation
- Operating near cutoff results in large mismatch
- Often threshold voltage variations dominate mismatch

$$\sigma_{\frac{|_{DR}}{|_{DN}}} \cong \frac{2}{V_{FB}\sqrt{WL}} A_{VT0}$$

Theorem: If the random part of two uncorrelated current sources I_1 and I_2 are identically distributed with normalized variance, σ_{I_R/I_0}^2 then the random

variable $\Delta I = I_2 - I_1$ has a variance given by the equation $\sigma_{\Delta I_{/I_N}}^2 = 2\sigma_{I_R/I_N}^2$

Proof:
$$\Delta I = I_1 - I_2$$

$$\frac{\Delta I}{I_N} = \frac{I_1}{I_N} - \frac{I_2}{I_N}$$

$$\frac{\Delta I}{I_N} = \frac{I_N + I_{R1}}{I_N} - \frac{I_N + I_{R2}}{I_N} = \frac{I_{R1}}{I_N} - \frac{I_{R2}}{I_N}$$

$$\sigma_{\frac{\Delta I}{I_N}}^2 = \sigma_{\frac{I_R}{I_N}}^2 + \sigma_{\frac{I_R}{I_N}}^2 = 2\sigma_{\frac{I_R}{I_N}}^2$$

The previous statistical analysis was somewhat tedious

Will try to formalize the process for obtaining two important statistics, the mean and variance, of a function of interest

Assume Y is a function of n uncorrelated random variables $x_{R1},...x_{Rn}$ where the mean and variance of x_{Ri} are "small"

$$\mathbf{Y} = \mathbf{f} \left(x_{R1}, x_{R2}, \dots x_{Rn} \right)$$

$$\mathbf{X}_{R} = \begin{bmatrix} x_{R1} \\ x_{R2} \\ \dots \\ x_{Rn} \end{bmatrix}$$

pdf of the random part of Y is invariably highly nonlinear joint function of a large number of random variables

Recall if
$$(x_{R1}, x_{R2}, ... x_{Rn})$$
 uncorrelated and $f = \sum_{i=1}^{m} a_i x_{Ri}$ then $\sigma_f^2 = \sum_{i=1}^{m} a_i^2 \sigma_{X_{Ri}}^2$

Since random variables are invariably small, will try to linearize the dependence of the random variables on Y and use previous theorem to obtain μ and σ

$$\mathbf{Y} = \mathbf{f} \left(x_{R1}, x_{R2}, \dots x_{Rn} \right) \qquad \mathbf{X}_{R} = \begin{bmatrix} x_{R1} \\ x_{R2} \\ \dots \\ x_{Rn} \end{bmatrix}$$

Assuming means are all 0, Y can be expressed in a Taylor's series expanded around mean as

$$\mathbf{Y} = f\left(X\right)\Big|_{X_R=0} + \sum_{j=1}^n \frac{\partial f}{\partial x_{Rj}}\Big|_{X_R=0} x_{Rj} + \mathcal{E}\left(x_{R1}, x_{R2}, \dots x_{Rn}\right)$$

where $\varepsilon(x_{R1}, x_{R2}, ... x_{Rn})$ is due to higher-order terms and is small

$$Y \simeq f(X)\Big|_{X_R=0} + \sum_{j=1}^n \frac{\partial f}{\partial x_{Rj}}\Big|_{X_P=0} x_{Rj}$$

Note power series expansion linearized Y in the variables $(x_{R1}, x_{R2}, ..., x_{Rn})$

$$\frac{\mathbf{Y}}{\mathbf{Y}_{\mathbf{N}}} = \frac{f(X)\Big|_{X_{R}=0}}{\mathbf{Y}_{\mathbf{N}}} + \sum_{j=1}^{n} \frac{1}{\mathbf{Y}_{\mathbf{N}}} \frac{\partial f}{\partial x_{Rj}}\Big|_{X_{R}=0} x_{Rj}$$

From Theorem:

$$\sigma_{\frac{\mathbf{Y}}{\mathbf{Y}_{\mathbf{N}}}}^{2} = \sum_{j=1}^{n} \left(\left(\frac{1}{\mathbf{Y}_{\mathbf{N}}} \frac{\partial f}{\partial x_{Rj}} \right|_{X_{R}=0} \right)^{2} \sigma_{x_{Rj}}^{2}$$

Define:

$$\hat{S}_{xRj}^{f} = \frac{1}{\mathbf{Y}_{N}} \frac{\partial f}{\partial x_{Rj}} \bigg|_{X_{R}=0}$$

$$\sigma_{\frac{\mathsf{Y}}{\mathsf{Y}_{\mathsf{N}}}}^{2} = \sum_{j=1}^{n} \left(\left[\hat{S}_{xRj}^{f} \right]^{2} \sigma_{x_{Rj}}^{2} \right)$$

But

$$\sigma_{\frac{Y}{Y_{N}}}^{2} = \sum_{j=1}^{n} \left(\left[\hat{S}_{xRj}^{f} \right]^{2} \sigma_{x_{Rj}}^{2} \right) = \sum_{j=1}^{n} \left(\left[\hat{S}_{xRj}^{f} \right]^{2} \left(\frac{X_{jN}}{X_{jN}} \right)^{2} \sigma_{x_{Rj}}^{2} \right) = \sum_{j=1}^{n} \left(\left[X_{jN} \hat{S}_{xRj}^{f} \right]^{2} \sigma_{x_{Nj}}^{2} \right)$$

Alternatively, from the more standard definition of sensitivity $S_{\mathit{xR}_i}^f$:

$$S_{xR_j}^f = \frac{x_{jN}}{Y_N} \frac{\partial f}{\partial x_{R_j}} \bigg|_{X_n = 0} \qquad \Longrightarrow \qquad S_{xR_j}^f = x_{jN} \hat{S}_{xR_j}^f$$

we thus obtain

$$\sigma_{\frac{\mathsf{Y}}{\mathsf{Y}_{\mathsf{N}}}}^{2} = \sum_{j=1}^{n} \left[\left[S_{xRj}^{f} \right]^{2} \sigma_{\frac{x_{Rj}}{x_{Ni}}}^{2} \right]$$

$$Y = f\left(x_{R1}, x_{R2}, ... x_{Rn}\right)$$

$$Y = f\left(x_{R1}, x_{R2}, ... x_{Rn}\right)$$
 Y is any function of interest
$$\sigma_{Y}^{2} = \sum_{j=1}^{n} \left(S_{xRj}^{f}\right)^{2} \sigma_{X_{Rj}}^{2}$$

$$\left(x_{R1}, x_{R2}, ... x_{Rn}\right)$$
 Random part of process parameters
$$\left(x_{R1}, x_{R2}, ... x_{Rn}\right)$$
 Determined by Circuit

Determined by Process

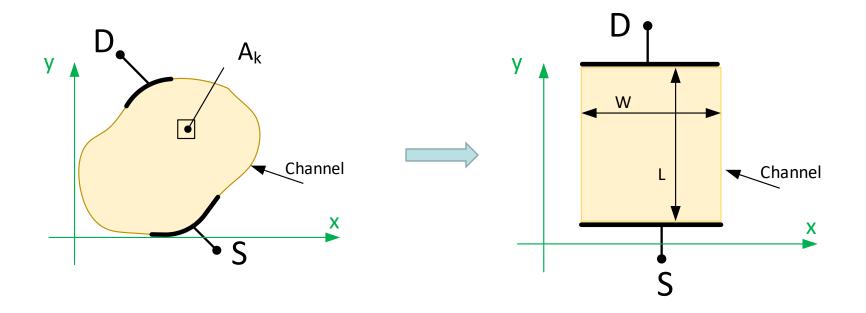
- Determine sensitivity function by analyzing circuit
- Determine variances by characterizing process

This approach is a formalized approach to statistical analysis that is more systematic than the ad hoc approach used in last lecture

Will now focus on characterizing the process parameters

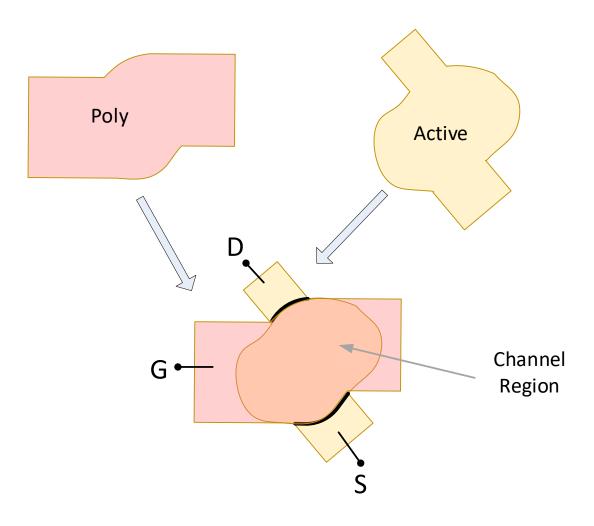
Theorem:

