Predicting Vt Variation and Static IR Drop of Ring Oscillators Using Model-Fitting Techniques

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- Circuit Model and Data Preparation
- Our Model-Fitting Framework
- Experimental Results
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Research Background and Motivation

Measuring Intra-die Process Variation

- Device variability does not scale as fast as the device dimensions, resulting in highly increased process variations, especially intra-die variation.

- Ring oscillators (ROs) as on-chip process monitor
  - Measured by digital ATE, which is cheaper and faster
  - Only one serial scan-based IO pad is needed
  - Simple circuit and easy to implement into a SoC

Challenge of Using RO to Measure the Intra-Die Variation

- Frequencies of ROs are determined by many factors, not just device characteristics, such as
  - NMOS Vt, PMOS Vt, IR drop, temperature

- Previous works for decomposing the factors
  - Incorporate extra circuit techniques onto ROs for extracting the targeted factors. [4][5][6][7]
    ⇨ extra area overhead

  - Build mathematical models based on SPICE simulation to predict the targeted factors. [8][9][10]
    ⇨ either using linear models or long SPICE simulation.

[9] I. A. K. M. Mahfuzul, A. Tsuchiya, K. Kobayashi, and H. Onodera, "Variation-Sensitive Monitor Circuits for Estimation of Global Process Parameter Variation", IEEE Transactions on Semiconductor Manufacturing, 25(4):571–580, Nov 2012.
[10] Y. Miyake, Y. Sato, S. Kajihara, and Y. Miura, "Temperature and Voltage Estimation Using Ring-Oscillator-Based Monitor for Field Test". In IEEE 23rd Asian Test Symposium, pages 156–161, Nov 2014.

Our Objective

- Our goal is to simultaneously predict

  (1) Vt shift of NMOS,

  (2) Vt shift of PMOS,

  (3) static IR drop,

  based only on the measured RO frequencies without adding any extra hardware.

- **Inputs :** frequencies of multiple ROs measured at multiple applied VDDs.

- **Outputs :** predicted Vt shift of NMOS, Vt shift of PMOS and static IR drop.

Our Objective

- Our goal is to simultaneously predict

  (1) Vt shift of NMOS,

  (2) Vt shift of PMOS,

  (3) static IR drop,

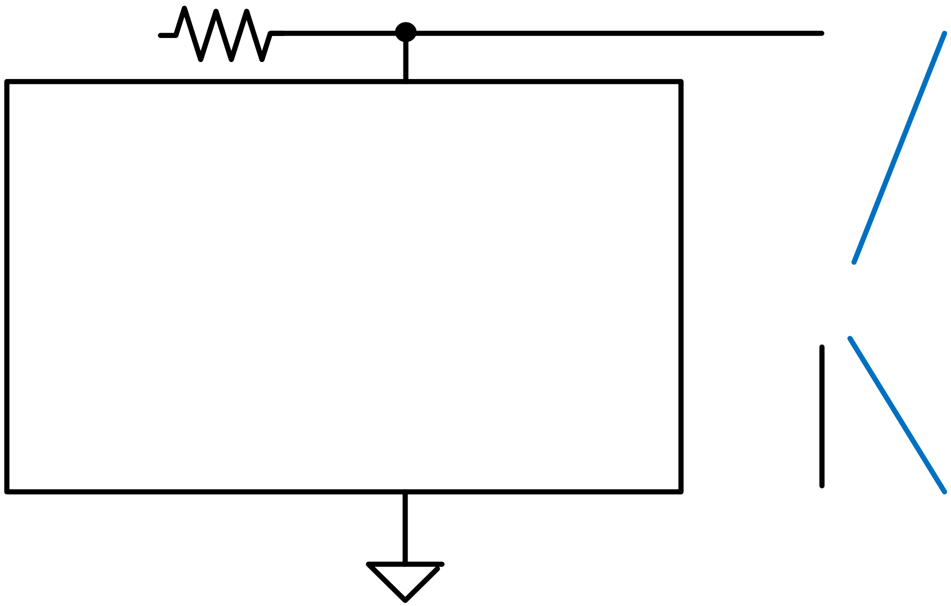
  based only on the measured RO frequencies without adding any extra hardware.

- **Prediction model:** trained by applying advanced machine learning techniques.

