Reliability Analysis of a Diplexer with Improved Quality for the Prediction of Failure Probabilities

Philippe Leduc – STMicroelectronics

Peter Krenz, Roland Niemeier – Ansys

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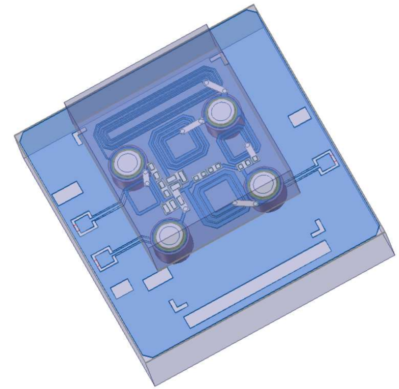
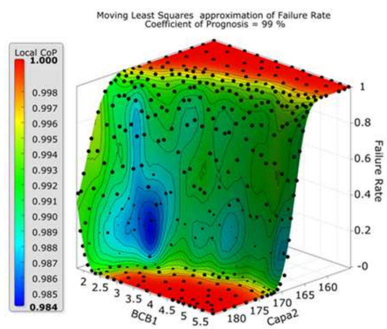
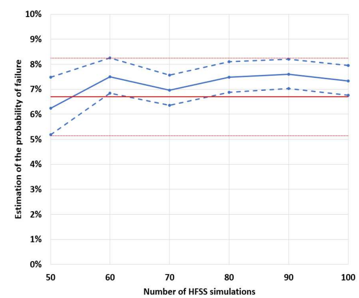
Agenda

- Reliability and Failure Probabilities: Motivation and Challenges
- The Diplexer Example
  - A Monte Carlo Reference Study
  - Robustness Evaluation using Latin Hypercube Sampling
  - Reliability Analysis with Fragility Surfaces
  - A Bayesian Model for Failure Risk Analysis
  - Application of the Bayesian Model to the Diplexer Case
  - A Sensitivity Analysis of Failure Probabilities
- Summary and Outlook

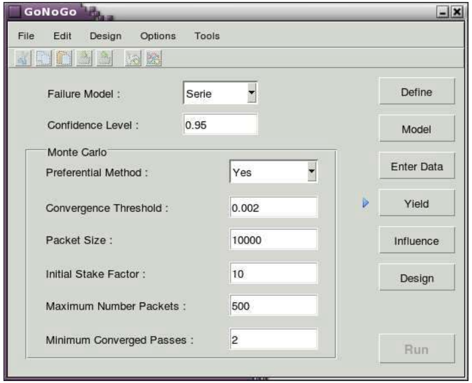


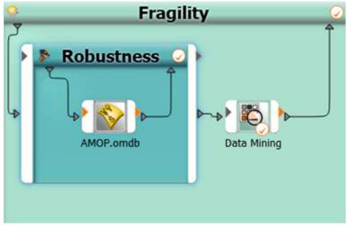


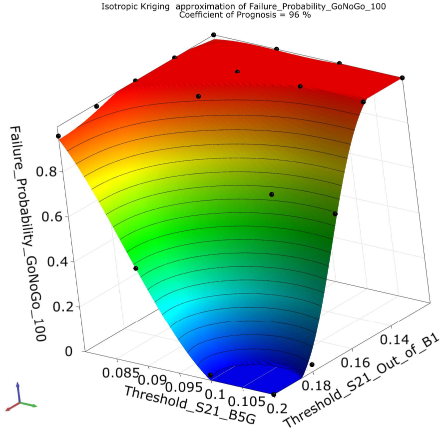


Reliability and Failure Probabilities

- Reliability is key for safety and for robust optimized products
- The key metric for reliability assessment is the probability of failure, which can be computed considering the variations, tolerances of the input parameters. Failure is usually defined by limits.
- Metamodels of failure probabilities require necessarily an estimation of the prediction quality
- These metamodels can be helpful in the whole product lifecycle from the early phase (layout / manufacturing) to product services (for example a product approaching failure limits during its lifetime)







The Diplexer Example

- A diplexer is a passive device sharing a single communication channel for two separate frequency bands, in our case 2G and 5G bands

- 12 output responses with defined limit values:
  Failure is defined either when a loss exceeds a limit or when an attenuation is too weak

- From a previous sensitivity analysis, 4 geometric parameters can impact the product performances:
  Capa2, **Meta2**, **BCB1**, **Meta1**

Table 2. Electrical characteristics and RF performance (T_{amb} = 25 °C)

