Ampère
Unité Mixte de Recherche CNRS
Génie Électrique, Électromagnétisme, Automatique, Microbiologie environnementale et Applications

Conducted Interferences of Power Converters with Parametric Uncertainties in the Frequency Domain

Moisés FERBER

Christian VOLLAIRE, Laurent KRÄHENBÜHL,
Jean-Louis COULOMB, João A. VASCONCELOS

Doctorant/Lab. Ampère à l'ECL

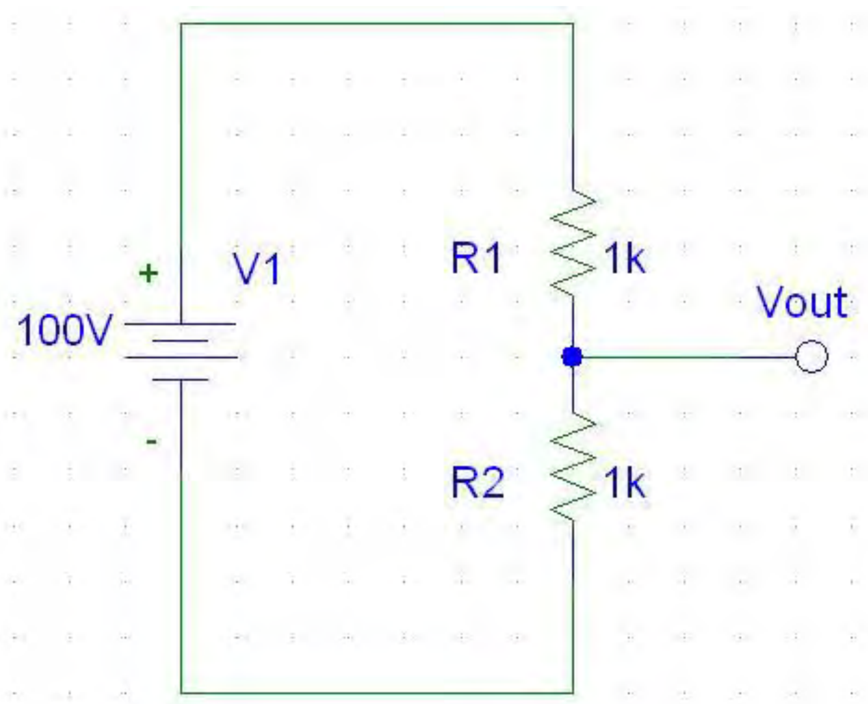
02 Février 2012

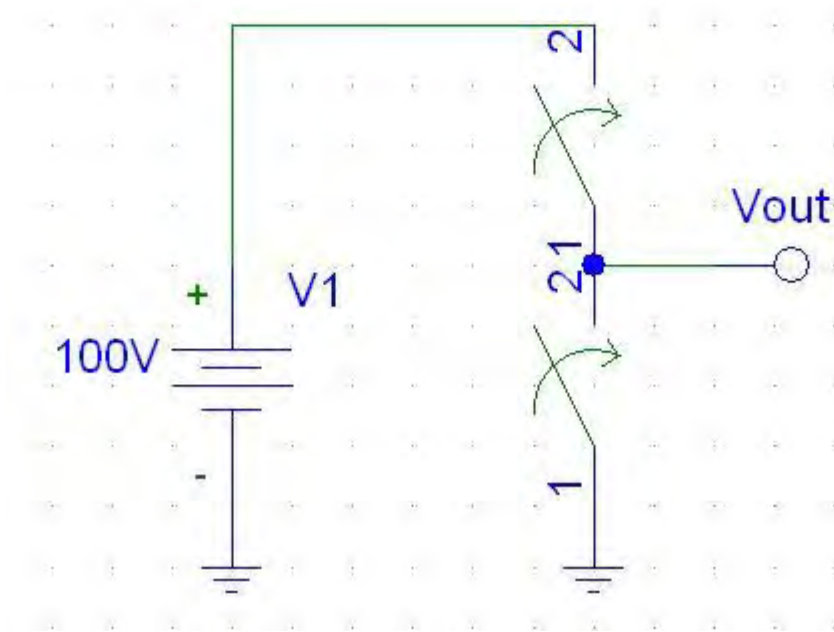
Contents

Introduction

Introduction

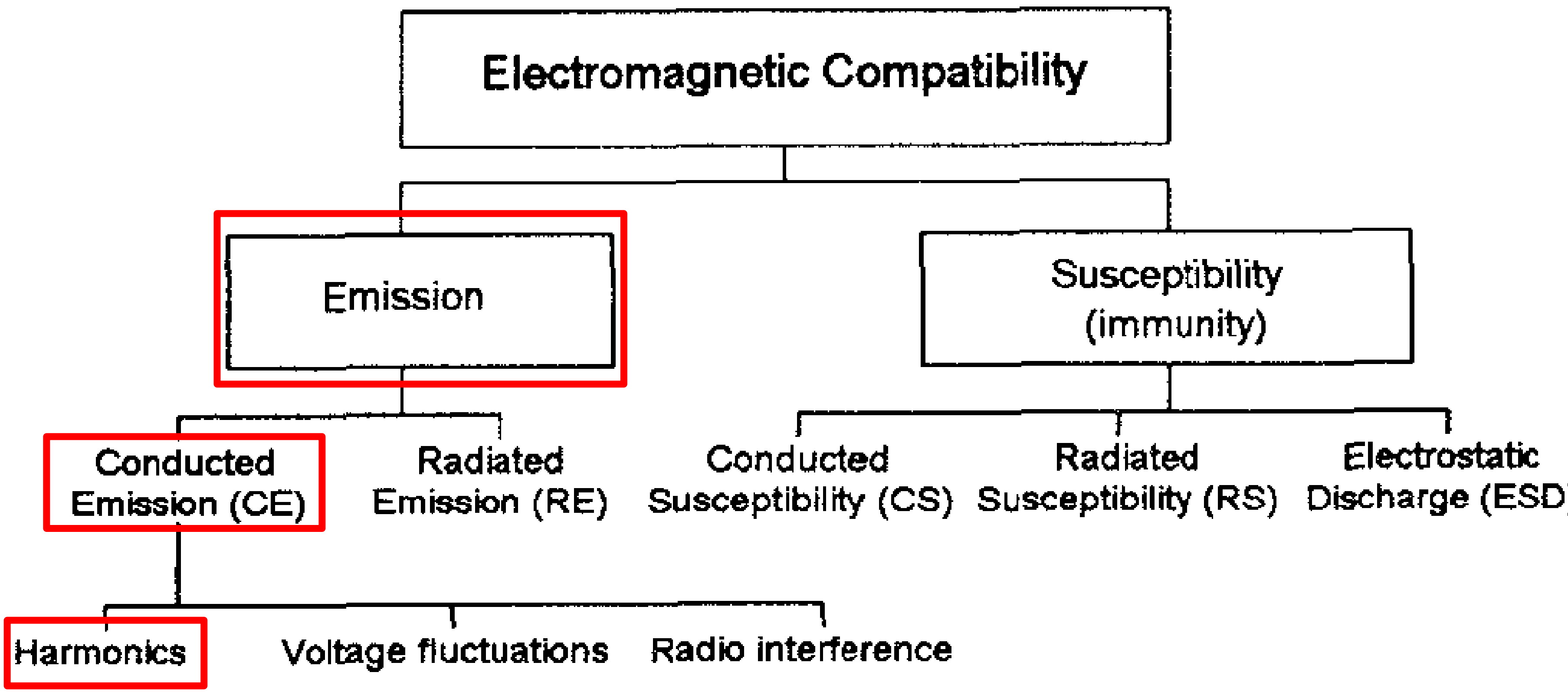
- Power Converter [1]





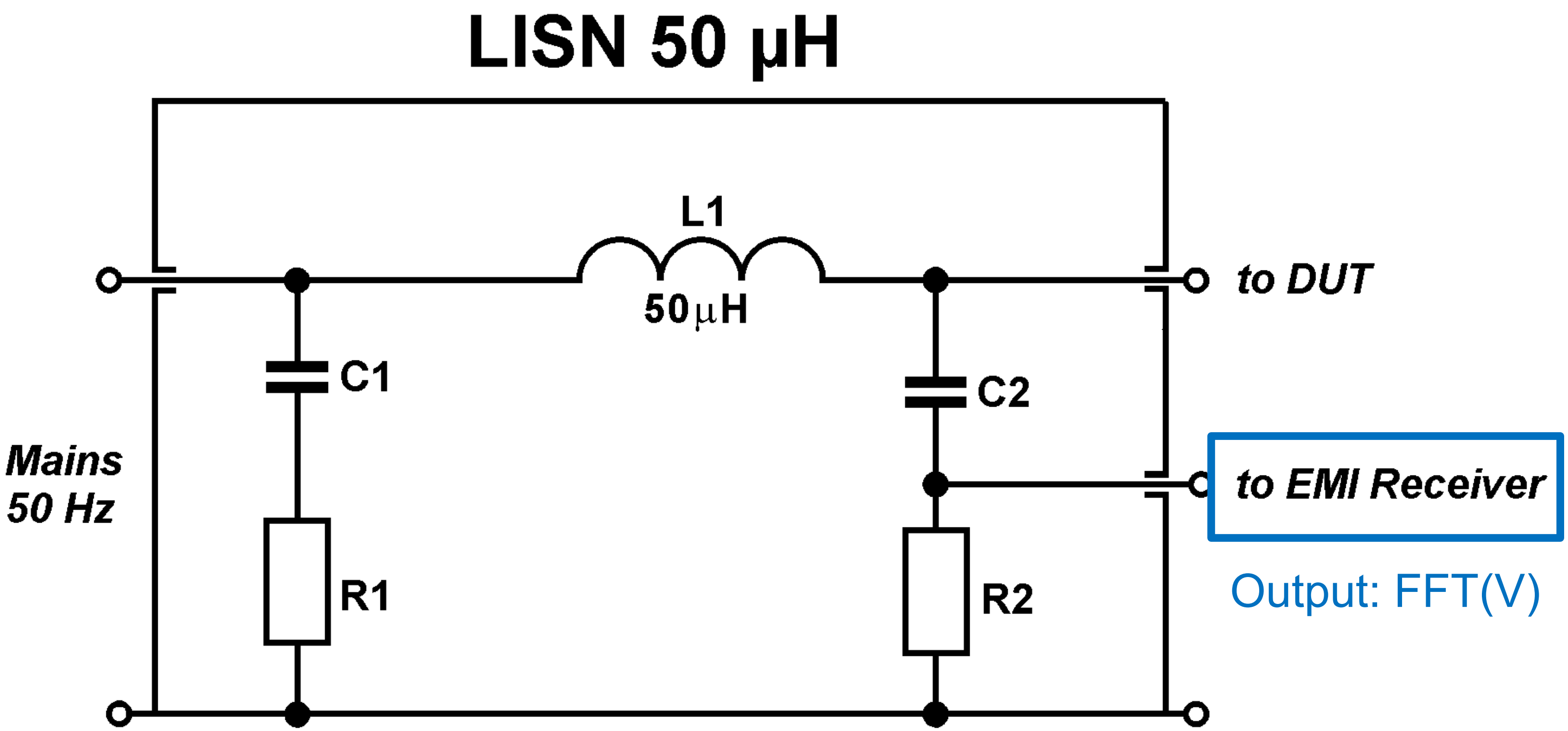
Introduction

- Electromagnetic Compatibility [2]



