



An Accurate Probabilistic Reliability Model for Silicon PUFs

Roel Maes
Intrinsic-ID, the Netherlands

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Introduction: Silicon PUFs and Reliability

- Basic PUF properties:
 1. **Uniqueness:**
Equivalent responses from distinct PUF instances are sufficiently different
 2. **(Un)reliability:**
Equivalent responses from one single PUF instance are sufficiently alike (up to a few errors)
- Both properties have an equally important impact on the PUFs usability and efficiency

PUF A

0 1 0 0 1 0 1 1

PUF B

1 0 0 1 1 0 0 0

$HD(A; B) = \text{large}$

PUF A:enroll

0 1 0 0 1 0 1 1

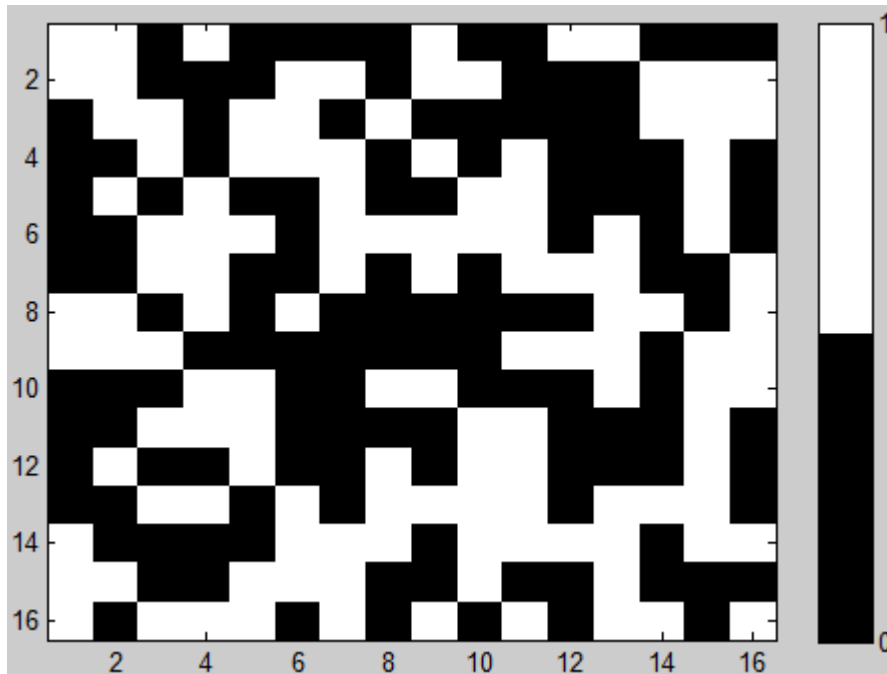
PUF A:reconstruct

0 1 1 0 1 0 1 1

$HD(A:\text{enroll}; A:\text{reconstruct}) = \text{small}$

Problem Statement: “Old” Error Model

PUF Response



Error model in use until now:

- single fixed error rate p_e
 - every cell equally likely to produce an error on every evaluation
- (= binary symmetric channel)

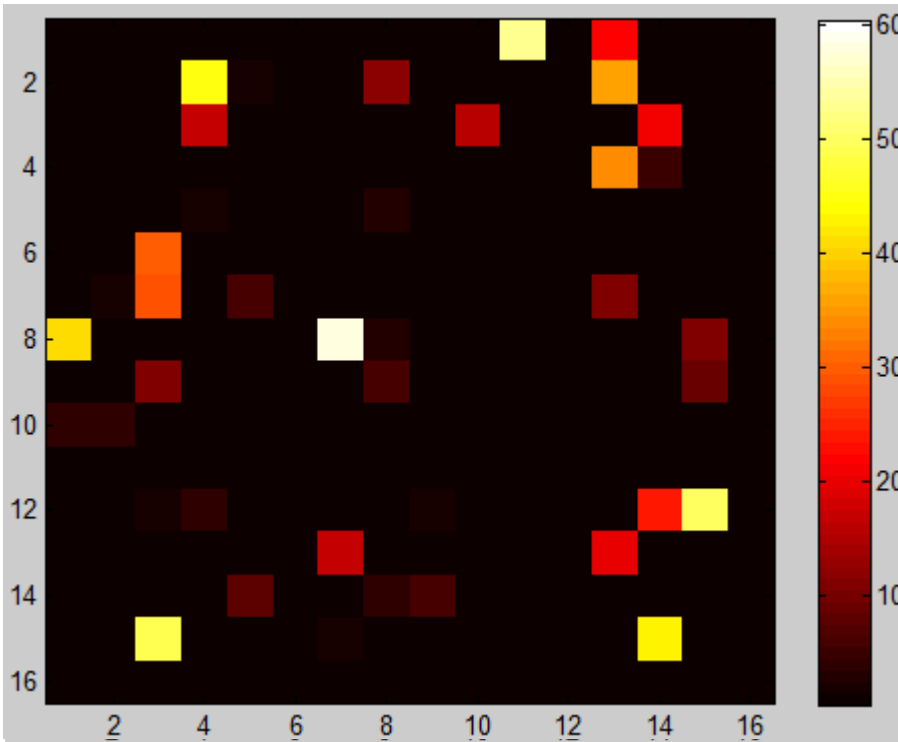
Problem:

Does not realistically/accurately describe actual PUF reliability behavior...

