Compact Modeling of Process Variations

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Outline

Introduction

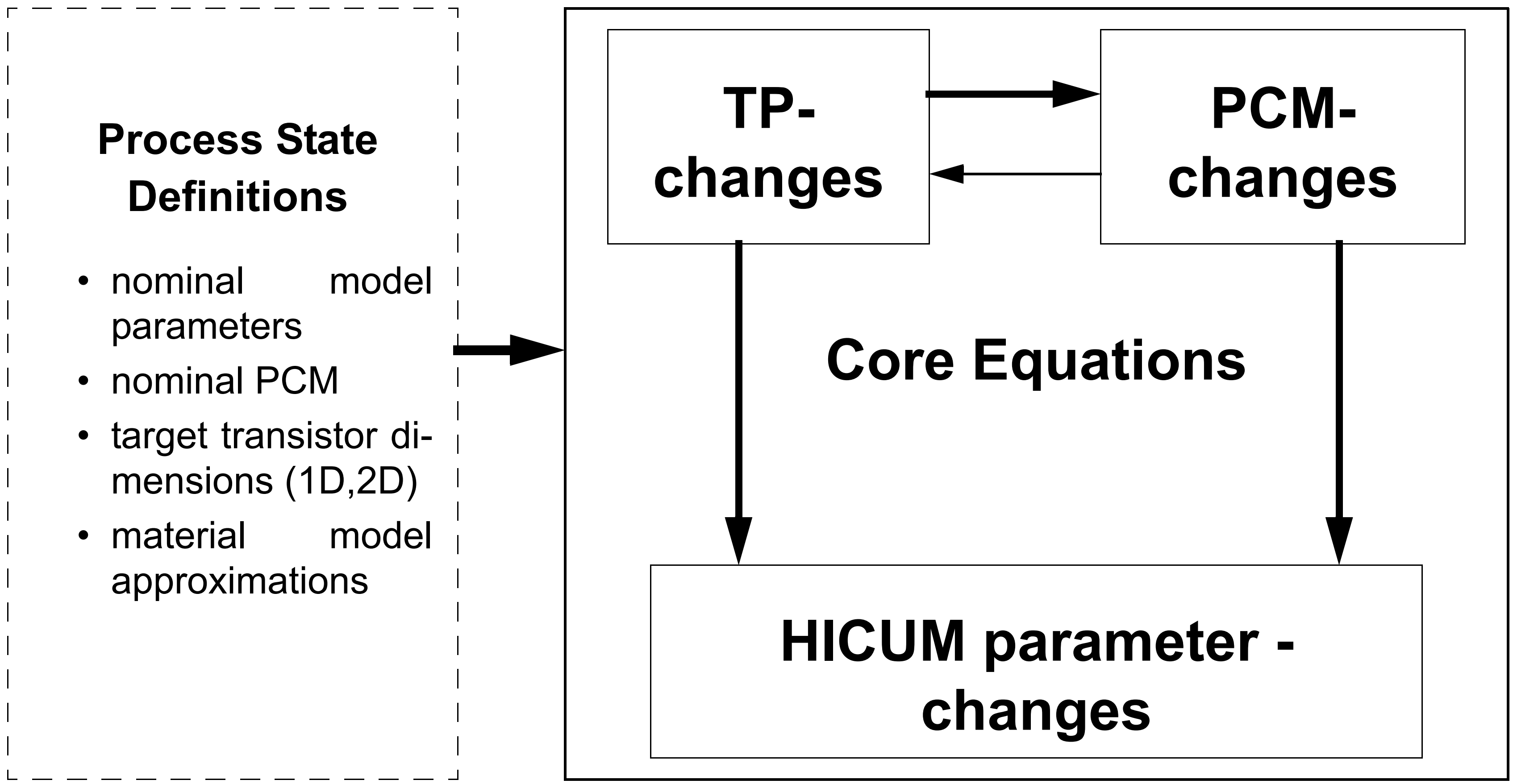
- Process variations related to fabrication equipment can not be modeled directly
  - epitaxial material concentration
  - activated doping concentration
  - etch solution concentration
  - lithographic variation

- Focus of research is on integrated SiGe HBT devices
  - Statistical process variations
  - Process shift after model parameter extraction
  - Process changes during further process development

- Methodologies are built around predictive modeling core equations

- **changes of transistor structure and material composition** are inputs for predictive modeling core equations

Predictive Modeling Core



TP - Technology Parameter
PCM - Process Control Monitor
HICUM - HIgh CUrrent Model

Assumptions for predictive modeling

Nominal process data calibrates modeling equations to given process

- HICUM parameters extracted using process-based scalable approach
- PCM data: single vector (predictive), distribution (statistical)
- use material models associated with process technology
- improve calibration to process by using doping profile and device simulation