Introduction

LISN (Line Impedance Stabilization Network)

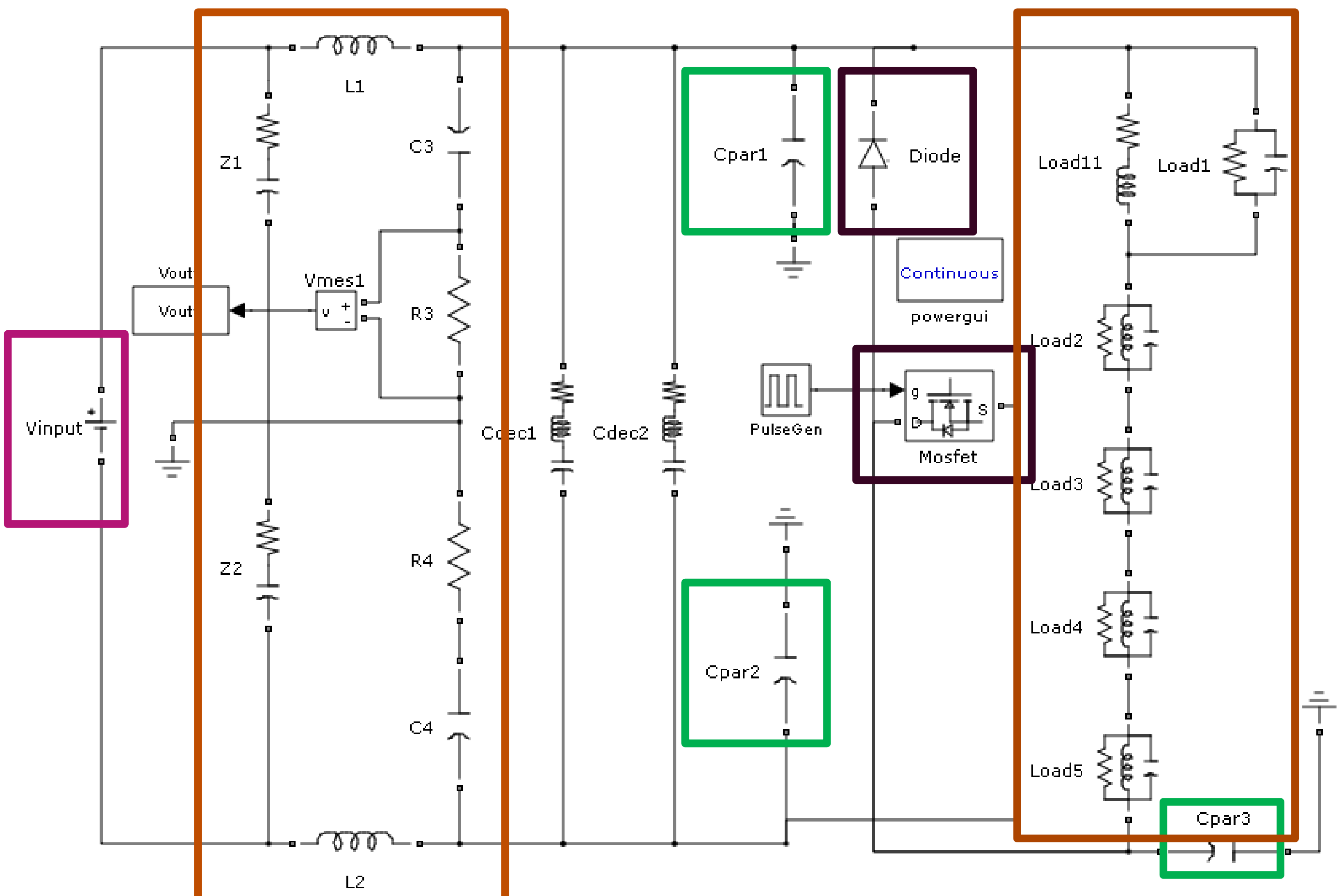


Introduction

- LISNs are multi-line low pass filter networks used for conducted emissions measurement. They are placed between the power mains and the EUT (Equipment Under Test) to stabilize line impedance, provide a 50 ohm RF connection, and eliminate unwanted RF signals from the line supply [3].

Introduction

- **Circuit Simulator (SimPower, SABER, SPICE, …)**



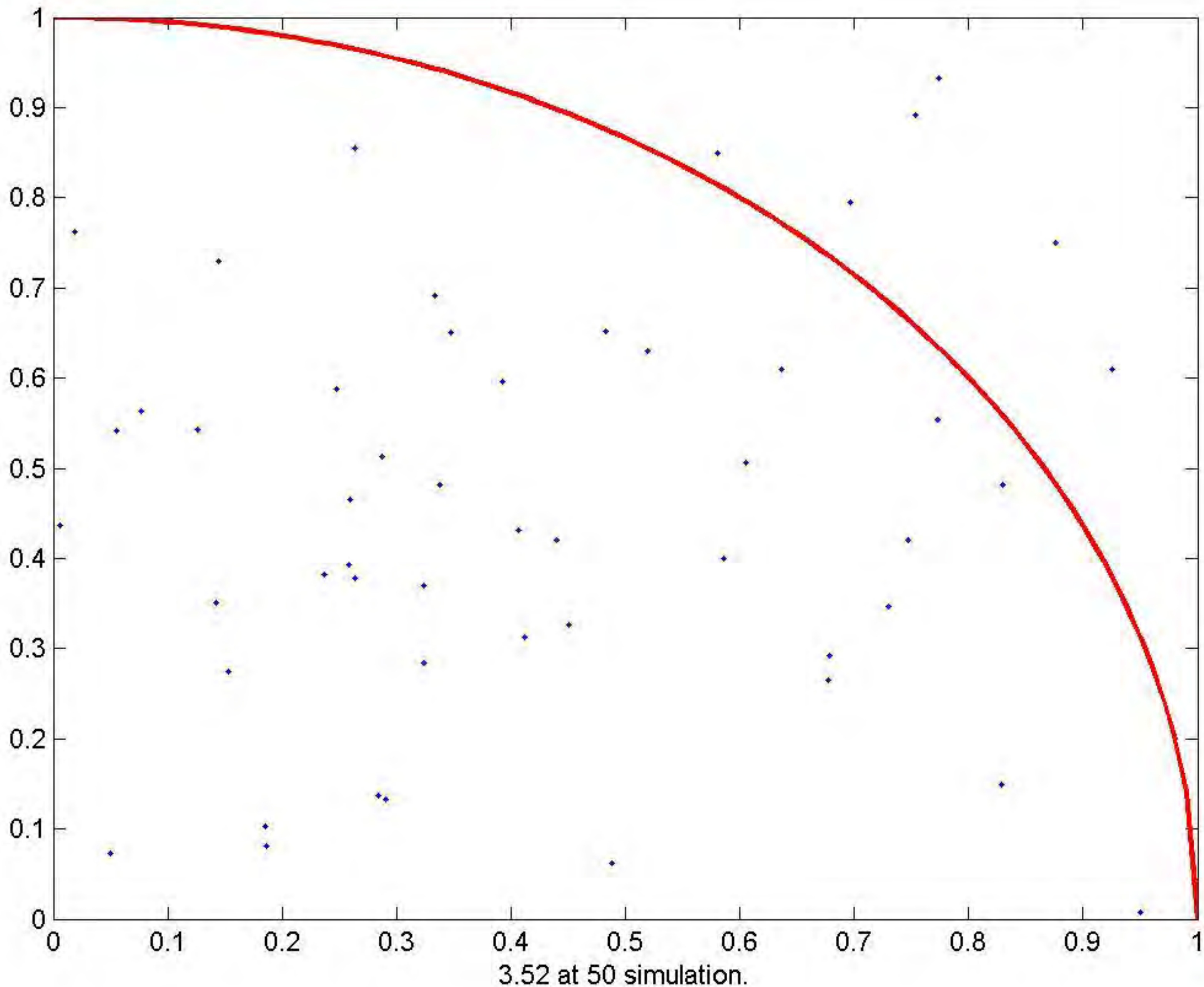
Introduction

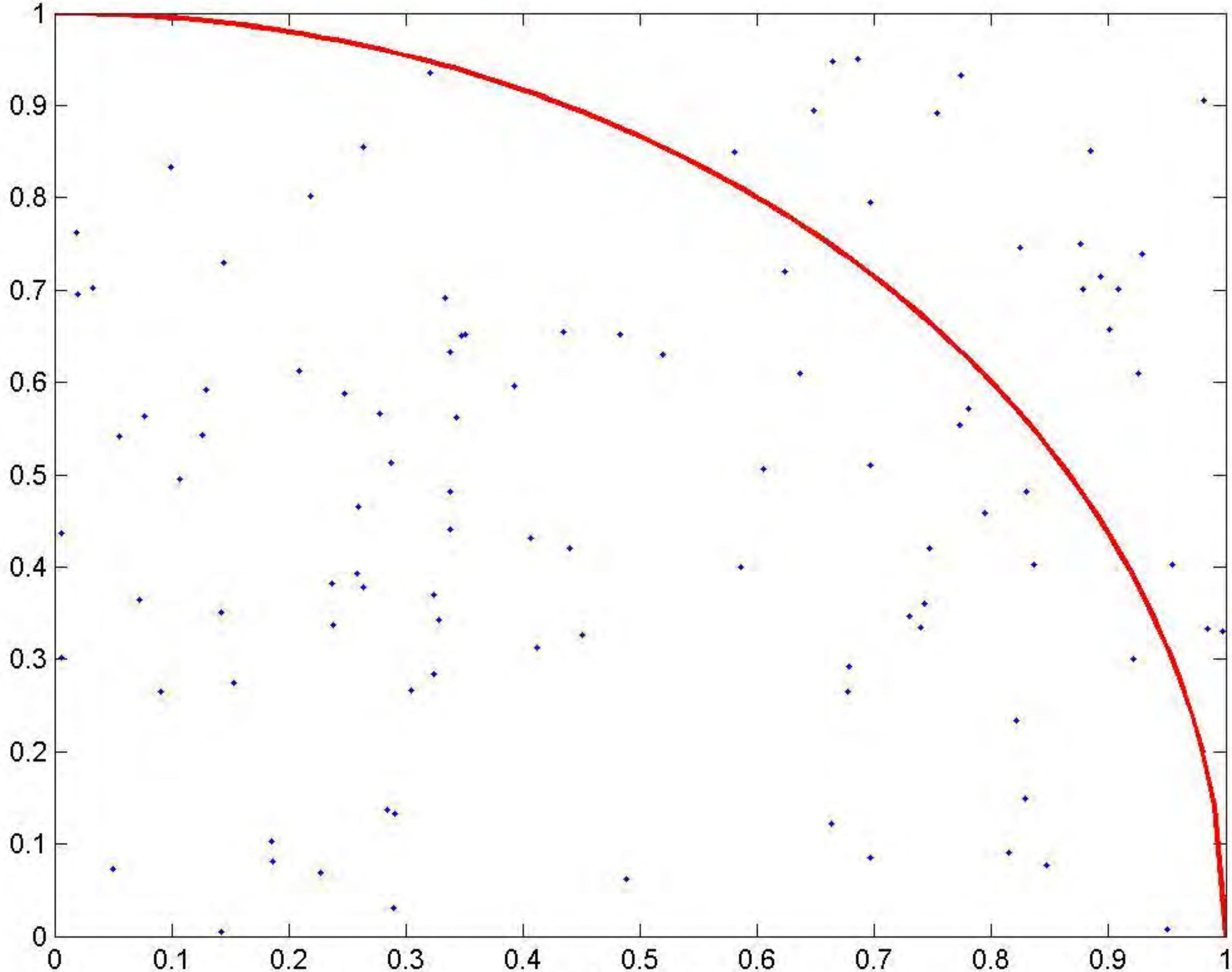
- Do we really know the exact values of the components?
- What about production dispersion?
- And ageing, temperature, humidity, etc. ?
- How do we take all these phenomena into account?

