Extracting Device-Parameter Variations using a Single Sensitivity-Configurable Ring Oscillator

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***Abstract*—The RO(Ring-Oscillator)-based sensor is one of easily-implementable variation sensors, but for decomposing the observed variability into multiple unique device-parameter variations, a large number of ROs with different structures and sensitivities to device-parameters is required. This paper proposes a scheme for sensing multiple device-parameter variations with just a single reconfigurable RO. This sensitivity-configurable RO has a number of configurations available and this property can be exploited for reducing sensor area while improving estimation accuracy through iterative estimation. To minimize the prospective error, the proposed estimation iterates: (1) selecting the best configuration that minimizes the prospective estimation error around the current estimates; and (2) updating the estimates with the selected configuration. This experiment was carried out assuming a 32-nm predictive technology model. Experimental results show that device-parameter extraction with a single RO is feasible and the error of the extracted parameters is reduced by 35 to 53% with the improved objective function and iterative estimation.**

I. Introduction

Manufacturing variability is becoming more harmful on circuit performance and parametric yield, and is predicted to get much severer according to device miniaturization [1]. To improve the circuit performance after fabrication and sustain parametric yield, several adaptation methods, such as voltage scaling and adaptive body bias, have been proposed [2], [3]. In order to adapt the performance efficiently, it is required to estimate for every chip how device-parameters varied from their typical values during the manufacturing process. In this paper, die-to-die variations including wafer-to-wafer and lot-to-lot are to be extracted. For example, when the magnitude of PMOS threshold voltage is high and NMOS threshold voltage is typical, forward body bias should be given to PMOSs, not to NMOSs. Otherwise, a large increase in leakage current would be introduced. For such a purpose, RO-based sensors have been intensively studied [4]–[7]. They can be easily implemented in a chip and can be used to assess variability and aging information even after the product shipment, because the oscillating frequencies of ROs can be easily measured with a simple circuit structure.

Fundamentally, for extracting n device-parameters, n types of sensors that have different sensitivities to device parameters are necessary. When implementing RO-based sensors using ordinary standard cells, the sensitivity vectors of the oscillation frequency to the device parameters (e.g. channel length and threshold voltages for NMOS and PMOS) are close to each other, and it is difficult to robustly estimate the device parameters from the observed oscillation frequencies, since the observed frequencies must include uncertainties originating from, such as, random variation and measurement. On the other hand, ROs that have high sensitivity to a single device-parameter have been proposed for decomposing the measured variations, which are the mixtures of variations contributed by each device parameter, into individual device-parameter variations [6], [7]. Using a set of these ROs with different sensitivities, device-parameters can be estimated. As mentioned above, supposing that the number of device-parameters to be extracted is n, at least n types of ROs with different sensitivities must be implemented. Furthermore, as within-die variations become significant, implementation of larger-stage ROs or a number of the same ROs on a chip is required to reasonably mitigate the uncertainty of the measured frequencies. In this case, larger area overhead for sensor implementation is inevitable.

We in this paper propose a device-parameter extraction system with a single type of RO whose sensitivities to the device parameters are reconfigurable in measurement time. By changing the configuration, we obtain more than n measured frequencies with different sensitivities from a single RO. This reconfiguration capability helps reduce silicon area necessary for the sensor, since the necessary number of RO types is reduced from n to 1. Here, to be precise, the structure of sensitivity-reconfigurable RO itself is presented in [8], [9]. However, it is used as one of ROs that provide a specific sensitivity. It has not been presented that only a single sensitivity-reconfigurable RO is capable of extracting device-parameter variation.

Furthermore, this redundant number of reconfiguration can be exploited for improving accuracy of device-parameter extraction. In general, RO frequency cannot be expressed well as a linear function of variational device parameters, and a higher-dimensional function is desirable for expressing the relation. This suggests that the best combination of sensitivity configurations for the accuracy varies in the variational parameter space. Figure 1 exemplifies how the prospective error varies in a parameter space. Each of three lines corresponds to a combination of sensitivity configurations, and x-axis expresses a representative device-parameter variation normalized by its standard deviation. We can see above 1 σ, the combination of (1) attains the minimum prospective error, between -2σ to σ, (2) does, and below -2σ, (3) becomes the minimum. It is

