EVALUATION OF MIXED-SIGNAL/RF DFT SOLUTIONS FOR SiP DEVICES USING STATISTICAL TECHNIQUES

S. Mir
TIMA Laboratory
46 Avenue Félix Viallet
38031 Grenoble
France

salvador.mir@imag.fr

Workshop on Reliability & DfX Engineering for SiP Technologies Pallanza, May 2008

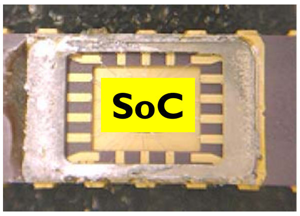
1

Outline

1. Introduction
2. Goals
3. DFT for mixed-signal/RF blocks
4. Statistical techniques for DFT evaluation
5. Conclusions

2

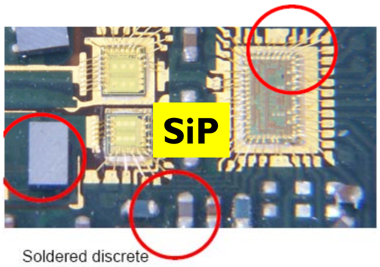
1 Introduction: SiP vs SoC



Single piece of silicon
Single technology
Single level of interconnection

Multiple chips
Multiple technologies
Multiple levels of interconnection...
...and 3D

Passive filter In Silicon With Flip chip connections



BICMOS die with Bond wire connections

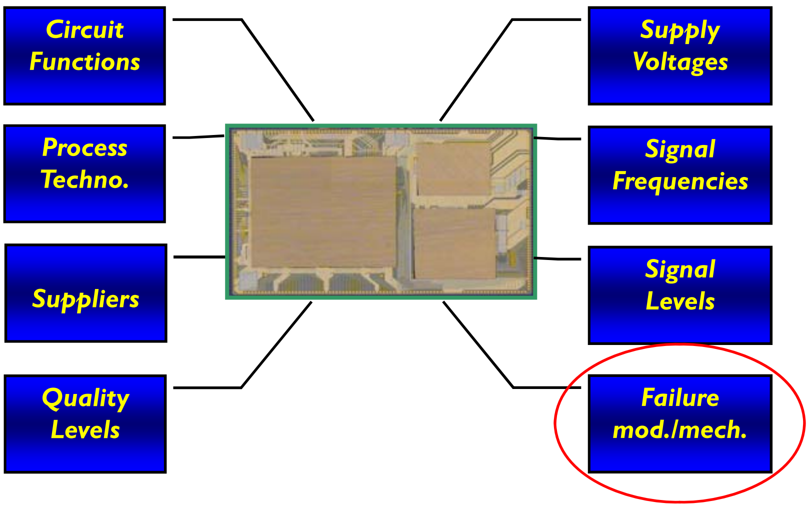
Soldered discrete passive devices

(Courtesy NXP Caen, France)

3

1 Introduction: SiP vs SoC

Compared to a SoC, a SiP may have more...



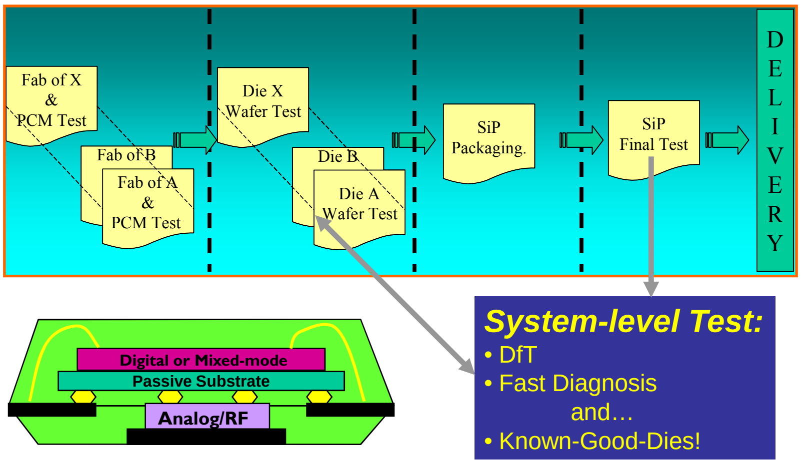
(Courtesy NXP Caen, France)

4

1 Introduction: SiP Testing

A Complex Test Flow…

Wafer Test *Final Test*



(Courtesy NXP Caen, France)