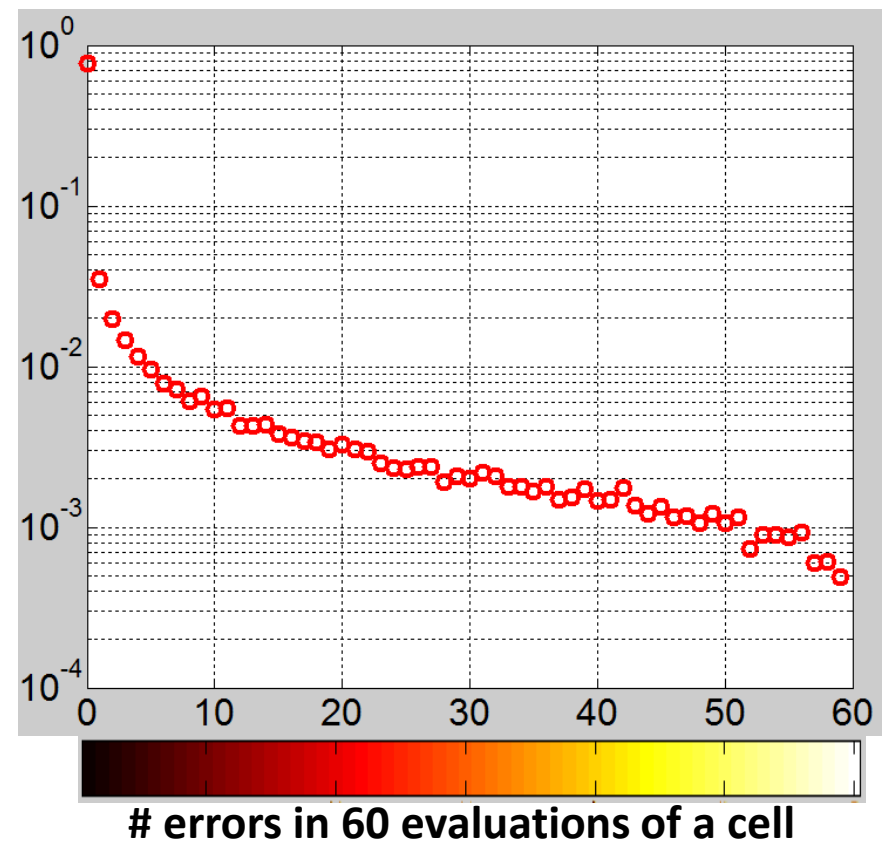
this becomes apparent when we evaluate the same PUF response many times...

Problem Statement: Experimental Observation

Response behavior over 60 evaluations



Histogram of error-counts over cells



New Model: Approach = Hidden Variable Model

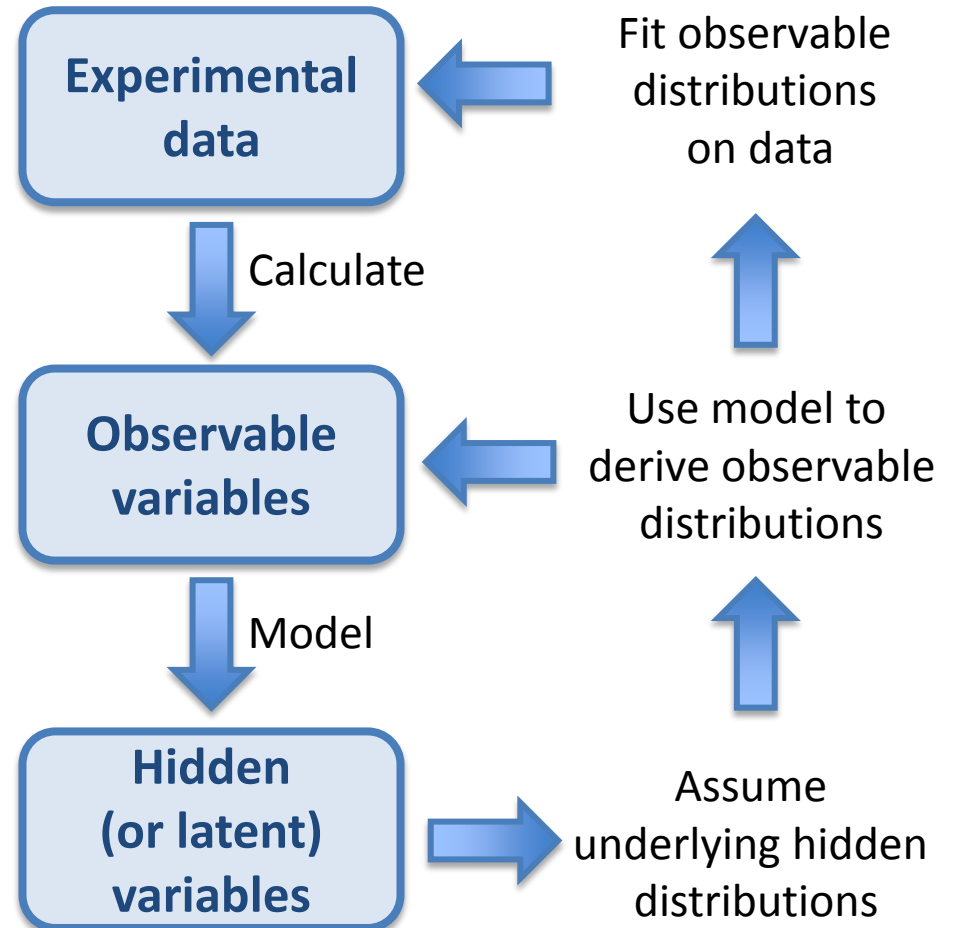
Response bit:
(evaluation j of cell i) $r_i^{(j)}$