Application modes

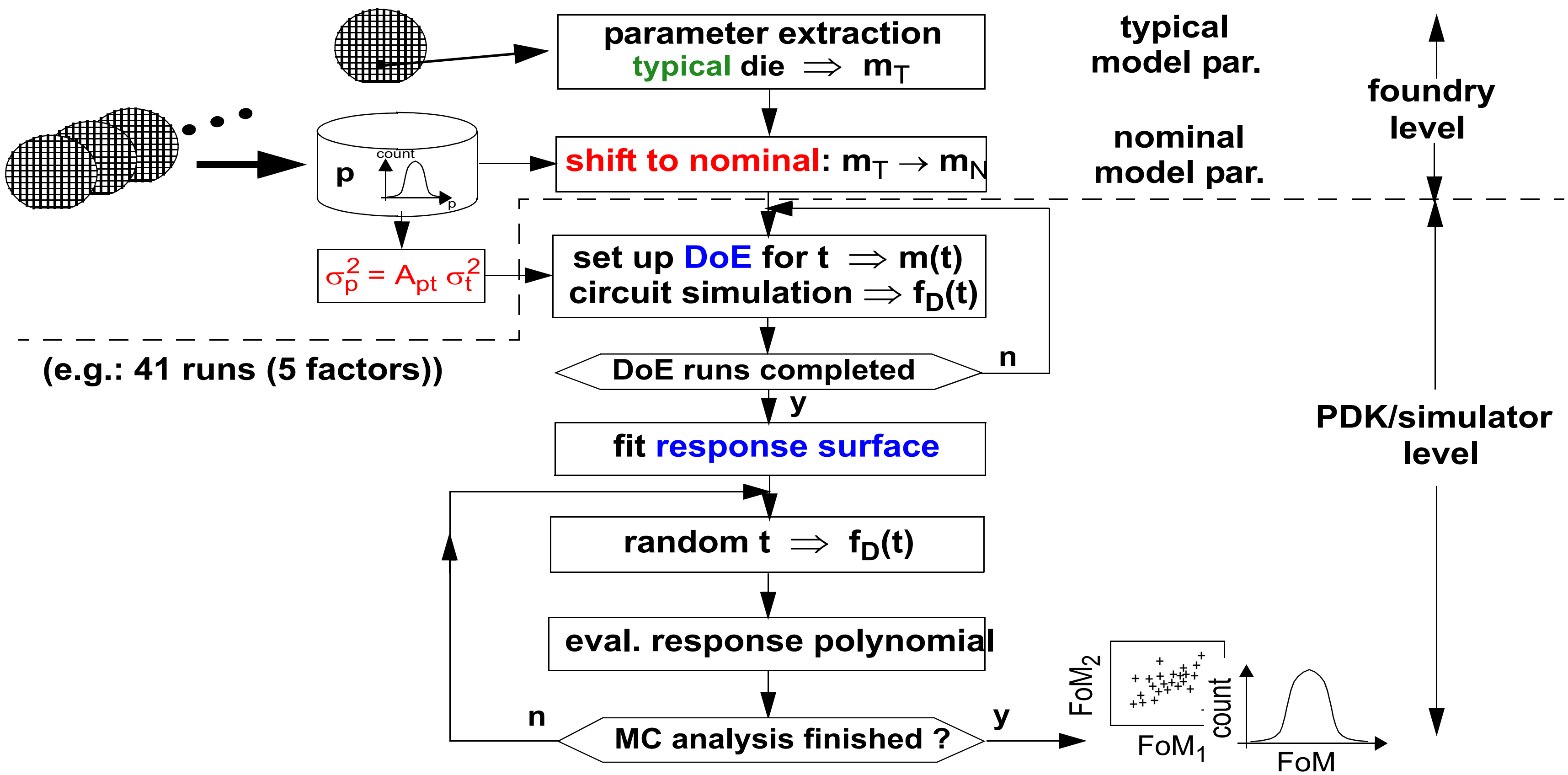
- PCM changes can be calculated from TP changes by forward application of predictive modeling core equations
- Using backward application TP-changes can be calculated from PCM changes
  => requires highly *accurate* representation of PCM(TP)

Most important TP and PCM

- Technology Parameters (TP)
  - (neutral) region widths for collector, base and emitters (w_E, w_B, w_C)
  - doping density of collector, base and emitter (N_E, N_B, N_C)
  - transistors dimensions, especially for emitter window (b_{E0}, l_{E0})
  - Germanium concentration in SiGe base (c_{Ge})
- Process Control Monitors (PCM)
  - zero-bias internal sheet resistance (R_{SBi0})
  - area-specific zero-bias base emitter and base collector capacitance (C_{jEi0}, C_{jCi0})
  - area-specific base-collector punch-through capacitance ($C_{jC,PT}$)
  - area-specific Collector current at low current densities ($I_{C,low}$)
  - forward current gain at low current densities ($B_{f,low}$)
  - sheet resistances and area-specific depletion capacitances of external transistor regions

System Overview

statistical modeling procedure using response surface method (RSM) and design of experiment (DoE)



=> this system is provided by TRADICA

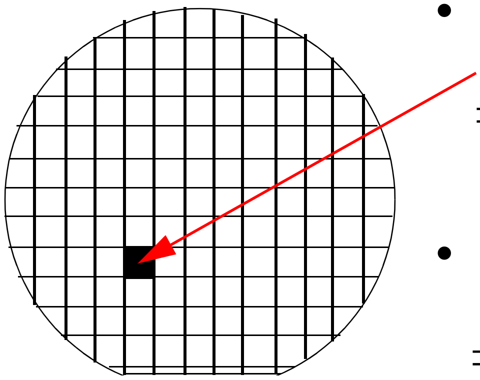
Physics- and PCM-based method: flowchart