5

1 Introduction: SiP Testing

- SiP package test:
  - ❖ Requires greater *diversity of ATE resources* than SoC
  - ❖ Requires greater *diversity of test & reliability screen methods* than SoC
  - ❖ Has large *disparities in test times and resource utilization* among die
- Solutions:
  - Insert in multiple testers
  - Better scheduling of test resources to allow independent, simultaneous test of each accessible chip in SiP
  - BIST/DfT/DSP
- DFT/BIST requires careful study of different alternatives and the evaluation of incurred costs
- BIST test costs such as silicon overhead and performance degradation are easily estimated at the design stage, but test costs due to the probability of test errors are much harder to evaluate

6

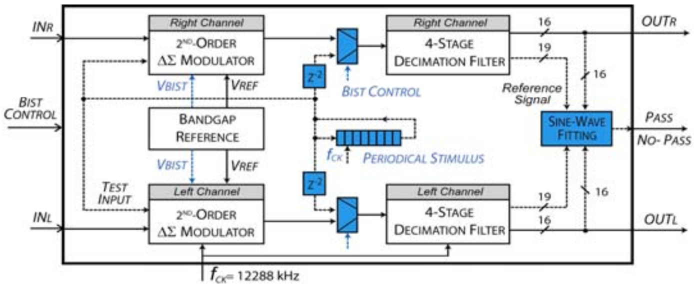
2 Goals

- To provide a methodology for the evaluation of BIST techniques at the design stage. The steps of this methodology are:
  - Statistical modeling of the CUT performances and test measurements
  - Setting of test measurement limits as a function of test metrics such as design parametric yield loss and defect level
  - Evaluation of test metrics (fault coverage, defect level) for single catastrophic and parametric faults that are not considered by the statistical models
- This methodology serves the purpose of comparing different BIST techniques and it can be exploited for analog functional test compaction

7

3 DFT for mixed-signal/RF blocks

Digital test of ΣΔ ADC



- Digital bit stream used as test stimuli for the ΣΔ modulator and for creating a reference signal
- Sine-wave fitting of the synchronized response and reference signals is used to extract performances such as SNDR
- Bandgap voltage reference is reused for the BIST that requires an attenuated input bit stream
- For stereo converter, no memory is needed for extracting the signature

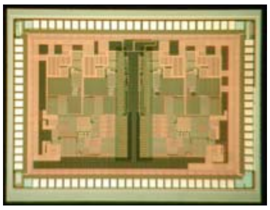
L. Rolíndez, S. Mir et al., ITC'07

8

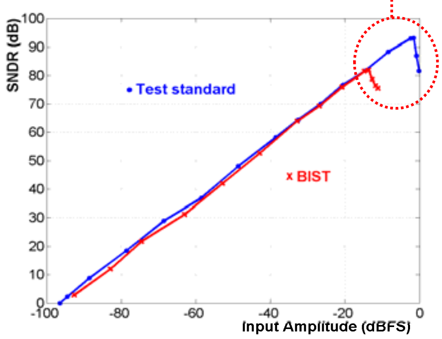
3 DFT for mixed-signal/RF blocks

Digital test of SD ADC

Not all performance space is covered



0.13 µm CMOS STM



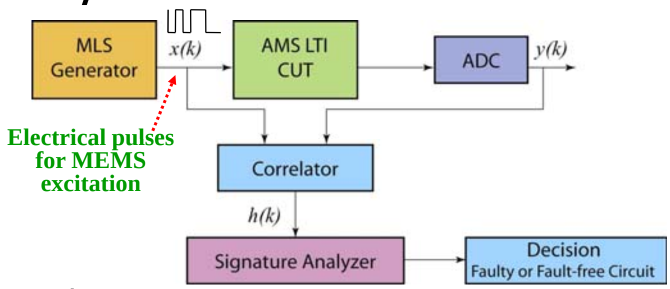
- Excellent correlation (but how good ?) between BIST and standard SNDR test for amplitudes up to –10 dB FS
- Full functional test is not performed ⇒ need to estimate the design parametric defect level and yield loss of the BIST technique