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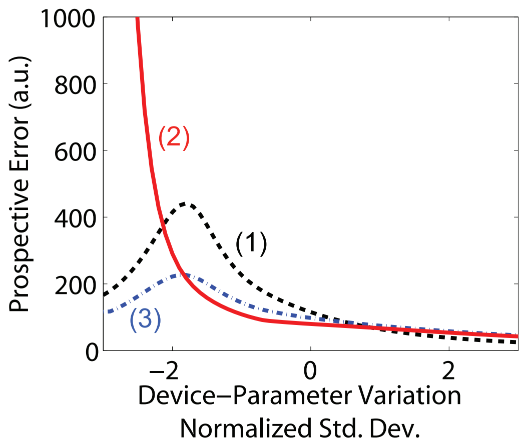


Fig. 1. The best combination varies in device-parameter space. Each of three lines (1) – (3) corresponds to a combination of sensitivity configurations. X-axis expresses a representative device-parameter variation normalized by its standard deviation.

not smart to use a single combination to estimate the device-parameter in the whole parameter space. In other words, by selecting the combination of sensitivity configuration depending on the estimates of device parameters, the most accurate and robust estimation can be expected. This adaptive selection is highly compatible with the sensitivity-configurable RO since the measurement with different sensitivity configurations does not require additional area overhead, and therefore the iterative estimation using the adaptive selection is promising. In contrast, for conventional ROs, this adaptive selection involves an increase in the number of RO types on a chip, which results in area overhead.

This paper especially focuses on a metric to derive the best combination of sensitivity configurations for achieving this adaptive selection. We devise a metric for robustly and accurately solving simultaneous non-linear equations taking into account the uncertainty of measured frequency values, and adopt it as the objective function for deciding the combination of sensitivity-configurations. The proposed metric, which represents the prospective estimation error, enhances the estimation accuracy compared with [9], where [9] uses the condition number of the sensitivity matrix aiming at solving simultaneous linear equations robustly a particular point in the variational parameter space.

The rest of this report is organized as follows. Section 2 explains device-parameter estimation that uses a single sensitivity-configurable ring oscillator, and formulates a problem to obtain the best combination of sensitivity configurations. Section 3 discusses the objective function for selecting the best combination of configurations, and Section 4 introduces an iterative estimation method to attain high estimation accuracy. In Section 5, experimental results are shown to validate our approach. Finally, Section 6 concludes the discussion.

II. Parameter extraction using a sensitivity-configurable ring oscillator

This section explains the parameter extraction using RO-based variation sensor and introduces the sensitivity-configurable ring oscillator. We then formulate a problem to obtain a combination of sensitivity-configurations for robustly and accurately estimating device-parameter variations.

A. Parameter extraction using RO-based variation sensor

We first explain a parameter extraction method using RO-based variation sensor. Here the RO-based sensor consists of m types of ROs (for the sensitivity-configurable RO, m configurations) that have different sensitivities to device-parameters. a_i, which denotes the measured value of the i-th type of RO (for the sensitivity-configurable RO, the i-th configuration), is expressed by Eq. (1),

$$a_i = f_i(\boldsymbol{\Delta G_x}), \quad (1)$$

where $\boldsymbol{\Delta G_x}$ is a vector representation of ΔG_x, and ΔG_x is the global variation component of parameter x. Function f_i is prepared in advance by, for example, circuit simulation, and its basis function and order are determined according to the function shape and demanded accuracy. Consequently, the simultaneous equations to be solved for estimating $\boldsymbol{\Delta G_x}$ using m types of ROs are as follow.

$$\begin{cases} a_1 = f_1(\boldsymbol{\Delta G_x}) \\ a_2 = f_2(\boldsymbol{\Delta G_x}) \\ \quad\vdots \\ a_m = f_m(\boldsymbol{\Delta G_x}) \end{cases} \quad (2)$$

In Eq. (2), the number of RO types used for estimation, m, must be larger than the number of parameters to be estimated, n. Besides, there are various numerical solving methods for non-linear simultaneous equations, such as Newton-Raphson method, and $\boldsymbol{\Delta G_x}$ is derived with one of them.

B. Sensitivity-configurable ring oscillator

Figure 2 shows a single inverting stage composing the sensitivity-configurable RO. In this structure, voltages given to four terminals (INVN/P and CAPN/P) change the sensitivity of oscillation frequency to device-parameter variations. The voltages for individual terminals can be selected from, for example, V_{dd}, V_{bn}, V_{bp}, and V_{ss}, where V_{bn} is the voltage generated by the bias generator shown in Figure 3 and V_{bp} is similarly generated by the complementary circuit, which are proposed in [7].

