Statistical Estimation of Aircraft InfraRed Signature Dispersion

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return on innovation

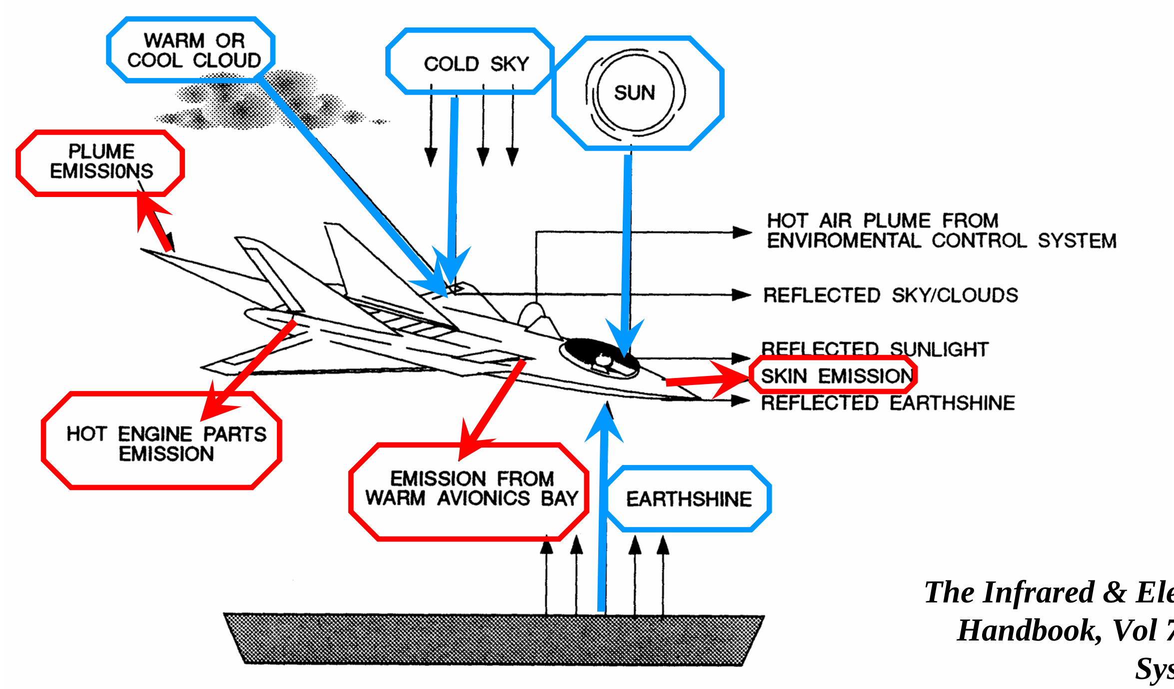
DOTA

Context

- Optimization of optronics sensor

Objectives: high detection probability – low false alarms rate

- Computer program to calculate aircraft IRS according to aircraft properties
  weather conditions
  attack profiles



The Infrared & Electro-Optical Systems Handbook, Vol 7, Countermeasure Systems

Uncertainty on input data

Uncertainty on input data

- Several data types:

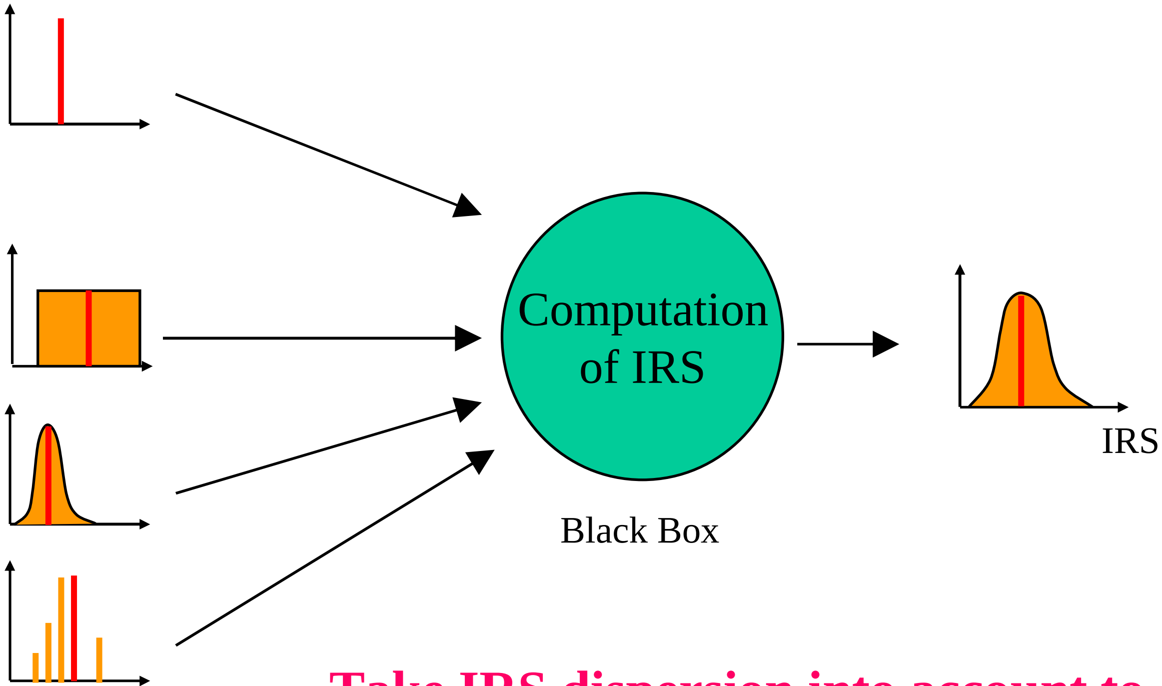
Fixed data or parameters defined by scenario