Circuit Model and Data Preparation

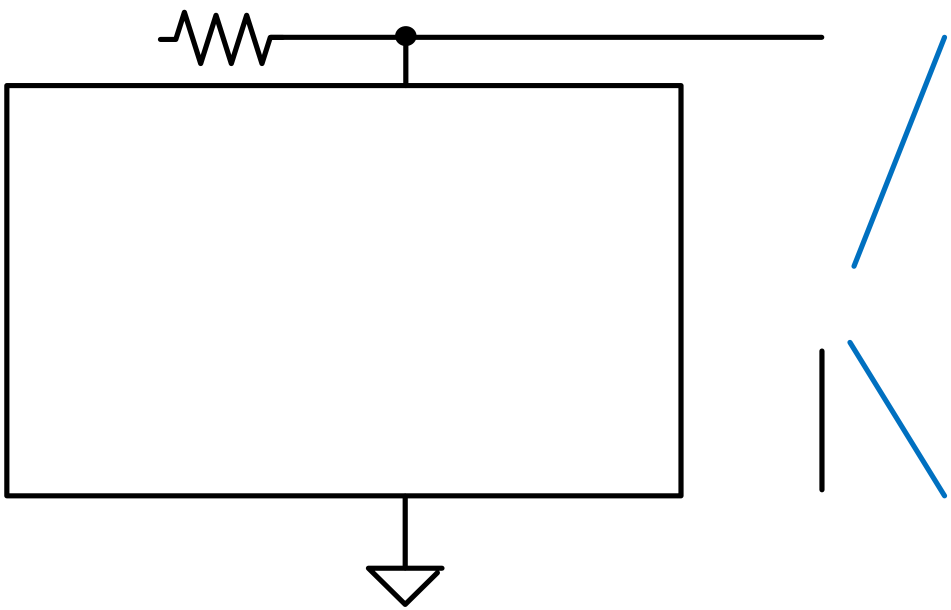
Our Circuit Model of a Ring Oscillator

- RO frequencies can be affected by
  - External applied voltage and temperature : VDD and T
  - Nearby static leakage current : I_{side}
  - Resistance imposed by the power network : R_{PN}
  - Variation of devices' threshold voltage : V_{tn}, V_{tp}



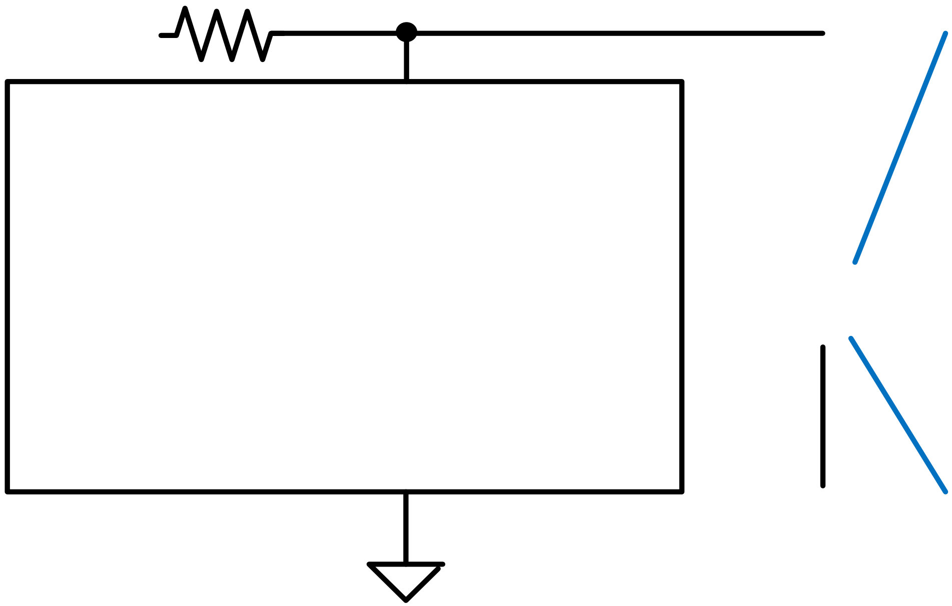
Our Circuit Model of a Ring Oscillator

- There are 6 variables :
  - VDD, T, I_{side}, R_{PN}, V_{tn} and V_{tp}



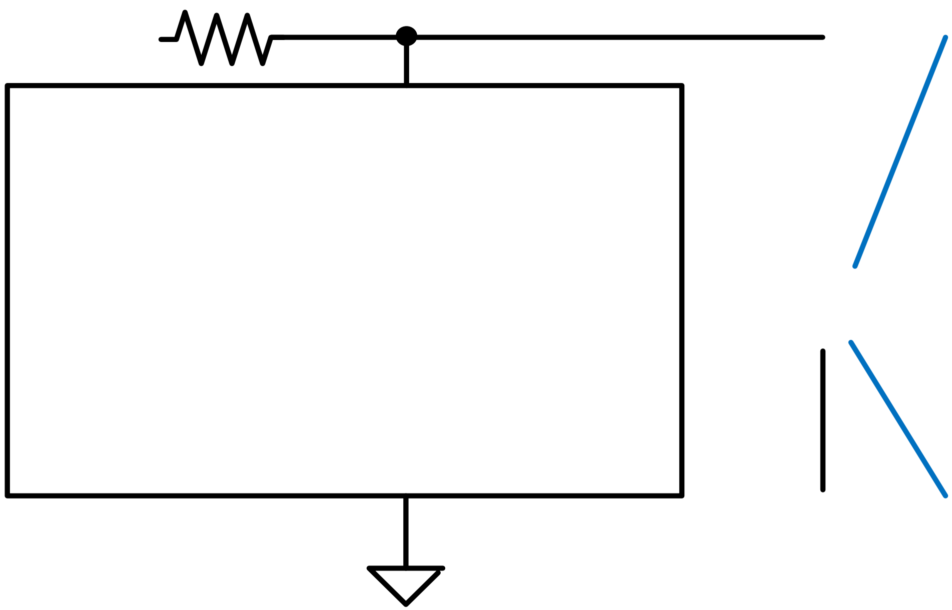
Our Circuit Model of a Ring Oscillator

- VDD and T are variables controlled by testing environment.
  - RO can be operated at different conditions of VDD and T to form different predictor features.