Cell error-probability:
(= $\Pr(R_i \neq r_i^{\text{enroll}})$) $p_{e,i}$

Cell error-count:
(= #errors in n eval's) $s_{e,i}^{(n)}$

Process variable:
(causes uniqueness) m_i

Noise variable:
(causes unreliability) $n_i^{(j)}$



New Model: Distribution Derivation

Model relation:

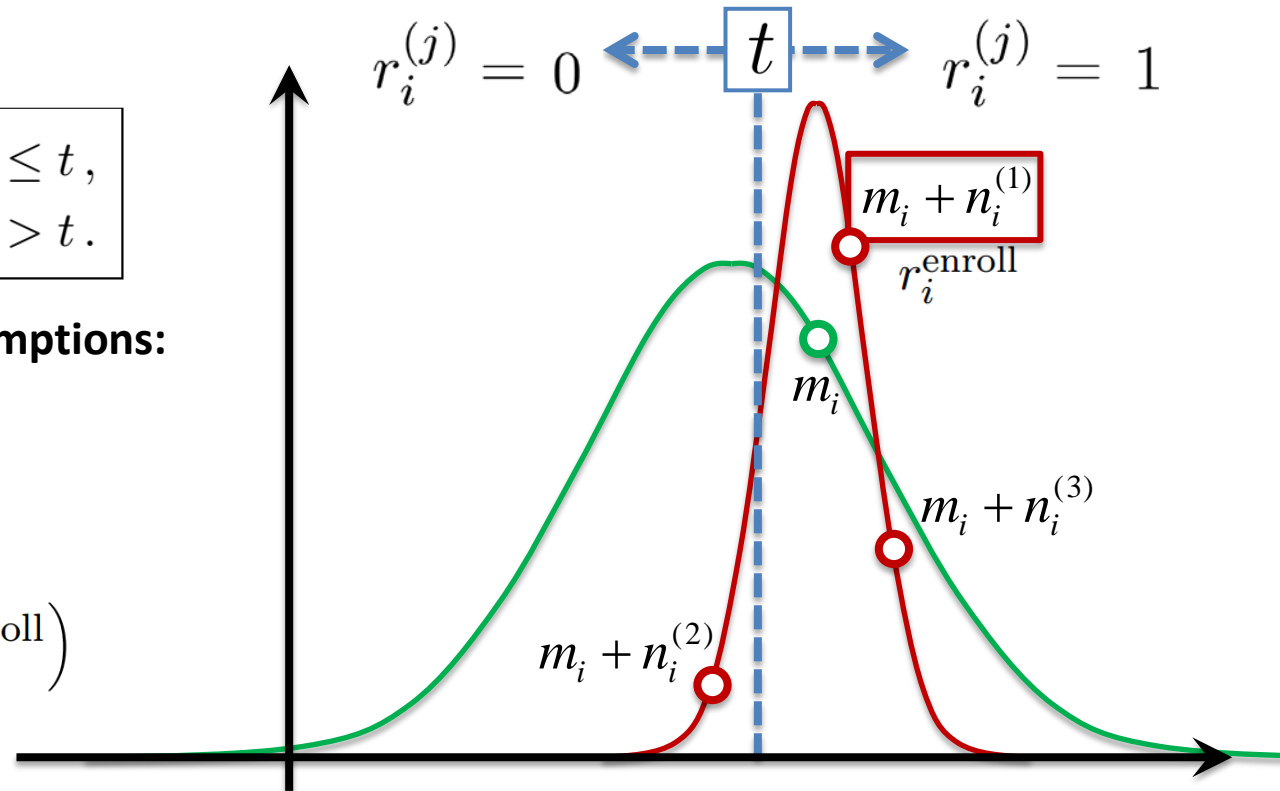
$$r_i^{(j)} = \begin{cases} 0, & \text{if } m_i + n_i^{(j)} \leq t, \\ 1, & \text{if } m_i + n_i^{(j)} > t. \end{cases}$$

Hidden distribution assumptions:

$$M \sim \mathcal{N}(\mu_M, \sigma_M^2)$$

$$N_i \sim \mathcal{N}(0, \sigma_N^2)$$

$$p_{e,i} \stackrel{\text{def}}{=} \Pr(R_i \neq r_i^{\text{enroll}})$$



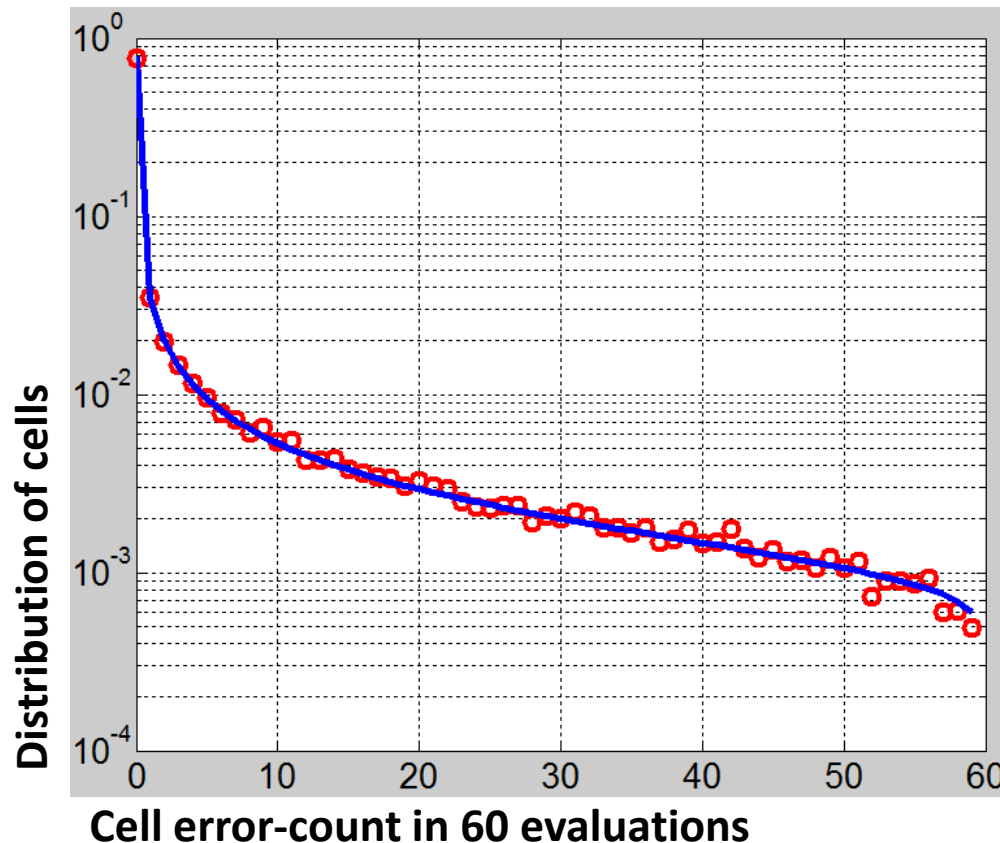
Cell error-probability distribution:

$$\text{cdf}_{P_e}(x) = \lambda_1 \cdot \int_{-\infty}^{\Phi^{-1}(x)} \Phi(-u) \cdot (\varphi(\lambda_1 u + \lambda_2) + \varphi(\lambda_1 u - \lambda_2)) \, du$$



New Model: Experimental Fit

Cell error-count distribution: $\text{pmf}_{S_e^{(n)}}(x) = \int_0^1 f_{\text{bino}}(x; n, u) \cdot \text{pdf}_{P_e}(u) du$



Experimental data:

from UNIQUE project

[Katzenbeisser et al., CHES-2012]

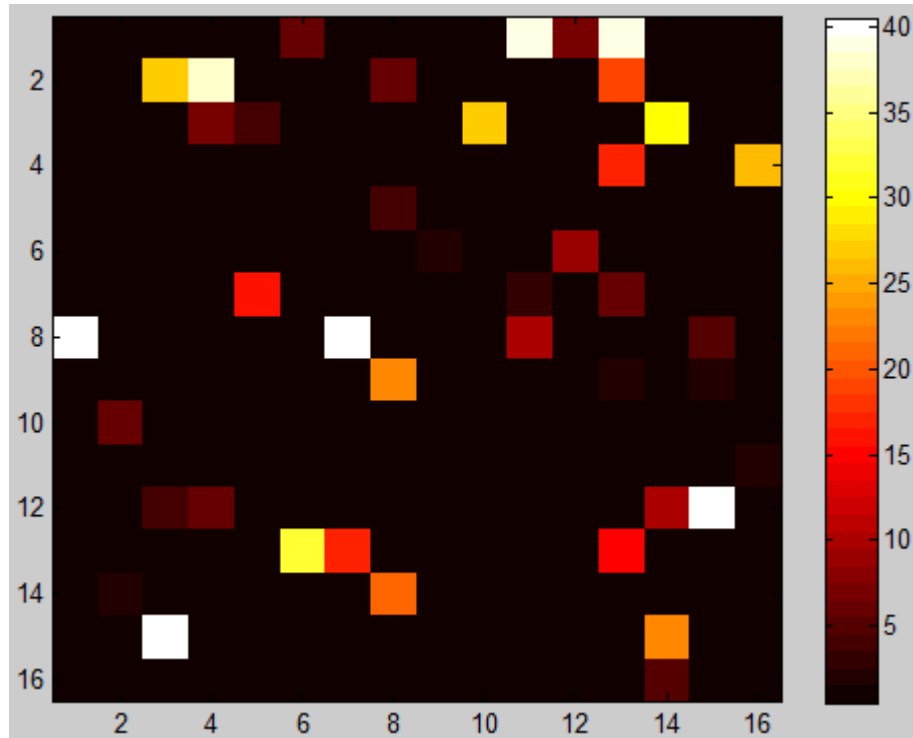
PUF type	MSE of fit	λ_1	λ_2
SRAM	4.5×10^{-9}	0.12	0.02
Buskeeper	5.8×10^{-10}	0.09	0.03
DFF	1.2×10^{-9}	0.08	0.04
Arbiter	1.8×10^{-9}	0.07	0.05



