Device-Parameter Estimation with On-Chip Variation Sensors Considering Random Variability

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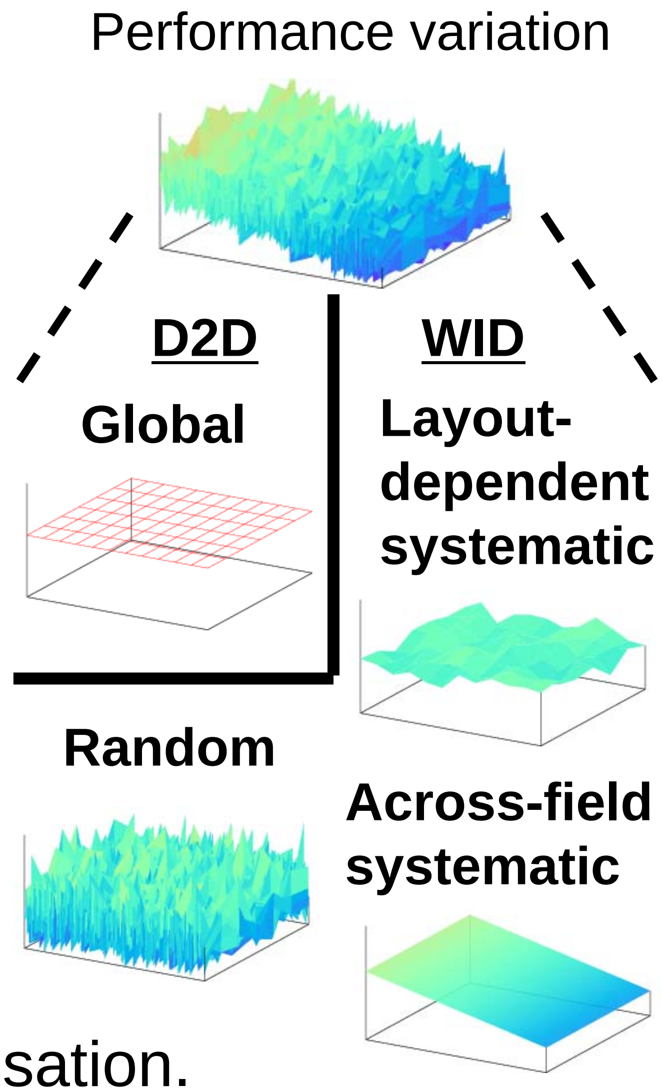
Outline

1. Introduction
2. Device-parameter extraction using RO-based variation sensors
3. Proposed method using maximum likelihood estimation
4. Simulation-based validation of the proposed estimation
5. Conclusion

Background (1 / 2)

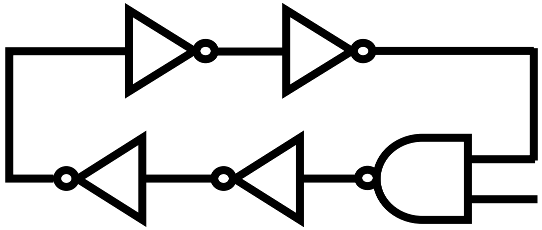
- Process variations
  - make chip performance different chip by chip and even transistor by transistor.
  - are classified into D2D (die-to-die) and WID (within-die).



- Post-silicon performance adjustment is important.
  - e.g., adaptive body bias, supply voltage scaling.
  - Estimates of device-parameters are required for appropriate compensation.

Background (2 / 2)

- RO(ring oscillator)-based on-chip sensors are Often used for parameter estimation.
  - Easy to measure oscillating frequencies of ROs,
  - Easier to implement ROs than I-V curve measurement system.