Excluding invalid voltage assignments (e.g. stopping oscillation), 144 ($= 3^2 4^2$) data can be obtained using only this RO in this setup. It is possible to increase the number of data further by increasing the number of assignable voltages, but in this work 144 combinations are supposed to available. This means that the sensor area can be roughly reduced to one m-th compared with obtaining m measurement data from m types of ROs.

C. Formulating a problem to obtain the best combination of sensitivity-configurations

We here discuss how we can improve the estimation accuracy when using a single sensitivity-configurable ring oscillator as a variation sensor. In this estimation, the combination of m sensitivity-configurations determines the robustness and accuracy of the estimation, since it corresponds to the simultaneous non-linear equations (Eq. (2)) to be solved and the easiness of the equation solution depends on the characteristics of individual equations and their mutual relations, for example orthogonality.

On the other hand, the sensitivities of the ring oscillator to device-parameters can be varied by changing the supply voltage in addition to the four terminal voltages in Figure 2. If we measure the oscillating frequencies at l supply voltages, we can obtain $144 \times l$ measurement data from a single ring oscillator. In fact, when using the sensitivity-configurable ring oscillator, $144 \times l$ measurement data can be obtained without an increase in area. However, the necessary measurement time increases, and hence still a smaller number of measurements that can attain high accuracy is desirable.

Based on the discussion above, the optimization problem solved in this paper is defined as follows.

> A combination consisting of $m(\geq \quad n)$ sensitivity-configurations, which attains the smallest prospective estimation error of $\boldsymbol{\Delta G_x}$, is selected from $144 \times l$ sensitivity-configurations, where n, m and l are supposed to be given.

III. Objective function for pursuing a combination of sensitivity configurations with minimum prospective error

This section presents the criterion for pursuing a combination of sensitivity-configurations that brings out highly accurate estimation of parameters, i.e. the objective function for the optimization problem defined in Section II-C.

In the prior research [8], [9], the condition number of a matrix is used as the metric. The condition number of a matrix $\boldsymbol{M}$, $cond(\boldsymbol{M})$, is mathematically defined as follows [10], [11],

$$cond(\boldsymbol{M}) = ||\boldsymbol{M}||_2 \cdot ||\boldsymbol{M}^{-1}||_2. \tag{3}$$

$||\boldsymbol{M}||_2$ is the 2-norm of $\boldsymbol{M}$. $\boldsymbol{M}$ is a partial differential coefficient matrix at the origin, i.e. , $\boldsymbol{J(\Delta G_x)}$ substituted with $\boldsymbol{\Delta G_x} = \boldsymbol{0}$ [1]. $\boldsymbol{J(\Delta G_x)}$ is the Jacobian matrix of the right side of Eq. (2). Supposing $\boldsymbol{\Delta G_x} = (\Delta G_{x_1} \cdots \Delta G_{x_n})^T$, Jacobian matrix $\boldsymbol{J(\Delta G_x)}$ is expressed as follows.

$$\boldsymbol{J(\Delta G_x)} = \begin{pmatrix} \dfrac{\partial f_1}{\partial(\Delta G_{x_1})} & \cdots & \dfrac{\partial f_1}{\partial(\Delta G_{x_n})} \\ \vdots & \ddots & \vdots \\ \dfrac{\partial f_m}{\partial(\Delta G_{x_1})} & \cdots & \dfrac{\partial f_m}{\partial(\Delta G_{x_n})} \end{pmatrix}. \tag{4}$$

That is, $\boldsymbol{M}$ consists of the sensitivity vectors which are determined by the configuration of sensitivity-configurable RO. It is well known that smaller condition number gives a better solution in numerical computation [11] and it is accompanied with the better orthogonality of the vectors.

However, it should be noted that the condition number of the matrix $\boldsymbol{M}$ is valid as long as the right sides of Eq. (2) are linear or $f_i(\boldsymbol{\Delta G_x})$ can be reasonably approximated to a linear function in the region of interest. As illustrated in Figure 4, the differential coefficient (gradient) is parameter-independent in the case that the function is linear, but in the case of a non-linear function, the differential coefficient is dependent on parameters $\boldsymbol{\Delta G_x}$ to be estimated. Even when the condition number of the sensitivity matrix $\boldsymbol{M}$ is small and the orthogonarity of sensitivity vectors is high at the origin in the variation parameter space, we cannot expect accurate numerical computation results in the whole parameter space. What we can expect is that the estimation is accurate only in the case that the true estimates are at and around the origin. On the other hand, in reality, the response of RO oscillation frequency to device-parameter variation is not linear, and hence the condition number of the sensitivity matrix at the origin of $\boldsymbol{\Delta G_x} = 0$, which was used in [9], is not sufficient as the objective function for selecting the combination of sensitivity-configurations.