- use process-control monitor (PCM) data directly from fab
- utilize physics-based compact models: **m**(**p**(**t**), **t**)

$\Rightarrow$ procedure for statistical model set-up

$\Downarrow$

Step 1: Process development phase



- extraction on single die with typical device characteristics

  $\Rightarrow$ consistent sets: $\mathbf{s}_T$ ($\mathbf{p}_T$), $\mathbf{d}_T$ $\Rightarrow$ $\mathbf{m}_T$

- no statistical information available yet

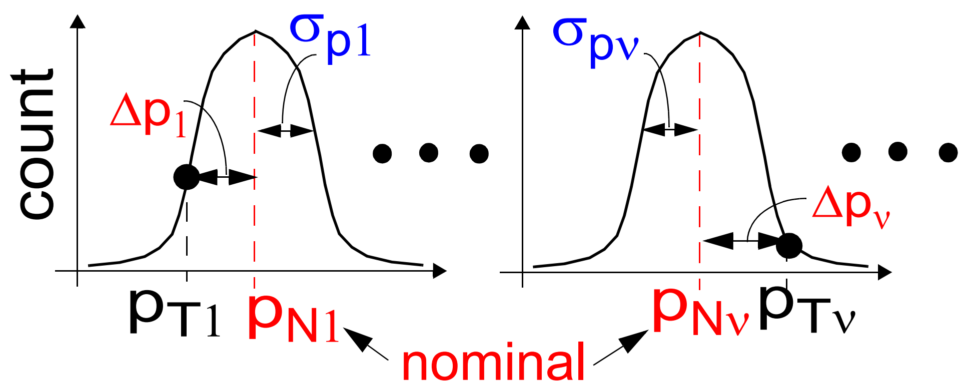
  $\Rightarrow$ need to predict statistical variations of **m** from Δ**t**
  (can use known process information)

$\Rightarrow$ statistics are centered around the ***typical*** data set

PCM based method - Step 2

process qual stage $\Rightarrow$ first production parameter set

first set of consistent PCM measurements



$\Rightarrow$ mean vector $\mathbf{p}_N = \bar{\mathbf{p}}$

$\Rightarrow$ **shift typical to nominal data**

$\Rightarrow$ standard deviation vector σ_p

$\Rightarrow$ determine ***standard deviation*** of TPs

$\Delta \boldsymbol{p} = \boldsymbol{p}_N - \boldsymbol{p}_T$

solve nonlinear system
$\Delta \boldsymbol{p}(\Delta \boldsymbol{t}) = 0$
$\Rightarrow$ nominal TPs $\boldsymbol{t}_N$

nominal SPs: $\boldsymbol{s}_N(\boldsymbol{t}_N)$
shift design rules: $\boldsymbol{d}_T \rightarrow \boldsymbol{d}_N$

device config.
$(b_E, l_E, n_E, \ldots)$

nominal MPs $\boldsymbol{m}_N(\boldsymbol{s}_N, \boldsymbol{d}_N)$

library
(nom)

PCM based method - Step 3

process qual stage $\Rightarrow$ statistical parameter sets

- assume sufficiently small variations $\Rightarrow$ can use *propagation of variances*

$$\begin{bmatrix} \cdots \\ \sigma^2_{p,\nu} \\ \sigma^2_{p,\nu+1} \\ \cdots \end{bmatrix} = \begin{bmatrix} \cdots & \cdots & \cdots & \cdots \\ \cdots & \left(\frac{\partial p_\nu}{\partial t_\nu}\right)^2 & \left(\frac{\partial p_\nu}{\partial t_{\nu+1}}\right)^2 & \cdots \\ \cdots & \left(\frac{\partial p_{\nu+1}}{\partial t_\nu}\right)^2 & \left(\frac{\partial p_{\nu+1}}{\partial t_{\nu+1}}\right)^2 & \cdots \\ \cdots & \cdots & \cdots & \cdots \end{bmatrix} \begin{bmatrix} \cdots \\ \sigma^2_{t,\nu} \\ \sigma^2_{t,\nu+1} \\ \cdots \end{bmatrix} \Rightarrow \text{solve for } \sigma_t^2$$