Symbol	Parameter	Test condition	Value			Unit
			Min.	Typ.	Max.	
Pass band						
f	2 G band pass		2400		2483.5	MHz
	5 G band pass		4900		5850	MHz
Z	Nominal impedance			50		Ω
Return loss		All ports			-17	dB
S21	2 G to antenna insertion loss	2400 to 2483.5 MHz		0.6	0.7	dB
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Attenuation						
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Out of band attenuation						
S21	2 G to antenna attenuation	5850 to 7000 MHz	15			dB
		7000 to 9500 MHz	7			
		9800 to 10500 MHz	16			
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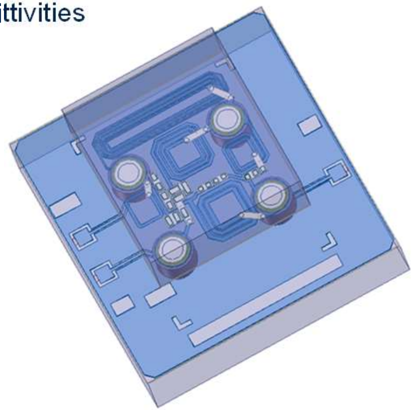
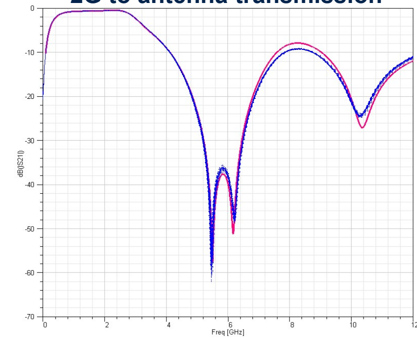
Technology cross section

Numerical Model

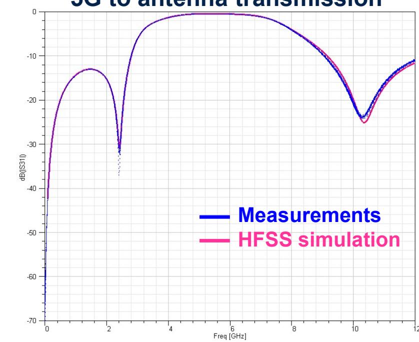
- Electromagnetics physics ⇒ Ansys HFSS solver
- Parameterized geometric 3D model
  - Variables : thicknesses, conductivities, permittivities
  - **Enable parametric studies**
- Simulation results show excellent agreement with measurements
- Simulation statistics
  - Elapsed time ~ 5 hours (8 cores)
  - Memory ~ 25 Gb
- A brute-force Monte Carlo simulation is not effective