L. Rolíndez, S. Mir et al., ITC'07

9

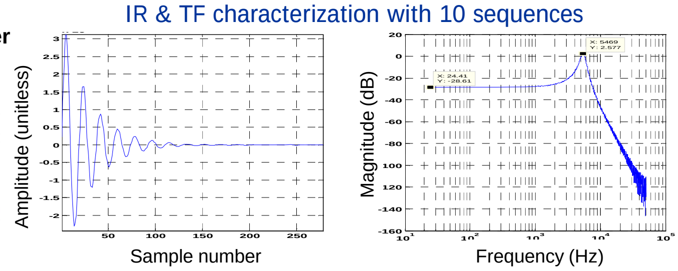
3 DFT for mixed-signal/RF blocks

MEMS pseudo-random BIST



Analog Devices ADXL103 accelerometer

IR & TF characterization with 10 sequences



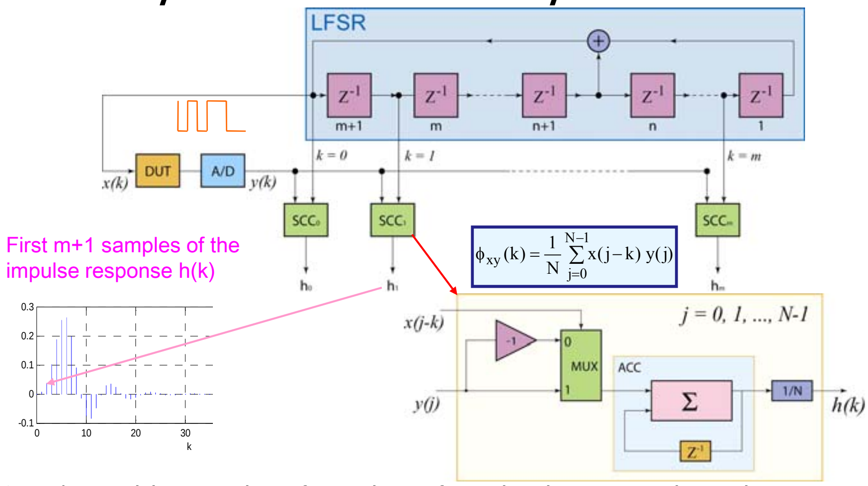
Characterization time = M.N.Ts = 10 x 16353 x 2.26 x 10^{-5} = 3.7 sec

A. Achraf, S. Mir & L. Rufer, DATE'06

10

3 DFT for mixed-signal/RF blocks

MEMS pseudo-random BIST implementation



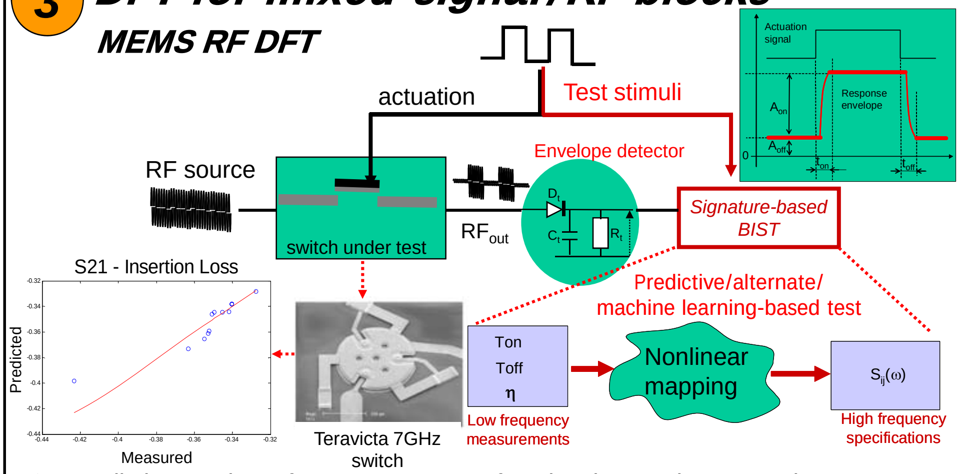
- A/D precision, number of samples to form the signature and sample tolerance limits are function of the required test metrics
- Again, full functional test is not performed ⇒ need to estimate the design parametric defect level and yield loss of the BIST technique

L. Rufer, S. Mir & E. Simeu, JETTA'05

11

3 DFT for mixed-signal/RF blocks

MEMS RF DFT



- Predictive test is performed rather than functional test using regression techniques ⇒ BIST parametric defect level and yield loss must be estimated
- Non-linear boundaries on test measurements can be obtained, rather than hypercubes
- The multidimensional regression model is a black box where data dependencies are difficult to interpret

E. Simeu, S. Mir et al., IOLTS'07

12

4 Statistical techniques for DFT evaluation

- Estimate BIST test metrics by modeling device performances s = $(s_1, s_2, \ldots, s_n)$ and BIST measurements t = $(t_1, t_2, \ldots, t_m)$ as random variables and estimating their joint Probability Density Function (PDF)