What exists already

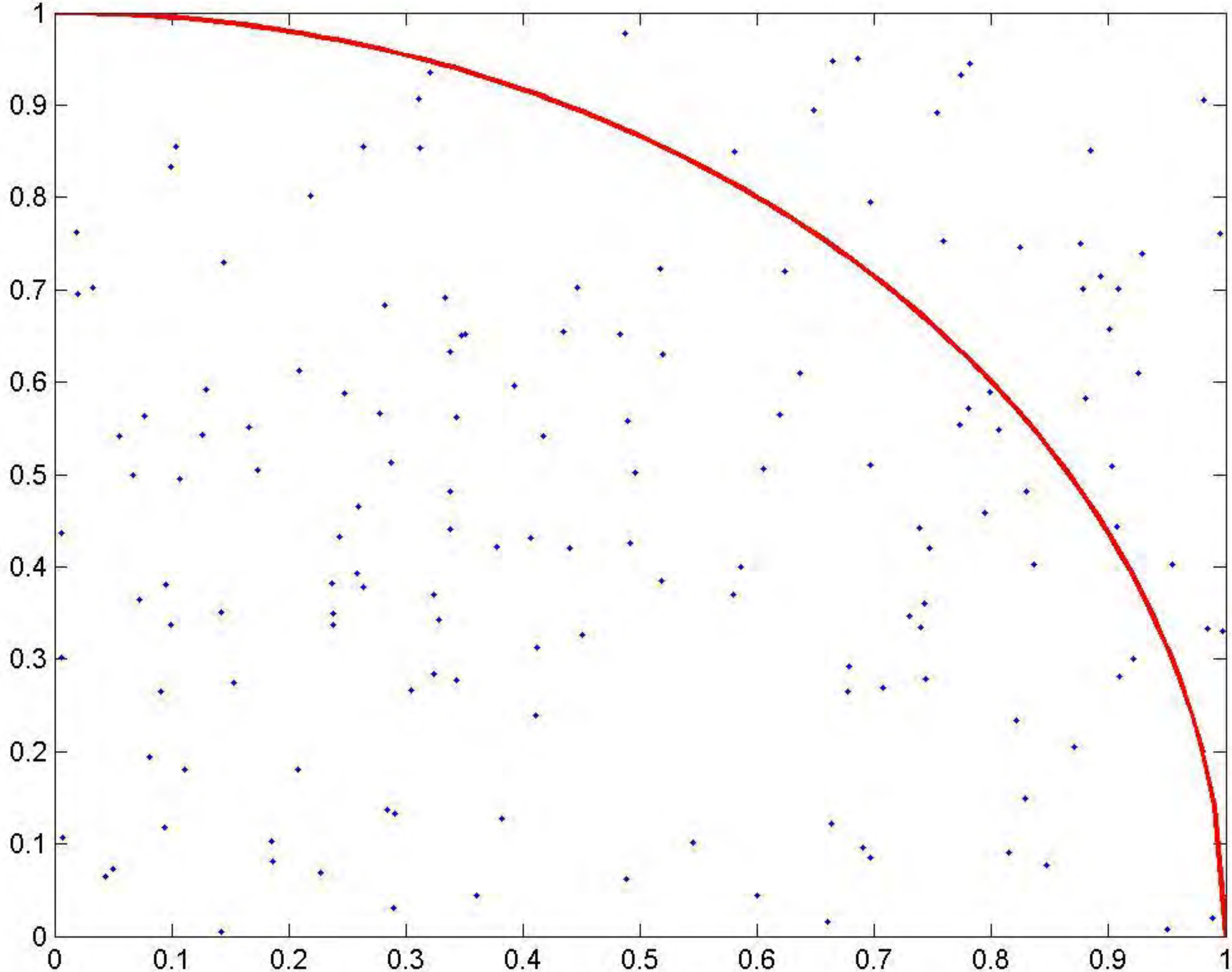
Monte Carlo Simulation

- Determine the Probability Density Function (PDF) of each unknown parameter.
- Generate many (10000 or more) sets of parameters following their PDFs.
- Solve the problem for all elements of the previous set.
- Estimate the output PDF (histogram or estimator).
- Estimation of the constant π using Monte Carlo (next)

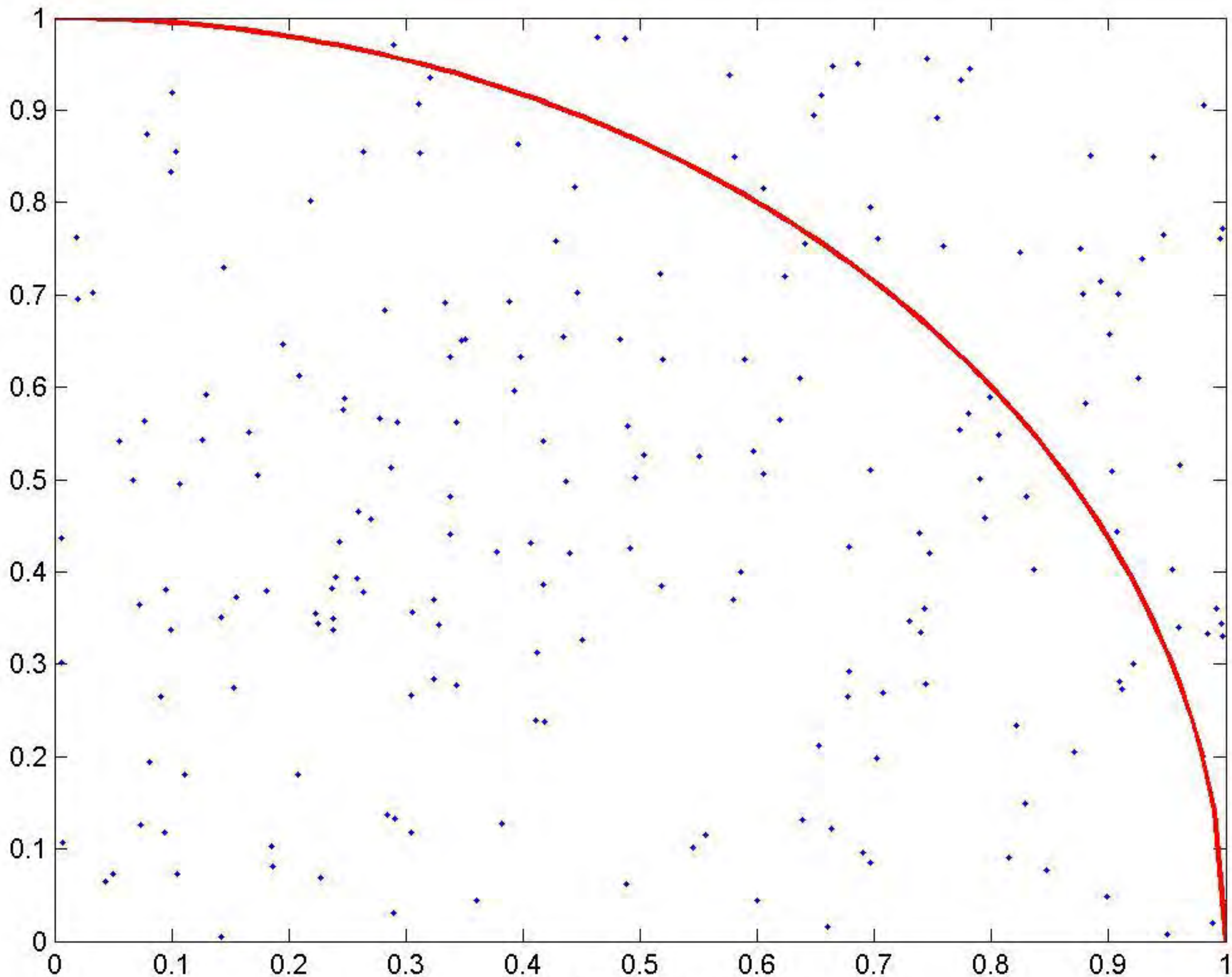

1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
3.52 at 50 simulation.