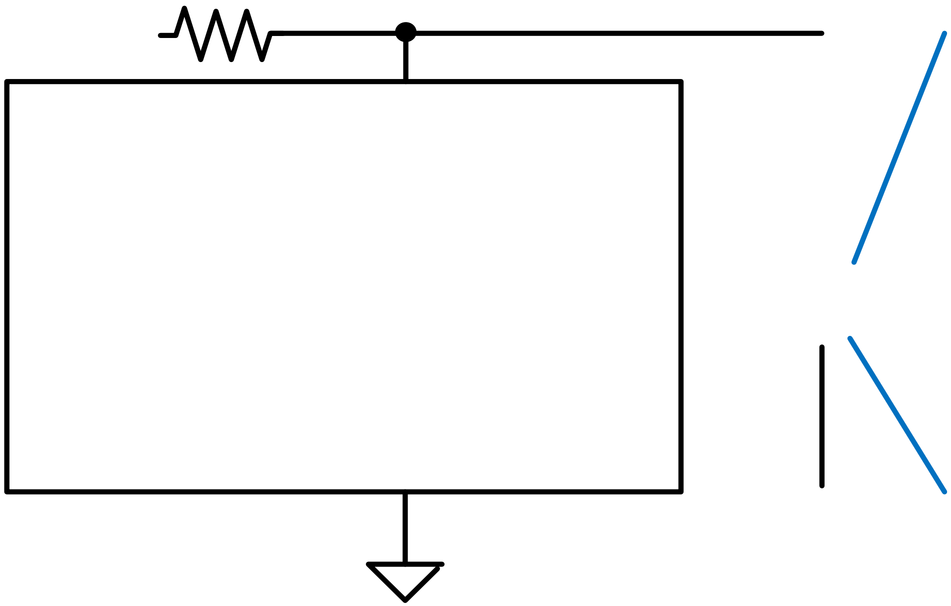
Our Circuit Model of a Ring Oscillator

- I_{side} is calculated by using table lookup of the leakage current of a unit-size buffer operating at different predefined voltages to avoid long simulation time.



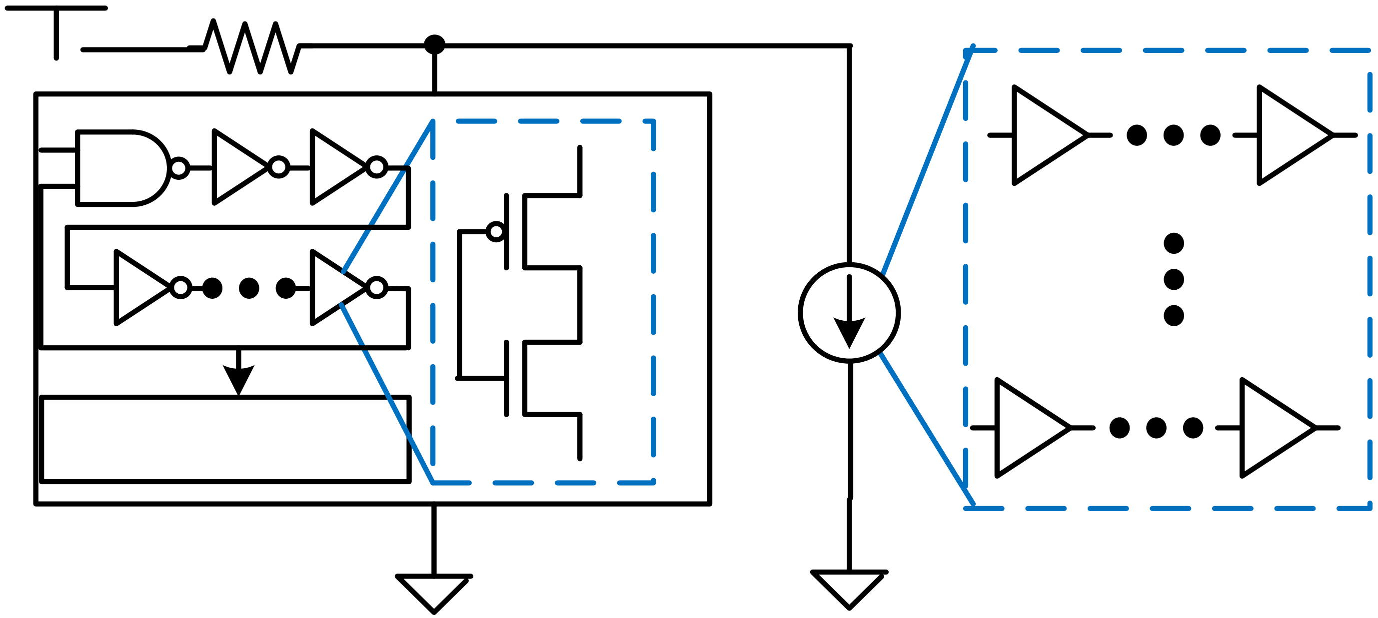
Our Circuit Model of a Ring Oscillator

- Variation range of R_{PN} can be estimated by using power simulation tool or an analytical mode.