Design Yield
Y=P(Functional) →
$$Y = \int_{A_1} \ldots \int_{A_n} f_S(s_1, \ldots, s_n)\ ds_1 \ldots ds_n$$

Design Test Yield
Y_T = P(Pass) →
$$Y_T = \int_{B_1} \ldots \int_{B_m} f_T(t_1, \ldots, t_m)\ dt_1 \ldots dt_m$$

$$P_{PF} = \int_{A_1} \ldots \int_{A_n} \int_{B_1} \ldots \int_{B_m} f_{ST}(s_1, \ldots, s_n, t_1, \ldots, t_m)\ ds_1 \ldots ds_n\ dt_1 \ldots dt_m$$

P_{PF} = P(Pass and Functional)

Design Yield Loss
Y_L = 1-Y_C=1-P(Pass/Functional) →
$$Y_C = \frac{P_{PF}}{Y}$$

Design Defect Level
D_L = P(Faulty/Pass)
= 1-P(Functional/Pass) →
$$D = 1 - \frac{P_{PF}}{Y_T}$$

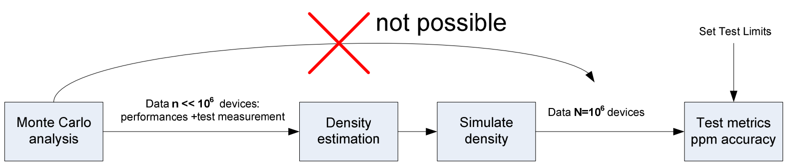
- Test metrics are calculated for given specifications $(A_1, \ldots, A_n)$ and test limits $(B_1, \ldots, B_n)$ or, vice versa, test limits are set to meet test metrics constraints
- Density estimation techniques can provide models easier to interpret than regression models

13

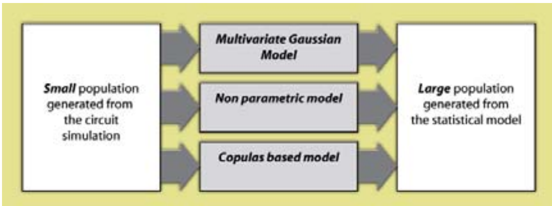
4 Statistical techniques for DFT evaluation

Density estimation techniques

- An initial small population is obtained via Monte Carlo simulation
- Estimation of test metrics from this population is misleading since there is insufficient data to represent properly devices out of specifications



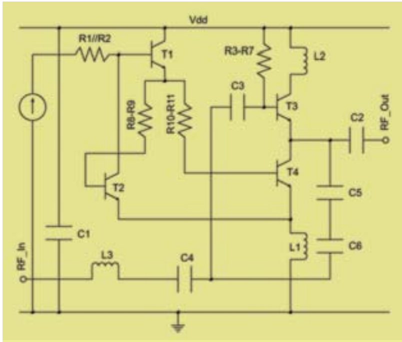
- A statistical model is obtained from the initial population using density estimation. This model is sampled to generate a large population (>1e6) from which test metrics can be calculated with relative frequencies



14

4 Statistical techniques for DFT evaluation

Case-study: LNA BIST



LNA 0.25 µm BiCMOS STM

BIST measurement:

$$i_0 = \frac{i_1 i_2 r_{31} r_{42}}{i_1 r_{31} + i_2 r_{42}}$$

current i_0 that results from the cross-correlation between the LNA output rms current i_1 and LNA rms supply current i_2

(*Machado da Silva*, INESC)

LNA Specifications

NF	S_{11}	Gain	1-db CP	IIP_3
≤ 1.3 db	≤ -9 db	≥ 17 db	≥ -11.3 dBm	≥ -5.1 dBm

15

4 Statistical techniques for DFT evaluation

Density estimation using multinormal law

Multinormal PDF with N random variables $x = (x_1, x_2, \ldots, x_N)$

$$f(x) = \frac{1}{\sqrt{det(2\pi\Sigma)}} \cdot exp\left[-\frac{(x-\mu)^T\Sigma^{-1}(x-\mu)}{2}\right]$$

Multinormal parameters: μ *and* Σ

$$\Sigma = \begin{pmatrix} \sigma_1^2 & \cdots & COV(X_1, X_N) \\ \vdots & \ddots & \vdots \\ COV(X_N, X_1) & \cdots & \sigma_N^2 \end{pmatrix} \qquad \mu = (\mu_1, \mu_2, \ldots, \mu_N) \qquad COV(X_1, X_2) = \frac{\sum_{i=1}^{N} X_1^i \cdot X_2^i}{N} - \mu_1\mu_2$$