Besides, when solving simultaneous equations $\boldsymbol{H(z)} = \boldsymbol{u}$, parameter $\hat{\boldsymbol{z}}$ instead of $\boldsymbol{z}$ is obtained because of existing measurement error $\hat{\boldsymbol{u}} - \boldsymbol{u}$, where $\boldsymbol{H(\hat{z})} = \hat{\boldsymbol{u}}$ holds. Regarding $\boldsymbol{z}$ as the true value of the parameter to be estimated, the relationship between the relative measurement error norm $||\hat{\boldsymbol{u}} - \boldsymbol{u}||_2 / ||\boldsymbol{u}||_2$ and the relative estimate error norm $||\hat{\boldsymbol{z}} - \boldsymbol{z}||_2 / ||\boldsymbol{z}||_2$ is

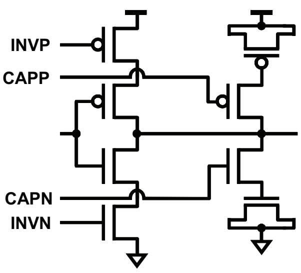


Fig. 2. Single inverting stage for sensitivity-configurable RO.

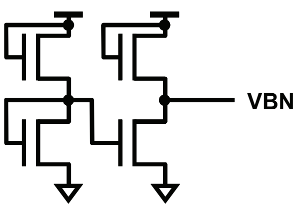
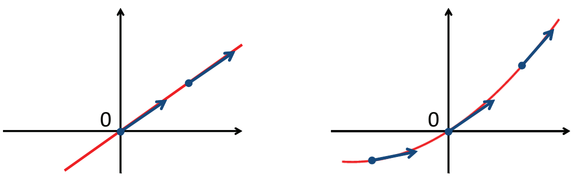


Fig. 3. V_{bn} bias generator.



(a) linear function (b) non-linear function

Fig. 4. Gradient (sensitivity) of linear and non-linear functions.

[1]Other points instead of $\boldsymbol{\Delta G_x} = \boldsymbol{0}$ are fine as well, but here the occurrence probability of $\boldsymbol{\Delta G_x} = \boldsymbol{0}$ is usually higher and then is selected.

expressed by [11]

$$\frac{||\hat{\boldsymbol{z}}-\boldsymbol{z}||_2}{||\boldsymbol{z}||_2} \leq \kappa(\boldsymbol{z})\frac{||\hat{\boldsymbol{u}}-\boldsymbol{u}||_2}{||\boldsymbol{u}||_2}. \quad (5)$$

$\kappa(\boldsymbol{z})$ in Eq. (5) is the condition number explained above. Eq. (5) means that the condition number gives the upper bound of the relative error norm ratio, which is defined as Eq. (6).

$$\frac{||\hat{\boldsymbol{u}}-\boldsymbol{u}||_2/||\boldsymbol{u}||_2}{||\hat{\boldsymbol{z}}-\boldsymbol{z}||_2/||\boldsymbol{z}||_2}. \quad (6)$$

In other words, $\kappa(\boldsymbol{z})$ is the maximum gain of $||\hat{\boldsymbol{u}}-\boldsymbol{u}||_2/||\boldsymbol{u}||_2$ to $||\hat{\boldsymbol{z}}-\boldsymbol{z}||_2/||\boldsymbol{z}||_2$.

Eq. (5) tells us that the following two points are important to diminish estimation error norm $||\hat{\boldsymbol{z}}-\boldsymbol{z}||_2$. First, m configurations of sensitivity-configurable RO that can attain small condition number should be selected and used for estimation. With this, we can minimize the gain of $||\hat{\boldsymbol{u}}-\boldsymbol{u}||_2/||\boldsymbol{u}||_2$ to $||\hat{\boldsymbol{z}}-\boldsymbol{z}||_2/||\boldsymbol{z}||_2$. Note that $\kappa(\boldsymbol{z})$ is a function of $\boldsymbol{z}$. This corresponds to the fact that the condition number is a function of $\boldsymbol{\Delta G_x}$ in our problem. Thus, the condition number of the combination of sensitivity-configurations varies in the variation parameter space. This issue will be resolved in the next section.