Our Circuit Model of a Ring Oscillator

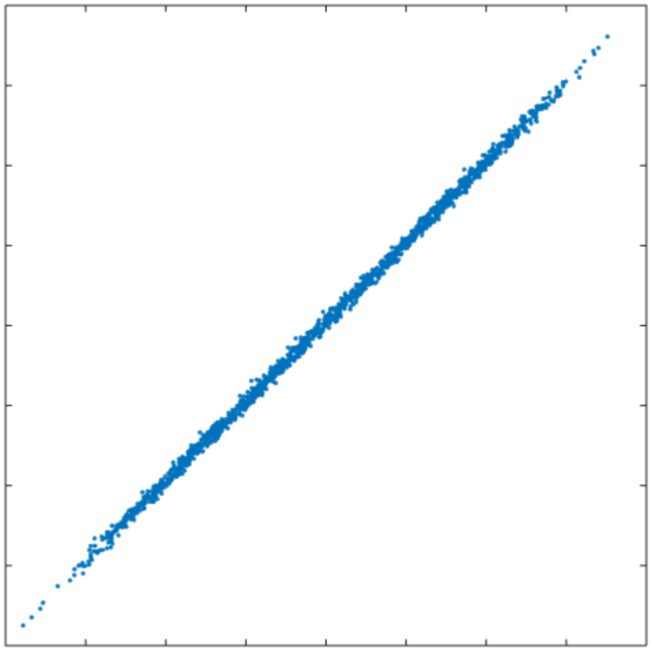
- Vtn (or Vtp) is set to a fixed value representing the mean Vt of NMOS (or PMOS) of the inversion cells when generating the training samples.



Impact of Local Variation on Vt

- Inject random Vt shift generated by $\mathcal{N}(0,10mV)$ into each inversion cells of the first RO.
- Set the Vt of the second RO to the mean of the random Vt of the first RO.

Demonstrate that using a mean V_t to represent the V_t shift is reasonable.



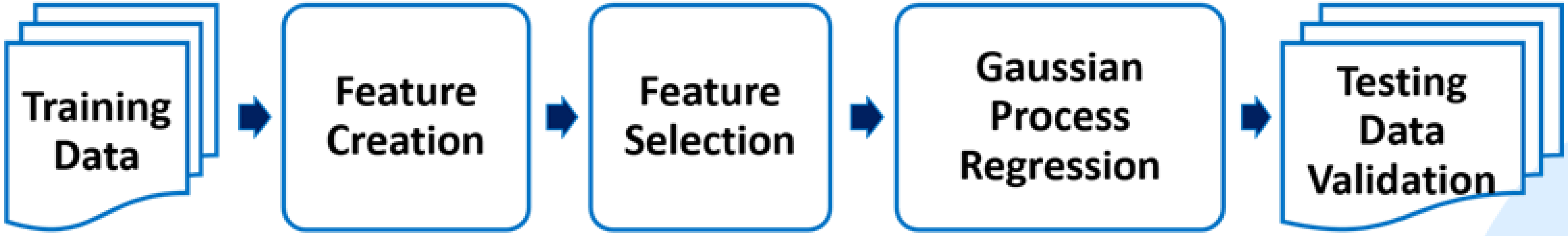
Data Preparation for Learning

- Controllable variables in the field to form features
  - T : fixed to 25°C
  - VDD : 0.4V – 1.2V, resolution step 0.1V
- Training data : 108300 samples per VDD
  - V_{tn} : -90mV – 90mV of nominal Vt , resolution step 10mV
  - V_{tp} : -90mV – 90mV of nominal Vt , resolution step 10mV
  - N_{bf} : 2K – 50K, resolution step 2K
  - R_{PN} : 1Ω – 12Ω , resolution step 1Ω
- Testing data : 40800 testing samples per VDD
  - V_{tn}, V_{tp}, N_{bf} and R_{PN} are randomly generated within the same range, and a local Vt variation $\mathcal{N}(0,10mV)$ is randomly added to each MOS in RO.

Our Model-Fitting Framework

Proposed Model-fitting Framework

- The proposed framework includes three stages:
  - **Feature Creation :** add new features by taking inverse, second order, third order, square root, logarithm and exponential of original RO frequencies.
  - **Feature Selection :** using stepwise regression to select the significant features, which iteratively perform:
    - **Forward selection** : select the most significant feature from unselected features.
    - **Backward elimination** : iteratively delete the least significant feature from selected features.
  - **Gaussian Process Regression :** fit the model.



Experimental Results

Experimental Setting

- **Our target** : predict the ΔVDD and shift of V_{tn}, V_{tp} operating at the nominal VDD 1.0V and 25°C.

- **Based on** : frequencies of INV, NAND, NOR-based RO measured at multiple applied VDDs
  - Each RO utilizes 21 inversion cells, which are built with minimum sizing NMOS and PMOS of 28nm technology.
  - One temperature, 25°C, is used for every training data.

Using Different Types of ROs

- 9 VDDs are used: 0.4V – 1.2V, resolution step 0.1V
- Using NOR-based RO can achieve the best accuracy for predicting V_{tn} and V_{tp}, but its maximum error is large.