For any arbitrarily shaped transistor there exists a rectangular transistor that has the same static I-V characteristics



Only channel is shown which is the intersection of Poly and Active

Arbitrarily Shaped Transistor



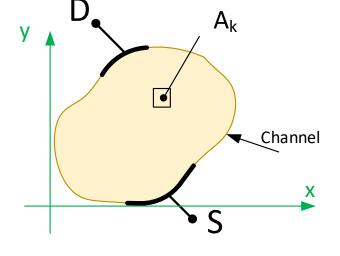
Consider first the mobility

Claim:
$$\sigma_{\frac{\mu_R}{\mu}}^2 = \frac{A_{\mu}^2}{A}$$

where A_{μ} is the Pelgrom matching parameter and A is the gate area

Argument:

Let S_k be a square of area A_k in the channel

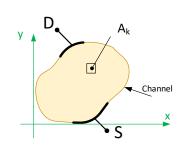


$$\mu_{\text{eq}} = \frac{\sum_{i=1}^{N} \int_{A_{ki}} \mu(x, y) dx dy}{A}$$

where the channel has been partitioned into N disjoint regions each of area Aki

For convenience, assume $A_{ki}=A_{kj}=A_k$ for all i,j

Claim:
$$\sigma_{\frac{\mu_R}{\mu_N}}^2 = \frac{A_{\mu}^2}{A}$$



Argument continued:

$$\mu_{\text{eq}} \simeq \frac{\sum_{i=1}^{N} \int_{A_{ki}} \mu(x, y) dx dy}{A}$$

Assume the random variables $\int \mu(x,y) dxdy$ are uncorrelated and identically distributed with variance σ_u^2

It thus follows that $\sigma_{\mu_{eq}}^2 \simeq \frac{1}{\Delta^2} N \sigma_{\mu_- A_k}^2$

But nominal A_k is $A_{kN} = A_N \longrightarrow N = A/A_{kN} \longrightarrow \sigma_{\mu_{eq}}^2 \simeq \frac{1}{A^2} \frac{A}{A} \sigma_{\mu_{-}A_k}^2 = \frac{1}{A} \frac{\sigma_{\mu_{-}A_k}^2}{A}$

Define
$$A_{\mu} = \frac{\sigma_{\mu_{-}A_{k}}}{\mu_{N}\sqrt{A_{kN}}}$$

$$\longrightarrow \sigma_{\frac{\mu_{eq}}{\mu_{N}}}^{2} = \frac{1}{A} \frac{\sigma_{\mu_{-}A_{k}}^{2}}{\mu_{N}^{2}A_{kN}} = \frac{A_{\mu}^{2}}{A}$$

Concept can be extended so now have:

$$\sigma_{\underline{\mu_R}}^2 = \frac{A_\mu^2}{WL}$$

$$\sigma_{\frac{C_{OXR}}{C_{OXN}}}^2 = \frac{A_{Cox}^2}{WL}$$

$$\sigma_{V_{THR}}^2 = \frac{A_{VT0}^2}{WL}$$

$$\sigma_{\frac{R}{R_N}}^2 = \frac{A_{R_{\square}}^2}{WL}$$

where A_{μ} , A_{Cox} , A_{VT0} , A_{R}_{\square} are Pelgrom process parameters

Statistical Simulations

Often simulations are used to predict statistical performance of a circuit

Variable of interest are often Gaussian (e.,g. R_R, C_R, V_{OSR}, I_R,....)

Most CAD tools do not have a rich set of random variable distributions (maybe not even the Gaussian distribution)

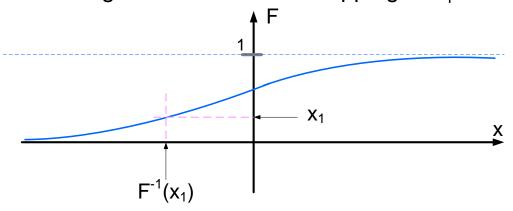
Many tools only have a single random variable generator that is U [0,1]

Theorem: f(y) and F(y) are any pdf/cdf pair and if $X \sim U[0,1]$, then $y = F^{-1}(x)$ has a pdf of f(y).

Corollary: If h is a rv with $F(h) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{h} e^{-\frac{x}{2}} dx$

then $y=F^{-1}(h)$ is N[0,1]

CDF showing random variable mapping of x₁ from U(0,1)



Theorem: If $y \sim N[0,1]$, then $z = \sigma y + \mu$ is $N[\mu, \sigma]$

$$F(h) = \frac{1}{2} \left[1 + \operatorname{erf}\left(\frac{h - \mu}{\sigma\sqrt{2}}\right) \right]$$

In Excel:

NORM.S.INV(h)= $F^{-1}(h)$ where

$$F(h) = \int_{-\infty}^{h} \frac{1}{\sqrt{2}\pi} e^{-\frac{x^2}{2}} dx$$

NORM.DIST(h, μ , σ ,TRUE) = f(h) where

$$f(h) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{h-\mu}{\sigma}\right)^2}$$

NORM.DIST(h, μ , σ ,FALSE) = F(h) where

$$F(h) = \int_{-\infty}^{h} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^{2}} dx$$

Some useful relationships:

$$ERF(x) = \frac{2}{\pi} \int_{0}^{x} e^{-t^{2}} dt$$

The CDF of the N(0,1) random variable x is given by

$$F_N(x) = \frac{1}{2} \left(1 + ERF \left(\frac{x}{\sqrt{2}} \right) \right)$$

| Excel | Older Excel | |
|--------------|-------------|---------------|
| @NORM.DIST | | f(x) |
| @NORM.S.DIST | | $f_N(x)$ |
| @NORM.INV | @NORMINV | $F^{-1}(x)$ |
| @NORM.S.INV | @NORMSINV | $F_N^{-1}(x)$ |
| | @NORMDIST | $F_{N}(x)$ |
| | @NORMINV | F(x) |

where f: PDF F:CDF

Example: Determine the area required for the resistors for an n-bit R-string DAC to achieve a yield of P if the device is marketable provided $|INL_{kMAX}| < \frac{1}{2}LSB$

Solution:

Want:
$$P = \int_{x=-\frac{1}{2}}^{x=+\frac{1}{2}} f(INL_{kMAX}) dx$$
Let
$$X_N = \frac{x}{\sigma_{INL_{kMAX}}} \quad \text{recall} \quad \frac{\mu_{INL_{kMAX}} = 0}{\sigma_{INL_{kMAX}}} = \frac{1}{2} \sum_{N=1}^{N} \frac{1}{\sqrt{N}} \frac{1}{2} \sigma_{\frac{R_R}{R_N}} = \frac{1}{\sqrt{N}} \sigma_{\frac{R_R}{R_N}}$$
thus
$$P = \int_{-X_N}^{X_N} f_N(x) dx \qquad f_N \sim N(0,1)$$

Since P is fixed, can solve for X_N

$$P = 2F_N(X_N) - 1 \longrightarrow X_N = F_N^{-1} \left(\frac{P+1}{2}\right)$$

where $F_N(X_N)$ is the CDF of a N(0,1) rv

$$X_N = \frac{1}{\sigma_{\frac{R_R}{R_N}} \sqrt{N}}$$
 recall $\sigma_{\frac{R_R}{R_N}} = \frac{A_R}{\sqrt{WL}}$

thus
$$X_N = \frac{\sqrt{WL}}{A_R \sqrt{N}}$$
 $\sqrt{WL} = A_R \sqrt{N} X_N$

thus, we obtain
$$\sqrt{WL} = A_R \sqrt{N} \bullet F_N^{-1} \left(\frac{P+1}{2} \right)$$

Since there are N=2ⁿ resistors, total area becomes

$$A_{TOT} = 2^{n}WL = 2^{n}A_{R}^{2}N \bullet \left(F_{N}^{-1}\left(\frac{P+1}{2}\right)\right)^{2} = 2^{n+1}A_{R}^{2} \bullet \left(F_{N}^{-1}\left(\frac{P+1}{2}\right)\right)^{2}$$

Summarizing:

$$A_{TOT} = 2^{n+1}A_R^2 \bullet \left(F_N^{-1}\left(\frac{P+1}{2}\right)\right)^2$$

All ADCs have comparators and many ADCs and DACs have operational amplifiers

The offset voltages of both amplifiers and comparators are random variables and invariably are key factors affecting the performance of a data converter

Operational Amplifiers:

Generally differential amplifiers whose offset is dominantly determined by randomness in the first stage

Comparators:

High Gain Operational Amplifiers
Latching Structures (often clocked)
Combination of High Gain Amplifiers and Latching Structures

- Offset voltages of high-gain amplifiers well understood
- Offset voltage of Latching Structures often difficult to determine and can be very large

Consider First Offset in Operational Amplifiers



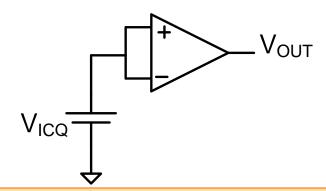
Input-referred Offset Voltage: Differential Voltage that must be applied to the input to make the output assume its <u>desired value</u>

With a good design, a designer will have V_{OUT} at the desired value if the components assume the values used in the design

Any difference in the output from what is desired when components assume the nominal values used in a design is attributable to a systematic offset voltage

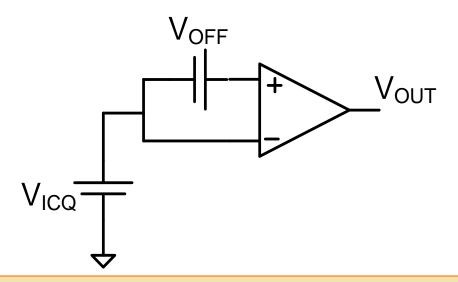
Two types of offset voltage:

- Systematic Offset Voltage
- Random Offset Voltage



Definition: The output offset voltage is the difference between the desired output and the actual output when V_{id} =0 and V_{ic} is the quiescent common-mode input voltage.