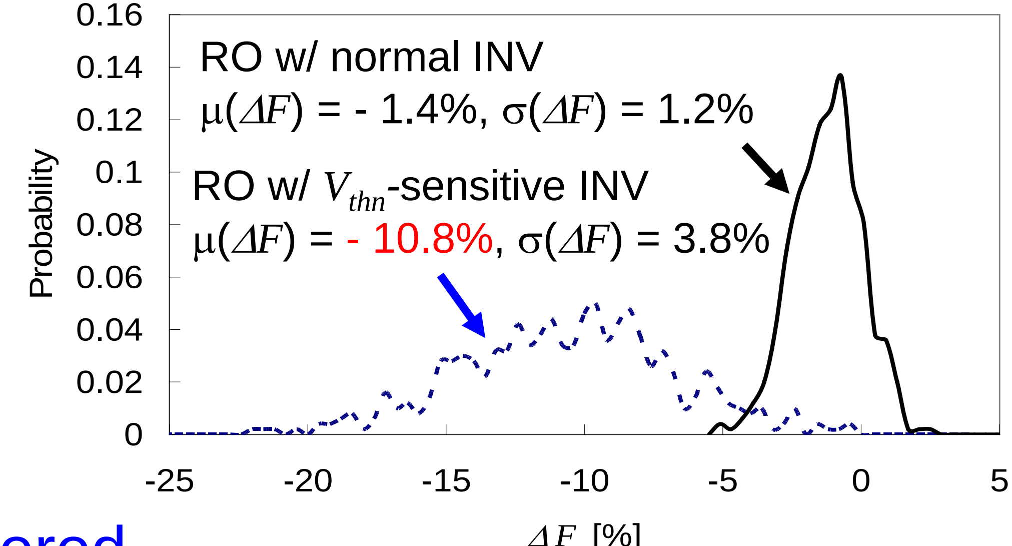


  - Has appropriate characteristics, i.e., averaging effect: as #RO-stages increases, σ/μ becomes smaller.
    - Conventional extraction methods assume ROs are not affected by random variations.
    - But random variations cannot be canceled out in some intelligent ROs.

Motivation of this work

- ROs highly-sensitive to a single device-parameter are proposed for more accurate estimation [1], [2].
  - E.g., #RO-stages: 101 sufficient to cancel out random variations
    - w/ only random variations: threshold voltage $\Delta V_{thn/p}$†, gate length $\Delta L_{n/p}$† (n/p denotes N/PMOS)
    - #MC trials: 500

ΔF: shift of oscillation frequency from its nominal value in each RO



RO frequency distributions

Shift of $\mu(\Delta F)$ must be considered.

† $\mu(\Delta V_{thn/p}) = \mu(\Delta L_{n/p}) = 0$,
$\sigma(\Delta V_{thn/p}) = 35$ mV, $\sigma(\Delta L_{thn/p}) = 1$ nm

[1] B. Wan, et al., "Ring Oscillators for Single Process-Parameter Monitoring," *TSD*, 2008.
[2] I. A. K. M. Mahfuzul, et al., "Process-sensitive Monitor Circuits for Estimation of Die-to-Die Process Variability," *TAU*, 2010, pp. 83-88.

Objective

To propose a parameter-estimation method that explicitly considers the effect of random variations

- Estimate device-parameters by MLE (Maximum Likelihood Estimation).
  - Aim to make better use of information of random variations: exploit it rather than ignore.
  - Estimation targets: $\boldsymbol{\Delta G_x}^{\dagger}$ and $\boldsymbol{\sigma_{\Delta R x}}^{\dagger}$.
    - Conventional methods estimate only $\boldsymbol{\Delta G_x}$.

† x: device-parameter
ΔG_x: global variation (same offset to all trs. on a chip)
ΔR_x: random variation (different tr. by tr.)