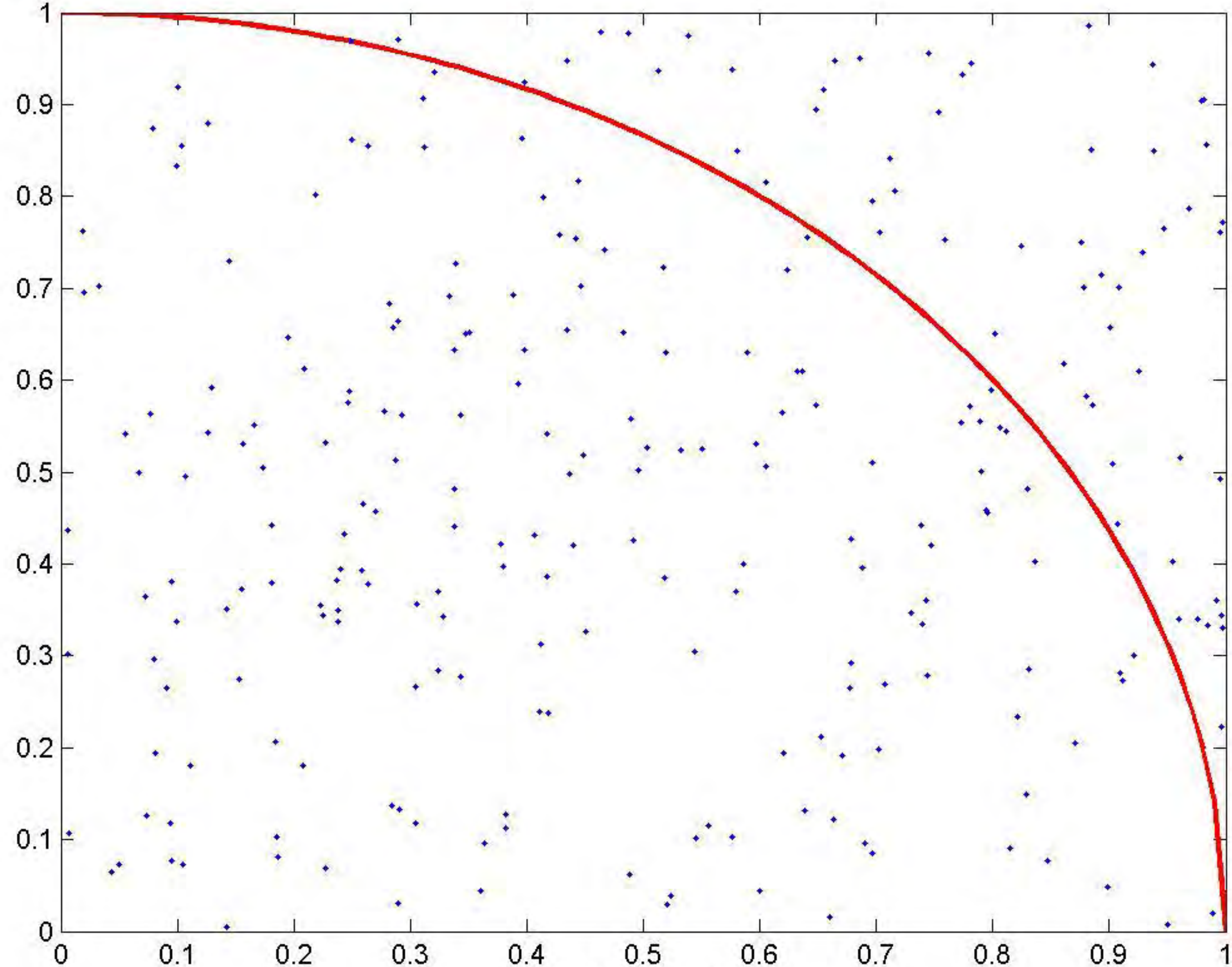
3.2 at 100 simulation.



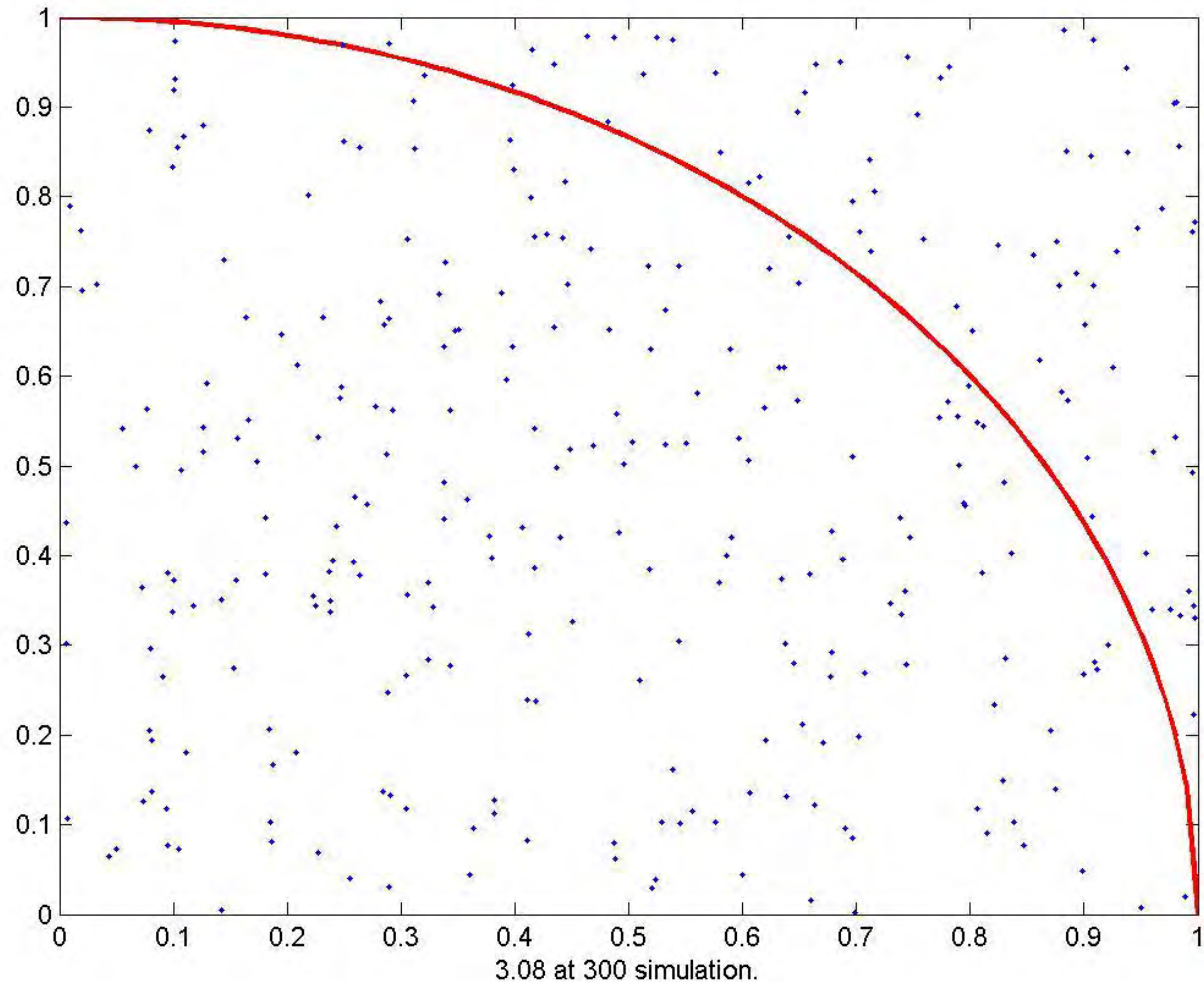
3.28 at 150 simulation.



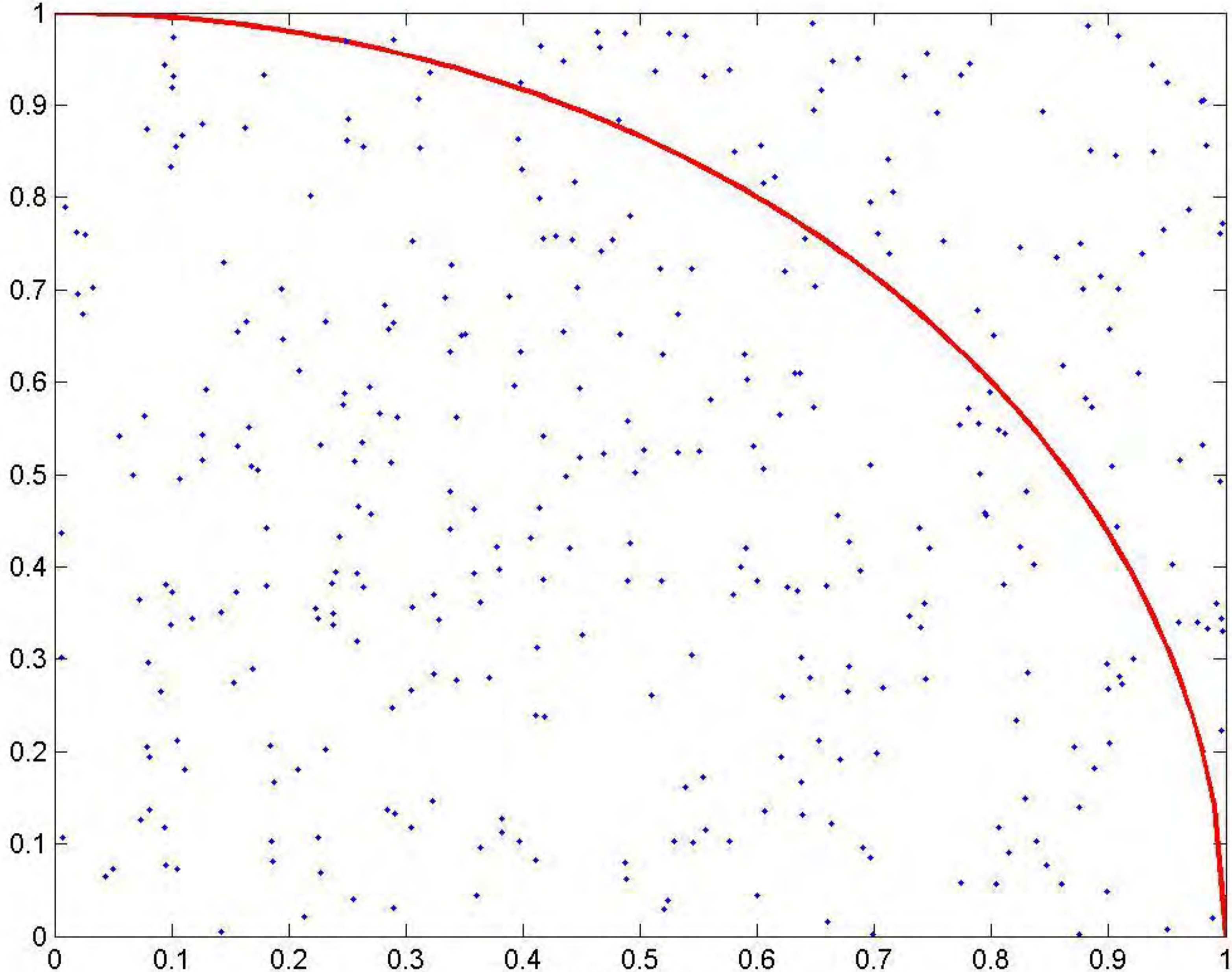
3.18 at 200 simulation.



3.056 at 250 simulation.



1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1
3.08 at 300 simulation.



3.1314 at 350 simulation.

Monte Carlo Simulation

- **Advantages: robust and easy to implement.**

- **Disadvantages: takes a LOT of time.**

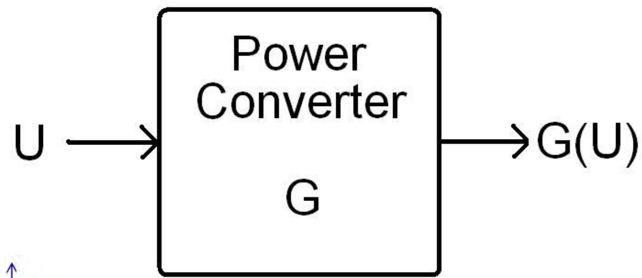
Collocation Methods

- Unscented Transform, Stroud, etc.
- Choose a few especific values of each parameter to simulate.
- Take a linear combination of the output to find the average and the variance.