Note: V_{OUTOFF} is dependent upon V_{ICQ} although this dependence is usually quite weak and often not specified



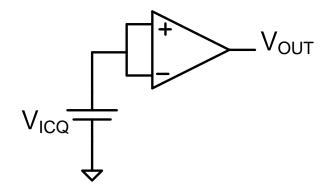
Definition: The input-referred offset voltage is the differential dc input voltage that must be applied to obtain the desired output when V_{ic} is the quiescent common-mode input voltage.

Note: V_{OFF} is usually related to the output offset voltage by the expression

$$V_{OFF} = \frac{V_{OUTOFF}}{A_D}$$

Note: V_{OFF} is dependent upon V_{ICQ} although this dependence is usually quite weak and often not specified

- Systematic Offset Voltage
- Random Offset Voltage



After fabrication it is impossible (difficult) to distinguish between the systematic offset and the random offset in any individual op amp

Measurements of offset voltages for a large number of devices will provide mechanism for identifying systematic offset and statistical characteristics of the random offset voltage

Systematic Offset Voltage

Offset voltage that is present if all device and model parameters assume their nominal value

Easy to simulate the systematic offset voltage

Almost always the designer's responsibility to make systematic offset voltage very small

Generally easy to make the systematic offset voltage small

Can tweak out systematic offset after design is almost done

Random Offset Voltage

Due to random variations in process parameters and device dimensions

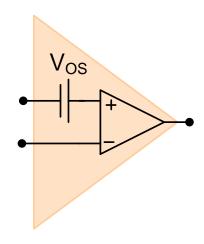
Random offset is actually a random variable at the design level but deterministic after fabrication in any specific device

Distribution of native offset nearly Gaussian (If offset compensation is not employed)

Has zero mean

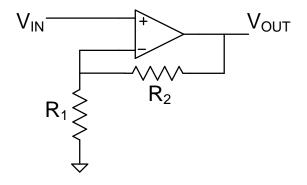
Characterized by its standard deviation or variance

Often strongly layout and area dependent

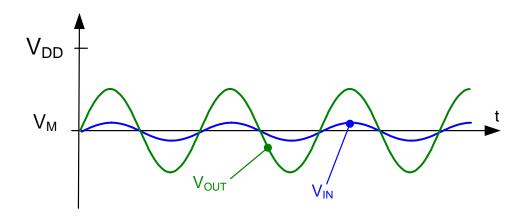


Can be modeled as a dc voltage source in series with the input (on either terminal)

Effects of Offset Voltage - an example

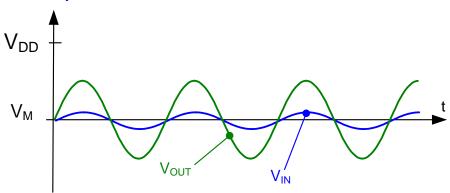


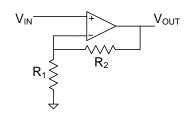
Desired I/O relationship



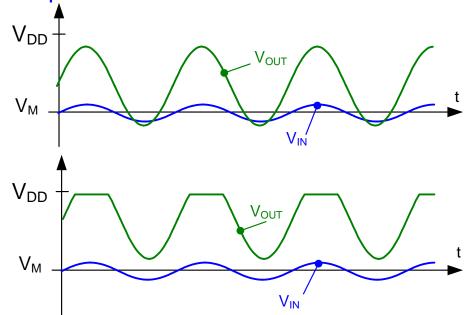
Effects of Offset Voltage - an example

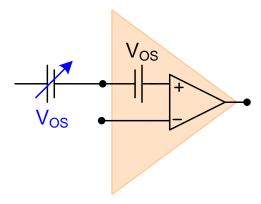
Desired I/O relationship





Actual I/O relationship due to offset





Effects can be reduced or eliminated by adding equal amplitude opposite phase DC signal (many ways to do this)

One such technique is "dynamic offset compensation"

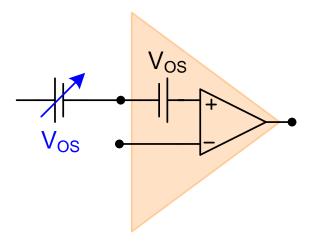
Another is chopper stabilization

Widely used in offset-critical applications

Comes at considerable effort and expense

Prefer to have designer make V_{os} small in the first place though penalty (e.g. cost) for making it sufficiently small without correction is often unacceptable

Dynamic Offset Compensation



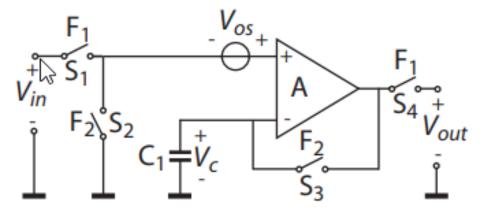


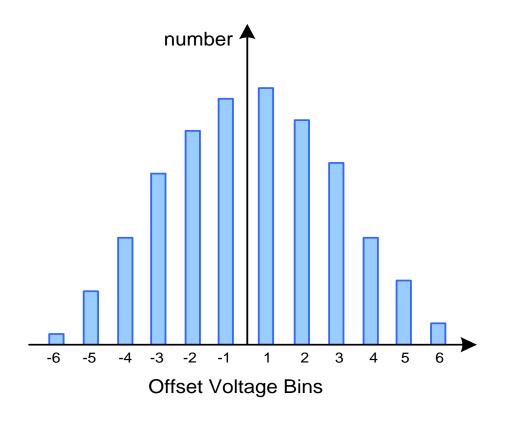
Fig. 2.2. Auto garoad amplifier with input offeat storage

Most basic dynamic offset compensation at input

Effects of Offset Voltage

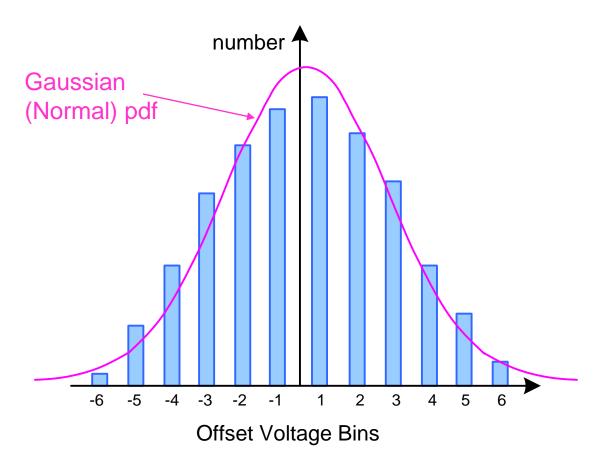
- Deviations in performance will change from one instantiation to another due to the random component of the offset
- Particularly problematic in high-gain circuits
- A major problem in many other applications
- Not of concern in many applications as well

Offset Voltage Distribution



Typical histogram of native offset voltage (binned) after fabrication

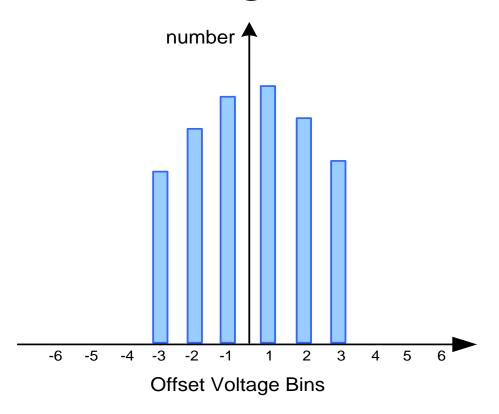
Offset Voltage Distribution



Typical histogram of offset voltage (binned) after fabrication

Mean is nearly 0 (actually the systematic offset voltage)