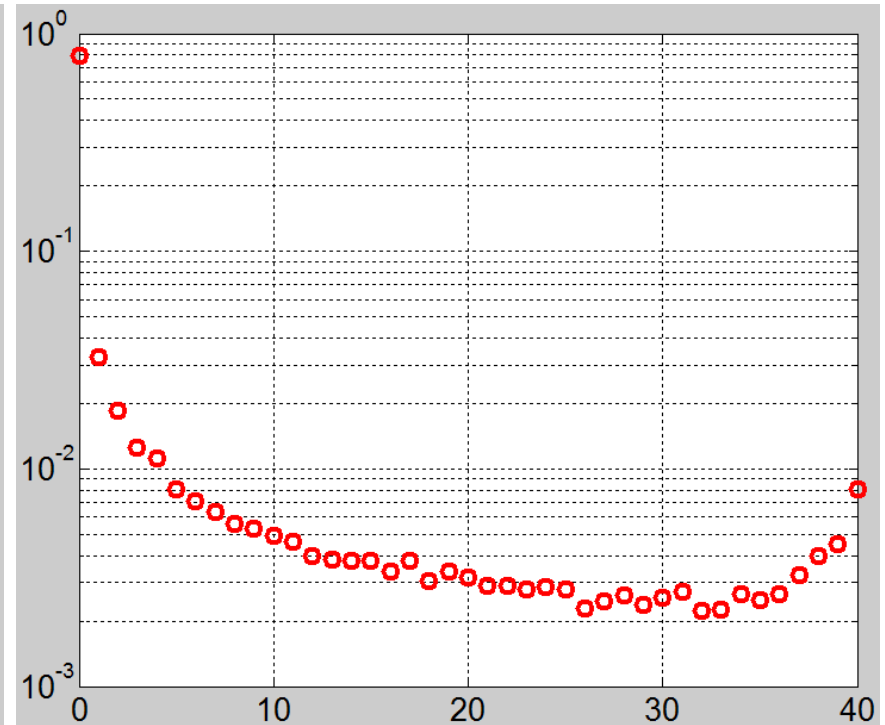
New Model + Temperature?

Error behavior and fixed temperature (25°C):

40 evaluations @ 85°C w.r.t. enrollment @ 25°C



Histogram of error-counts over cells



errors in 40 evaluations (@25°C) of a cell
(w.r.t. enrollment @ 25°C)



New Model + Temperature: Distribution Derivation

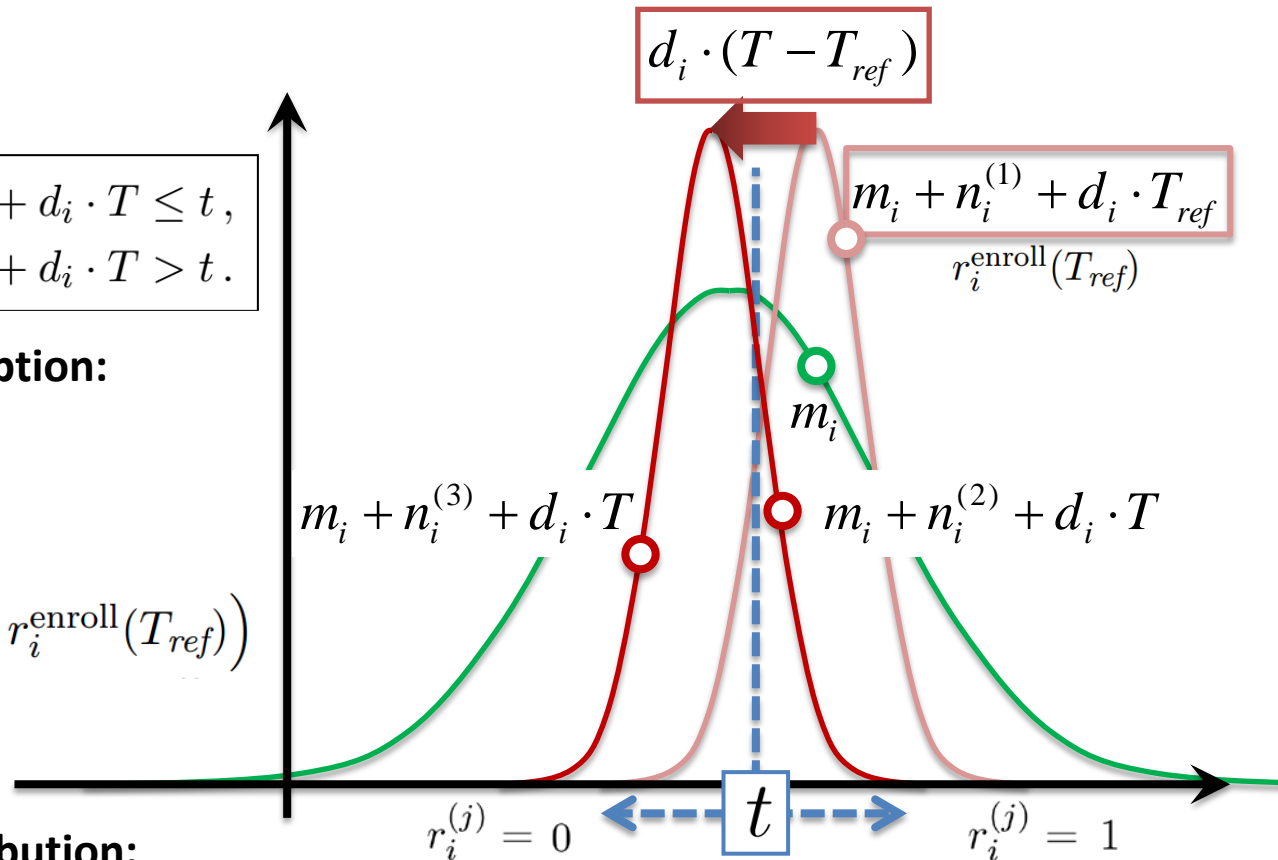
Model relation:

$$r_i^{(j)}(T) = \begin{cases} 0, & \text{if } m_i + n_i^{(j)} + d_i \cdot T \leq t, \\ 1, & \text{if } m_i + n_i^{(j)} + d_i \cdot T > t. \end{cases}$$

Hidden distribution assumption:

$$D \sim \mathcal{N}(0, \sigma_D^2)$$

$$p_{e,i}(T; T_{ref}) = \Pr(R_i(T) \neq r_i^{enroll}(T_{ref}))$$

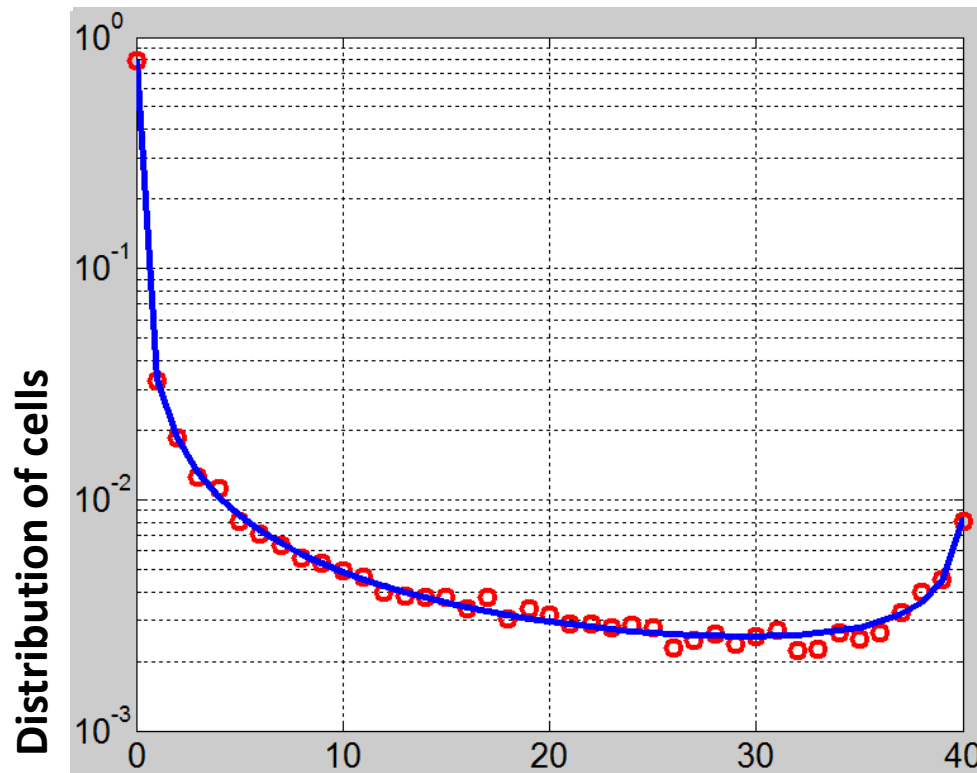


Cell error-probability distribution:

$$\text{cdf}_{P_e(T; T_{ref})}(x) = \frac{\lambda_1 \theta}{|\Delta T|} \cdot \int_{-\infty}^{\Phi^{-1}(x)} \int_{-\infty}^{+\infty} \left[\Phi(-u) \varphi\left(\theta \frac{v-u}{|\Delta T|}\right) + \Phi(u) \varphi\left(\theta \frac{v+u}{|\Delta T|}\right) \right] \cdot \varphi(\lambda_1 u + \lambda_2) \, du \, dv$$