2G to antenna transmission

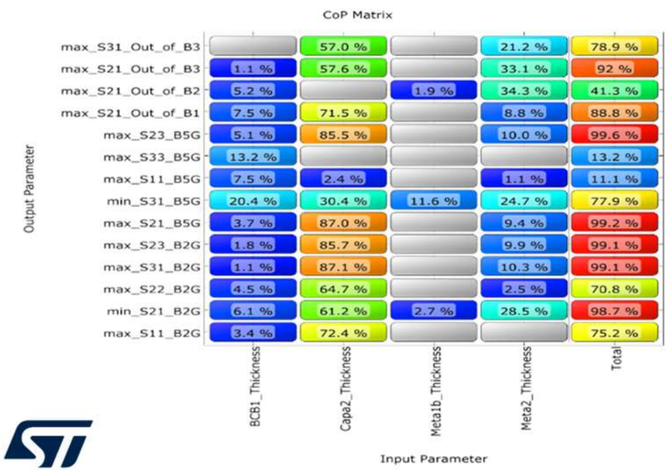


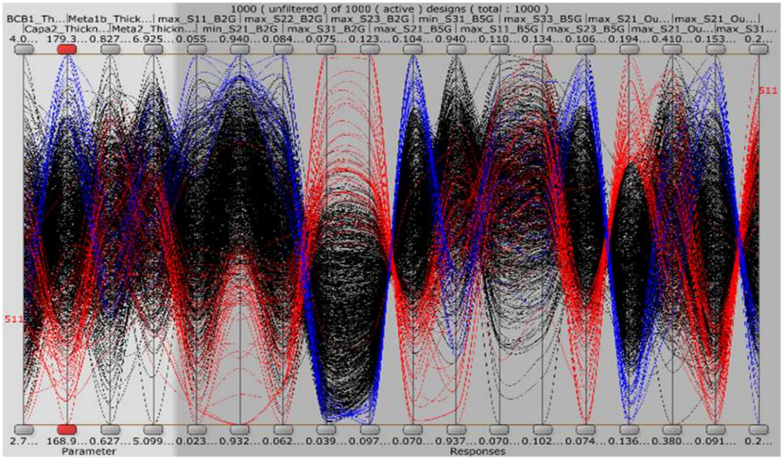
5G to antenna transmission



The Monte Carlo Reference Study

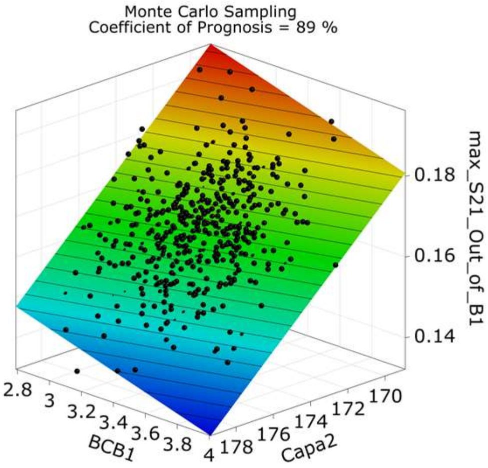
- 1000 simulations, 4 input parameters (geometric thicknesses BCB1, Capa2, Meta1b, Meta2)
- Gaussian distributions based on manufacturing tolerances
- Designs failed either for max_S21_B5G (blue lines in Parallel Coordinate Plots) or for max_S21_Out_of_B1 (red lines). Failure Rates 4.8% for max_S21_Out_of_B1 and 1.9% for max_S21_B5G; Total Failure Rate is 6.7%.
- High Coefficient of Prognosis (CoP) for these output parameters

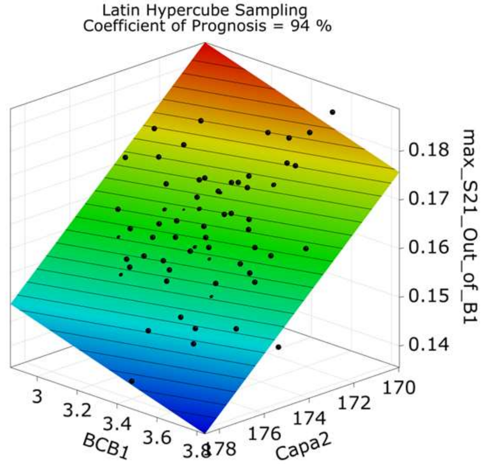


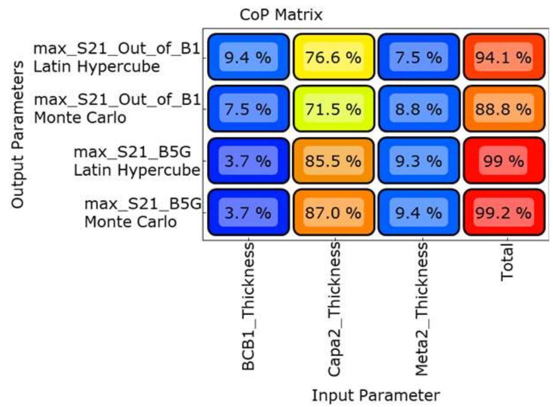


Robustness Evaluation using Latin Hypercube Sampling

- 100 simulations using Latin Hypercube Design of Experiment instead of 1000 simulations
- Equivalent CoP, very similar MOPs
- Therefore, MOPs can be used for initial reliability analysis, verification can be done with the Latin hypercube sampling







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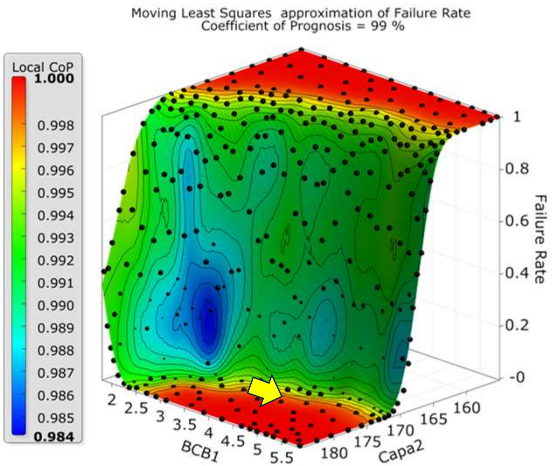
Reliability with Fragility Surfaces

- High quality MOP is used for analysis of failure probabilities
- Fragility surfaces generated by varying the mean values of two important input parameters
- Increasing mean value BCB1 reduces the failure probability (indicated by yellow arrow on fragility surface)
- Verification with 5 mean value pairs and 100 simulation runs for each pair



BCB1	Capa2	Failure rate (explicit simulations)	Failure rate (fragility surface)
3.41	170.08	57 %	62.5 %
4.09	168.52	60 %	58.8 %
2.50	177.50	7 %	12.5 %
4.20	174.00	0 %	0.3 %
3.80	174.00	1 %	1.7 %