measured known from model desired

$\Rightarrow$ statistical production ***model*** now ready to be deployed

... but still need to define statistical ***simulation*** procedure

Relation between TPs and PCMs

full matrix for **p** vs. **t** dependence

$p \downarrow \backslash t \rightarrow$	N_B	w_B	N_{Ci}	δV_{gm}	b_{E0}	J_{BEiS}	ρ_{kE}	w_E	N_E	w_C	N_{Cx}	N_{Bs}	N_{bl}	N_{su}
R_{SBi0}	**xxx**	**xx**	**(x)**	-	**(x)**	-	-	-	-	-	-	-	-	-
C_{jE0}	**xxx**	-	-	**x**	**xx**	-	-	**yyy**	**yyy**	-	-	-	-	-
C_{jCi0}	**(x)**	-	**xxx**	**x**	-	-	-	-	-	-	-	-	-	-
$I_{C,low}$	**xxx**	**xx**	**(x)**	**xxx**	**xx**	-	-	-	-	-	-	-	-	-
$I_{B,low}$	-	-	-	-	**xx**	**xxx**	**(xx)**	-	-	-	-	-	-	-
$B_{f,low}$	**xxx**	**xx**	**(x)**	**xxx**	**x**	**xxx**	**(xx)**	-	-	-	-	-	-	-
R_E	-	-	-	-	-	-	**xxx**	**y**	**y**	-	-	-	-	-
$C_{jCi,PT}$	-	-	-	-	-	-	-	-	-	**xxx**	-	-	-	-
C_{jCb0}	-	-	-	-	-	-	-	-	-	-	**xxx**	-	-	-
R_{Ssp}	-	-	-	-	-	-	-	-	-	-	-	**xxx**	-	-
R_{Sbl}	-	-	-	-	-	-	-	-	-	-	-	-	**xxx**	-
ρ_{su}	-	-	-	-	-	-	-	-	-	-	-	-	-	**xxx**

- internal transistor: mostly nonlinear, correlated parameters
- external transistor: mostly simple uncorrelated relations (e.g. $R = R_S * b/l$)
- do not need to use *all* components of **t** for a given application

Do’s and Don’ts of statistical simulation

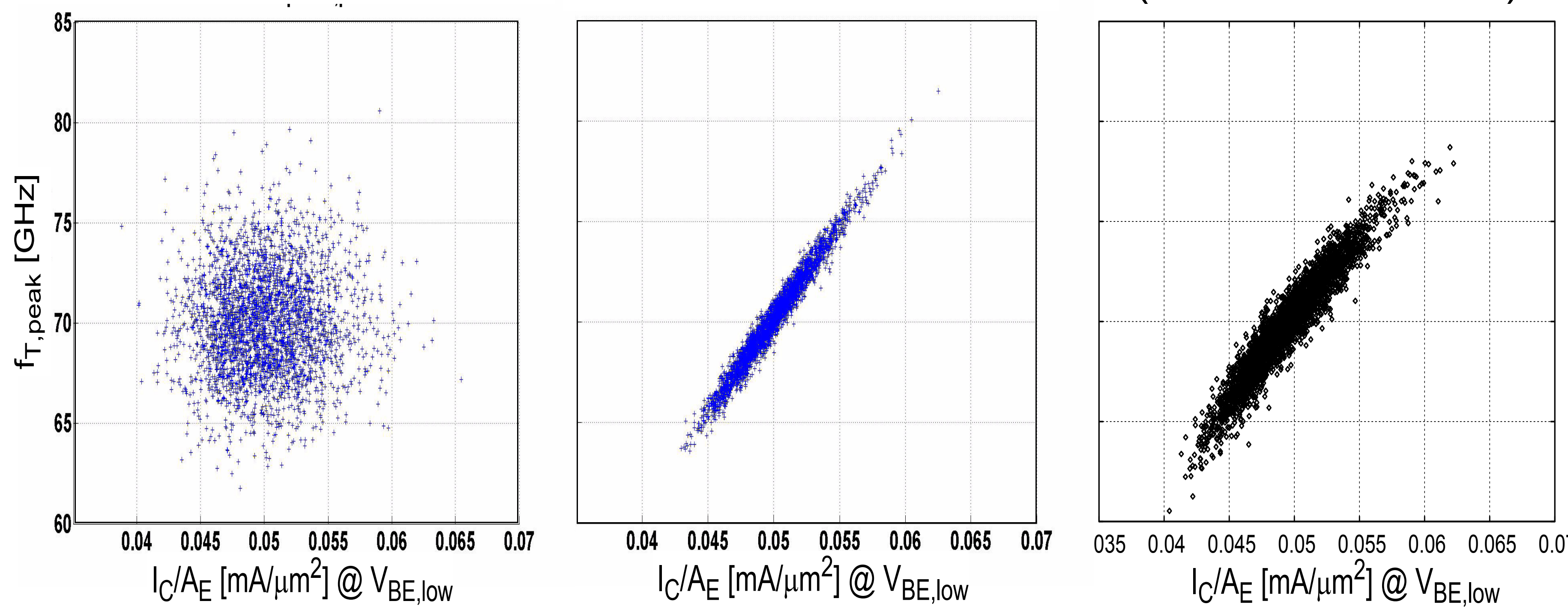
random variation of different parameter types

impact on transit frequency and high-frequency device performance

MC model par. variation
(c_{10} Q_{p0} C_{jEi0} C_{jCi0} τ_0 r_{Ci0} V_{PT} τ_{hcs})

PCM based simulation

reference
(device simulation)



⇒ correct correlation only from physics-based approach

Parametric Model Card (PMC)

PMCs (a.k.a. statistical model cards) are often used as simple approaches for statistical modeling and simulation

- built-in statistical algorithms of circuit simulators are employed by expressing model parameters ***m*** as function of varying process parameters Δ***p***:

$$\boldsymbol{m} = \boldsymbol{m}_0 + \sum_j a_j \Delta p_j + \sum_j b_j \Delta p^2{}_j + \ldots$$