Unscented Transform [4]

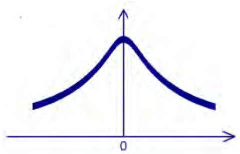
Parameters

R, L, C, …



Output

fft(Vlisn)



average

weights

ΔU

$$\bar{G} = E\{G(\bar{U} + \hat{u})\} = w_0 G(\bar{U}) + \sum_{i=1}^{N} w_i G(\bar{U} + S_i)$$

$$\sigma_G^2 = E\{(G(\bar{U} + \hat{u}) - \bar{G})^2\} = w_0 (G(\bar{U}) - \bar{G})^2 + \sum_{i=1}^{N} w_i (G(\bar{U} + S_i) - \bar{G})^2$$

CNRS ÉCOLE CENTRALE LYON INSA Lyon 1

Unscented Transform [4]

$$G(\bar{U} + \hat{u}) = G(\bar{U}) + \frac{dG}{du}\hat{u} + \frac{1}{2!}\frac{d^2G}{du^2}\hat{u}^2 + \frac{1}{3!}\frac{d^3G}{du^3}\hat{u}^3 + \cdots$$

$$w_0 = 1 - \sum_i w_i$$

$$\sum_i w_i S_i^k = E\{\hat{u}^k\}$$

Order	Normalized Sigma Points and Weights		
	Weights	**Sigma Points**	**Probability Distribution**
1	0.500 0.500	-0.577 0.577	$w(\hat{u}) = \begin{cases} \frac{1}{2} & \lvert\hat{u}\rvert < 1 \\ 0 & \lvert\hat{u}\rvert > 1 \end{cases}$
2	0.278 0.444 0.278	-0.775 0 0.775	
4	0.119 0.239 0.284 0.239 0.119	-0.906 -0.538 0 0.538 0.906	
1	0.500 0.500	-1 1	$w(\hat{u}) = \frac{1}{\sqrt{2\pi}} e^{-\frac{\hat{u}^2}{2}}$
2	0.167 0.666 0.167	-1.73 0 1.73	
4	0.011 0.222 0.534 0.222 0.011	-2.857 -1.356 0 1.356 2.857	

Unscented Transform [4]

Table 1: Minimum number of sigma points for the second and fourth orders approximation

n_{RV}	N_{eq} (second order)	N_s (second order)	N_{eq} (fourth order)	N_s (fourth order)
1	4	$2+1$	8	$4+1$
2	14	$5+1$	43	$15+1$
3	34	$9+1$	155	$39+1$
4	69	$14+1$	449	$90+1$
5	125	$21+1$	1121	$187+1$
6	209	$30+1$	2507	$359+1$
7	329	$42+1$	5147	$644+1$
8	494	$55+1$	9866	$1097+1$
9	714	$72+1$	16 874	$1788+1$
10	1000	$91+1$	30 887	$2807+1$

Table 2: Comparison between minimum sigma point numbers and the general set

Number of RVs	Minimum number of sigma points	Number of sigma points with set	Weight	
			1	2
1	$2+1$	$4+1$	$1/18$	$1/9$
2	$5+1$	$8+1$	$1/16$	$1/16$
3	$9+1$	$14+1$	$9/200$	$1/25$
4	$14+1$	$24+1$	$1/36$	$1/36$
5	$21+1$	$42+1$	$25/1568$	$1/49$
6	$30+1$	$76+1$	$9/1024$	$1/64$
7	$42+1$	$142+1$	$49/10368$	$1/81$
8	$55+1$	$272+1$	$1/400$	$1/100$
9	$72+1$	$530+1$	$121/61962$	$1/121$
10	$91+1$	$1044+1$	$1/1024$	$1/144$

Collocation Methods

- **Advantages: very fast.**

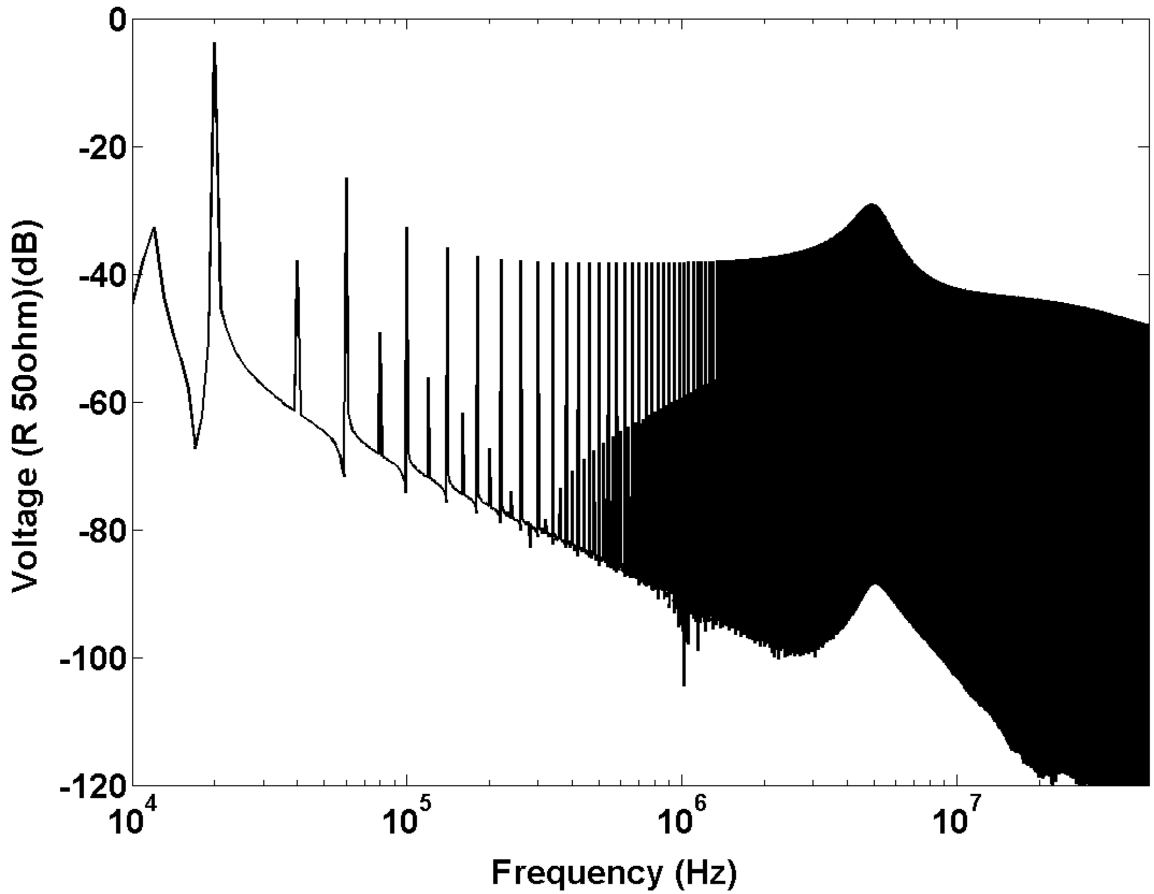
- **Disadvantages:**
  - **the result is a variance or other higher statistical moments, but not the PDF itself.**
  - **Can't guarantee precision (Taylor series).**
  - **Becomes slow with large number of unknown parameters.**

What we propose

What we propose

- We propose a methodology composed of the following steps:
- Output Reduction
- Sensitivity Analysis
- Model Reduction
- Transformation of Random Variables

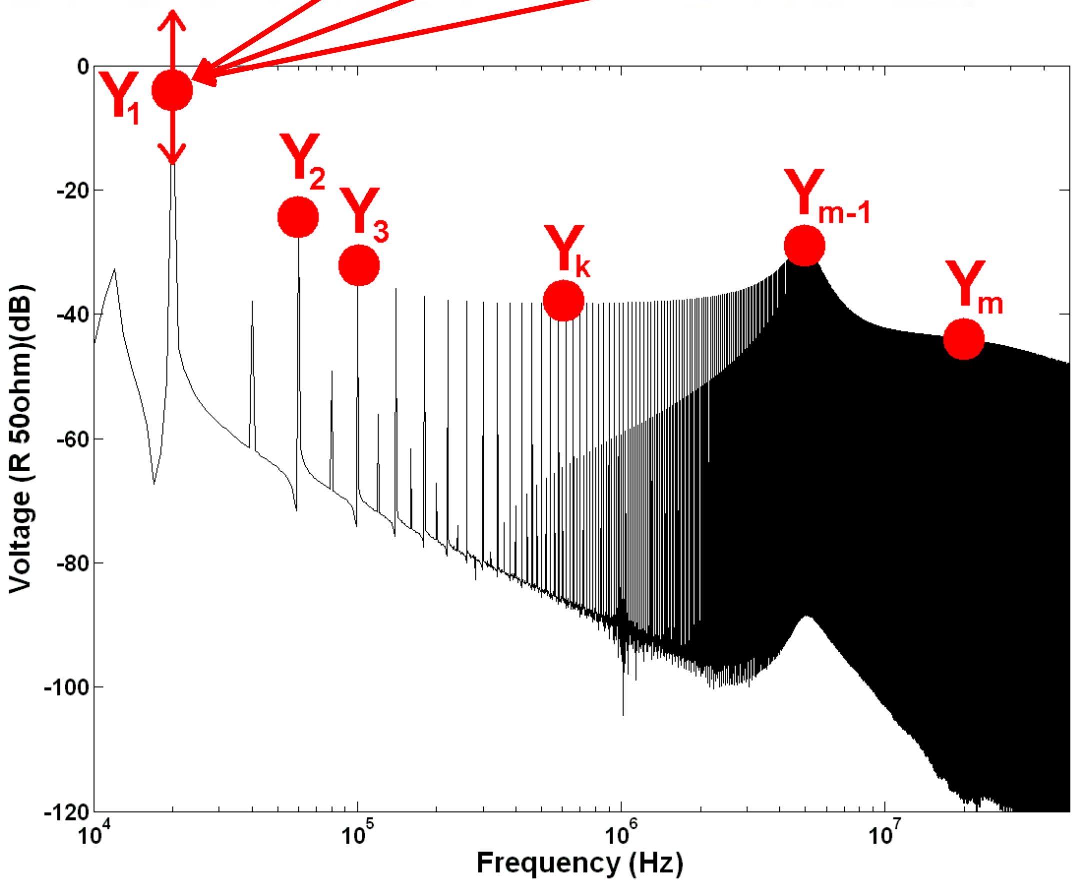
Output Reduction



$$\tilde{\boldsymbol{f}} = (f_1, f_2, \dots, f_m)\ G\ \ Y_k = G_k(X_1, X_2, \dots, X_n) = G_k(\boldsymbol{X})$$

Sensitivity Analysis

$$Y_k = G_k(X_1, X_2, \dots, X_n) = G_k(\boldsymbol{X})$$



Model Reduction

$$Y_k = G_k(X_1, X_2, X_3, X_4, X_5, X_6, \dots, X_n) = G_k(\boldsymbol{X})$$

$$\widetilde{Y_k} = \widetilde{G_k}(X_1, X_4, X_6) = \widetilde{G_k}(\widetilde{\boldsymbol{X}})$$

Transformation of Random Variables [5]

$\mathbf{X} = (X_1, X_2, \ldots, X_n)$ multivariate continuous, $\mathbf{Y} = (Y_1, Y_2, \ldots, Y_n) = \mathbf{g}(\mathbf{X})$. $\mathbf{g}$ is one-to-one, so that its inverse exists and is denoted by

$$\mathbf{x} = \mathbf{g}^{-1}(\mathbf{y}) = \mathbf{w}(\mathbf{y}) = (w_1(\mathbf{y}), w_2(\mathbf{y}), \ldots, w_n(\mathbf{y})).$$

Assume $\mathbf{w}$ have continuous partial derivatives, and let

$$J = \begin{vmatrix} \frac{\partial w_1(\mathbf{y})}{\partial y_1} & \frac{\partial w_1(\mathbf{y})}{\partial y_2} & \cdots & \frac{\partial w_1(\mathbf{y})}{\partial y_n} \\ \frac{\partial w_2(\mathbf{y})}{\partial y_1} & \frac{\partial w_2(\mathbf{y})}{\partial y_2} & \cdots & \frac{\partial w_2(\mathbf{y})}{\partial y_n} \\ \vdots & \vdots & & \vdots \\ \frac{\partial w_n(\mathbf{y})}{\partial y_1} & \frac{\partial w_n(\mathbf{y})}{\partial y_2} & \cdots & \frac{\partial w_n(\mathbf{y})}{\partial y_n} \end{vmatrix}$$

Then

$$f_{\mathbf{Y}}(\mathbf{y}) = f_{\mathbf{X}}(\mathbf{g}^{-1}(\mathbf{y}))|J|.$$

for $\mathbf{y}$ s.t. $\mathbf{y} = \mathbf{g}(\mathbf{x})$ for some $\mathbf{x}$, and $f_{\mathbf{Y}}(\mathbf{y}) = 0$, otherwise.