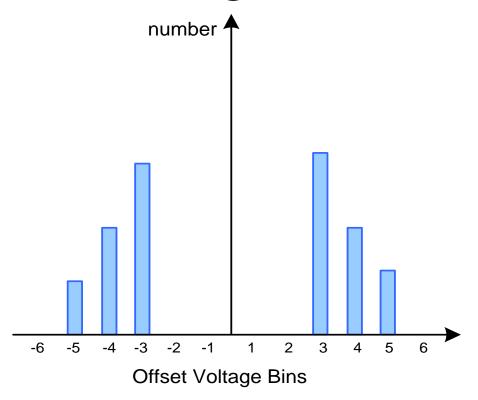
Offset Voltage Distribution



Typical histogram of offset voltage (binned) in shipped parts when entire population used for a single produce

Extreme offset parts have been sifted at test

Offset Voltage Distribution

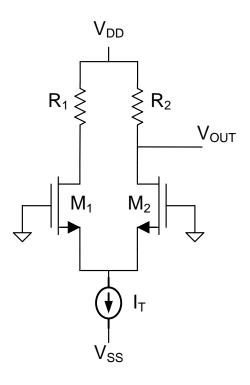


Typical histogram of offset voltage (binned) in shipped parts

Low-offset parts sold at a premium

Extreme offset parts have been sifted at test

Consider as an example:

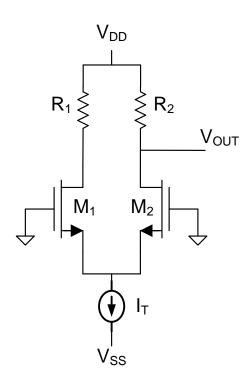


Ideally $R_1=R_2=R_N$, M_1 and M_2 are matched

$$V_{OUT} = V_{DD} - \left(\frac{I_T}{2}\right) R_N$$

Assume this is the desired output voltage (note not assuming $V_{OUT-DES}=0V$) Assume $V_{INCOM}=0V$ (could consider different common-mode inputs)

Consider as an example:



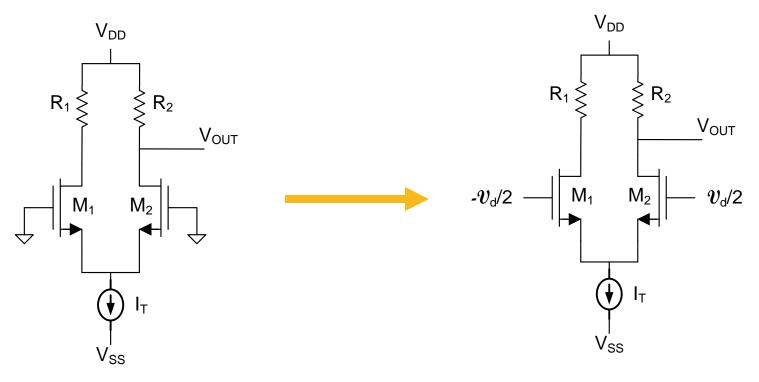
If everything ideal except R₁ and R₂

$$R_1 = R_N + R_{R1}$$
 $R_2 = R_N + R_{R2}$

Thus at the design stage, V_{OUT} is also a random variable

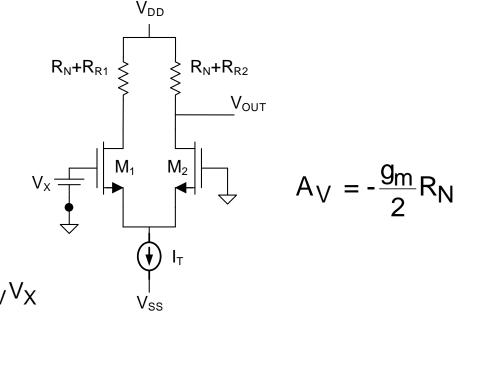
$$V_{OUT} = V_{DD} - \left(\frac{I_T}{2}\right) \left[R_N + R_{R2}\right]$$
$$V_{OUT-R} = -\left(\frac{I_T}{2}\right) R_{R2}$$

Consider as an example:



$$A_{VN} = -\frac{g_m}{2}R_N$$

Determine the offset voltage – i.e. value of V_X needed to obtain desired output



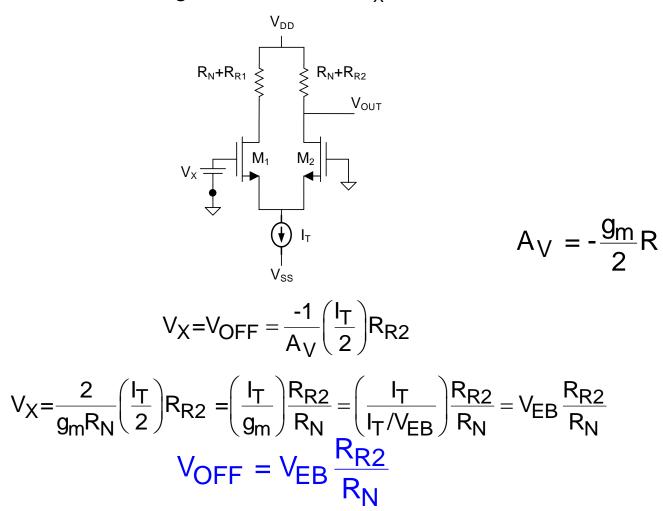
$$V_{OUT} = \left[V_{DD} - \left(\frac{I_T}{2} \right) R_N \right] - \left(\frac{I_T}{2} \right) R_{R2} - A_V V_X$$

$$V_{OUT-DES} = \left[V_{DD} - \left(\frac{I_T}{2} \right) R_N \right]$$

Setting $V_{OUT}=V_{OUT-DES}$ and solving for V_X , we obtain

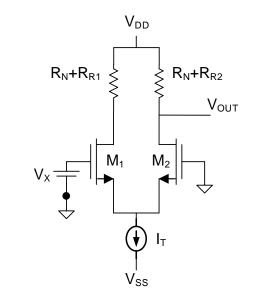
$$V_X = V_{OFF} = \frac{-1}{A_V} \left(\frac{I_T}{2} \right) R_{R2}$$

Determine the offset voltage - i.e. value of V_X needed to obtain desired output



As conjectured, V_{OFF} is a random variable!

Determine the offset voltage – i.e. value of V_X needed to obtain desired output



$$V_{OFF} = V_{EB} \frac{R_{R2}}{R_{N}}$$

$$\sigma_{V_{OFF}} = V_{EB} \sigma_{R_{R2}}$$

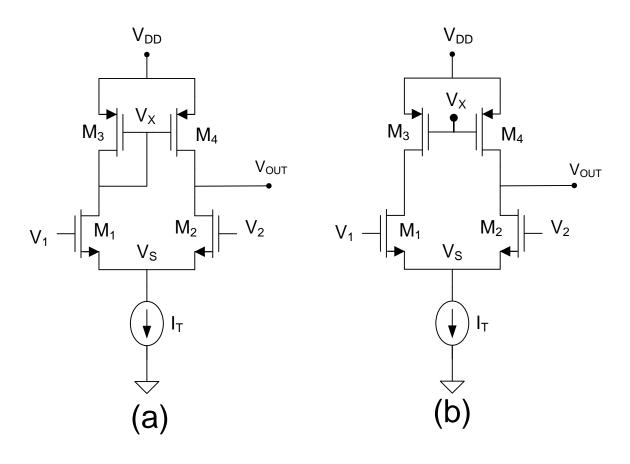
$$R_{N}$$

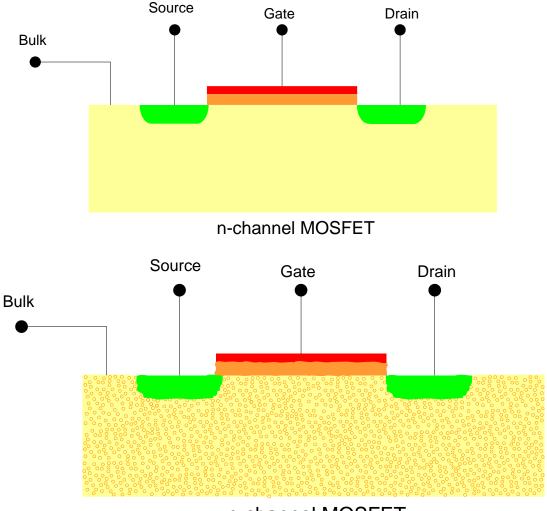
If resistors are integrated and A is the resistor area

$$\sigma_{\frac{R_{R2}}{R_N}} = \frac{A_R}{\sqrt{A}}$$
 where A_R is the Pelgrom parameter