- $\boldsymbol{m}_0$: nominal model parameter vector
- $a_{i,j}$, $b_{i,j}$: statistical model coefficients
- ***p***: mostly process control monitors and dimensions (e.g. b_{E0}, l_{E0}) for scaling and matching

Example for PMC

```
* HICUM/Level2    v2.2                                                    TRADICA A5.4
.SUBCKT P030401S02_01   3   2   1   9

parameters
 + b_e0 =0.350E-06    l_e0 =0.400E-05
 + r_nbei_l = r_nbei_rm_std*r_nbei_sm_std/sqrt(b_e0*l_e0)
 + r_nbei   = r_nbei_g_std+r_nbei_l
 :
 + a_be0_l = a_be0_rm_std*a_be0_sm_std/sqrt(l_e0)
 + a_be0    = a_be0_g_std+a_be0_l

Q     3   2   1   9   MOD
.model MOD  PNP level=9  TNOM= 26.85  version=2.2
 + c10 = 3.136E-29 + 1.403E-29*r_nbei + 1.345E-22*a_be0 + 1.441E-16*a_be0*a_be0 + ...
 + qp0 = 3.826E-14 + 3.826E-14*r_nbei + 3.826E-14*r_wb + 8.200E-08*a_be0 + 9.330E-09*a_le0
 :
 + cjei0 = 1.977E-14 + 5.253E-15*r_nbei + 1.201E-14*a_vgm + 4.237E-08*a_be0 + 4.821E-09*a_le0
 :
```

- general issues with PMCs
  - polynomials are mostly non-physical => coefficients are fit parameters
  - polynomials do not capture true dependence m(p), especially over larger variation ranges
  - higher order polynomials may include minima and maxima both within and outside of target variation range => non-physical and dangerous for yield optimization

PMC generation from measured data

- Procedure
  - choose sufficiently high number of samples (fully characterized dies with transistor parameters and known PCMs)
  - define and determine process parameters ***p*** => independent variables
  - perform model parameter extraction for every sample
  - build regression model for every model parameter ***m***(***p***)
- Advantages
  - directly from measured data may increase confidence
- Issues
  - model parameter extraction impacted by process variations, measurement errors, numerical optimization errors
    => superposition of undesired variations causes additional model parameter scattering
    => more samples required
  - model parameter extraction requires large effort (incl. detailed measurements)
  - limited use of DoE methods, rather: take as many data for linear, quadratic or higher order regression as possible
  - independent variables are mostly PCMs => correlated => to be determ. by measurements
  - correlations are difficult to include in circuit simulators

PMC generation with the aid of device simulation

- Procedure
  - model parameter extraction for nominal device
  - build 1D/2D doping profile for nominal transistor
  - simulate systematic process variations (DoE) to obtain data base for regression
  - perform parameter extraction for each selected process variation
  - Build regression model for every model parameter

- Advantages
  - significantly lowers the effort for extensive measurements and model parameter extraction
  - regression model is now based on TP

- Issues
  - need at least 1D profile (2D profile and process calibrated material models are a plus)
  - model parameters scatter after extraction
  - process variations used within DoE probably not conform with real process

PMC Generation from physics-based approach

... using TRADICA

- Procedure
  - Complete process characterization for use in TRADICA
  - Generating parametric model card with built in methods

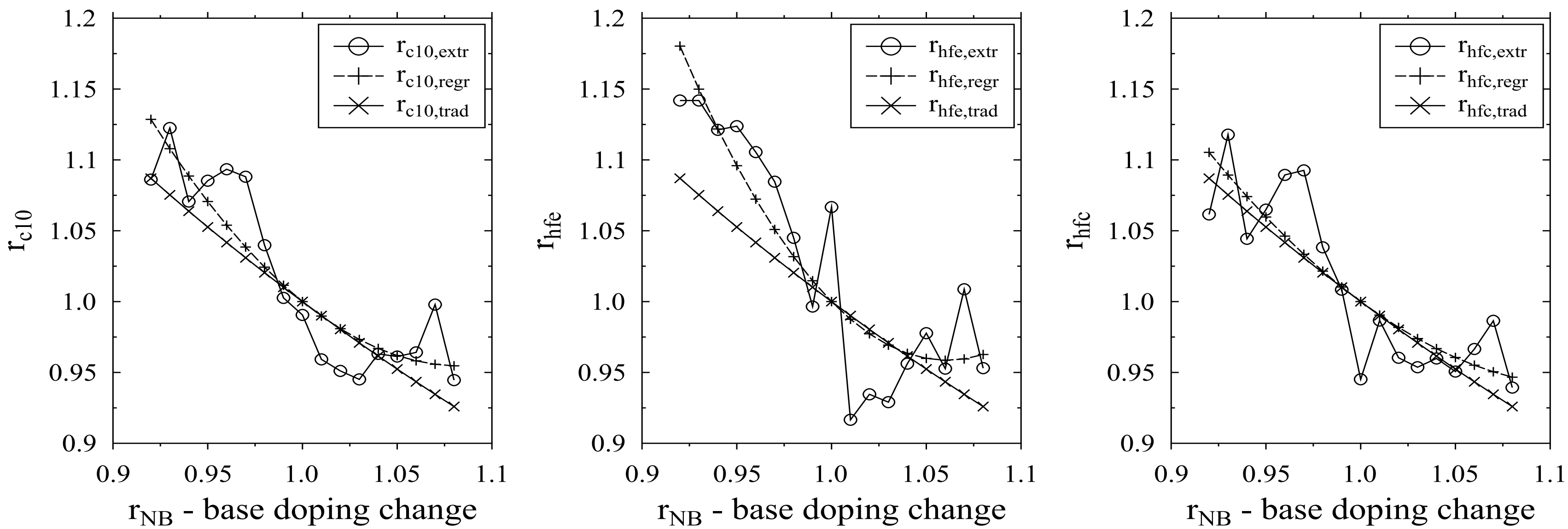
- Advantages
  - regression model is now based on TP
  - back propagation of variance makes DoE within TRADICA agree with that of real process
  - takes in-line PCMs directly => no additional cost