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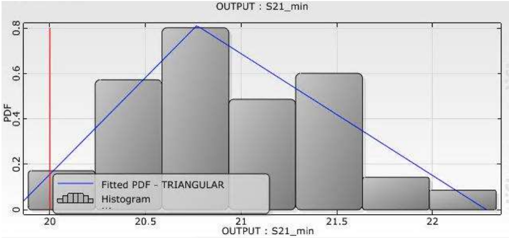
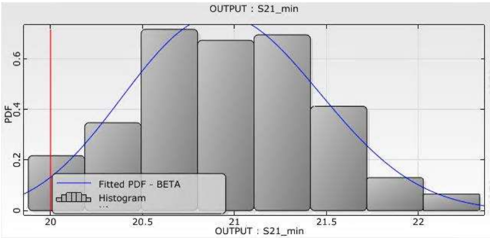
Influence of increasing BCB1 on other critical output parameter

- First step running 100 Ansys HFSS simulations lead to 2 failures for B5G
- Adding further 50 simulations (using Adaptive MOP technique) leads to 2 additional failures for B5G
- Total probability of failure using higher BCB1 mean value of 4.2 µm is about half of the initial failure rate !
- More simulations are necessary or other smart methods to reduce the number of necessary simulations and improve the prognosis quality



Hide Statistical data

Limit : Failure Limit			
	Lower value = 20	Upper value = not set	Total
P_rel:	0.02		0.02
P_fit:	0.0142775		0.0142775



Hide Statistical data

Limit : Failure Limit			
	Lower value = 20	Upper value = not set	Total
P_rel:	0.0333333		0.0333333
P_fit:	0.023859		0.023859

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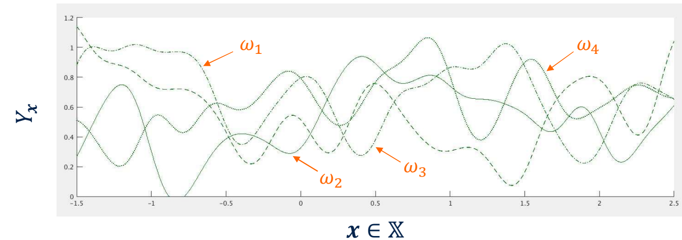
Bayesian interpolation

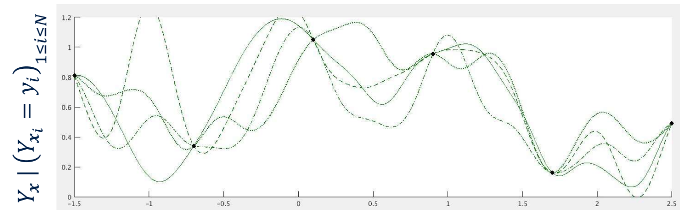
- A random field $(Y_x)_{x \in \mathbb{X}}$ is a random function defined over a factor space $\mathbb{X} \subseteq \mathbb{R}^d$, $d \in \mathbb{N}^*$
  $\Rightarrow$ A realization of a random field is a function $Y_{.}(\omega)$, indexed by $\omega \in (\Omega, \mathbb{P})$ (sample space)

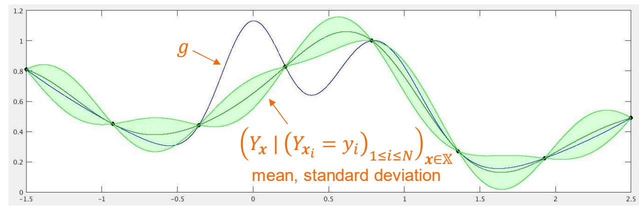
- The covariance of the random field fully defines the basis functions of the function space for the realizations and therefore their properties : regularity…

- The random field can be conditioned on $N \in \mathbb{N}^*$ observations $\left(Y_{x_i} = y_i\right)_{1 \le i \le N}$. It can be viewed as a learning process : realizations compatible with the observations are selected

- The conditioned random field can be used to interpolate an unknown function g defined over $\mathbb{X}$
  - g is supposed to be a realization of $(Y_x)_{x \in \mathbb{X}}$
  - Due to the finite information, several models are possible
  - The randomness can be interpreted as a modeling uncertainty





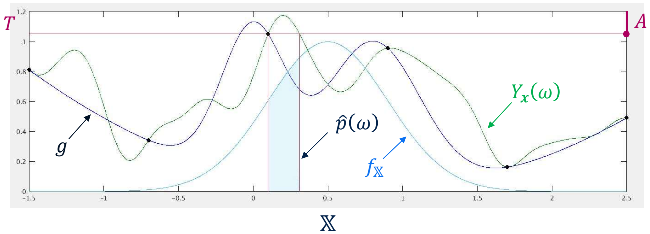


“Failure probability” random variable

- Factor space $(\mathbb{X}, \boldsymbol{P})$, accident set $A = [T, +\infty[$, interpolation model $(Y_{\boldsymbol{x}})_{\boldsymbol{x} \in \mathbb{X}}$ for an unknown function g