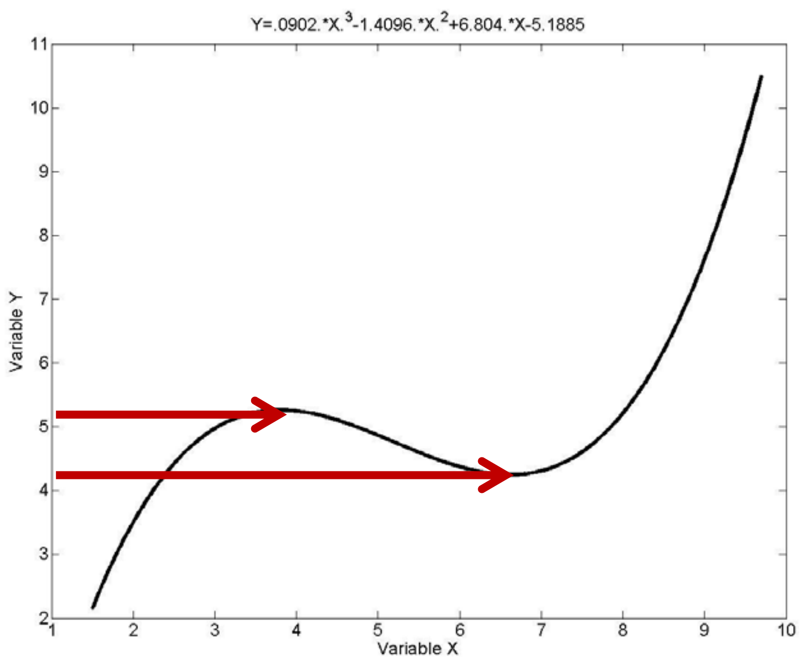
Transformation of Random Variables [5]

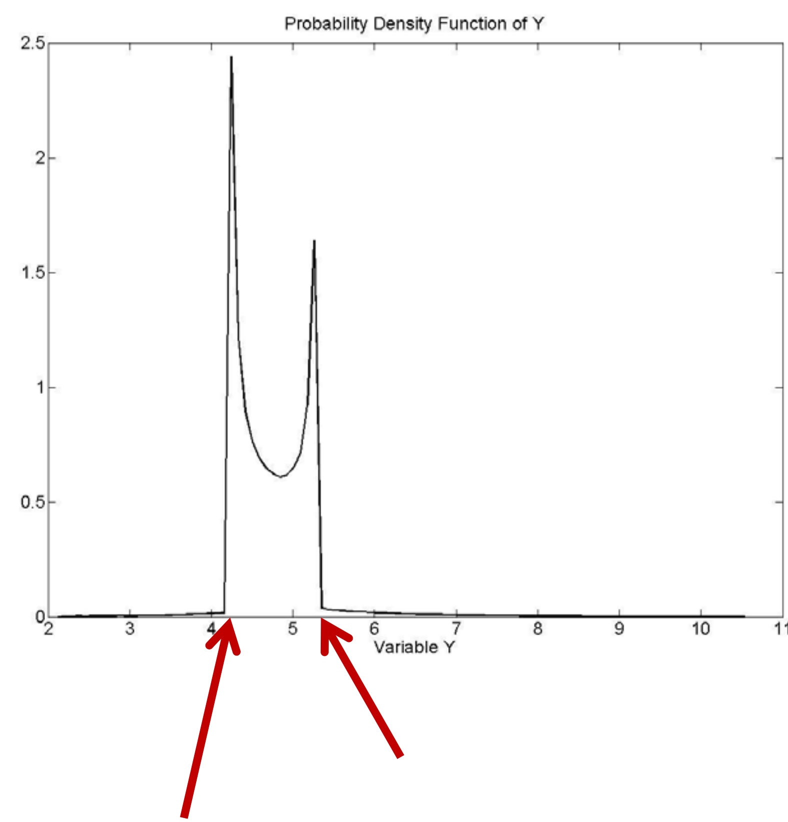
Let Y be a function of the random variables $X_1, X_2, \ldots, X_n$.

1. Find the region $Y \leq y$ in the $(x_1, x_2, \ldots, x_n)$ space.
2. Find $F_Y(y) = P(Y \leq y)$ by summing the joint pmf or integrating the joint pdf of $X_1, X_2, \ldots, X_n$ over the region $Y \leq y$.
3. (for continuous case) Find the pdf of Y by differentiating $F_Y(y)$, i.e., $f_Y(y) = \frac{d}{dy} F_Y(y)$.

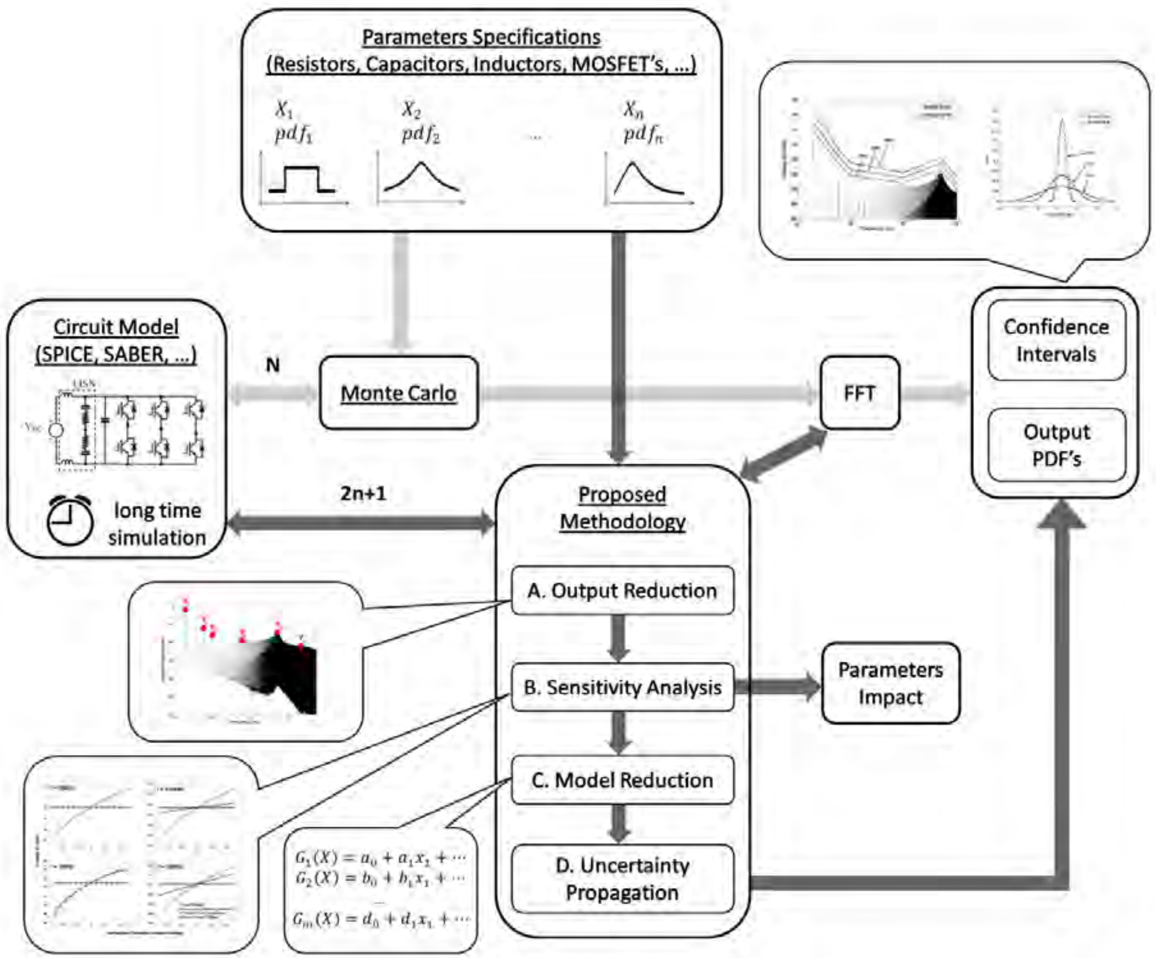
Note. It can be generalized to multivariate $\mathbf{Y} = (Y_1, Y_2, \ldots, Y_m)$.