- Direct integration is unfeasible for several random variables

$$P(A) = \frac{1}{\sqrt{det(2\pi\Sigma)}} \int_{A_1} \cdots \int_{A_p} exp\left[-\frac{(x-\mu)^T\Sigma^{-1}(x-\mu)}{2}\right] dx_1 dx_2 \cdots dx_p$$

- Sample the density and use relative frequencies

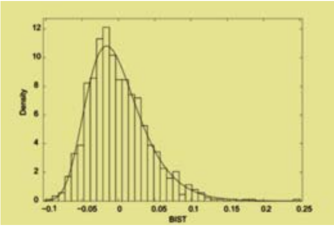
Run a Monte-Carlo circuit simulation → Calculate multinormal PDF parameters (µ and Σ) → Generate millions of circuit samples from the multinormal law

A. Bounceur, S. Mir et al., JETTA'07

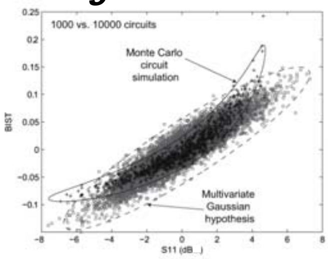
16

4 Statistical techniques for DFT evaluation

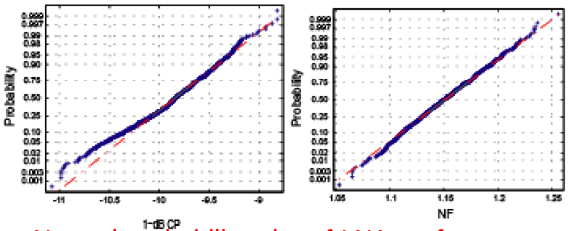
Density estimation using multinormal law: LNA BIST



BIST measurement does not have a Gaussian distribution



Joint distribution of BIST measurement and S11 parameter obtained by Monte Carlo simulation differs from distribution sampled from the Gaussian model



Normal probability plot of LNA performances: 1-dB CP non normal, NF normal

$$f(x)=\frac{1}{\sqrt{\det(2\pi\Sigma)}}\exp\left[-\frac{(x-\mu)^T\Sigma^{-1}(x-\mu)}{2}\right]$$

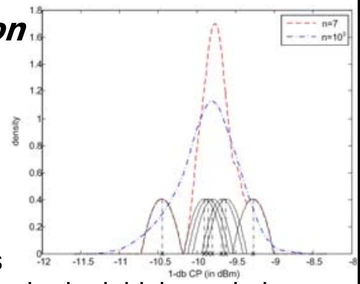
Setting BIST limits so that DL=10YL ⇒ DL= 100 dppm, but the multinormal model is not valid.

J. Tongbong, S. Mir et al. DATE'08

17

4 Statistical techniques for DFT evaluation

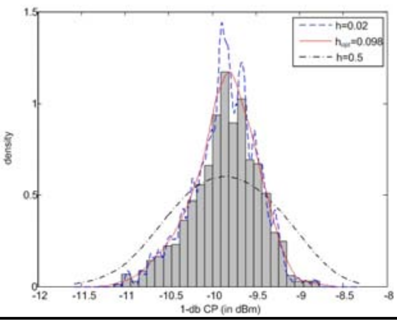
Non-parametric density estimation



- No hypothesis about the form of the true PDF

$$\tilde{f}(x)=\frac{1}{nh^d}\sum_{i=1}^{n}K\left(\frac{1}{h}(x-X_i)\right)$$

- With *K* Kernel estimator (Epanechnikov, Gaussian ...), *d* the number of random variables (performances + BIST measurements), *n* devices in the initial population, and *h* a factor called bandwidth that can be chosen with automatic rules



- *h* can be made to vary from one observation to another (adaptive Kernel Density Estimator, KDE) using broader kernels in regions of low density to avoid spurious noise at the tails:

$$\hat{f}(x)=\frac{1}{n}\sum_{i=1}^{n}\frac{1}{(h\cdot\lambda_i)^d}K\left(\frac{1}{h\cdot\lambda_i}(x-X_i)\right)$$

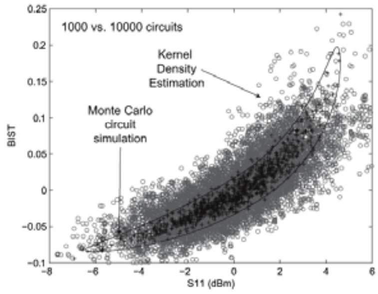
$$\lambda_i \sim \left(\tilde{f}(X_i)\right)^{-1}$$