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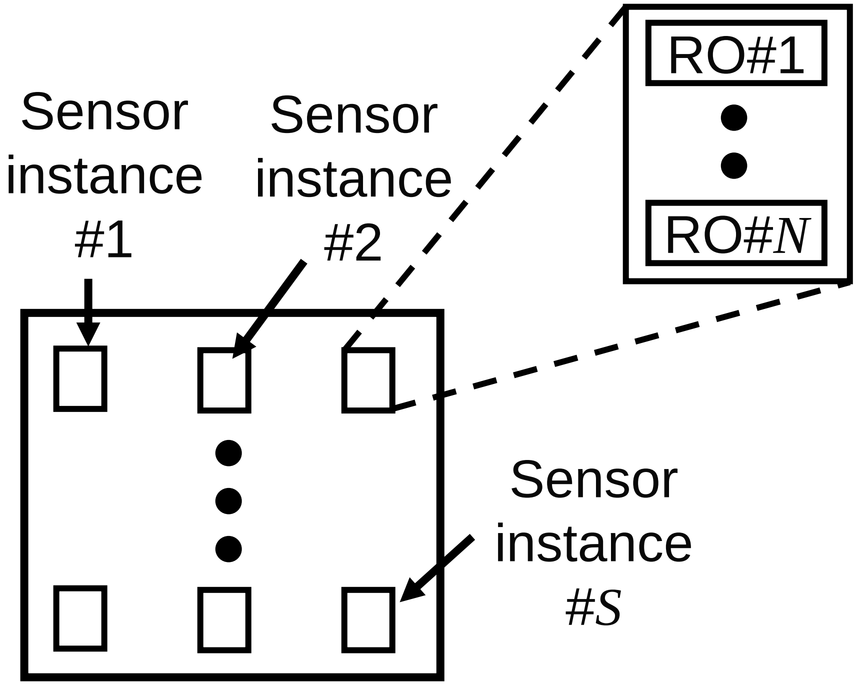
Assumed sensors in a chip

- Use several RO-based variation sensors.
  - Each sensor instance includes N types of ROs with different structures.
  - Selection of appropriate ROs for estimation are based on orthogonality of their frequency-sensitivity vectors.



Questions on implementation:

- How to choose N ROs?
- How many instances necessary?

Conventional parameter estimation method

- Shift of oscillation frequency in i-th type of RO (RO#i) from its nominal value, ΔF_i, is often modeled by

$$\Delta F_i = \sum_x k_{xi} \Delta G_x = \boldsymbol{k}_{xi}^{T} \boldsymbol{\Delta G_x}. \quad \cdots (1)^{\dagger}$$

k_{xi}: frequency-sensitivity to variation of x at RO#i

† Eq. (1) can be extended to 2nd or higher-order model to improve accuracy.

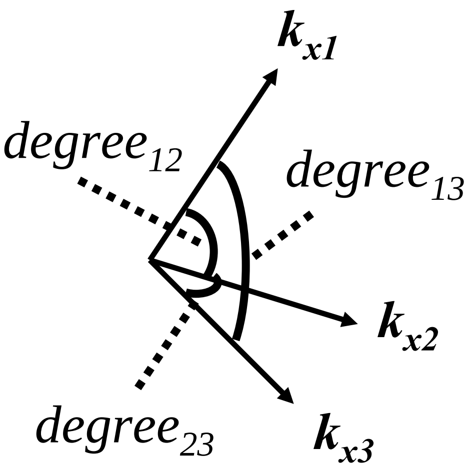
  - Random variations are assumed to be canceled out.
    - $\boldsymbol{\Delta R_x}$ does not appear.

- $\boldsymbol{\Delta G_x}$ can be estimated by $\boldsymbol{\Delta G_x} = \boldsymbol{K}^{-1} \boldsymbol{\Delta F} = \begin{pmatrix} \boldsymbol{k}_{x1}^{T} \\ \vdots \\ \boldsymbol{k}_{xn}^{T} \end{pmatrix}^{-1} \boldsymbol{\Delta F}. \quad \cdots (2)$
  - At least n ROs are necessary for estimating n parameters.
  - Estimation accuracy depends on $\boldsymbol{K}$.

How to determine effective set of ROs

- When sensitivity vectors are orthogonal to each other, estimation of $\boldsymbol{\Delta G_x}$ becomes accurate [2].
  - We derive an appropriate set of ROs with minimal RMSE (Route Mean Square Error) of angles in Eq. (3).

$$RMSE(ROset) = \sqrt{\frac{\sum_{\forall i \in (ROset)} \sum_{\forall j \in (ROset), j \neq i} (degree_{ij} - 90^\circ)^2}{{}_nC_2}} \cdots (3)$$



ROset: group of ROs used for estimation,

$degree_{ij}$: angle in degrees between $\boldsymbol{k_{xi}}$ and $\boldsymbol{k_{xj}}$,

${}_nC_2$: the number of combinations of vectors.