Transformation of R. Variables [5]



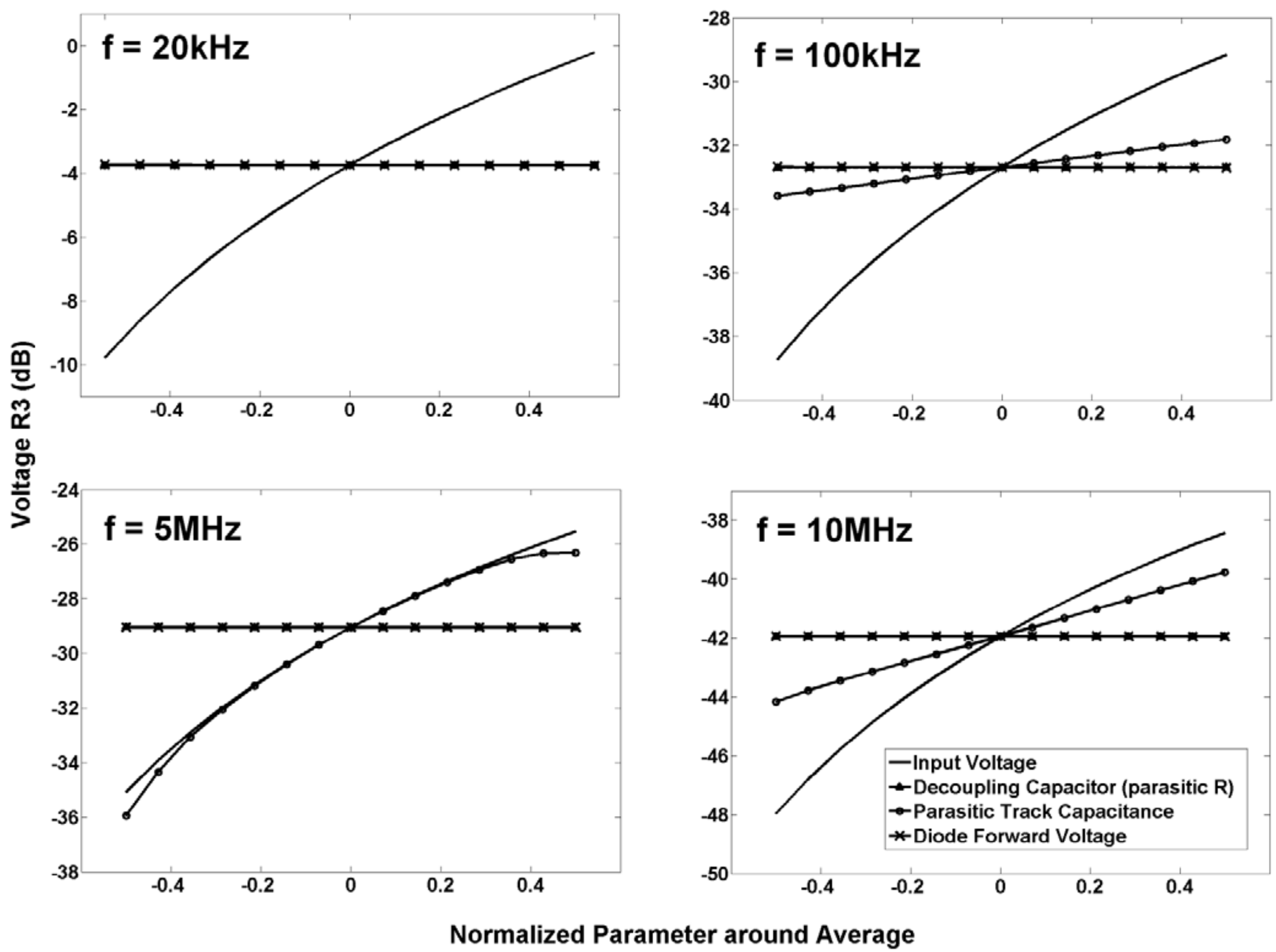


Overview

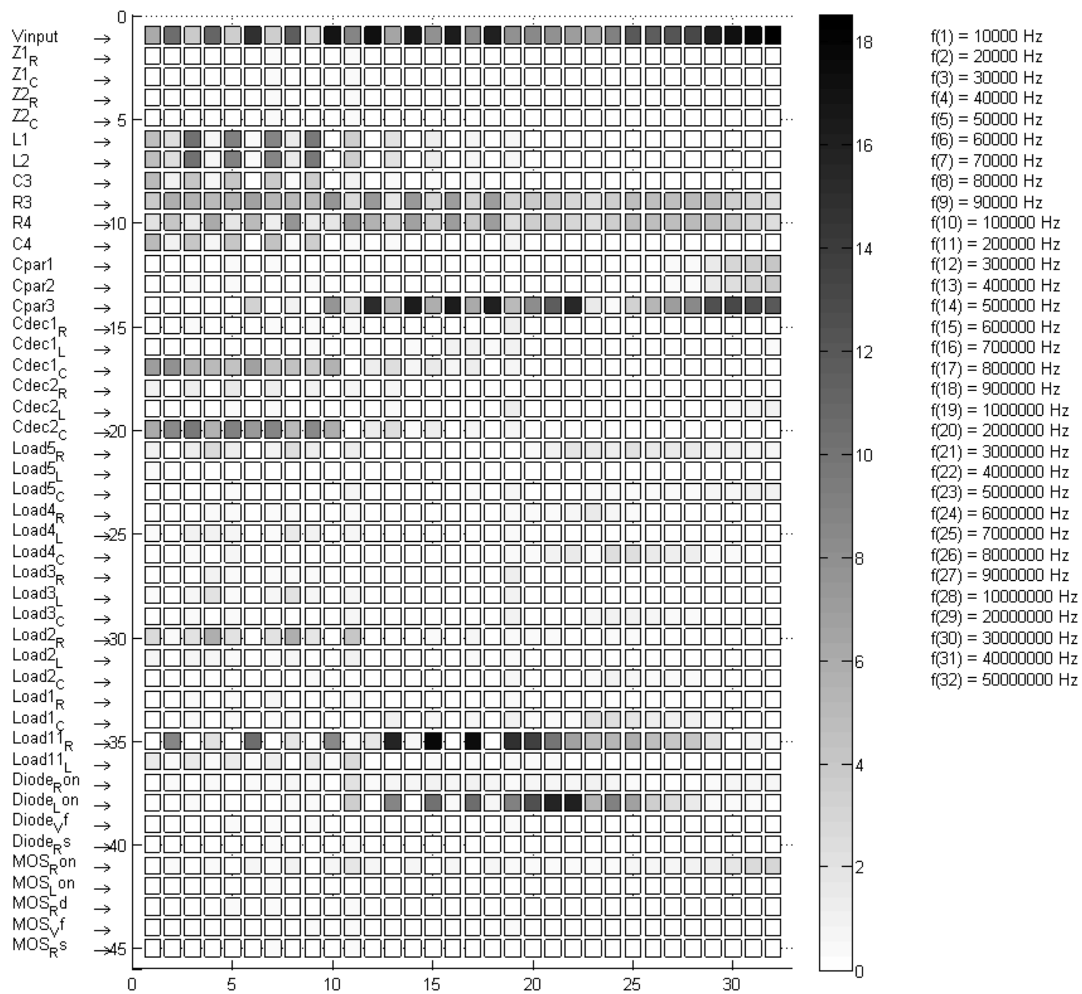

Parameters Specifications
(Resistors, Capacitors, Inductors, MOSFET's, ...)
X_1 pdf_1
X_2 pdf_2
...
X_n pdf_n
Circuit Model
(SPICE, SABER, ...)
long time simulation
N
Monte Carlo
FFT
Confidence Intervals
Output PDF's
2n+1
Proposed Methodology
A. Output Reduction
B. Sensitivity Analysis
C. Model Reduction
D. Uncertainty Propagation
Parameters Impact
$G_1(X) = a_0 + a_1x_1 + \cdots$
$G_2(X) = b_0 + b_1x_1 + \cdots$
$G_m(X) = d_0 + d_1x_1 + \cdots$