H. Stratigopoulos, J. Tongbong & S. Mir, DATE'08

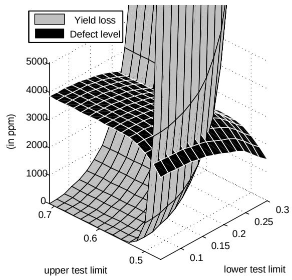
18

4 Statistical techniques for DFT evaluation

Non-parametric density estimation: LNA BIST



- Joint distribution of BIST measurement and S11 parameter obtained by Monte Carlo simulation is the same as the distribution sampled from the non-parametric model
- There is a larger dispersion of points than in the initial population: the larger the number of dimensions, the larger the initial population required to fit a KDE model



- Non-parametric Adaptive Kernel Density Estimation (KDE) with Epanechnikov kernel:

$$\hat{f}(x) = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{(h\cdot\lambda_i)^d}K\left(\frac{1}{h\cdot\lambda_i}(x - X_i)\right)$$

- After generation of 1e6 devices, setting BIST limits so that DL=10YL $\Rightarrow$ DL= 2139 dppm

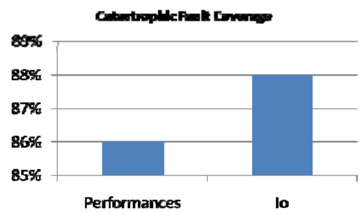
H. Stratigopoulos, J. Tongbong & S. Mir, DATE'08 19

4 Statistical techniques for DFT evaluation

Non-parametric density estimation: LNA BIST

- Fault simulation campaign to evaluate test metrics under the presence of faults not represented by the statistical models

1) *Catastrophic Faults*: 43 injected faults (out of 50) cause performance failure and are *all* detected by the BIST. In addition the BIST detects a short (10 Ω) across the bypassing capacitor C1). Undetected faults do not affect the circuit performances.



2) *Parametric faults*: we consider a parametric fault as the minimum deviation of a design parameter that results in a performance deviation. We consider passive components and the geometry of the bipolar transistors: performance failures due to local parametric deviations are rather difficult to detect

Y_F (%)	YL_F (%)	D_F (%)	F (%)	YT_F (%)
99.99	12.25	$4.11*10^{-6}$	24.76	87.72

H. Stratigopoulos, J. Tongbong & S. Mir, DATE'08 20

4 Statistical techniques for DFT evaluation

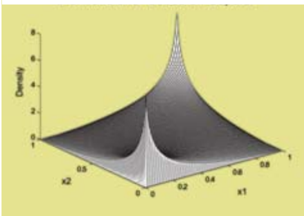
Density estimation based on Copulas

- For a multivariate n-dimensional CDF, the univariate marginal distributions and the variable dependence structure can be completed separated, with the latter being described by a **Copula** function (Sklar theorem, 1959)

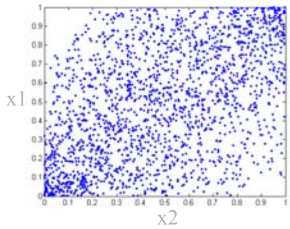
$$f(x_1,\ldots,x_n) = c(F_1(x_1),\ldots,F_n(x_n))\prod_{i=1}^{n} f_i(x_i)$$

  - A **Copula** is a multivariate joint distribution (CDF) defined on the hypercube $[0,1]^n$
  - Every marginal distribution of a copula is uniform on the interval [0, 1]

2-dimensional copula (CDF)



2-dimensional copula sample

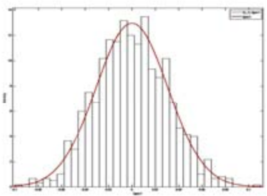


S. Mir & A. Bounceur, IMS3TW'08

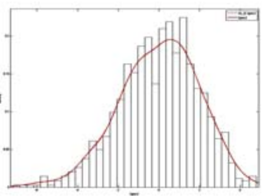
21

4 Statistical techniques for DFT evaluation

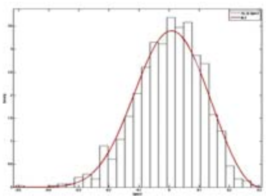
Density estimation based on Copulas: LNA BIST