⇨ **Using the information of only one RO is not sufficient to build a robust prediction model !**

used inversion cell	R^2(%)			RMSE(mV)			Max. error(mV)		
	V_{tn}	V_{tp}	ΔVDD	V_{tn}	V_{tp}	ΔVDD	V_{tn}	V_{tp}	ΔVDD
INV	99.677	98.233	99.810	2.95	6.91	3.48	26.19	40.16	24.06
NAND	98.980	97.301	99.881	5.24	8.54	2.75	66.43	84.47	23.34
NOR	99.794	99.467	99.824	2.36	3.80	3.35	125.69	84.13	272.41

Different Combinations of ROs with 9 VDDs

- If only two ROs can be chosen, using NAND-based and NOR-based ROs at once is the most effective combination.
- Using 3 ROs at once are suggested due to its best accuracy and significant reduction on max error.

used inversion cell	R^2(%)			RMSE(mV)			Max. error(mV)		
	V_{tn}	V_{tp}	ΔVDD	V_{tn}	V_{tp}	ΔVDD	V_{tn}	V_{tp}	ΔVDD
Best of using only one RO	99.794	99.467	99.881	2.36	3.80	2.75	26.19	40.16	23.34
INV, NAND	99.910	99.902	99.944	1.56	1.63	1.89	18.42	34.31	39.67
INV, NOR	99.904	99.801	99.893	1.61	2.32	2.60	44.71	36.07	56.03
NAND, NOR	99.947	99.926	99.950	1.20	1.41	1.79	14.89	24.12	13.18
INV, NAND, NOR	99.955	99.935	99.964	1.10	1.33	1.51	4.56	15.07	8.66

Different Numbers of VDDs When Using Three ROs at Once

- Accuracy is increased when the number of applied VDDs increases while the **improvement saturates when 9 VDDs are applied**.

# of VDD	applied VDDs (V)	R^2(%)			RMSE(mV)			Max. error(mV)		
		V_{tn}	V_{tp}	ΔVDD	V_{tn}	V_{tp}	ΔVDD	V_{tn}	V_{tp}	ΔVDD
1	1.0	89.407	66.452	81.023	16.90	30.11	34.71	56.14	93.62	113.39
3	0.8,1.0,1.2	99.627	98.816	99.401	3.17	5.66	6.17	12.85	44.81	25.12
5	0.4,…,1.0,1.2	99.945	99.889	99.936	1.22	1.73	2.02	7.15	33.27	24.63
9	0.4,…,1.1,1.2	99.955	99.935	99.964	1.10	1.33	1.51	4.56	15.07	8.66
17	0.4,…,1.15,1.2	99.960	99.939	99.968	1.10	1.32	1.50	4.43	14.99	8.59

Different Numbers of VDDs When Using Three ROs at Once

- The difference on both RMSE and maximum error between using nine VDDs and seventeen VDDs is around **0.01**mV for each of V_{tn}, V_{tp} and ΔVdd.

# of VDD	applied VDDs (V)	R^2(%)			RMSE(mV)			Max. error(mV)		
		V_{tn}	V_{tp}	ΔVDD	V_{tn}	V_{tp}	ΔVDD	V_{tn}	V_{tp}	ΔVDD
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5	0.4,…,1.0,1.2	99.945	99.889	99.936	1.22	1.73	2.02	7.15	33.27	24.63
9	0.4,…,1.1,1.2	99.955	99.935	99.964	1.10	1.33	1.51	4.56	15.07	8.66
17	0.4,…,1.15,1.2	99.960	99.939	99.968	1.10	1.32	1.50	4.43	14.99	8.59

Different Numbers of VDDs When Using Three ROs at Once

- The difference between using five VDDs and nine VDDs is still quite significant, **especially on maximum error**.

# of VDD	applied VDDs (V)	R^2(%)			RMSE(mV)			Max. error(mV)		
		V_{tn}	V_{tp}	ΔVDD	V_{tn}	V_{tp}	ΔVDD	V_{tn}	V_{tp}	ΔVDD
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17	0.4,…,1.15,1.2	99.960	99.939	99.968	1.10	1.32	1.50	4.43	14.99	8.59

Comparison among Different Model-fitting Methods

- The proposed framework outperforms other model fitting methods from 21.8% to 78.7%.

model fitting method	R^2(%)			RMSE(mV)			Max. error(mV)		
	V_{tn}	V_{tp}	ΔVDD	V_{tn}	V_{tp}	ΔVDD	V_{tn}	V_{tp}	ΔVDD
GP+FSelect(ours)	**99.955**	**99.935**	**99.964**	**1.10**	**1.33**	**1.51**	**4.56**	**15.07**	**8.66**
GP only	99.943	99.862	99.928	1.24	1.93	2.15	10.58	20.00	17.53
Stepwise	99.513	99.360	99.423	3.62	4.16	6.05	**21.44**	28.45	65.01
Bayesian+FSelect	99.425	**99.861**	**99.941**	3.94	**1.94**	**1.93**	27.74	43.46	34.73
Ridge+FSelect	99.854	99.836	99.924	1.98	2.10	2.19	26.82	**19.42**	**18.73**
RF+FSelect	99.379	99.614	99.483	4.09	3.23	5.73	75.75	63.71	26.53
SVM+FSelect	**99.922**	97.633	99.540	**1.45**	8.00	5.41	48.87	139.64	119.81
$\frac{\text{best of Others} - \text{ours}}{\text{best of others}}$				24.1%	31.4%	21.8%	78.7%	22.4%	53.8%

Comparison among Different Model-fitting Methods

- The proposed framework outperforms other model fitting methods from 21.8% to 78.7%.