Example of $ROset \subset$ (#1, #2, #3)

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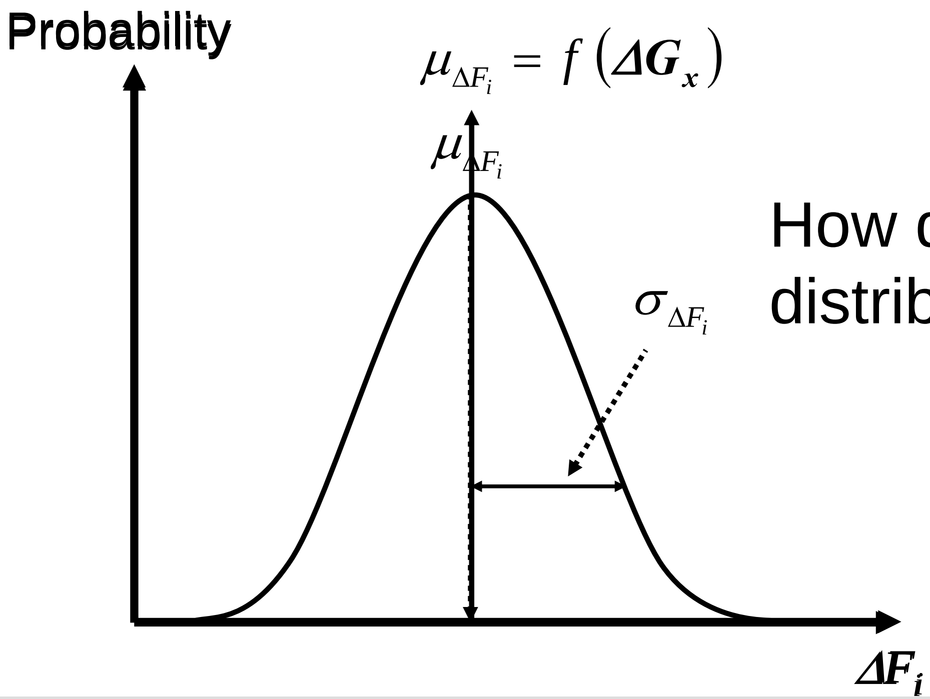
Inappropriate disregard of random variations

- Assumption in conventional method is equivalent to $\mu_{\Delta Fi} = f(\boldsymbol{\Delta G_x})$ … (4) and $\sigma_{\Delta Fi} = 0$.
  - All ΔF_i in the chip are: $\Delta F_i = \mu_{\Delta Fi}$
  - But as demonstrated above, $\boldsymbol{\Delta R_x}$ should not be ignored.
- Actual distribution of ΔF_i has some deviations.



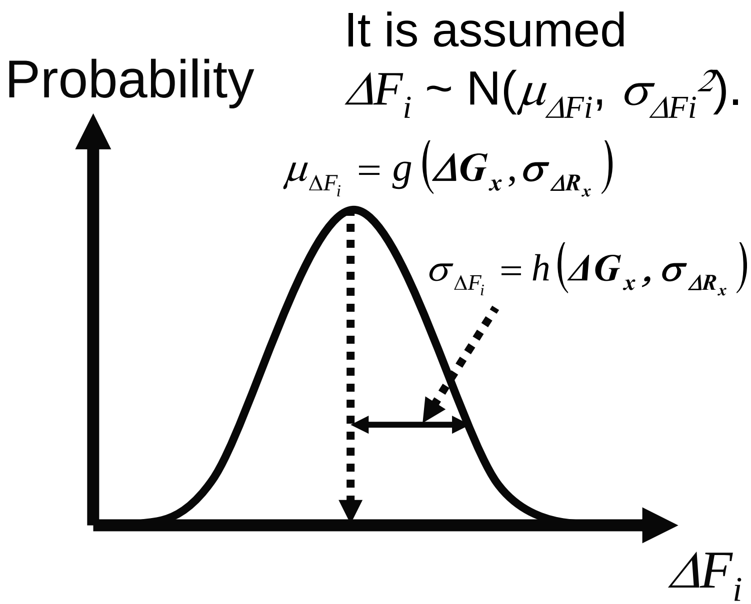
How do we characterize distribution?

Device-parameter extraction using MLE (1 / 2)

- Estimate the actual distribution by MLE.
  - Maximize the probability that assumed probability distributions produce measured data.