- Either p the failure probability, it can be written :

$$p = \int_{\mathbb{X}} \mathbb{I}_{g(\boldsymbol{x}) \in A} \, d\boldsymbol{P}(\boldsymbol{x}) = \int_{\mathbb{X}} \mathbb{I}_{g(x) \geq T} \, f_{\mathbb{X}}(\boldsymbol{x}) d\boldsymbol{x}$$



- The estimator $\hat{p}$ is obtained substituting g with $Y_{\boldsymbol{x}}$:

$$\hat{p}(\omega) = \int_{\mathbb{X}} \mathbb{I}_{Y_{\boldsymbol{x}}(\omega) \in A} \, d\boldsymbol{P}(\boldsymbol{x})$$

- $\hat{p}$ and the stochastic process $(Y_{\boldsymbol{x}})_{\boldsymbol{x} \in \mathbb{X}}$ share the same randomness
  $\Rightarrow$ The model uncertainty is propagated

- Adding data points reduces this uncertainty :

More observations …

“Risk-of-failure probability” random variable

- To learn about the distribution of $\hat{p}$ is difficult
  - The exact Bayesian inference of the posterior distribution of $\hat{p}$ is intractable
  - Statistical inference from the analysis of realizations of $\hat{p}$ is unreasonable in practice, as it requires to simulate trajectories of the random field

- The random variable $\tilde{p}$ (risk-of-failure probability) is proposed as an alternative estimator

$$\tilde{p}(\alpha) = \int_{\mathbb{X}} \mathbb{I}_{\mathbb{P}(Y_{\boldsymbol{x}} \in A) \geq \alpha} \, d\boldsymbol{P}(\boldsymbol{x})$$

- It is numerically efficient, as it only requires the knowledge of marginal distributions

- It stochastically dominates (in the convex order) the random variable $\hat{p}$: $\hat{p} \leq_{cx} \tilde{p}$
  - They share the same mean value : $\boldsymbol{E}[\hat{p}] = \mathbb{E}[\tilde{p}]$
  - Bounds on the quantiles of $\hat{p}$, more accurate than Markov bounds, can be derived from the quantile function $F_{\tilde{p}}^{-1}$ of $\tilde{p}$:
  - From the inequalities above, one can easily derive credibility intervals for $\hat{p}$

$$\frac{1}{\alpha} \int_0^{\alpha} F_{\tilde{p}}^{-1}(t) \, dt \leq F_{\hat{p}}^{-1}(\alpha) \leq \frac{1}{1-\alpha} \int_{\alpha}^{1} F_{\tilde{p}}^{-1}(t) \, dt$$

- The multi-response case $(K > 1)$ can be easily managed using the Fréchet upper bound

$$\mathbb{P}\left(\bigcup_{k=1}^{K} Y_{\boldsymbol{x}}^{(k)} \in A_k \right) \leq \sum_{k=1}^{K} \mathbb{P}\left(Y_{\boldsymbol{x}}^{(k)} \in A_k \right)$$

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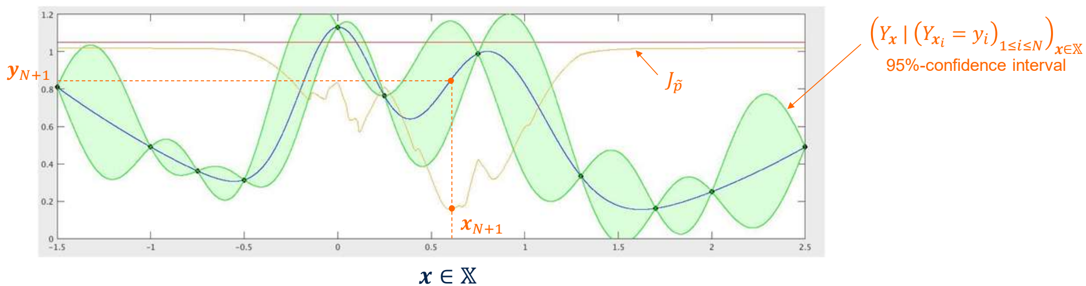
Design of experiments

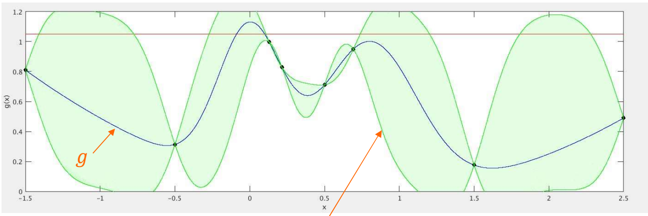
- In order to increase the model accuracy, new observations are required
- As each data point is computationally expensive to get, they should be carefully chosen to maximize the information obtained
- They are selected using a Stepwise Uncertainty Reduction (SUR) strategy
  - Intended to reduce the uncertainty on the estimation of $\hat{p}$
  - The design of experiment, of size N, is enriched sequentially
  - A cost function $J_{\tilde{p}}$, based on $\mathrm{var}[\tilde{p}]$, is minimized to identify the optimal candidate $(\boldsymbol{x}_{N+1}, y_{N+1})$
  - Global optimization is performed using a genetic algorithm