Thus
$$\sigma_{V_{OFF}} = V_{EB} \frac{A_R}{\sqrt{A}}$$

The random offset voltage is almost entirely that of the input stage in most op amps





n-channel MOSFET

Impurities vary randomly with position as do edges of gate, oxide and diffusions

Model and design parameters vary throughout channel and thus the corresponding equivalent lumped model parameters will vary from device to device

The random offset is due to missmatches in the four transistors, dominantly missmatches in the parameters $\{V_T, \mu, C_{OX}, W \text{ and } L\}$

The relative missmatch effects become more pronounced as devices become smaller

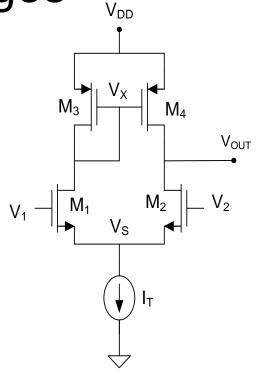
$$V_{Ti}=V_{TN}+V_{TRi}$$

$$C_{OXi}=C_{OXN}+C_{OXRi}$$

$$\mu_{i}=\mu_{N}+\mu_{Ri}$$

$$W_{i}=W_{N}+W_{Ri}$$

$$L_{i}=L_{N}+L_{Ri}$$



Each design and model parameter is comprised of a nominal part and a random component

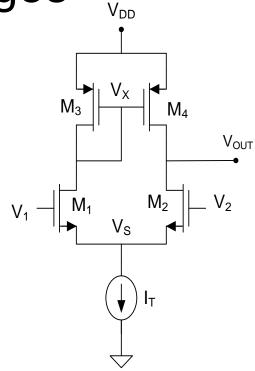
$$V_{Ti} = V_{TN} + V_{TRi}$$

$$C_{OXi} = C_{OXN} + C_{OXRi}$$

$$\mu_{i} = \mu_{N} + \mu_{Ri}$$

$$W_{i} = W_{N} + W_{Ri}$$

$$L_{i} = L_{N} + L_{Ri}$$



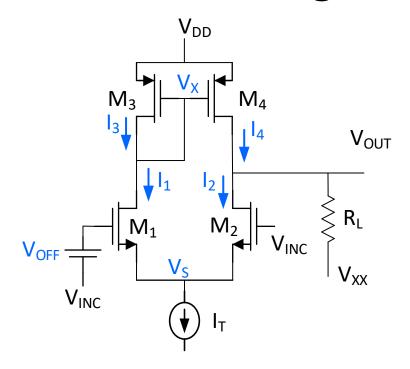
For each device, the device model is often expressed as

$$I_{Di} = \frac{\left(\mu_{N} + \mu_{Ri}\right)\left(C_{OXN} + C_{OXRi}\right)\left(W_{N} + W_{Ri}\right)}{2\left(L_{N} + L_{Ri}\right)} \left(V_{GSi} - (V_{TN} + V_{TRi})\right)^{2} \left(1 + \left(\lambda_{N} + \lambda_{Ri}\right)\left[V_{DS}\right]\right)$$

Because of the random components of the parameters in every device, matching from the left-half circuit to the right half-circuit is not perfect

This mismatch introduces an offset voltage which is a random variable

Offset Voltages



Assume currents at output node must satisfy relation $I_2=I_4$ (this is equivalent to assuming desired output voltage is V_{XX} in this circuit)

Strategy:

- Obtain expression for V_{OFF} (referred to input) that forces I₂=I₄
- 2) Linearize expression in terms of design variables and decorrelate
- 3) Obtain σ_{VOS}

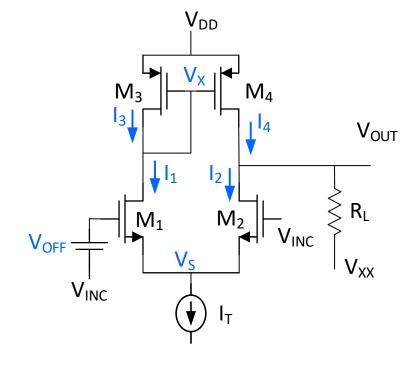
Analysis of Offset Voltage (Neglect R_L)

$$\begin{split} &I_{D1} = \frac{\mu_{n1} C_{OX1} W_1}{2 L_1} \left(V_{OFF} + V_{INC} - V_S - V_{TH1} \right)^2 \\ &I_{D2} = \frac{\mu_{n2} C_{OX2} W_2}{2 L_2} \left(V_{INC} - V_S - V_{TH2} \right)^2 \\ &I_{D3} = \frac{\mu_{p3} C_{OX3} W_3}{2 L_3} \left(V_X - V_{DD} - V_{TH3} \right)^2 \\ &I_{D4} = \frac{\mu_{p4} C_{OX4} W_4}{2 L_4} \left(V_X - V_{DD} - V_{TH4} \right)^2 \end{split}$$

$$\begin{split} &I_{D4}\!=\!\frac{\mu_{p4}C_{OX4}W_4}{2L_4}\big(V_{X}\!-\!V_{DD}\!-\!V_{TH4}\big)^2\\ &\text{Since}\quad \sqrt{I_{D1}}=\sqrt{I_{D3}}\\ &V_{\mathit{OFF}}\!+\!V_{INC}\!-\!V_{S}\!-\!V_{TH1}\!=\!\sqrt{\frac{\mu_{p3}C_{OX3}W_3L_1}{\mu_{n1}C_{OX1}W_1L_3}}\big(V_{X}\!-\!V_{DD}\!-\!V_{TH3}\big) \end{split}$$

Since
$$\sqrt{I_{D2}} = \sqrt{I_{D4}}$$

 $V_{INC} - V_S - V_{TH2} = \sqrt{\frac{\mu_{p4} C_{OX4} W_4 L_2}{\mu_{p2} C_{OX2} W_2 2 L_4}} (V_X - V_{DD} - V_{TH4})$



Define:
$$a = \sqrt{\frac{L_1 \mu_{p3} C_{OX3} W_3}{L_3 \mu_{p1} C_{OX1} W_1}} \qquad b = \sqrt{\frac{L_2 \mu_{p4} C_{OX4} W_4}{L_4 \mu_{p2} C_{OX2} W_2}}$$

Substituting for a and b, it follows on eliminating V_S that

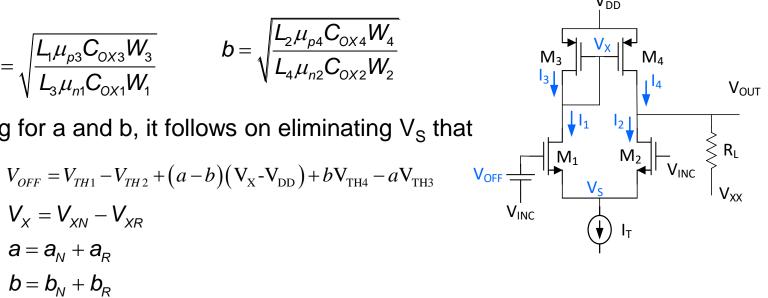
$$V_{OFF} = V_{TH1} - V_{TH2} + (a - b)(V_{X} - V_{DD})$$
Assume
$$V_{X} = V_{XN} - V_{XR}$$

$$a = a_{N} + a_{R}$$

$$b = b_{N} + b_{R}$$

$$V_{Tni} = V_{TnN} + V_{TnRi} \quad i = 1, 2$$

$$V_{Tpi} = V_{TpN} + V_{TpRi} \quad i = 3, 4$$



Observe $a_N = b_N$ and $V_{XN} - V_{DD} - V_{TDN} = V_{FR3N}$

Since the random part of V_x multiplies only a-b which is small, it follows that

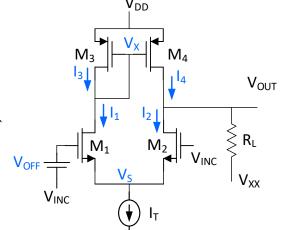
$$\begin{split} V_{OFF} &= V_{TH1} - V_{TH2} + \big(a - b\big)\big(V_{EB3N}\big) + bV_{TH4} - aV_{TH3} \\ V_{OFF} &= V_{THR1} - V_{THR2} + \big(a_R - b_R\big)V_{EB3N} + a_N\big(V_{THR4} - V_{THR3}\big) \\ \sigma_{V_{OFF}}^2 &= 2\sigma_{V_{TnR}}^2 + a_N^2 2\sigma_{V_{TpR}}^2 + V_{EB3N}^2 \sigma_{V_{a_R - b_R}}^2 \end{split}$$