Conventional: throws away variability information,
Proposed: exploits it as it is.

- Proposed extraction step:
  1. Model $\mu_{\Delta Fi}$ and $\sigma_{\Delta Fi}$ as
     $\mu_{\Delta Fi} = g(\boldsymbol{\Delta G_x}, \boldsymbol{\sigma_{\Delta Rx}})$ …(5)†,
     $\sigma_{\Delta Fi} = h(\boldsymbol{\Delta G_x}, \boldsymbol{\sigma_{\Delta Rx}})$ …(6)†.



† The orders of equations could be freely chosen according to required accuracy.

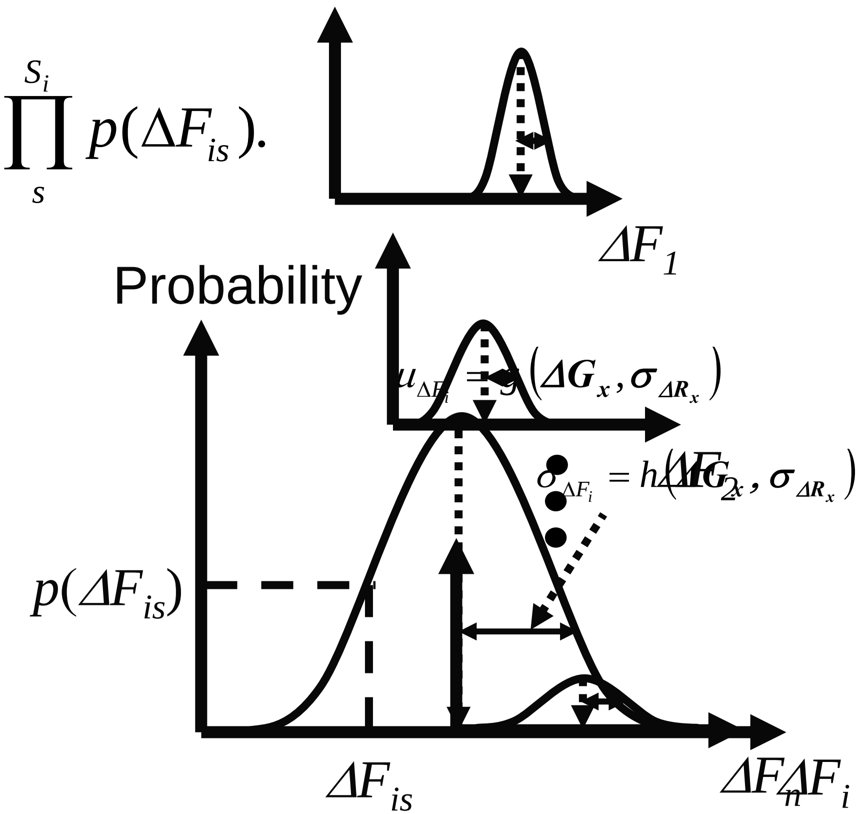
Device-parameter extraction using MLE (2 / 2)

2. Find $\boldsymbol{\Delta G_x}$ and $\boldsymbol{\sigma_{\Delta Rx}}$ that maximize Eq. (7).

$$\prod_{i}^{n}\prod_{s}^{S_i} p(\Delta F_{is})\cdots(7)$$

$p(\Delta F_i)$: probability density function of ΔF_i
S_i: the number of instances of RO#i
ΔF_{is}: measured data from s-th instance of RO#i

– Why this equation?
  - The likelihood function of ΔF_i: $\prod_{s}^{S_i} p(\Delta F_{is})$.
  - Using n ROs
    -> the overall likelihood
    function becomes Eq. (7).



Maximize the likelihood that each probability density function of ΔF_i produces measured data set.