New Model + Temperature: Experimental Fit

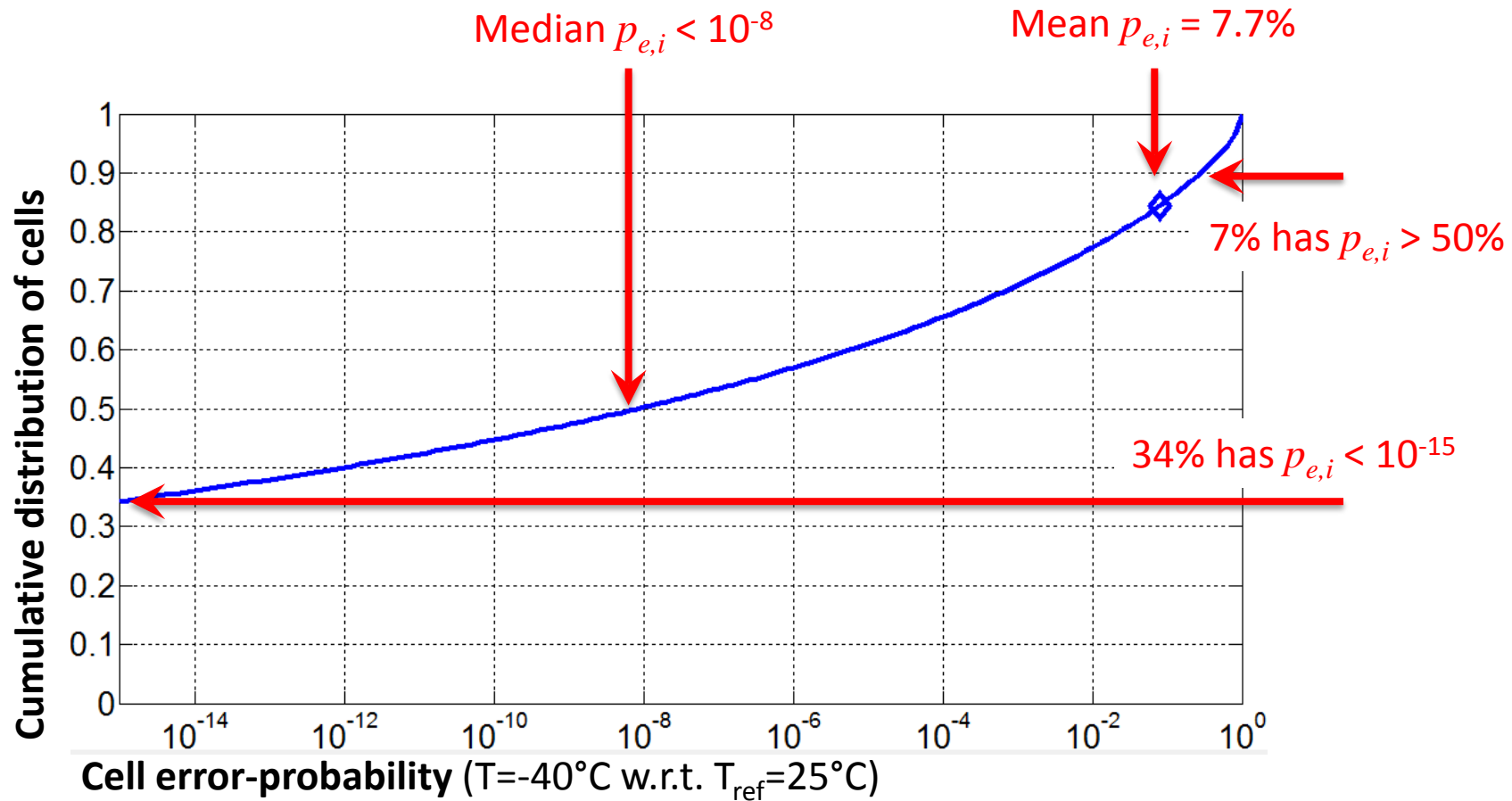


Cell error-count in 40 evaluations ($T = -40^\circ\text{C}$ w.r.t. $T_{\text{ref}} = 25^\circ\text{C}$)

Fit for SRAM PUF (from UNIQUE):

- over range $T = [-40^\circ\text{C} \dots +85^\circ\text{C}]$
- optimal fit for $\theta = 45.0$
(independent of T)
- average MSE = 1.6×10^{-6}
(over full T -range)

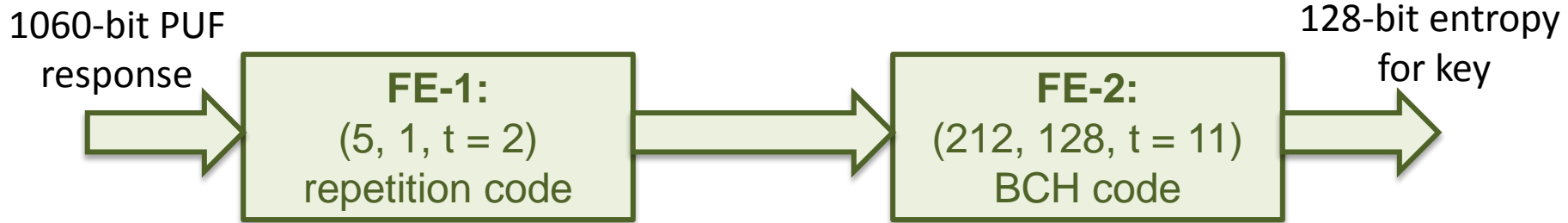
Interpretation of New Model Error Distribution



Majority of errors in a PUF response are caused by a small minority of cells

Implications for PUF-based Key Generation

Fuzzy Extractor System: (spec.: 128-bit entropy with $> 1-10^{-9}$ reliability)



Old model: (for every key generator)

$$p_e = 7.7\% \longrightarrow 1 - F_{\text{bino}}(2, 5, 7.7\%) = 0.4\% \longrightarrow 1 - F_{\text{bino}}(11, 212, 0.4\%) = 1.5 \times 10^{-10} = p_{\text{fail}}$$