Will now obtain a_R and b_R

$$V_{OFF} = V_{TnR2} - V_{TnR2} + \left(b_{R} - a_{R}\right)V_{EB3} + a_{N}\left(V_{TpR3} - V_{TpR4}\right)$$

$$a = \sqrt{\frac{(L_{N1} + L_{R1})(\mu_{Np3} + \mu_{R3})(C_{OXN3} + C_{OXR3})(W_{N3} + W_{R3})}{(L_{N3} + L_{R3})(\mu_{Nn1} + \mu_{R1})(C_{OXN1} + C_{OXR1})(W_{N1} + W_{R1})}}$$

$$V_{OFF} \downarrow V_{INC} \downarrow V_$$



Recall for x small, $\sqrt{1+x} \cong 1+\frac{x}{2}$ $\frac{1}{1+x} \cong 1-x$

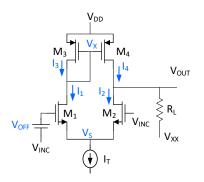
$$a = \sqrt{\frac{\left(L_{N1}\mu_{Np3}W_{N3}\right)}{\left(L_{N3}\mu_{Nn1}W_{N1}\right)}} \left(1 + \frac{1}{2} \left[\frac{L_{R1}}{L_{N1}} - \frac{L_{R3}}{L_{N3}} + \frac{\mu_{R3}}{\mu_{Np3}} - \frac{\mu_{R1}}{\mu_{Nn1}} + \frac{C_{OXR3}}{C_{OXN3}} - \frac{C_{OXR1}}{C_{OXN1}} + \frac{W_{R3}}{W_{N3}} - \frac{W_{R3}}{W_{N3}}\right]\right)$$

$$a_{R} = \sqrt{\frac{\left(L_{N1}\mu_{Np3}W_{N3}\right)}{\left(L_{N3}\mu_{Nn1}W_{N1}\right)}} \frac{1}{2} \left[\frac{L_{R1}}{L_{N1}} - \frac{L_{R3}}{L_{N3}} + \frac{\mu_{R3}}{\mu_{N3}} - \frac{\mu_{R1}}{\mu_{N1}} + \frac{C_{OXR3}}{C_{OXN3}} - \frac{C_{OXR1}}{C_{OXN1}} + \frac{W_{R3}}{W_{N3}} - \frac{W_{R3}}{W_{N3}}\right]$$

$$a_{N} = \sqrt{\frac{\left(L_{N1}\mu_{Np3}W_{N3}\right)}{\left(L_{N3}\mu_{Nn1}W_{N1}\right)}}$$

Likewise

$$b_{R} = \sqrt{\frac{\left(L_{N1}\mu_{Np3}W_{N3}\right)}{\left(L_{N3}\mu_{Nn1}W_{N1}\right)}} \frac{1}{2} \left[\frac{L_{R2}}{L_{N2}} - \frac{L_{R4}}{L_{N4}} + \frac{\mu_{R4}}{\mu_{Np4}} - \frac{\mu_{R2}}{\mu_{Nn2}} + \frac{C_{OXR4}}{C_{OXN4}} - \frac{C_{OXR2}}{C_{OXN2}} + \frac{W_{R4}}{W_{N4}} - \frac{W_{R2}}{W_{N2}}\right]$$



$$a_{R} - b_{R} = \sqrt{\frac{\left(L_{N1}\mu_{Np3}W_{N3}\right)}{\left(L_{N3}\mu_{Nn1}W_{N1}\right)}} \frac{1}{2} \begin{bmatrix} \frac{L_{R1} - L_{R2}}{L_{N1}} + \frac{L_{R4}}{L_{N2}} + \frac{L_{R3}}{L_{N4}} - \frac{\mu_{R3}}{\mu_{Np3}} - \frac{\mu_{R4}}{\mu_{Np3}} + \frac{\mu_{R2}}{\mu_{Np4}} - \frac{\mu_{R1}}{\mu_{Nn1}} \\ + \frac{C_{OXR3}}{C_{OXN3}} - \frac{C_{OXR4}}{C_{OXN4}} + \frac{C_{OXR2}}{C_{OXN2}} - \frac{C_{OXR1}}{C_{OXN1}} + \frac{W_{R3}}{W_{N3}} - \frac{W_{R4}}{W_{N4}} + \frac{W_{R2}}{W_{N2}} - \frac{W_{R3}}{W_{N3}} \end{bmatrix}$$

$$\sigma_{a_{R}-b_{R}}^{2} = \frac{\left(L_{N1}\mu_{Np3}W_{N3}\right)}{\left(L_{N3}\mu_{Nn1}W_{N1}\right)}\frac{1}{2}\left[\sigma_{\frac{L_{R1}}{L_{N1}}}^{2} + \sigma_{\frac{L_{R3}}{L_{N3}}}^{2} + \sigma_{\frac{\mu_{R3}}{\mu_{Np3}}}^{2} + \sigma_{\frac{\mu_{R2}}{\mu_{Nn2}}}^{2} + \sigma_{\frac{C_{OXR3}}{C_{OXN3}}}^{2} + \sigma_{\frac{W_{R3}}{C_{OXN1}}}^{2} + \sigma_{\frac{W_{R3}}{W_{N3}}}^{2} + \sigma_{\frac{W_{R1}}{W_{N1}}}^{2}\right]$$

Thus

$$\begin{split} \sigma_{V_{OFF}}^2 &= 2\sigma_{V_{TnR2}}^2 + 2\frac{L_{N1}\mu_{Np3}W_{N3}}{L_{N3}\mu_{Nn1}W_{N1}}\sigma_{V_{TpR3}}^2 \\ &+ V_{EB3N}^2\frac{\left(L_{N1}\mu_{Np3}W_{N3}\right)}{\left(L_{N3}\mu_{Nn1}W_{N1}\right)}\frac{1}{2}\Bigg[\sigma_{\frac{L_{R1}}{L_{N1}}}^2 + \sigma_{\frac{L_{R3}}{L_{N3}}}^2 + \sigma_{\frac{\mu_{R3}}{\mu_{Np3}}}^2 + \sigma_{\frac{\mu_{R2}}{\mu_{Nn2}}}^2 + \sigma_{\frac{C_{OXR3}}{C_{OXN3}}}^2 + \sigma_{\frac{W_{R3}}{W_{N3}}}^2 + \sigma_{\frac{W_{R1}}{W_{N1}}}^2\Bigg] \end{split}$$

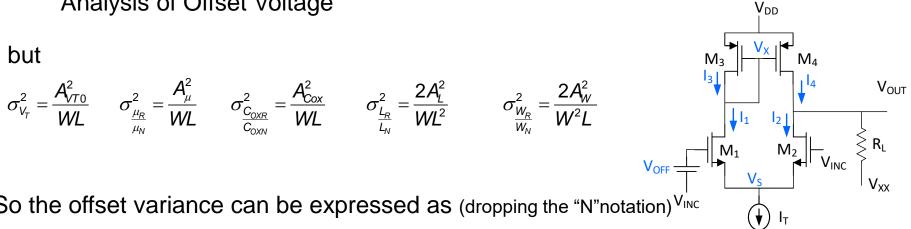
$$\sigma_{V_T}^2 = \frac{A_{VT0}^2}{WL}$$
 $\sigma_{\frac{\mu_R}{\mu_N}}^2 = \frac{A_V^2}{V}$

$$\sigma_{\frac{\mu_R}{\mu_N}}^2 = \frac{A_\mu^2}{WL}$$

$$\sigma_{\frac{C_{OXR}}{C_{OXN}}}^2 = \frac{A_{Cox}^2}{WL}$$

$$\sigma_{\frac{L_R}{L_H}}^2 = \frac{2A_L^2}{WL^2}$$

$$\sigma_{\frac{W_R}{W_M}}^2 = \frac{2A_W^2}{W^2L}$$



So the offset variance can be expressed as $(dropping the "N" notation)^{V_{INC}}$

$$\begin{split} \sigma_{V_{OFF}}^2 &= 2\frac{A_{VTn0}^2}{W_1L_1} + 2\frac{\mu_pL_1}{\mu_nW_1}\frac{A_{VTp0}^2}{L_3^2} \\ &+ V_{EB3}^2\frac{\mu_pL_1W_3}{\mu_nL_3W_1}\frac{1}{2}\Bigg[\frac{A_{\mu_n}^2}{W_3L_3} + \frac{A_{\mu_p}^2}{W_1L_1} + A_{Cox}^2\bigg(\frac{1}{W_3L_3} + \frac{1}{W_1L_1}\bigg) + A_W^2\bigg(\frac{2}{W_3^2L_3} + \frac{2}{W_1^2L_1}\bigg) + A_L^2\bigg(\frac{2}{W_1L_1^2} + \frac{2}{W_3L_3^2}\bigg)\Bigg] \end{split}$$