model fitting method	R^2(%)			RMSE(mV)			Max. error(mV)		
	V_{tn}	V_{tp}	ΔVDD	V_{tn}	V_{tp}	ΔVDD	V_{tn}	V_{tp}	ΔVDD
GP+FSelect(ours)	**99.955**	**99.935**	**99.964**	**1.10**	**1.33**	**1.51**	**4.56**	**15.07**	**8.66**
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$\frac{\text{best of Others} - \text{ours}}{\text{best of others}}$				24.1%	31.4%	21.8%	78.7%	22.4%	53.8%

Comparison with Previous Works

Vt Variation Accuracy Compared to [9]

- **[9] iteractively updates the predicted factors** by simulating the ROs with the new factors obtained from solving the simultaneous equations of multiple ROs.

iteration of simulation	R^2(%)		RMSE(mV)		Max. error(mV)	
	V_{tn}	V_{tp}	V_{tn}	V_{tp}	V_{tn}	V_{tp}
1st iteration	96.090	93.369	10.27	13.39	71.04	64.72
2nd iteration	99.376	99.034	4.10	5.11	66.23	47.62
3rd iteration	99.807	99.750	2.28	2.60	59.49	36.84
4th iteration	99.921	99.908	1.46	1.58	51.25	31.37
5th iteration	99.958	99.949	1.07	1.18	42.39	26.49
ours	99.955	99.935	1.10	1.33	4.56	15.07

[9] I. A. K. M. Mahfuzul, A. Tsuchiya, K. Kobayashi, and H. Onodera. "Variation-Sensitive Monitor Circuits for Estimation of Global Process Parameter Variation". IEEE Transactions on Semiconductor Manufacturing, 25(4):571–580, Nov 2012.

Vt Variation Accuracy Compared to [9]

- After their fifth iteration, their corresponding R^2 and RMSE can become better than ours while **their maximum error is still significantly higher than ours**.

iteration of simulation	R^2(%)		RMSE(mV)		Max. error(mV)	
	V_{tn}	V_{tp}	V_{tn}	V_{tp}	V_{tn}	V_{tp}
1st iteration	96.090	93.369	10.27	13.39	71.04	64.72
2nd iteration	99.376	99.034	4.10	5.11	66.23	47.62
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4th iteration	99.921	99.908	1.46	1.58	51.25	31.37
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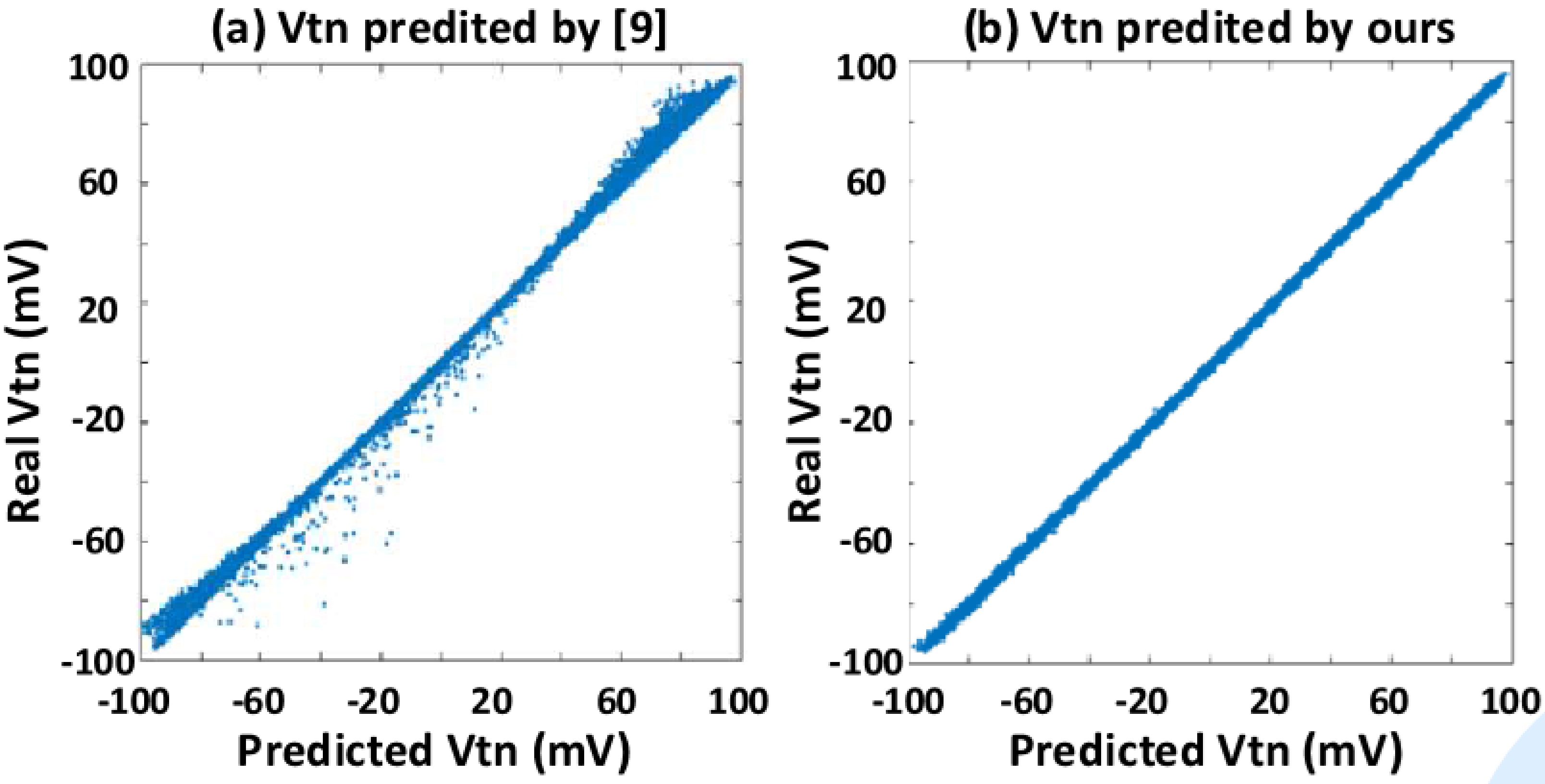
Vt Variation Accuracy Compared to [9]

- Our predicted values can constantly fall close to the diagonal while the values predicted by [9] cannot.