- Issues
  - general disadvantages of PMC (possibly non monotonously second order functions) still remain

PMC Example

...based on device simulation => ideal environment

- model parameter ratios vs. base doping ratio: according to model equations, variation should be the same for shown parameters



- observations
  - non-physical minima in second-order model parameter equation possible
  - scattered extraction results (increase sample number necessary for regression)

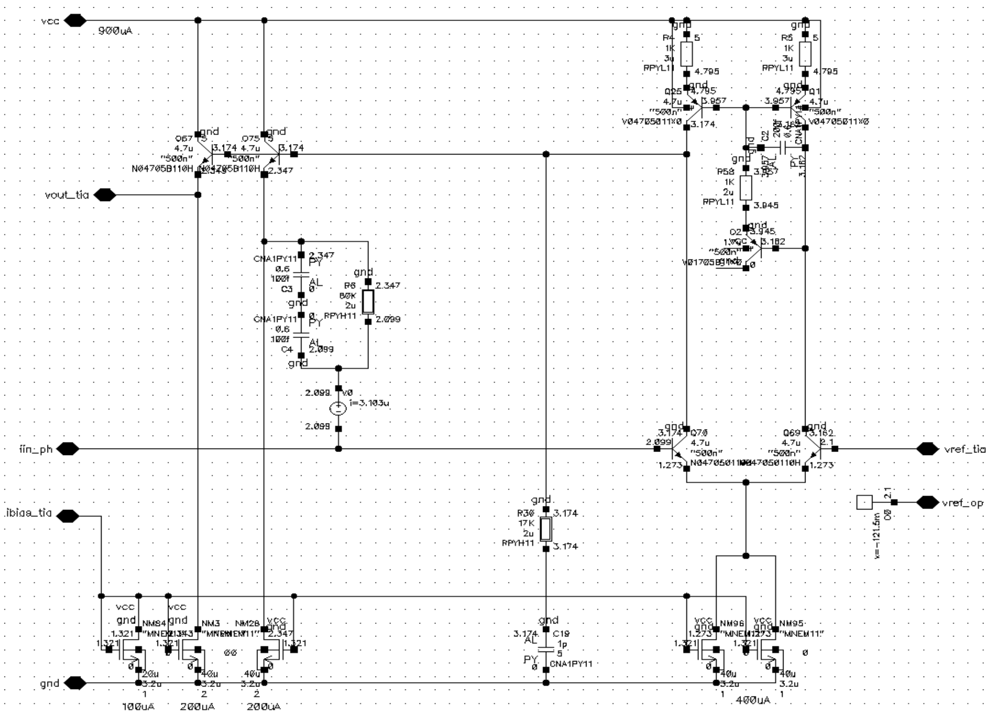
=> extraction-based PMC generation is inferior solution

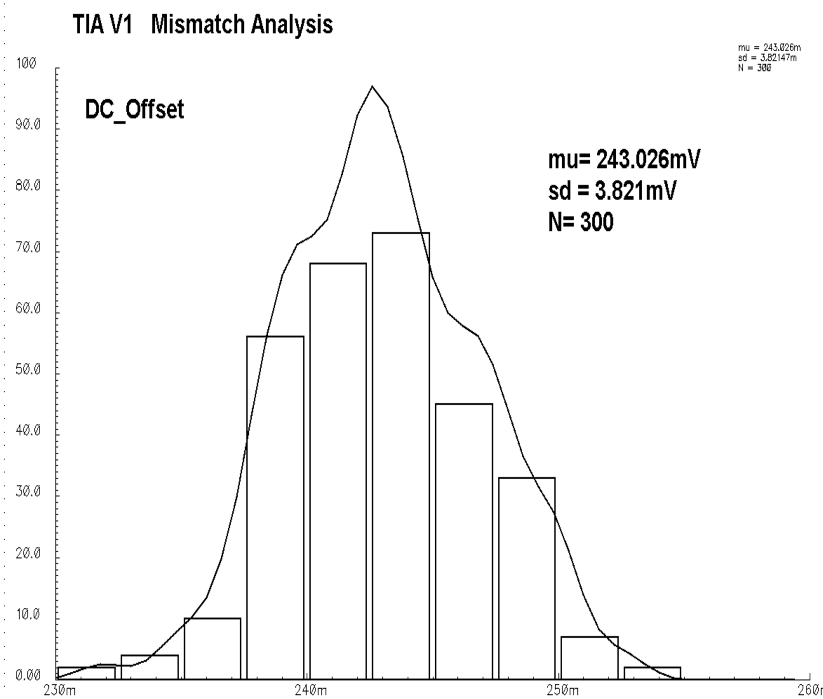
Comparison of modeling process variations