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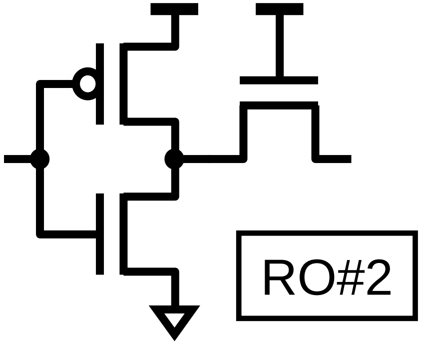
Experimental condition

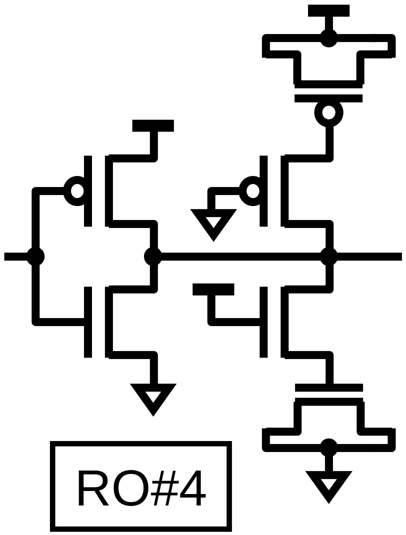
- Target of estimation: four parameters ($V_{thn/p}$ and $L_{n/p}$)
  – We generate these parameters according to $\sigma_{\Delta G/RVthn/p}$ = 35 mV, $\sigma_{\Delta G/RLn/p}$ = 1 nm.
- Modeling equations:
  – Eqs. (4) and (5): 3rd polynomials, Eq. (6): 2nd polynomials.
- Sensor block consists of eight 101-stage ROs (shown in the next slide).
  – Supply voltages: 1.5, 1.2, and 0.9 V

RO components and their circuit diagrams

RO No.	Component
1	Normal INV
2	INV followed by NMOS tr.
3	INV followed by PMOS tr.
4	INV followed by CMOS-controlled loads – 1
5	INV followed by CMOS-controlled loads – 2
6	Current-starved INV followed by PMOS-controlled loads [1]
7	Current-starved INV followed by NMOS-controlled loads [1]
8	Customized INV

- RO#2-7 have high sensitivity to one or two parameters.





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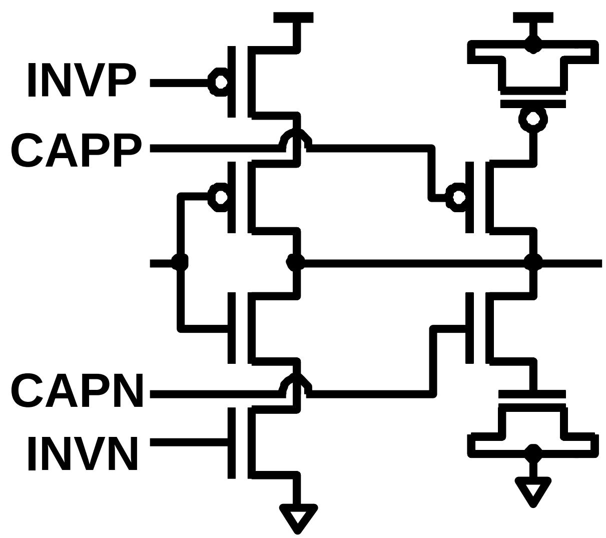
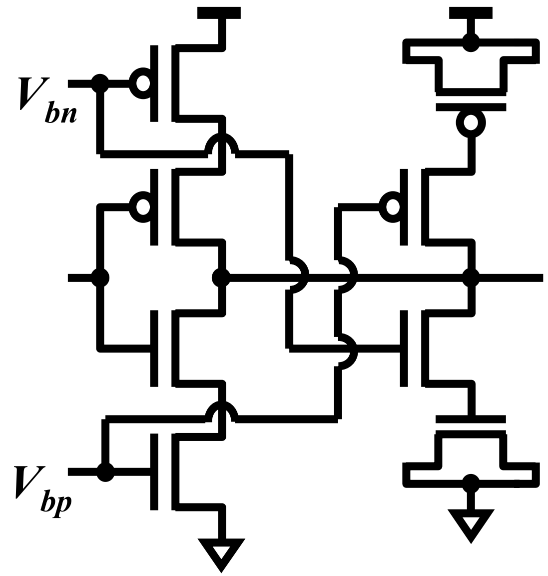
8	Customized INV

- Component of RO#8 is slightly modified from L-sensitive INV [1]
  - It has four controllable terminals to change sensitivity.
    - Selective voltages: V_{dd}, V_{bn}, V_{bp}, V_{ss}.
    - 144 (=$3^2 4^2$) data can be obtained using only RO#8.