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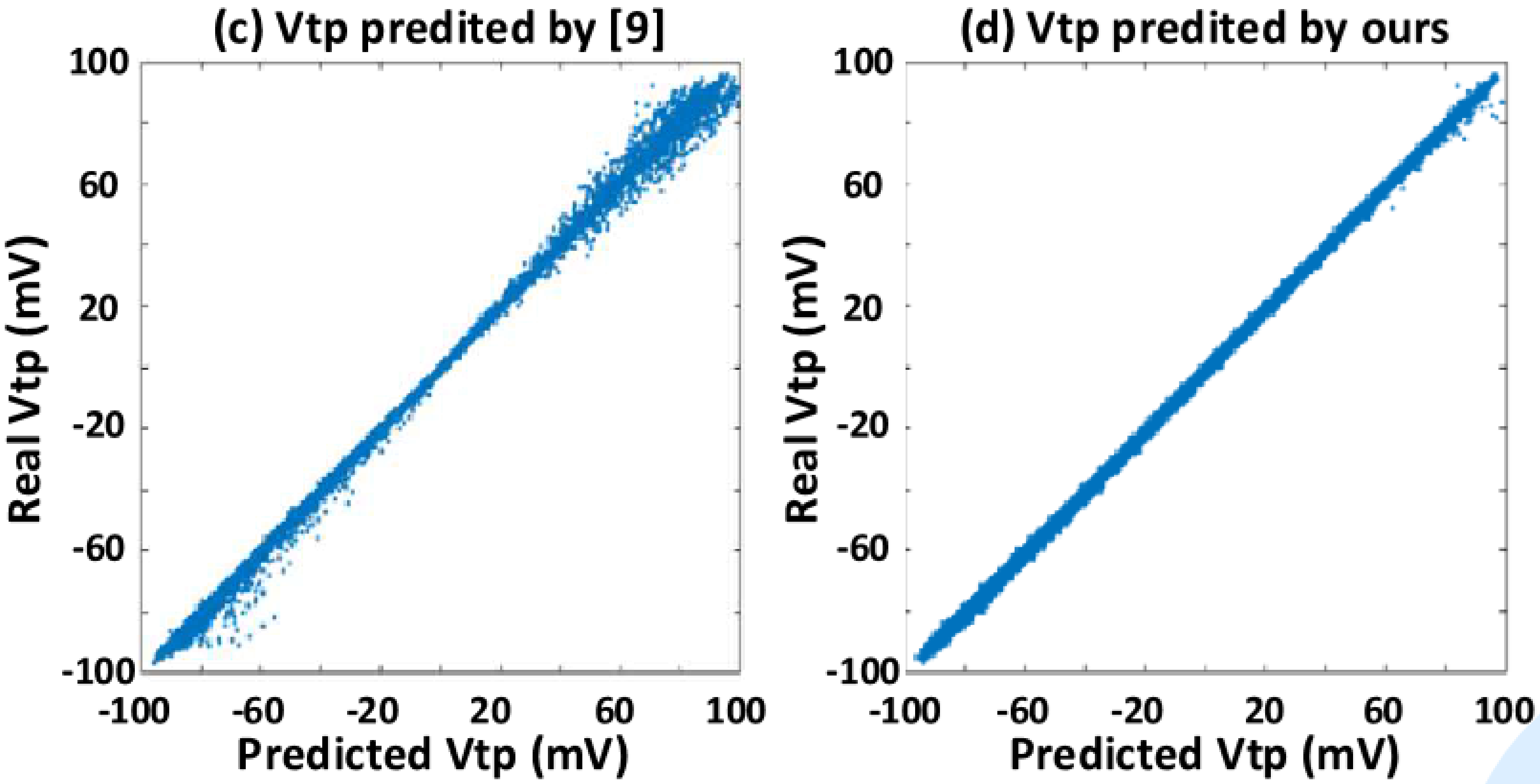


Runtime Compared to [9]

- Using SPICE simulation to iteratively adjust the predicted V_{tn} and V_{tp} **impose significant runtime overhead to [9].**

- Following shows the runtime of 5 iterations of [9] and our proposed framework runtime.

	avg. runtime for predicting one Vt	runtime for predicting 64800 samples' Vt	normalized to ours
[9]	5.2598s	340835s	380.3X
ours	0.0138s	896s	1X

- Our framework can quickly report the predicted V_{tn} and V_{tp} for each new chip.

Static IR Drop Accuracy Compared to [10]

- [10] predicts the delta of the targeted factor by using a two-stage **linear regression models** with a calibration ratio added to each delta term of RO frequency.