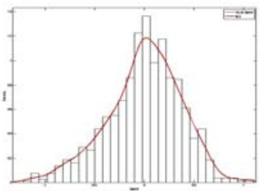
NF: Gaussian



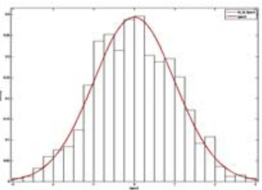
S11: Non-parametric



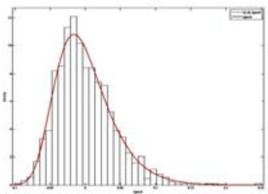
Gain: General Extreme Value



1dB CP: Non-parametric



IIP3: Gaussian



BIST: General Extreme Value

- Fitting of marginal densities for each performance and BIST measurement

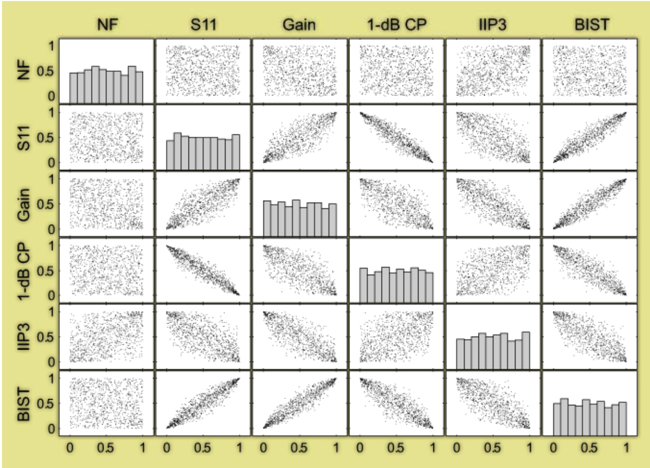
A. Bounceur & S. Mir, IMS3TW'08

22

4 Statistical techniques for DFT evaluation

Density estimation based on Copulas: LNA BIST

- Calibrate a Gaussian Copula with the correlation matrix of the analyzed data (other type of Copula functions are possible)

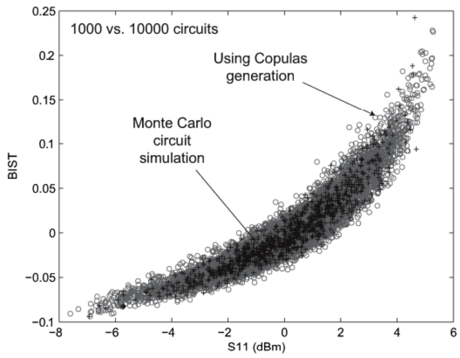


A. Bounceur & S. Mir, IMS3TW'08

23

4 Statistical techniques for DFT evaluation

Density estimation based on Copulas: LNA BIST



$$f(x) = c(F_1(X_1),\dots,F_n(X_n))\prod_{i=1}^{n} f_i(X_i)$$

- After generation of 1e6 devices, setting BIST limits so that DL=10YL ⇒ DL= 49 dppm

- Joint distribution of BIST measurement and S11 parameter obtained by Monte Carlo simulation is just the same as the distribution sampled from the Copulas model (Gaussian Copula)
- Marginal distributions are easier to estimate and assumption on data dependencies (such as Gaussian Copula) provide very accurate results

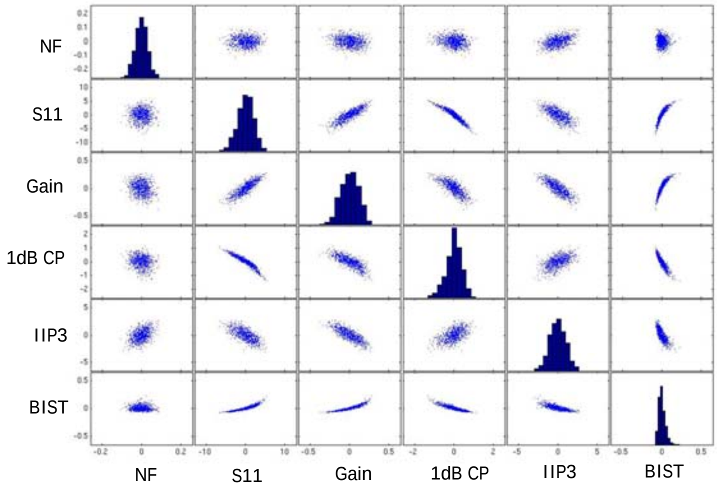
Estimated parametric defect level			
	Normal	KDE	Copulas
DPPM	100	2188	49