RO#8



L-sensitive INV [1]

Best/worst ROset

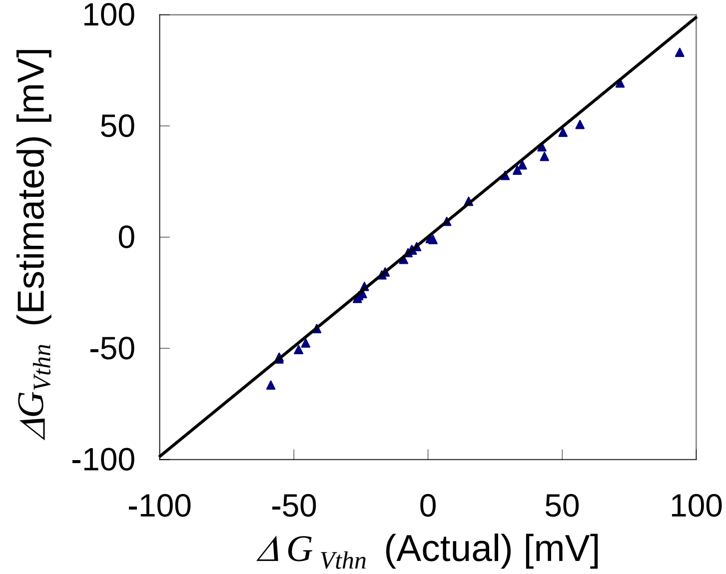
- RMSE in Eq. (3) (4 of 8 ROs are used as ROset): best = 8.60º, worst = 89.3º.

Best (top row), worst (bottom row) ROset
(Voltages enclosed by [] at RO#8 correspond to
INVN, INVP, CAPN, and CAPP shown in circuit diagram.

RO No. (V_{dd})	RO No. (V_{dd})	RO No. (V_{dd})	RO No. (V_{dd})
2 (0.9)	8 (1.5) [V_{bn}, V_{bp}, V_{bn}, V_{ss}]	8 (1.5) [V_{bn}, V_{ss}, V_{dd}, V_{bn}]	8 (1.2) [V_{bp}, V_{bp}, V_{bp}, V_{bp}]
8 (0.9) [V_{bp}, V_{bp}, V_{bp}, V_{bn}]	8 (0.9) [V_{bp}, V_{bp}, V_{bp}, V_{bp}]	8 (0.9) [V_{bp}, V_{bp}, V_{bp}, V_{ss}]	8 (0.9) [V_{dd}, V_{bp}, V_{bp}, V_{ss}]

Validation of the proposed method (1 / 2)

- 30 chips are virtually fabricated with only global variations.
  - $\sigma_{\Delta RVthn/p} = \sigma_{\Delta RLn/p} = 0$.
  - Conventional computation (Eq. (4)) is used for estimating ΔG_x.



Given ΔG_{Vthn} vs. estimated ΔG_{Vthn}

Absolute value of average estimate error.

RO set	ΔG_{Vth_n}[mV]	ΔG_{Vth_p}[mV]	ΔG_{L_n}[nm]	ΔG_{L_p}[nm]
Best	2.19	4.24	0.69	1.00
Worst	63.94	34.40	2.79	2.09

Each global variation is accurately estimated when using best ROset.

Validation of the proposed method (2 / 2)

- Proposed (MLE using Eqs. (5), (6)) and Conventional (least-square approach using Eq. (4)) are compared.
  - 3 chips are virtually fabricated.
    - Each chip has 100 sensor instances including best ROset.
    - All of sensor data are used for estimation.

Average estimate error of global variations.

Method	ΔG_{Vth_n}[mV]	ΔG_{Vth_p}[mV]	ΔG_{L_n}[nm]	ΔG_{L_p}[nm]
Proposed	0.54	4.03	1.23	2.11
Conventional	8.51	13.71	1.49	0.54

Proposed method improves average accuracy.