Prediction of ΔVDD	R^2(%)	RMSE (mV)	Max. error (mV)
[10]	86.146	18.21	137.60
ours	99.964	1.51	8.66

[10] Y. Miyake, Y. Sato, S. Kajihara, and Y. Miura. "Temperature and Voltage Estimation Using Ring-Oscillator-Based Monitor for Field Test". In IEEE 23rd Asian Test Symposium, pages 156–161, Nov 2014.

Static IR Drop Accuracy Compared to [10]

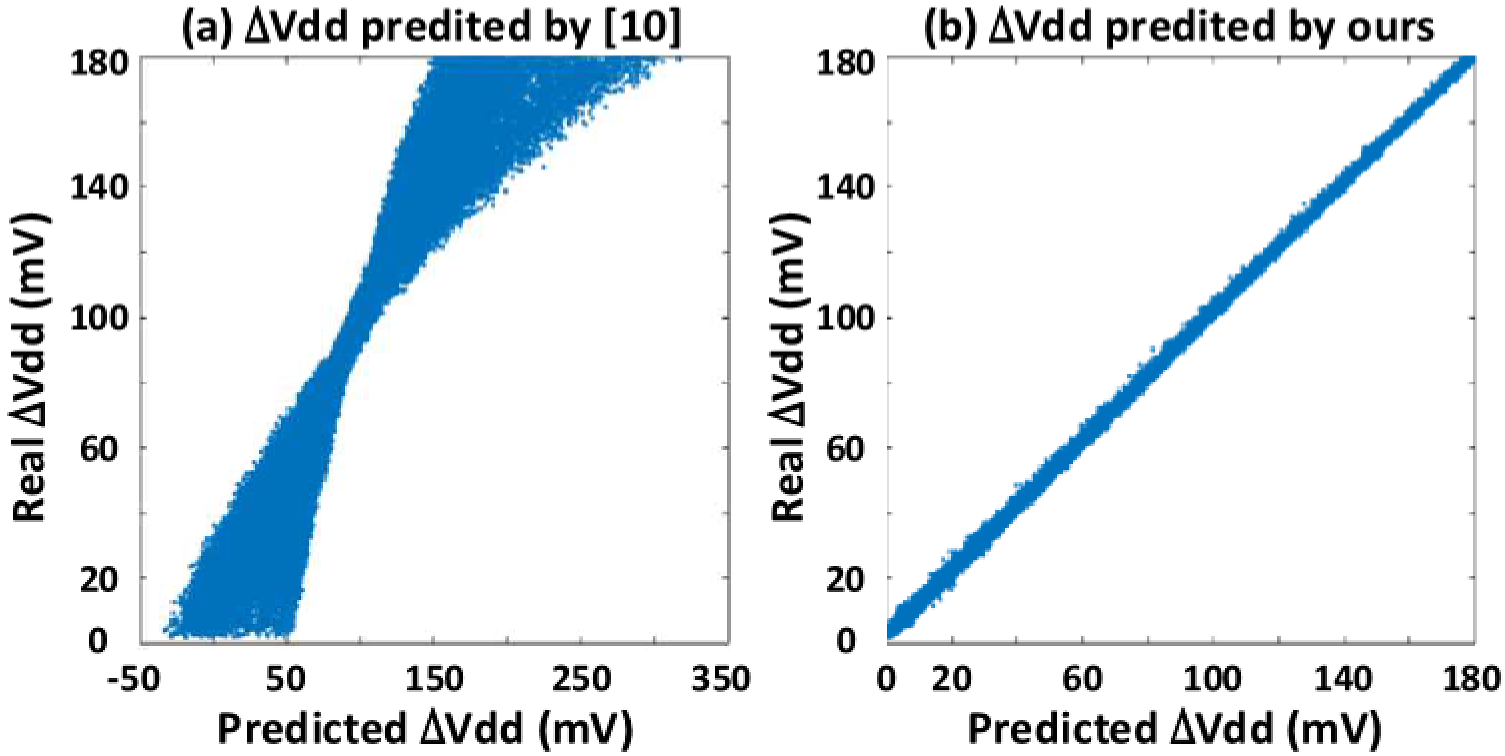
- Our framework can outperform [10] on all of **R^2**, **RMSE** and **max error**.
- Predicting ∆VDD needs a **higher dimensional** and more expressive model instead of linear model.

Prediction of ∆VDD	R^2(%)	RMSE (mV)	Max. error (mV)
[10]	86.146	18.21	137.60
ours	99.964	1.51	8.66

[10] Y. Miyake, Y. Sato, S. Kajihara, and Y. Miura. "Temperature and Voltage Estimation Using Ring-Oscillator-Based Monitor for Field Test". In IEEE 23rd Asian Test Symposium, pages 156–161, Nov 2014.

Static IR Drop Accuracy Compared to [10]

- Our predicted values of ΔVdd also consistently fall more closely on the diagonal than those of [10].



Conclusion

- We proposed a model-fitting framework that can accurately decompose V_{tn}, V_{tp} and ΔVDD based on the RO frequencies measured from three types of ROs placed together.
- The experimental results based on 28nm technology simulation show that our framework can achieve a R^2 more than 99.93%.
- Our framework can significantly outperform other popular model-fitting methods and previous works without adding extra monitoring circuitry.

Thank You For Your Listening

Reference paper

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