TRADICA	PMC from extraction
physics-based predictive modeling equations	non-physical polynomial equation for every model parameter
calibration to process due to nominal HICUM parameters and measured PCM	Calibration using coefficients within polynomial => includes also artefacts of model parameter extraction
can select uncorrelated device parameters and dimensions as independent variables	selected independent variables are mostly correlated => contradiction to statistical circuit simulation requirements
integrated in PDK preferable; can be used with built-in statistical capability of circuit simulator	limited to use of built-in statistical capability of circuit simulator

Example

Atmel (Telefunken) presented at DATE2007 a successful implementation of TRADICA in their Design Frame Work (DFW)





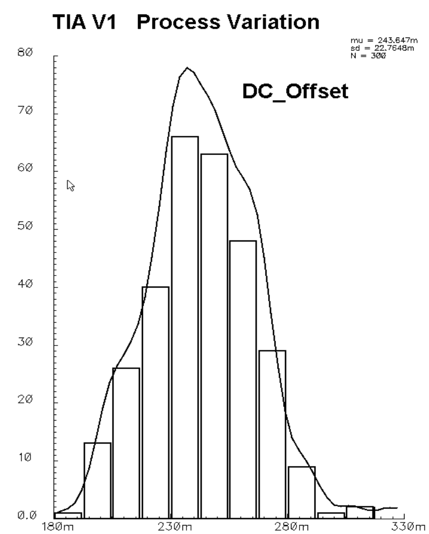
- low-cost amplifier, high-volume production => yield is critical economic factor
- mismatch (only) analysis => 243 mV offset voltage, 3.8 mV standard deviation

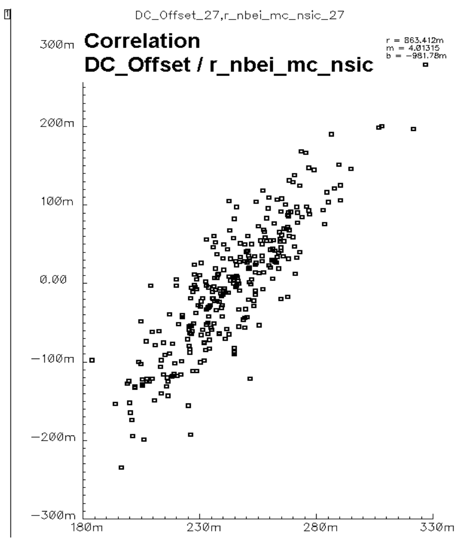
Analysis of Process Tolerance Impact

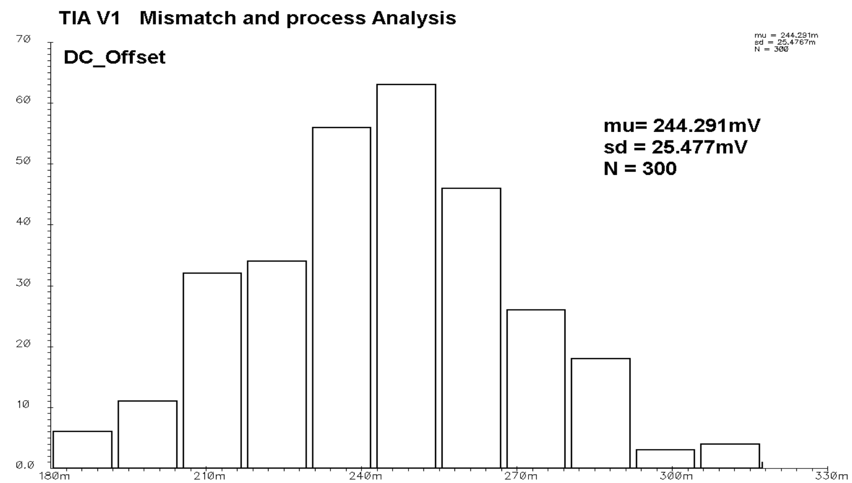
- sensitivity analysis using 300 MC simulations to identify TPs of highest impact

=> internal base doping has highest impact

- *combined* analysis using lateral (i.e. incl. mismatch) *and* vertical process variation show offset mean of 244.3 mV with a standard deviation of 25.5 mV
- offset increased because of additional consideration of vertical transistor variations