The second point is to make the relative measurement error norm, $||\hat{\boldsymbol{u}}-\boldsymbol{u}||_2/||\boldsymbol{u}||_2$, smaller. This corresponds to diminishing the relative error of measured value $\boldsymbol{a}$ in our problem. If the probability distribution of relative measurement error is independent of the sensitivity-configuration and constant in the variation parameter space, we do not have to pay attention to the measurement error in selecting the combination of the sensitivity-configurations. However, this is not true in our problem, since the measurement error here includes the uncertainty of the measured frequencies due to random variations, and the susceptibility to the random variations depends on the configuration.

We therefore adopt the objective function Obj below and minimize it.

$$Obj = \kappa(\boldsymbol{z})\frac{||\hat{\boldsymbol{u}}-\boldsymbol{u}||_2}{||\boldsymbol{u}||_2}. \quad (7)$$

This objective function directly represents the prospective estimation error, while the conventional condition number used in [9] represents the robustness of solving the simultaneous linear equations. The combination of sensitivity-configurations that minimizes Eq. (7) is expected to attain more accurate estimation. The remaining issues are the dependency of $\kappa(\boldsymbol{z})$ on the estimates $\boldsymbol{z}$, which will be discussed in the next section, and how to efficiently obtain configuration-dependent $||\hat{\boldsymbol{u}}-\boldsymbol{u}||_2/||\boldsymbol{u}||_2$, since its direct computation is very expensive. The approximate computation is discussed in V-B.

IV. Proposed iterative estimation method

This section presents the proposed iterative estimation method for attaining robust and accurate device-parameter estimation. The procedure for the proposed iterative estimation method is described below.

Step 1: Regression expressions ($f_i(\boldsymbol{\Delta G_x})$, in Eq. (2)) are constructed for each sensitivity-configuration, and initial values of the estimates, such as $\boldsymbol{\Delta G_x} = \boldsymbol{0}$, are decided.

Step 2: A combination of sensitivity-configurations that minimizes the objective function of Eq. (7), which is the product of condition number at the current estimates and the measurement error norm, is derived using the regression expressions constructed at Step 1.

Step 3: $\boldsymbol{\Delta G_x}$ is estimated from measured frequencies corresponding to the combination of sensitivity-configurations derived at Step 2 and the regression expressions constructed at Step 1. If the iteration count is less than a pre-defined value, go back to Step 2.

As mentioned above, the condition number $\kappa(\boldsymbol{z})$ is as a function of $\boldsymbol{z}$, which means the condition number depends on $\boldsymbol{\Delta G_x}$ in our problem. On the other hand, $\boldsymbol{\Delta G_x}$ is unknown because it is the set of parameters to be estimated. Thus, the initial estimates are temporarily set at Step 1, and the best combination at the initial estimates is derived at Step 2. $\boldsymbol{\Delta G_x}$ is estimated with this combination at Step 3. The true values are likely to exist around the estimates. For this reason, the best combination at the current estimates is re-derived at Step 2, and re-estimation is performed with it at Step 3. By iterating these steps, robust and accurate estimation is expected.

V. Experimental results

This section experimentally confirms the accuracy improvement of extracted device-parameter variations with the proposed iterative estimation.

A. Experimental setup

One hundred chips are virtually fabricated on the basis of Monte Carlo simulation, and their die-to-die variations are estimated. Here, a 32-nm predictive technology model [12], [13] with nominal Vt is used for evaluation. The number of stages of the sensitivity-configurable RO (Figure 2) was set to seven. Also, three discrete voltages (0.7, 0.9, 1.1[V]) were given to the sensitivity-configurable RO and bias generators as the supply voltage, which means l is three. In this setup, there are 144×3=432 configurations. All the sensor outputs in each chip are evaluated with circuit simulator [14].