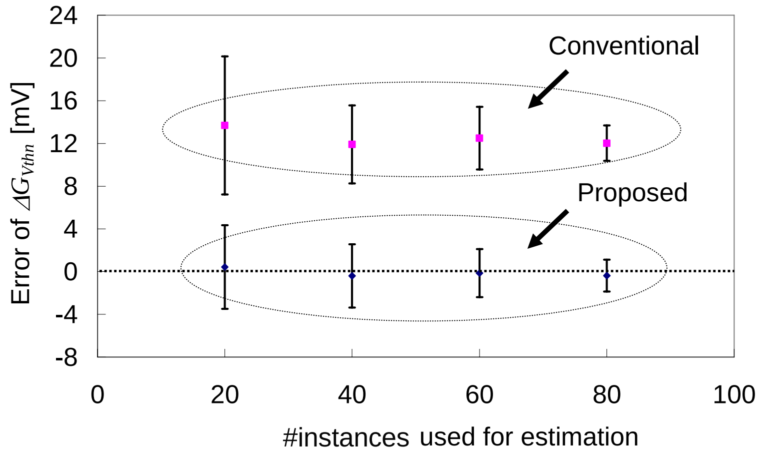
Average estimate error of stddev. of random (Proposed).

$\sigma_{\Delta R_{Vth_n}}$[mV]	$\sigma_{\Delta R_{Vth_p}}$[mV]	$\sigma_{\Delta R_{L_n}}$[nm]	$\sigma_{\Delta R_{L_p}}$[nm]
6.30	2.91	0.13	0.10

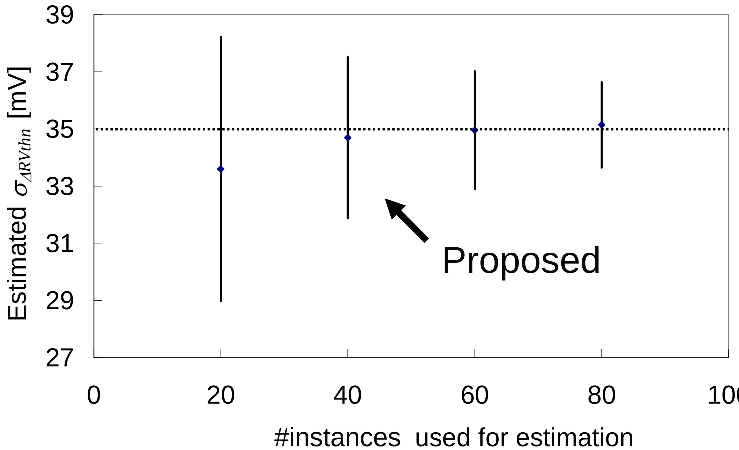
Random variations are accurately estimated.

#instances vs. accuracy

- We demonstrate how #instances, i.e., S_i, affects accuracy.
  - Evaluated S_i: 20, 40, 60, 80.
    - For each S_i, 500 instance sets in a chip are randomly generated.
  - Distribution of estimation errors is evaluated.
- More instances, more accurate result could be obtained.
  - E.g., to suppress error of $\mu_{\sigma\Delta RVthn}+3\sigma_{\sigma\Delta RVthn}$ below 20 %, at least 60 instances are necessary in a chip.



#instances vs. error of ΔG_{Vthn}.



#instances vs. error of $\sigma_{\Delta RVthn}$.

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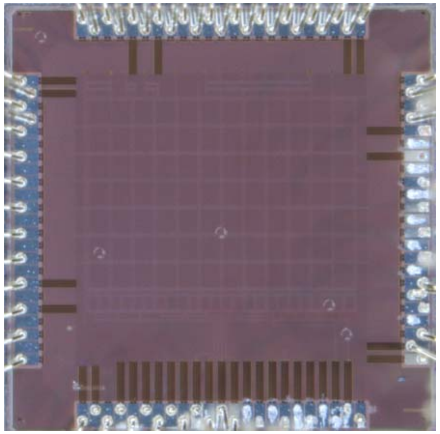
Conclusion

- We proposed a device-parameter estimation method with on-chip variation sensors.
  - Proposed method takes into account random variations with maximum likelihood estimation.
  - We experimentally verified that the proposed method can accurately estimate variations.

- Future work
  - Verifying the proposed method using actual RO-based sensors in test chips we designed.



Test chip in 65-nm process.

Thank you !