Often this can be approximated by

$$\sigma_{V_{OFF}}^{2} = 2\frac{A_{VTn0}^{2}}{W_{1}L_{1}} + 2\frac{\mu_{p}L_{1}}{\mu_{n}W_{1}}\frac{A_{VTp0}^{2}}{L_{3}^{2}} + V_{EB3}^{2}\frac{\mu_{p}L_{1}W_{3}}{\mu_{n}L_{3}W_{1}}\frac{1}{2}\left[\frac{A_{\mu_{n}}^{2}}{W_{3}L_{3}} + \frac{A_{\mu_{p}}^{2}}{W_{1}L_{1}} + A_{Cox}^{2}\left(\frac{1}{W_{3}L_{3}} + \frac{1}{W_{1}L_{1}}\right)\right]$$

Or even approximated by

$$\sigma_{V_{OFF}}^2 = 2\frac{A_{VTn0}^2}{W_1 L_1} + 2\frac{\mu_p L_1}{\mu_n W_1} \frac{A_{VTp0}^2}{L_3^2}$$

Since V_{EBn} and V_{EBp} are related, this is often expressed in simpler form as:

$$\sigma_{V_{OS}}^{2} = 2 \left[\frac{A_{VTO\,n}^{2} + \frac{\mu_{\,p}}{\mu_{\,n}} \frac{L_{\,n}}{W_{\,n}L_{\,p}} A_{VTO\,p}^{2} + \frac{V_{EB\,n}^{2}}{4} \left[\frac{1}{W_{\,n}L_{\,n}} A_{\,\mu_{n}}^{2} + \frac{1}{W_{\,p}L_{\,p}} A_{\,\mu_{p}}^{2} + A_{COX}^{2} \left[\frac{1}{W_{\,n}L_{\,n}} + \frac{1}{W_{\,p}L_{\,p}} \right] \right] + A_{\,W}^{2} \left[\frac{1}{L_{\,n}W_{\,n}^{2}} + \frac{1}{L_{\,p}W_{\,p}^{2}} \right] \right]$$

where the terms A_{VT0} , A_{μ} , A_{COX} , A_{L} , and A_{W} are process parameters

Representative values of Pelgrom parameters (0.5µ process)

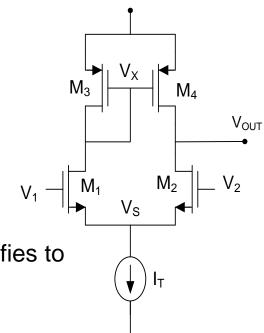
$$A_{VT0} \simeq \begin{cases} 21 mV \cdot \mu & \text{(n-ch)} \\ 25 mV \cdot \mu & \text{(p-ch)} \end{cases}$$

$$\sqrt{A_{\mu}^2 + A_{C_{OX}}^2} \simeq \begin{cases} .016 \mu & \text{(n-ch)} \\ .023 \mu & \text{(p-ch)} \end{cases}$$

$$A_L = A_W \simeq 0.017 \mu^{\frac{3}{2}}$$

Usually the A_{VT0} terms are dominant, thus the variance simplifies to

$$\sigma_{V_{OS}}^{2} \cong 2 \left[\frac{A_{VTO\,n}^{2}}{W_{n}\,L_{n}} + \frac{\mu_{p}}{\mu_{n}} \frac{L_{n}}{W_{n}\,L_{p}^{2}} A_{VTO\,p}^{2} \right]$$



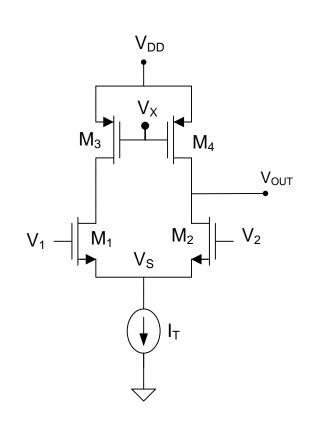
Correspondingly for 5T op amp w/o current mirror load:

$$\sigma_{v_{os}}^{2} = 2 \left[\frac{A_{vTOn}^{2}}{W_{n}L_{n}} + \frac{\mu_{p}}{\mu_{n}} \frac{L_{n}}{W_{n}L_{p}^{2}} A_{vTOp}^{2} + \frac{V_{EBn}^{2}}{4} \left(\frac{1}{W_{n}L_{n}} A_{\mu_{n}}^{2} + \frac{1}{W_{p}L_{p}} A_{\mu_{p}}^{2} + A_{COX}^{2} \left[\frac{1}{W_{n}L_{n}} + \frac{1}{W_{p}L_{p}} \right] + A_{w}^{2} \left[\frac{1}{L_{n}W_{n}^{2}} + \frac{1}{L_{p}W_{p}^{2}} \right] \right) \right]$$

which again simplifies to

$$\sigma_{V_{OS}}^{2} \cong 2 \left[\frac{A_{VTO\;n}^{2}}{W_{n}\;L_{n}} + \frac{\mu_{p}}{\mu_{n}} \frac{L_{n}}{W_{n}\;L_{p}^{2}} A_{VTO\;p}^{2} \right]$$

Note these offset voltage expressions are identical!



Example: Determine the 3σ value of the input offset voltage for the MOS differential amplifier if

- a) M₁ and M₃ are minimum-sized and
- b) the area of M₁ and M₃ are 100 times minimum size

Assume $L_{MIN}=W_{MIN}=0.5u$, $A_{VTOn}=0.021V$ and $A_{VTOP}=0.025V$ Will neglect μ_R , C_{OXR} , W_R and L_R on all devices

$$\sigma_{V_{OS}}^{2} \cong 2 \left[\frac{A_{VTO\,n}^{2}}{W_{n} L_{n}} + \frac{\mu_{p}}{\mu_{n}} \frac{L_{n}}{W_{n} L_{p}^{2}} A_{VTO\,p}^{2} \right]$$

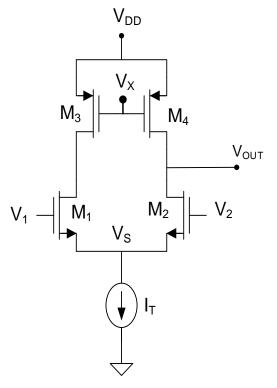
$$\sigma_{V_{OS}}^{2} \cong \frac{2}{W_{n} L_{n}} \left[A_{VTO}^{2} n^{+} \frac{\mu_{p}}{\mu_{n}} A_{VTOp}^{2} \right]$$

a)
$$\sigma_{V_{OS}}^{2} \cong \frac{2}{(0.5\mu)^{2}} \left[.021^{2} + \frac{1}{3}.025^{2} \right]$$

$$\sigma_{V_{OS}} \cong 72\text{mV}$$

$$3 \sigma_{V_{OS}} \cong 216\text{mV}$$

 $\sigma_{V_{OS}} \cong 72 \text{mV}$ $3 \, \sigma_{V_{OS}} \cong 216 \text{mV}$ Note this is a very large offset voltage!



Example: Determine the 3σ value of the input offset voltage for the MOS differential amplifier if

- a) M₁ and M₃ are minimum-sized and
- b) the area of M₁ and M₃ are 100 times minimum size

Assume
$$L_{MIN}=W_{MIN}=0.5u$$
, $A_{VTOn}=0.021V$ and $A_{VTOP}=0.025V$

$$\sigma_{V_{OS}}^{2} \cong 2 \left[\frac{A_{VTO\,n}^{2}}{W_{n} L_{n}} + \frac{\mu_{p}}{\mu_{n}} \frac{L_{n}}{W_{n} L_{p}^{2}} A_{VTO\,p}^{2} \right]$$

$$\sigma_{V_{OS}}^{2} \cong \frac{2}{W_{n} L_{n}} \left[A_{VTO\,n}^{2} + \frac{\mu_{p}}{\mu_{n}} A_{VTO\,p}^{2} \right]$$

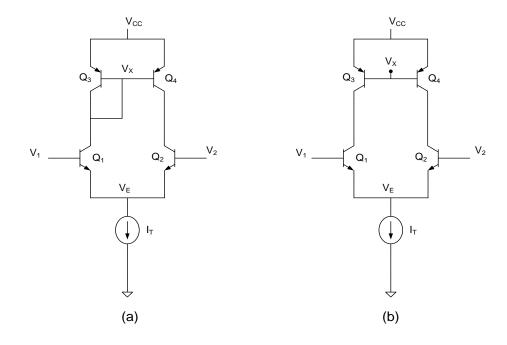
b)
$$\sigma_{V_{OS}}^{2} \cong \frac{2}{\left[100(0.5\mu)\right]^{2}} \left[.021^{2} + \frac{1}{3}.025^{2}\right]$$

$$\sigma_{V_{OS}} \cong 7.2\text{mV}$$

 $\label{eq:sigma} 3\,\sigma_{V_{OS}} \cong 21.6 mV$ Note this is much lower but still a large offset voltage !

 V_{DD} V_{OUT}

The areas of M₁ and M₃ need to be very large to achieve a low offset voltage !!