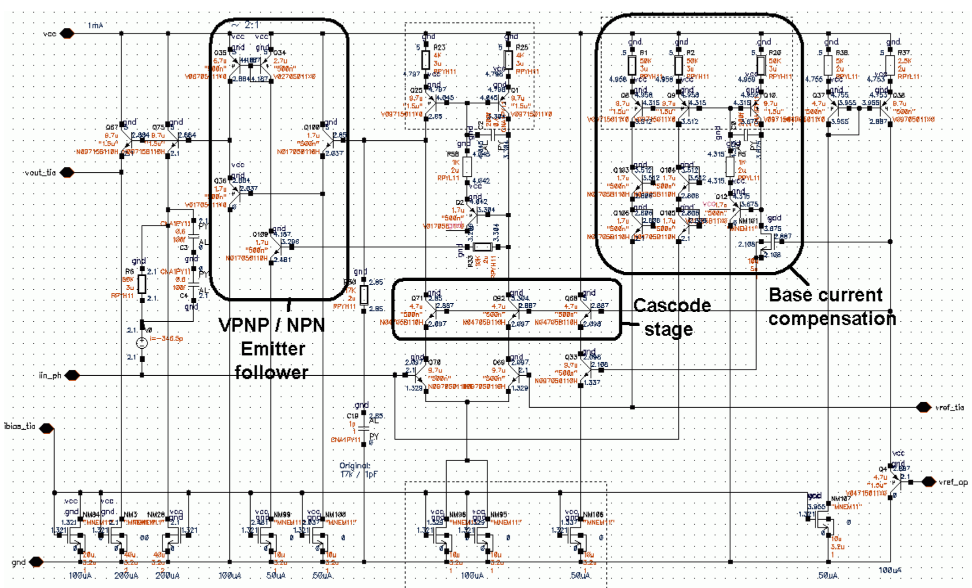


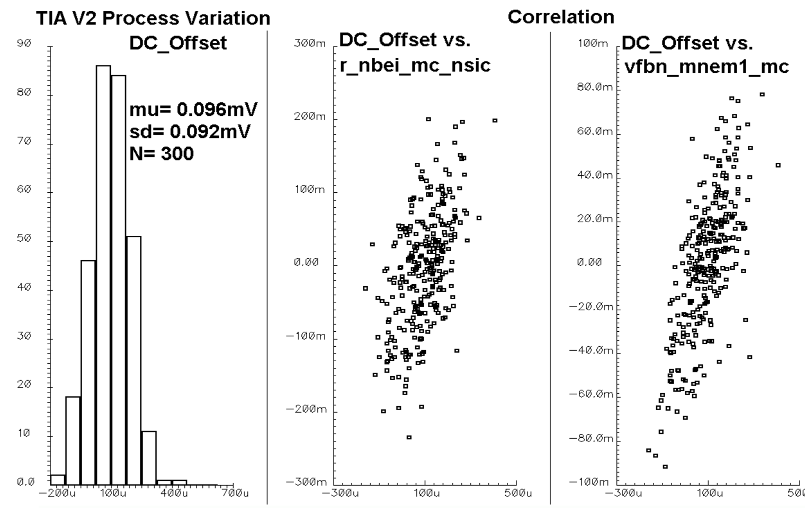
=> TRADICA based sensitivity analysis reproduces measured data

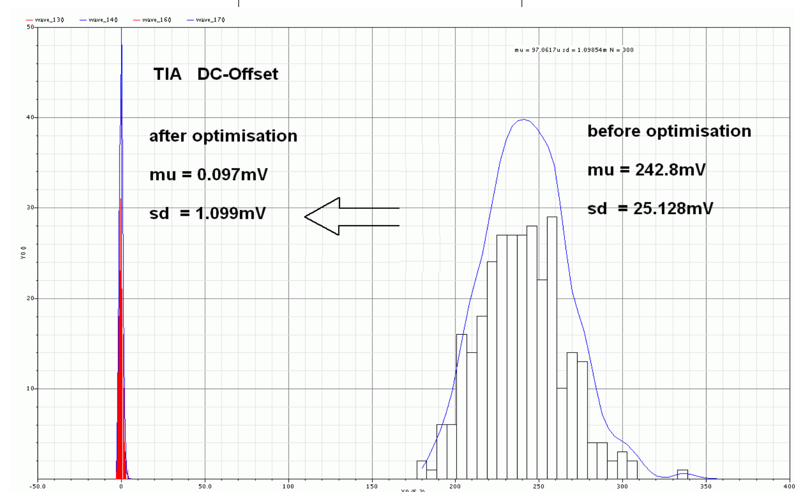
Results for redesigned circuit

- compensation circuits added
- optimization supported by TRADICA
- offset mean reduction from 243mV to 0.1mV
- offset std reduction from 25.1mV to 1.1mV

=> experimentally verified!







=> procedure has been used at Atmel (now Telefunken) for generating statistical models in their PDKs

Summary

various approaches existing for modeling of process variations

- MC simulation of model parameters => simple but ***bad*** idea (no correlation)
- parametric model cards (often found approach)
  - discussed alternatives for generating PMCs
  - issues were pointed out
    => inferior solution to fully physics-based approach

process-based scalable (physics-based) approach

- includes smooth and accurate dependence of model parameters on process parameters
- includes correlation between model parameters,
- enables analysis of device matching

future trend: expect increasing process variations

=> proper statistical modeling will improve circuit yield