A. Bounceur & S. Mir, IMS3TW'08

24

4 Statistical techniques for DFT evaluation

Density estimation based on Copulas: LNA BIST



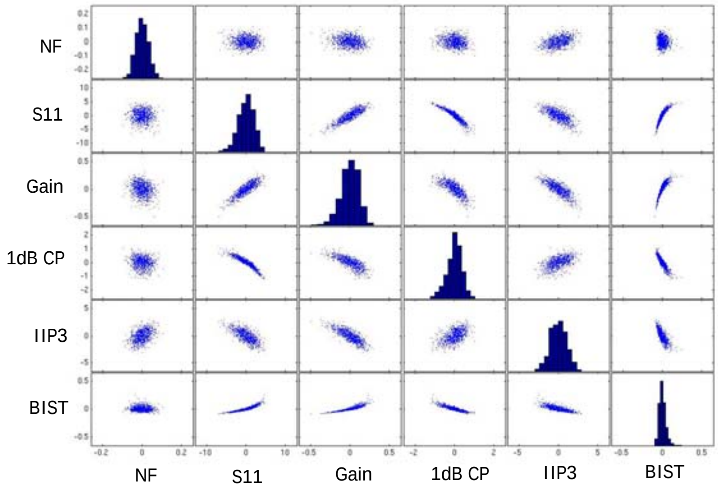
- 2-dimensional joint densities obtained by 1000 samples from the **Copulas model**

A. Bounceur & S. Mir, IMS3TW'08

25

4 Statistical techniques for DFT evaluation

Density estimation based on Copulas: LNA BIST



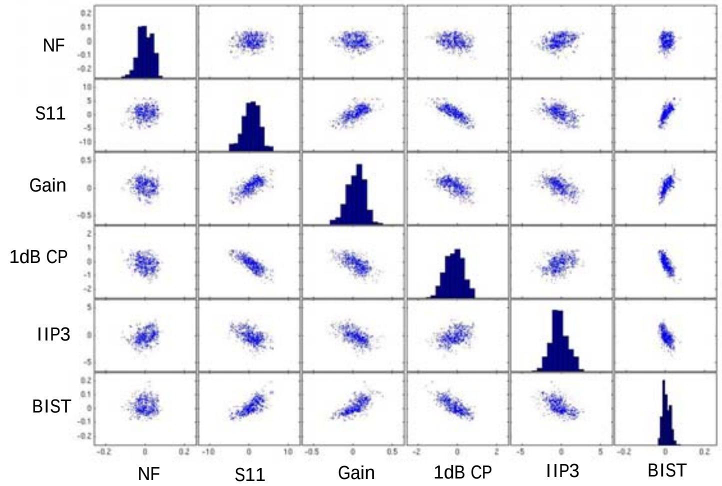
- 2-dimensional joint densities obtained from the initial **Monte Carlo population** (1000 circuits)

A. Bounceur & S. Mir, IMS3TW'08

26

4 Statistical techniques for DFT evaluation

Density estimation based on Copulas: LNA BIST



- 2-dimensional joint densities obtained by 1000 samples from the **Non-parametric model**

A. Bounceur & S. Mir, IMS3TW'08

27

5 Conclusions

- DFT/BIST requires careful study of different alternatives and the evaluation of incurred costs, in particular the probability of test errors such as parametric defect level and yield loss
- Density estimation techniques provides a way to estimate these metrics
  - Test limits can be set to achieve desired trade-offs between test metrics
  - An array of BIST solutions can be compared on the basis of the estimated metrics
- For linear circuits with Gaussian performances, the multinormal Gaussian model is very simple and powerful
- For non-linear circuits, Kernel Density Estimation techniques can be applied if the number of dimensions is relatively small, but is very difficult to avoid biasing the fitted model
- Copulas model appears to be very powerful since the estimation of the marginals may be rather accurate and simple data dependencies assumptions seem to work very well
- Futher work is directed towards a better estimation of the tails of the marginal distributions of circuit performances and the study of more complex Copulas for modeling data dependencies

28

Thanks to:

- A. Bounceur: estimation with Gaussian and Copulas models
- A. Dhayni, L. Rufer, E. Simeu: pseudorandom MEMS BIST
- L. Rolíndez: ΣΔ converter BIST
- E. Simeu: estimation with Gaussian model and RF MEMS DFT
- H. Stratigopoulos: estimation with non-parametric Kernel
- ng: LNA BIST

RMS Group

29