Results

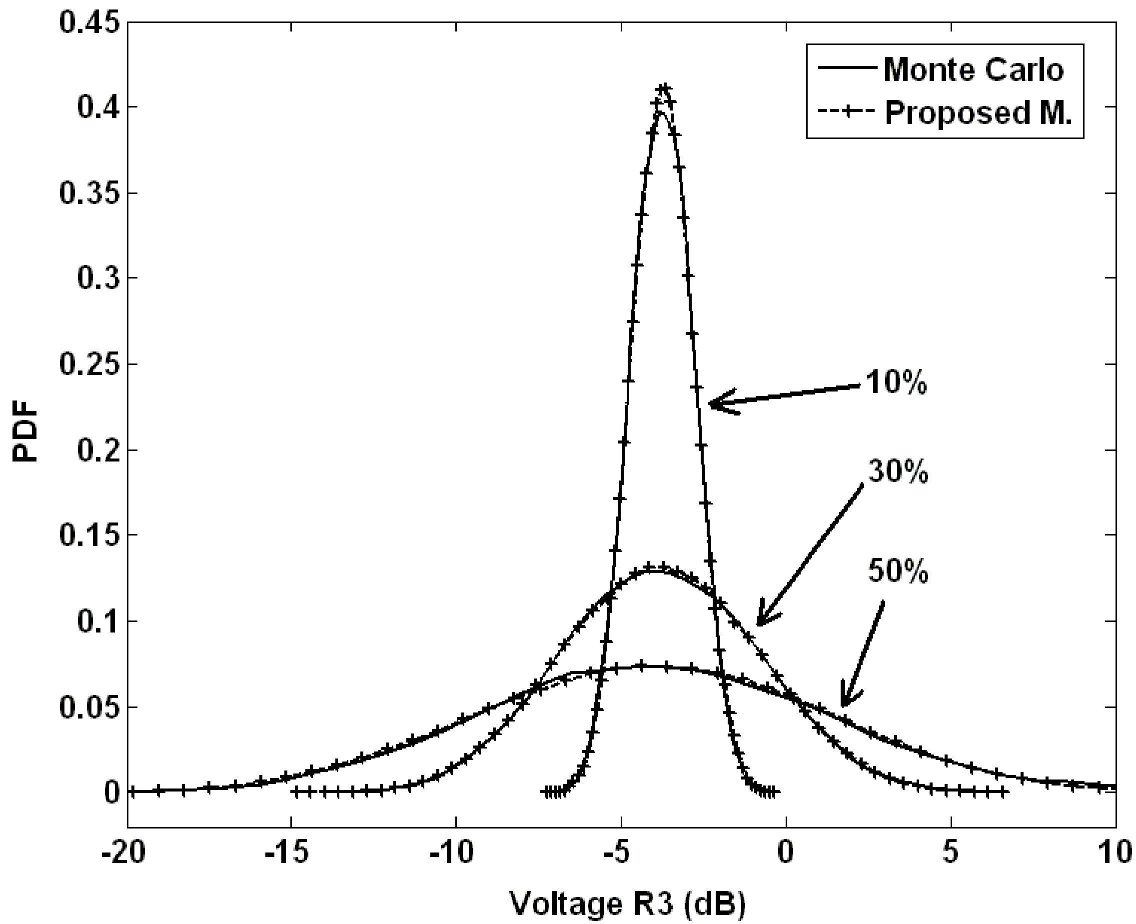
Results – Sensitivity Analysis



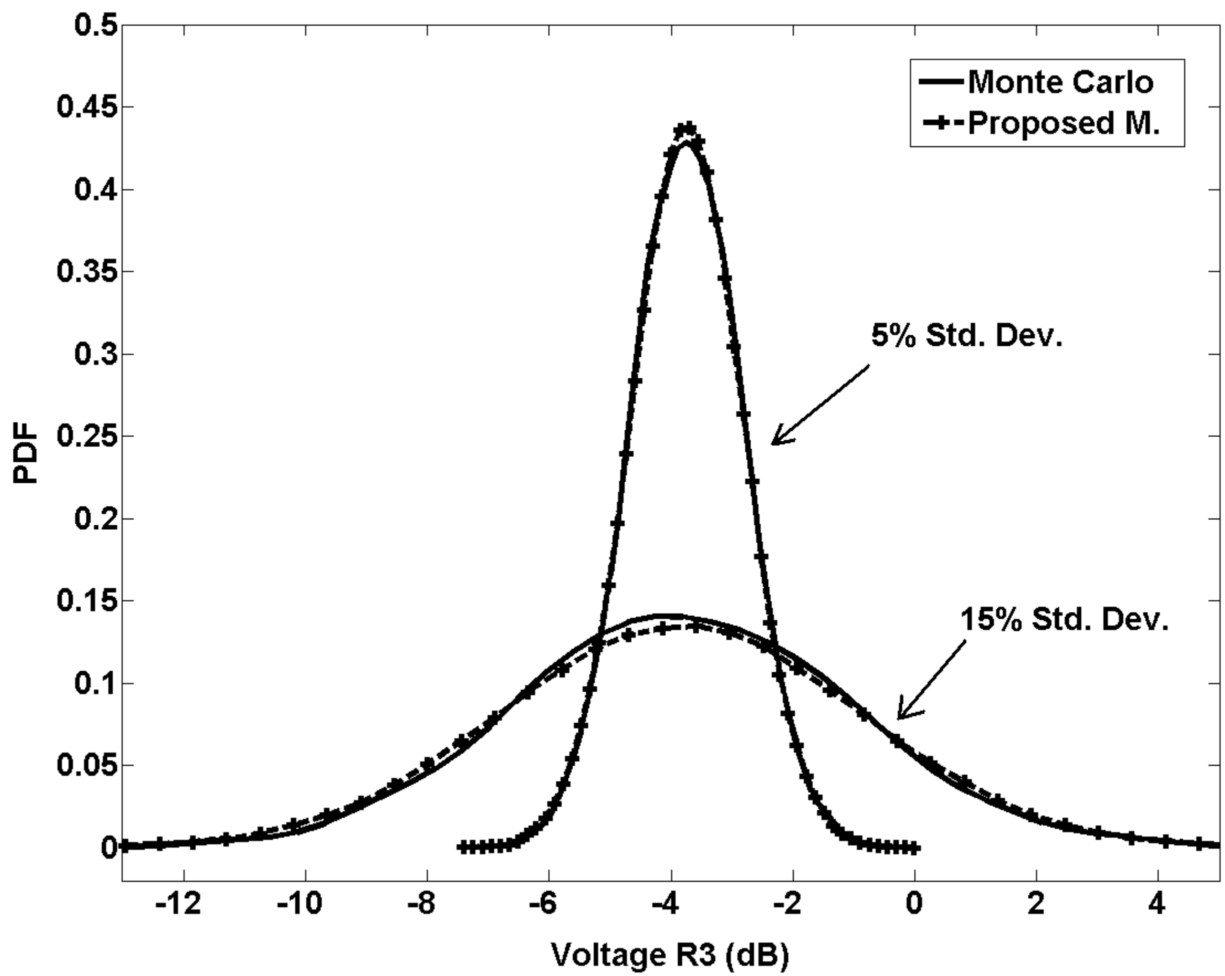
Results – Impact of Variables



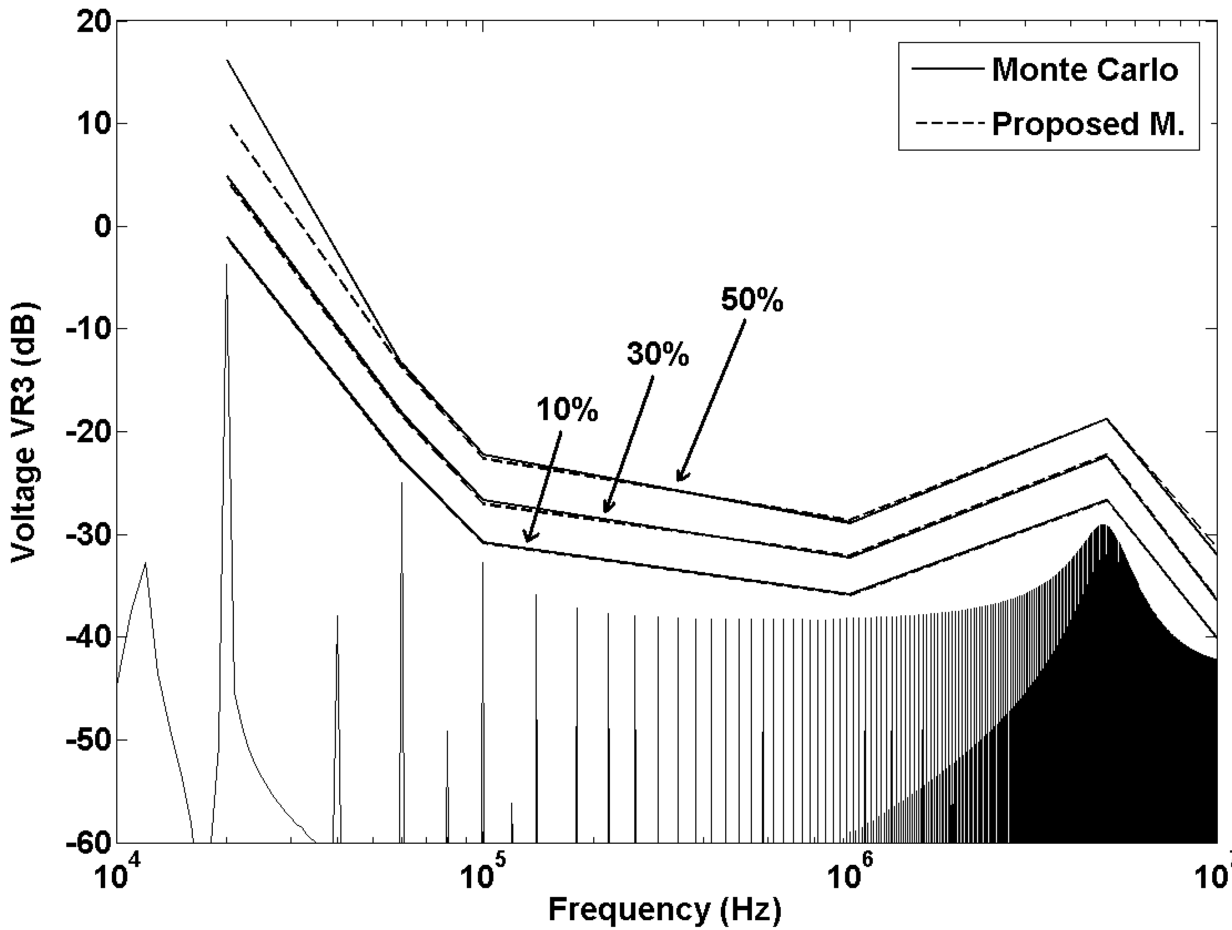
Results – Output PDFs (normal input) @20kHz



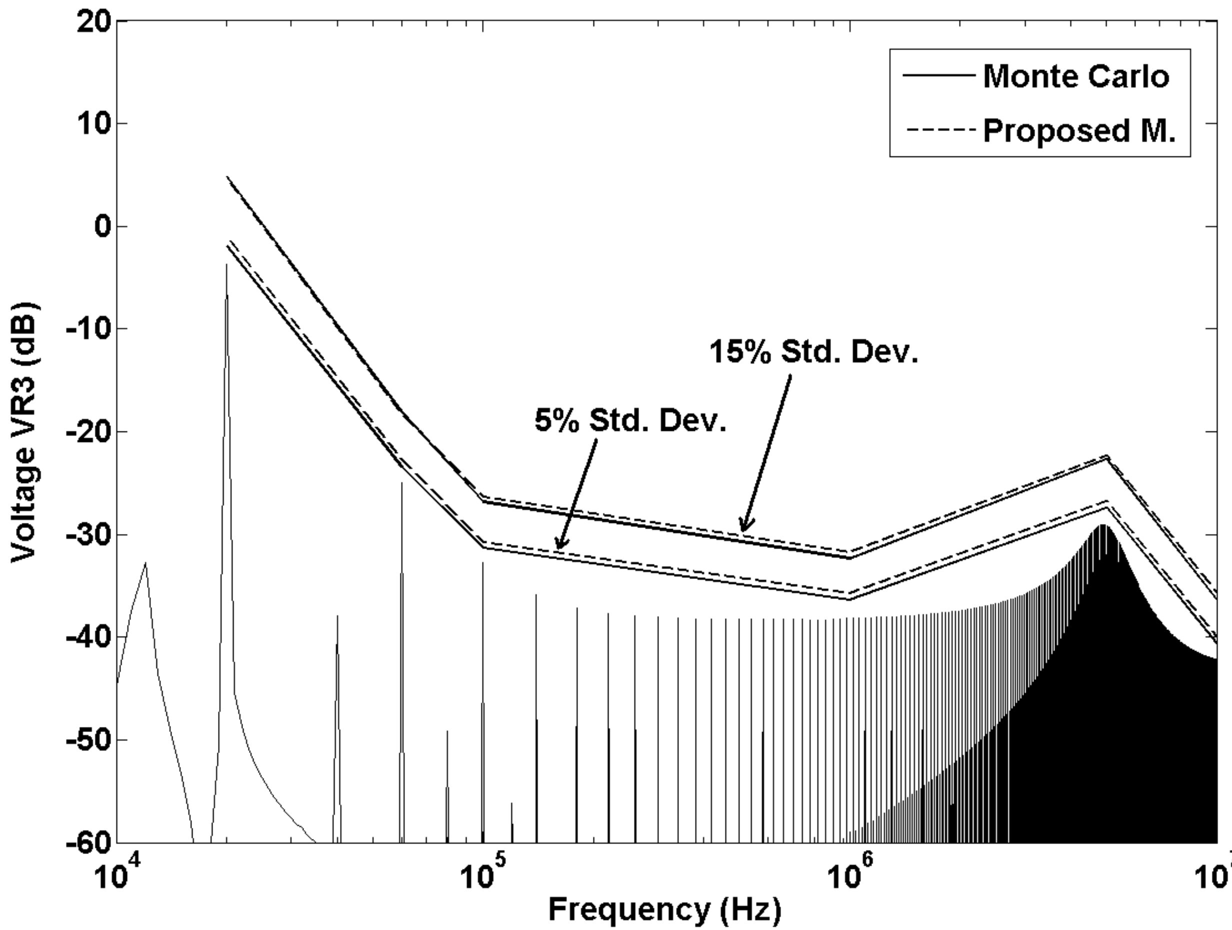
Results – Output PDFs (uniform input) @20kHz



Results – Confidence Intervals 99.9%



Results – Confidence Intervals 99.9%



Future Research

- **Polynomial Chaos**

(Drawback: not efficient for large N of variables)

- **Random Matrix Theory (Edelman 2005)**

- **Heaviside and Dirac Generalized Functions**

(Shamilov 2006)

References

- [1] http://product-image.tradeindia.com/00381377/b/3/AC-To-DC-Power-Converter-Multi-Output.jpg
- [2] Redl, R.; , "Power electronics and electromagnetic compatibility," Power Electronics Specialists Conference, 1996. PESC '96 Record., 27th Annual IEEE , vol.1, no., pp.15-21 vol.1, 23-27 Jun 1996.
- [3] http://www.ets-lindgren.com/pdf/3810-2.pdf
- [4] 1. R. A X. de Menezes et al., "Efficient computation of stochastic EM problems using unscented transforms", IET Sci. Meas. Technol., vol. 2(2), pp. 88-95, 2008.
- [5] 02_Probability_part3.PDF