Gradient-enhanced Bayesian interpolation

- HFSS solver is based on the transfinite element method
  - The gradient of the S-parameters is a by-product of the simulation
  - It is not a finite-difference approximation (that would be computationally expensive to get for a high-dimensional factor space $\mathbb{X}$)
- A random field can also be conditioned on the gradients obtained at the observation points $\left(\vec{\nabla} Y_{\boldsymbol{x}_i} = \boldsymbol{\gamma}_i\right)_{1 \leq i \leq N}$
- This additional information is a manna !
  - It increases the quality of the predictions
  - The selection process is more stringent
    $\Rightarrow$ The predictive uncertainty is significantly reduced

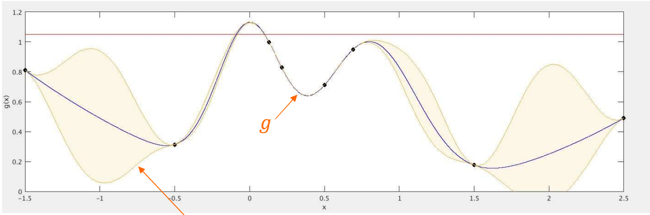
Without derivatives



$\left(Y_{\boldsymbol{x}} \mid \left(Y_{\boldsymbol{x}_i} = y_i\right)_{1 \leq i \leq N}\right)_{\boldsymbol{x} \in \mathbb{X}}$

95%-confidence interval

With derivatives



$\left(Y_{\boldsymbol{x}} \mid \left(Y_{\boldsymbol{x}_i} = y_i \cap \vec{\nabla} Y_{\boldsymbol{x}_i} = \boldsymbol{\gamma}_i\right)_{1 \leq i \leq N}\right)_{\boldsymbol{x} \in \mathbb{X}}$

95%-confidence interval

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Toy model

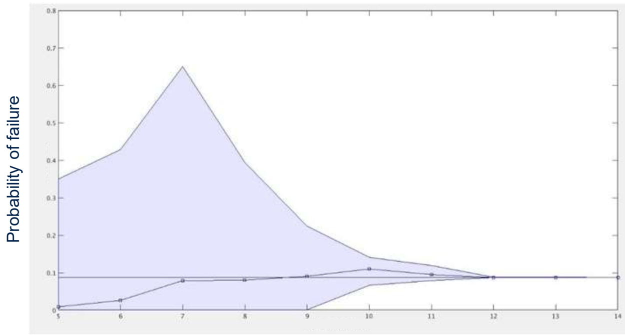
- We consider the following illustrative example :

$$g : \begin{cases} \mathbb{R} \longrightarrow \mathbb{R} \\ x \longmapsto (0.4x - 0.3)^2 + e^{-11x^2} + e^{-5(x-0.8)^2} \end{cases} \qquad T = 1.05 \qquad f_{\mathbb{X}} = \mathcal{N}(0.5, 0.4^2)$$

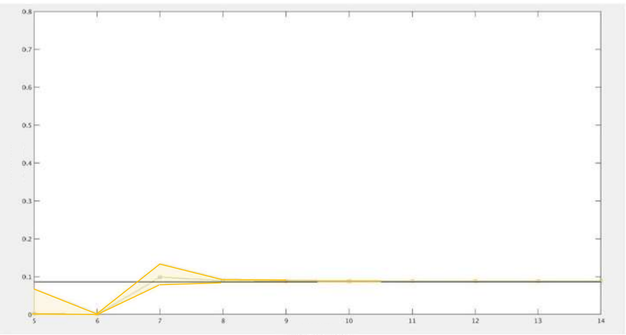
- A sequential design of experiments is built using the SUR strategy

- Convergence of the results are compared, without and with derivatives
  $\Rightarrow$ The derivative information significantly improves the predictions

Without derivatives



With derivatives



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Extremal responses

- The product datasheet bears upon the modules $|S_{ij}|$ of the S-parameters S_{ij} over specific frequency ranges $\mathcal{F}_k = \left[f_{min}^{(k)}, f_{max}^{(k)}\right]$, $1 \leq k \leq K$