It is assumed that the variational device-parameters to be extracted are threshold voltages of NMOS and PMOS, V_{thn} and V_{thp}, and channel length, L, which means n is three, and the variability is composed of two components, that are global and random variations. Global variation here means die-to-die variation which causes the same variation-offset to all transistors in a chip, while random variation corresponds to within-die variation which is different transistor by transistor. Then, the offset of a device-parameter x from its nominal value ΔV_x is expressed by Eq. (8),

$$\Delta V_x = \Delta G_x + \Delta R_x, \quad (8)$$

where ΔR_x denotes random variability of parameter x, and x could be V_{thn}, V_{thp} or L. In what follows, it is assumed that $\sigma_{\Delta G_{Vthn/p}} = \sigma_{\Delta R_{Vthn/p}} = 20[\text{mV}]$ and $\sigma_{\Delta G_L} = \sigma_{\Delta R_L} = 1[\text{nm}]$. The random variations are size-dependent [15], and the standard deviations above are set for $L = 32[\text{nm}]$ and $W = 256[\text{nm}](\text{NMOS})/328[\text{nm}](\text{PMOS})$. In the Monte Carlo simulation, the size-dependency is considered by scaling the deviation.

The oscillating frequency of each sensitivity-configuration depends on not only parameters to be estimated, $\boldsymbol{\Delta G_x}$, but also to the random component of variation. To suppress the influence of random component, one hundred sensitivity-configurable ROs are placed on a chip, and the mean of oscillating frequencies $\bar{a_i}$ is used as the measurement value. Investigating the required number of ROs is one of our future works. Besides, third-order polynomial expressions of $\boldsymbol{\Delta G_x}$ are derived assuming that Eq. (1) is approximately expressed by the following empirical equation of Eq. (10) referring to [9] because preparing samples for the regression analysis strictly considering random variation (Eq. (9)) is computationally expensive.

$$\begin{aligned} \bar{a_i} &= f_i(\boldsymbol{\Delta G_x})\Big|^{\sigma_{\Delta R_L}=1[\text{nm}]}_{\sigma_{\Delta R_{Vth_{n/p}}}=20[\text{mV}]} && (9)\\ &\approx f_i(\boldsymbol{\Delta G_x})\big|_{\boldsymbol{\sigma_{\Delta R_x}=0}} && (10)\\ &+ f_i(\boldsymbol{\Delta G_x}=\boldsymbol{0})\Big|^{\sigma_{\Delta R_L}=1[\text{nm}]}_{\sigma_{\Delta R_{Vth_{n/p}}}=20[\text{mV}]}. \end{aligned}$$

The second term of Eq. (10) corresponds to the shift of average oscillation frequency caused by random variations. This frequency shift is significant in some configurations due to the highly non-linear characteristics of oscillating frequency to device parameters, which is pointed out in [9]. $\boldsymbol{\Delta G_x}$ is estimated by solving simultaneous equations like Eq. (2), where each equation is modeled as Eq. (10), and $m(\geq n = 3)$ is three considering necessary measurement time. The number of iterative estimation including the initial value assignment is two, since further iterations hardly contribute to accuracy improvement. The combination of sensitivity-configurations which minimizes the objective function is exhaustively searched.

B. Computation of objective function

Section III defined the objective function for selecting a combination of sensitivity-configurations aiming at high estimation accuracy. The dependency of the condition number on the estimates is handled through the iterative estimation explained in Section IV. The remaining issue is the computation of $||\hat{\boldsymbol{u}} - \boldsymbol{u}||_2/||\boldsymbol{u}||_2$ in Eq. (7). Here, let us remind that the sources of measurement error include the uncertainty of average oscillating frequency originating from the random variation, the difference between the regression expression (Eq. (10)) and actual response, and so on. In the current problem, the first uncertainty is the major measurement error source, and hence we estimate the amount of this uncertainty and use it as $||\hat{\boldsymbol{u}} - \boldsymbol{u}||_2$.

We then adopt the standard deviations of the measured frequency a_i due to the random variation as $||\hat{\boldsymbol{u}} - \boldsymbol{u}||_2$. Also, $||\bar{\boldsymbol{a_i}}||_2$ is adopted as $||\boldsymbol{u}||_2$. Here, $\bar{a_i}$ is derived by substituting the current estimates in $f_i(\Delta G_x)$. Now, the objective function becomes as follows.

$$\kappa(\boldsymbol{\Delta G_x}) \times \frac{\left|\left|\boldsymbol{\sigma_{a_i}}\left(\boldsymbol{\Delta G_x}=\boldsymbol{0}\right)\Big|^{\sigma_{\Delta R_L}=1[\text{nm}]}_{\sigma_{\Delta R_{Vth_{n/p}}}=20[\text{mV}]}\right|\right|_2}{||\bar{\boldsymbol{a_i}}||_2}. \quad (11)$$

In Eq. (11), σ_{a_i} is the standard deviation of measured frequency a_i. Note that this standard deviation could be dependent on $\boldsymbol{\Delta G_x}$, but here it is not considered due to the computational time, since deriving the standard deviation requires many, such as 100, circuit simulations at each point of $\boldsymbol{\Delta G_x}$.