New model: (for one particular key generator)

$$\mathbf{p}_e = (p_{e,1}, \dots, p_{e,1060}), \text{ with } p_{e,i} \sim \text{cdf}_{P_e(T; T_{\text{ref}})} \longrightarrow 1 - F_{\text{PB}}(2, 5, \mathbf{p}_e) = \mathbf{p}_{e,\text{int}} \longrightarrow 1 - F_{\text{PB}}(11, 212, \mathbf{p}_{e,\text{int}}) = p_{\text{fail}}$$

$(\lambda_1 = 0.12, \lambda_2 = 0.02, \theta = 45.0)$

F_{PB} = Poisson-Binomial distribution:

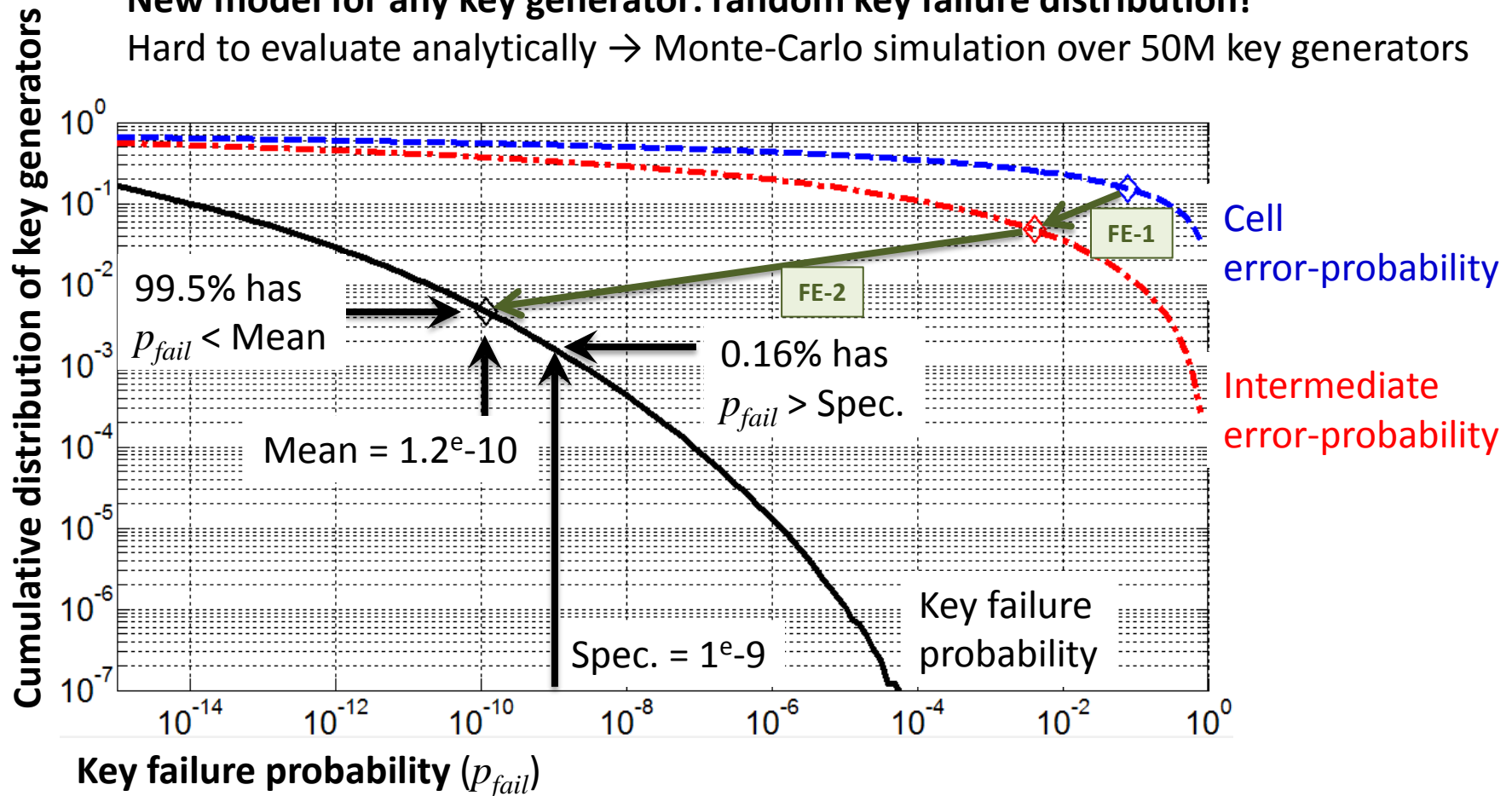
when trials are independent but no longer identically distributed



Implications for PUF-based Key Generation

New model for any key generator: random key failure distribution!

Hard to evaluate analytically → Monte-Carlo simulation over 50M key generators



Main Conclusions

- New PUF reliability model is realistic, generic and very accurate:
 - Hidden variable model makes **cell-specific behavior** explicit
 - Yields analytic expressions for **error-probability distributions**
 - Can be **fit very accurately** on experimental observations, including **temperature dependent** behavior
 - Applicable to most Silicon PUF types, both memory- and delay-based
- Allows to study full PUF reliability behavior
 - **As opposed to only average-case behavior in old model**
 - Shows **very skewed distributions**:
“large majority of PUF errors are caused by small minority of PUF cells”
 - Enables **Monte-Carlo simulations** to study effect on PUF-based applications, e.g. key generators



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Thank you!

Any questions?