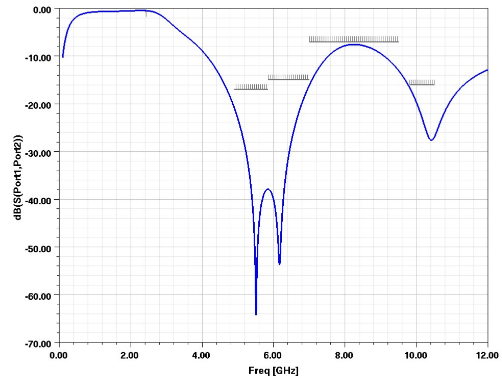
- We consider the restrictions of $|S_{ij}|$ to $\mathcal{F}_k$: $(\boldsymbol{x}, f) \mapsto g_k(\boldsymbol{x}, f) = \left|S_{ij}|_{\mathcal{F}_k}(\boldsymbol{x}, f)\right|$

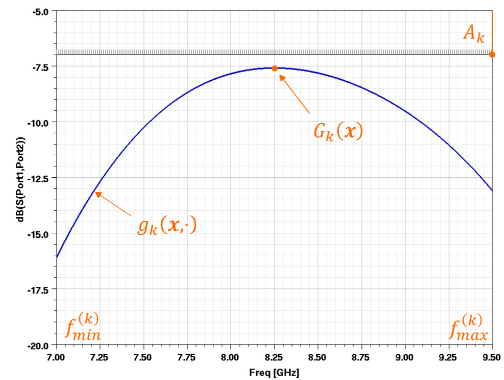
- It can be assigned to each function g_k an accident set A_k :
  specification k is not met when $g_k \in A_k$

- In case the accident set A_k is connected, it is possible simplify the problem excluding the frequency parameter from the analysis, by introducing extremal responses

  $$G_k = \max_{f \in \mathcal{F}_k}[g_k(\cdot, f)]$$

- **We have established the following result :**
  - G_k is differentiable almost everywhere on $\mathbb{X}$
    $\Rightarrow$ It can be reasonably represented with a differentiable random field
  - An explicit expression for the gradient $\vec{\nabla} G_k$ has been derived





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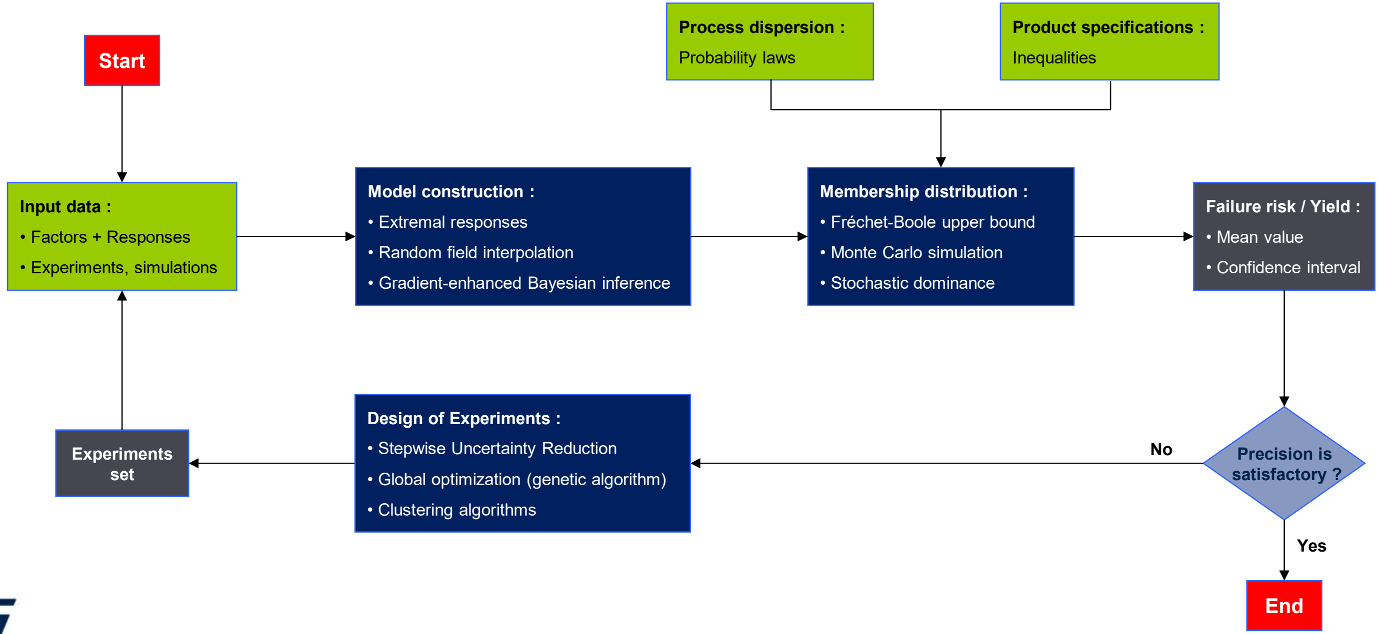
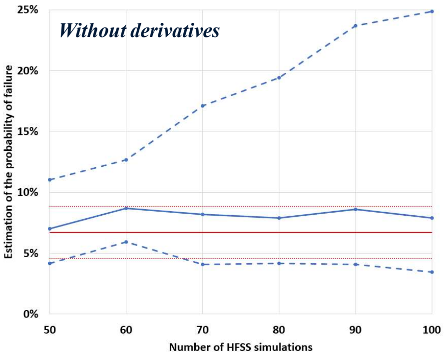
Failure risk analysis