C. Estimation accuracy evaluation

To evaluate accuracy improvement by iterative estimation, device-parameter extraction is conducted under following 3 conditions.

- C1: Conventional estimation using the combination of the sensitivity-configurations that minimizes the condition number of the sensitivity matrix at $\boldsymbol{\Delta G_x} = \boldsymbol{0}$ [9].
- C2: Initial estimation using the combination of sensitivity-configurations that minimizes the objective function of Eq. (11) at the point of $\boldsymbol{\Delta G_x} = \boldsymbol{0}$ (the initial estimation of the proposed method).
- C3: Second estimation with the combination minimizing the objective function at the point of the initial estimates obtained from **C2**.

Table I shows the averages of the absolute estimation errors of $\boldsymbol{\Delta G_x}$ from the variations given to each chip. In Table I, the values in brackets are the errors normalized by respective standard deviations $\sigma_{\Delta G_x}$. In addition, the norm of estimation error is computed from the normalized errors, which expresses the overall accuracy.

The conventional and initial estimation were carried out using the combination of sensitivity-configurations that minimized each objective function at the point of $\boldsymbol{\Delta G_x} = 0$. Both C1 and C2 are not expected to give good estimates distant from $\boldsymbol{\Delta G_x} = \boldsymbol{0}$, which may make the accuracy improvement less visible. Nevertheless, we can see the normalized error norm, which represents the overall estimation error to be minimized, is reduced from 0.227 to 0.185 by 19% comparing C1 to C2 in Table I. This indicates that the objective function of Eq. (7) is better than the condition number and it better expresses the overall prospective estimation error.

Table I also shows that the estimation accuracy improved through iterative estimation. The normalized error norm is reduced from 0.185 to 0.123 by 34%. 44% reduction of $\Delta G_{V_{thn}}$ and 55% reduction of ΔG_L overwhelms 8% increase of $\Delta G_{V_{thp}}$. In addition, the each absolute error normalized by respective standard deviation is 0.070 ($\Delta G_{V_{thn}}$), 0.068 ($\Delta G_{V_{thp}}$) and 0.049 (ΔG_L), and thus the estimation errors of these three device-parameters are well balanced. These numbers also clarify that the device-parameter estimation

TABLE I
ESTIMATION RESULTS.

Estimate condition	$\Delta G_{V_{thn}}$ [mV]	$\Delta G_{V_{thp}}$ [mV]	ΔG_L [nm]	Normalized error norm
C1: Conventional [9]	2.15 (0.1075)	2.91 (0.1455)	0.0803 (0.0803)	0.227
C2: Initial	2.48 (0.1240)	1.26 (0.0630)	0.1094 (0.1094)	0.185
C3: Second	1.39 (0.0695)	1.36 (0.0680)	0.0489 (0.0489)	0.123
Err. Reduction from Initial	44%	-8%	55%	34%
Err. Reduction from Conventional [9]	35%	53%	39%	46%

Values in brackets are the errors normalized by respective standard deviations $\sigma_{\Delta G_x}$.

using a single type of sensitivity-configurable RO is feasible, and the reconfiguration capability can be exploited for the accuracy improvement.

We lastly show the overall accuracy improvement from [9], which is listed at the bottom row of Table I. Thanks to the improved objective function representing the prospective estimation error and the proposed iterative estimation, the estimation error is reduced by 35 to 53%.

VI. CONCLUSION

This paper proposed a device-parameter extraction method using the sensitivity-configurable ring oscillator. The proposed method iteratively selects a combination of sensitivity-configurations that minimizes the prospective estimation error at the current estimates and estimates the device-parameter using the combination. The prospective estimation error is computed by the product of the condition number of sensitivity matrix and the measurement error, and this is minimized as the objective function in selecting the combination of sensitivity-configurations. Experimental results using virtually fabricated test chips in 32-nm process show that the proposed method reduces the estimation error by 35 to 53%, and the device-parameter variation can be estimated only with the sensitivity-configurable RO.

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