It can be shown that

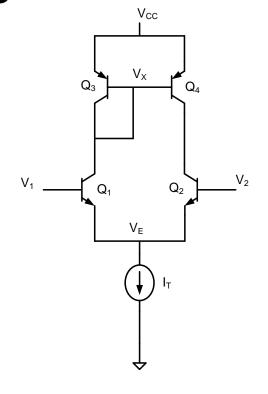
$$\sigma_{V_{OS}}^2 \cong 2V_t^2 \left[\frac{A_{Jn}^2}{A_{En}} + \frac{A_{Jp}^2}{A_{Ep}} \right]$$

where very approximately

$$A_{Jn} = A_{Jp} = 0.1\mu$$

Example: Determine the 3σ value of the offset voltage of this bipolar input stage if $A_{E_1} = A_{E_3} = 10\mu^2$

$$\begin{split} &\sigma_{V_{OS}}^2 \cong 2 \text{V}_{t}^2 \left[\frac{\text{A}_{Jn}^2}{\text{A}_{En}} + \frac{\text{A}_{Jp}^2}{\text{A}_{Ep}} \right] \\ &\sigma_{V_{OS}} \cong \sqrt{2} \text{V}_{t} \text{A}_{J} \frac{\sqrt{2}}{\sqrt{\text{A}_{E}}} \\ &\sigma_{V_{OS}} \cong 2 \bullet 25 \text{mV} \bullet 0.1 \mu \bullet \frac{1}{\sqrt{10 \mu^2}} = 1.6 \text{mV} \\ &3 \sigma_{V_{OS}} \cong 4.7 \text{mV} \end{split}$$



Note this value is much smaller than that for the MOS input structure!

Typical offset voltages:

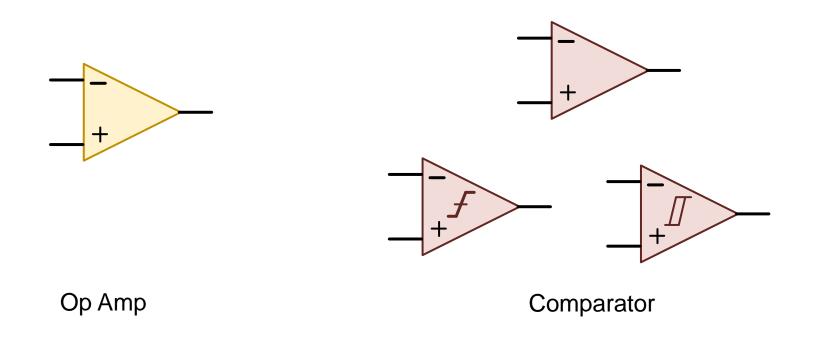
MOS - 5mV to 50MV

BJT - 0.5mV to 5mV

These can be scaled with extreme device dimensions

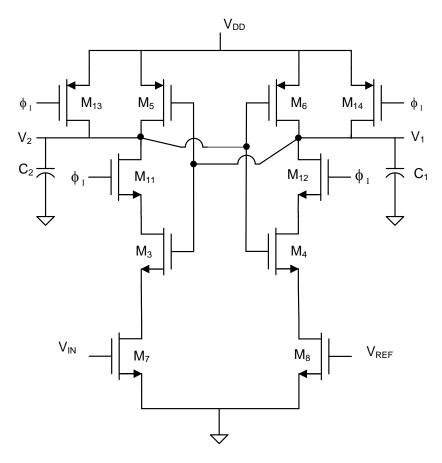
Often more practical to include offset-compensation circuitry

Offset Voltage in Comparators



- Op Amps Can be used as Comparators
- Comparators often have hysteresis in transfer characteristics
- Offset voltage of Comparators often key parameter in data converters

Offset voltage difficult to determine in come classes of comparators



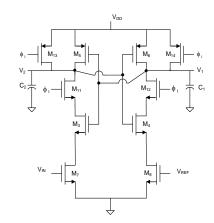
Dynamic clocked comparator

When ϕ_1 is low, V_1 and V_2 are precharged to V_{DD} and no static power is dissipated When ϕ_1 is high, enters evaluate state and no static power is dissipated

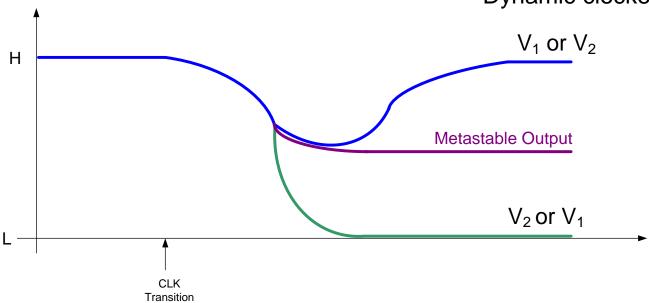
Offset voltage difficult to determine in come classes of comparators

Very small, very fast, low power

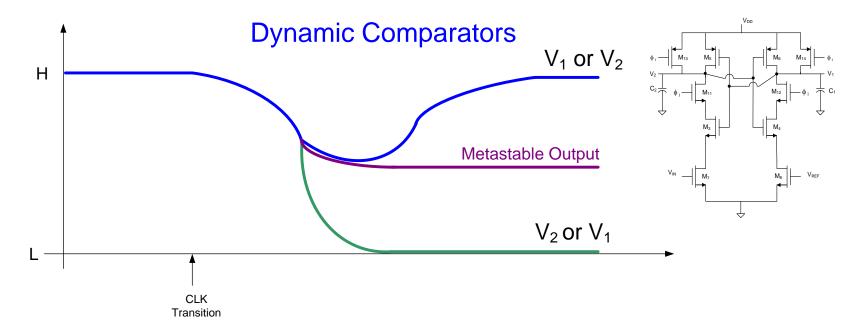
But offset voltage can be large (100mV or more)



Dynamic clocked comparator



Decision is being made shortly after clock transition when devices are deep in weak inversion and signal levels are very small



Dynamic Comparators widely used because of low power dissipation

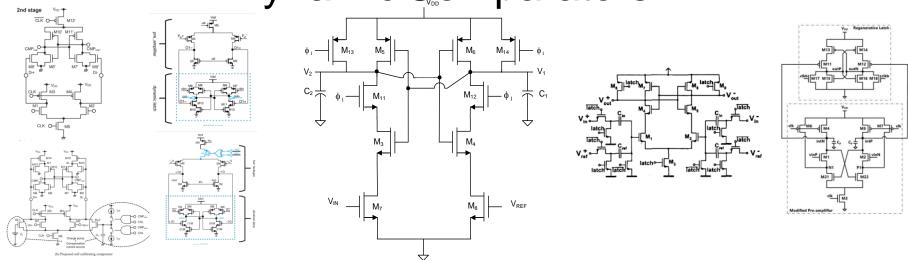
Often include one or more pre-amp stages before regeneration applied

Previous-code dependence and kickback both of concern in dynamic comparators

Noise may significantly affect performance and difficult to analyze and simulate because transient noise models in deep weak inversion are questionable

Still major opportunities to make significant improvement in dynamic comparators

Dynamic Comparators



Relatively small number of dynamic comparators have been introduced

Significant difference in performance among those available

Analysis and performance assessment either analytically or via simulation not trivial

Opportunity to make significant advances in dynamic comparator design likely available

Analyses of static and dynamic random offset voltages in dynamic comparators J He, S Zhan, D Chen, RL Geiger - IEEE Transactions on ..., 2009 - ieeexplore.ieee.org ... Geiger, "Yield enhancement with optimal area allocation for ratio critical analog circuits," ... He, S. Zhan, D. Chen, and RL Geiger, "A simple and accurate method to predict offset voltage in ... $$\Rightarrow$$ Save \$99\$ Cite Cited by 244 Related articles All 15 versions Web of Science: 105

Additional details about offset voltage, statistical circuit analysis, and matching can be found in the draft document

"Statistical Characterization of Circuit Functions" by R.L. Geiger

Summary of Offset Voltage Issues

- Random offset voltage is generally dominant and due to mismatch in device and model parameters
- MOS Devices have large V_{OS} if area is small
- σ decreases approximately with $1/\sqrt{A}$
- Multiple fingers for MOS devices offer benefits for common centroid layouts but too many fingers will ultimately degrade offset because perimeter/area ration will increase (A_W and A_L will become of concern)
- Offset voltage of dynamic comparators is often large and analysis not straightforward

Offset compensation often used when low offsets important

MOS:
$$\sigma_{V_{OS}}^2 \cong 2 \left| \frac{A_{VTO\,n}^2}{W_n L_n} + \frac{\mu_p}{\mu_n} \frac{L_n}{W_n L_p^2} A_{VTO\,p}^2 \right|$$

Bipolar:
$$\sigma_{V_{OS}}^2 \cong 2V_t^2 \left[\frac{A_{Jn}^2}{A_{En}} + \frac{A_{Jp}^2}{A_{Ep}} \right]$$



Stay Safe and Stay Healthy!

End of Lecture 11