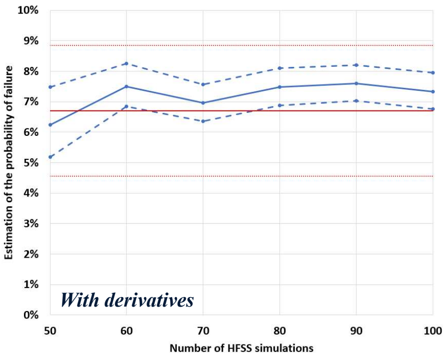
- Modeling flow for the GoNoGo application



Application to the diplexer case

- A Brute-Force Monte-Carlo simulation is performed as a reference :
  - 1000 samples
  - Duration ~ 1 month
  - Failure Probability estimation :
    $\boldsymbol{E[\hat{p}_{MC}] = 6.7\%, \hat{p}_{MC}} \in [\boldsymbol{4.15\%, 8.25\%}]$ (95% confidence interval)
- Uncertainty propagation is crucial to assess the model quality for the quantity of interest
- Using the gradient information drastically improve the prediction capabilities of the model :
  - 100 samples
  - Failure Probability estimation :
    $\boldsymbol{E[\hat{p}] = 7.33\%, \hat{p}} \in [\boldsymbol{6.77\%, 7.95\%}]$ (95% confidence interval)
- The number of simulations required to (significantly) outperform the Monte-Carlo confidence interval is (at least) an order of magnitude lower





Threshold dependence of the failure probability

Table 2. Electrical characteristics and RF performance (T_{amb} = 25 °C)

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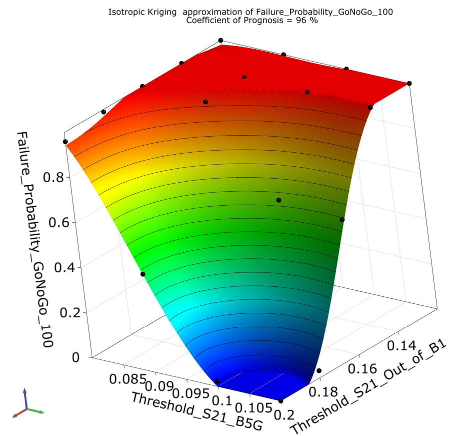

- The datasheet can be optimized, with a yield constraint, by testing different threshold values
- This leads to different failure probabilities for the same input parameter distributions
- Using the precise failure probabilities calculated with GoNoGo and coupling to optiSLang makes this type of study simple

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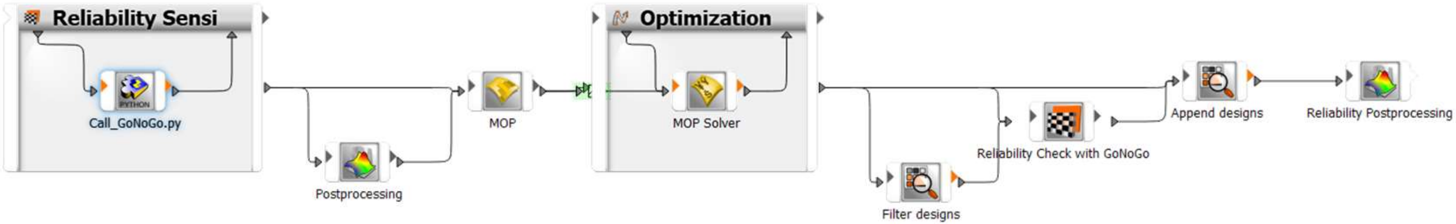
Summary and outlook

- Reliability analysis including the prediction of failure probabilities is nowadays feasible:
  - Methods and algorithms to reduce the number of necessary simulations are key
  - The MOP can be used to build fragility surfaces to understand the transition region in parameter space
  - Verification, especially in the transition region from failure to non failure, is important
  - Ansys HFSS derivatives, using a rigorous Bayesian inference framework, can be used for an improved quality for the prediction of failure probabilities
  - Coupling GoNoGo with optiSLang enables to study for example the impact of the threshold value
- These methods can be very helpful for the reduction of the production yield losses and for the adaptation to specific requirements
- For many parameters, an automation process like outlined below will be helpful



Outline for a future approach of the optimization for the production yield

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Thank you very much for your attention!

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