Uncertain data:

• bounds min.-max. (coating, engine, aircraft orientation…)

• statistical (weather conditions…)

• qualitative (season, flight above: sea-land,…)



- Correlations

Take IRS dispersion into account to estimate optronics sensor properties

scalar response: difference between target and background irradiance

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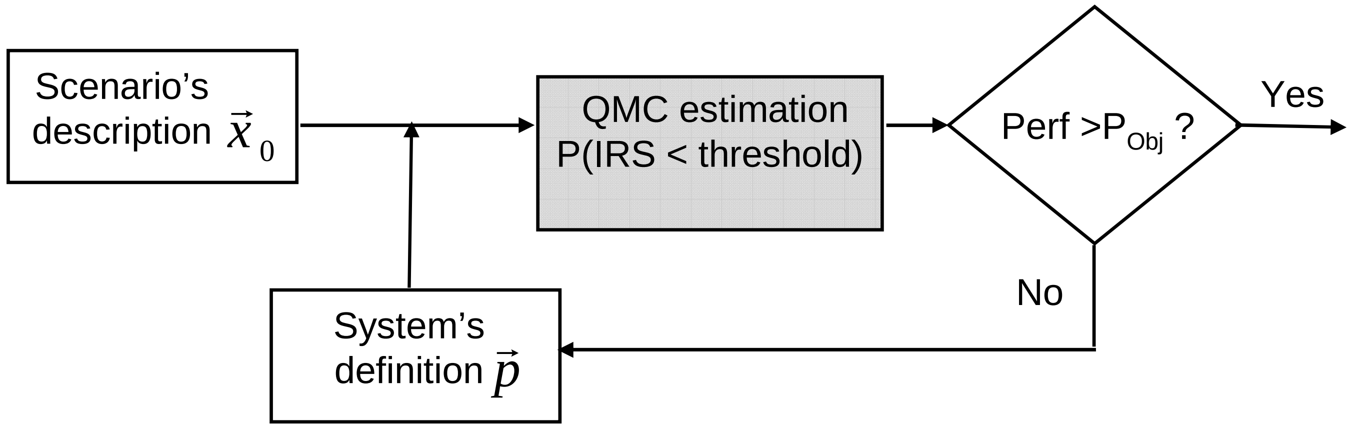
Outline



- Identification of uncertainty associated to each input: variations range - correlations
- Sensitivity analysis: **identify most important inputs**
- P (IRS < threshold) by Quasi Monte Carlo
- Metamodel (neural network): faster – enables sensor properties optimization

Sensitivity Analysis

5000 experiments max. – 28 factors – must account for interactions ➡ **design of experiments**

Procedure: - two levels (min. - max.) for each input data – functions of scenario

- factors are assumed to be independent
- standardization: -1 and +1
- **choice of underlying model** (depending on accuracy, interactions level…)

$$Y = Cste + \sum_i c_i . X_i + \sum_{i<j} c_{ij} . X_i . X_j + \sum_{i<j<k} c_{ijk} . X_i . X_j . X_k + \ldots$$

Response — Main effects — Two-factors interactions

- **choice of experimental design (DOE)**
- collect response data for all numerical experiments prescribed by matrix:

$$X_j^i \qquad i = 1..n_{fact} \quad j = 1..n_{calc}$$

- estimation of **main effects** and **factors interactions** (stepwise – Student's test)

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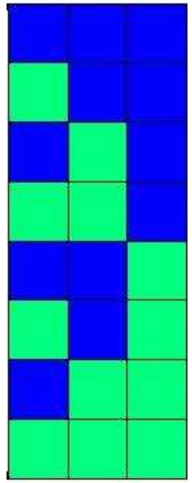
Factorial Designs



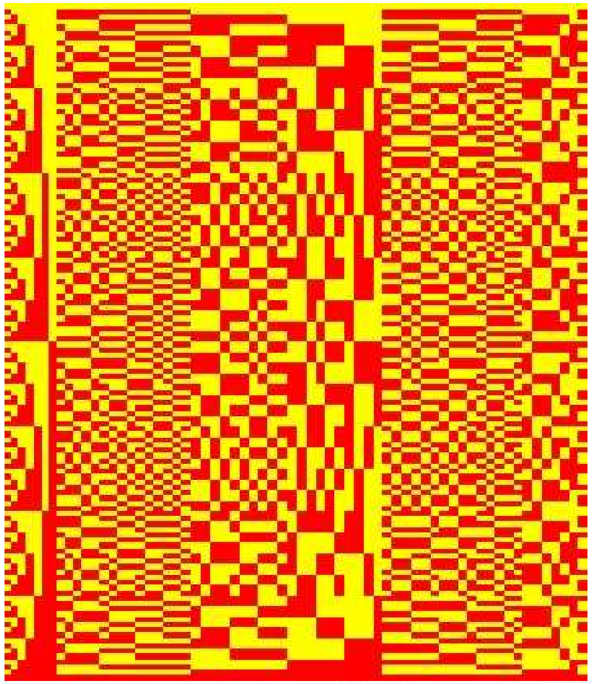
Each level of each factor is combined with each value of each and every other factor

$N = 2^n$ experiments, n factors

Too expensive => fraction of this design **Fractional factorial design**

Fractional factorial design: $N = 2^{n-p}$ experiments

Can't estimate all coefficients, but set of aliased coefficients



Aim: study main effects and two-factors interactions

+ take into account three-factors interactions - not negligible

Design property: resolution

For a resolution R design, main effects are aliased with interactions involving at least (R-1) factors

$$Y = cste + \sum_i c_i X_i + \sum_{i,j} c_{ij} X_i X_j + \varepsilon_r$$

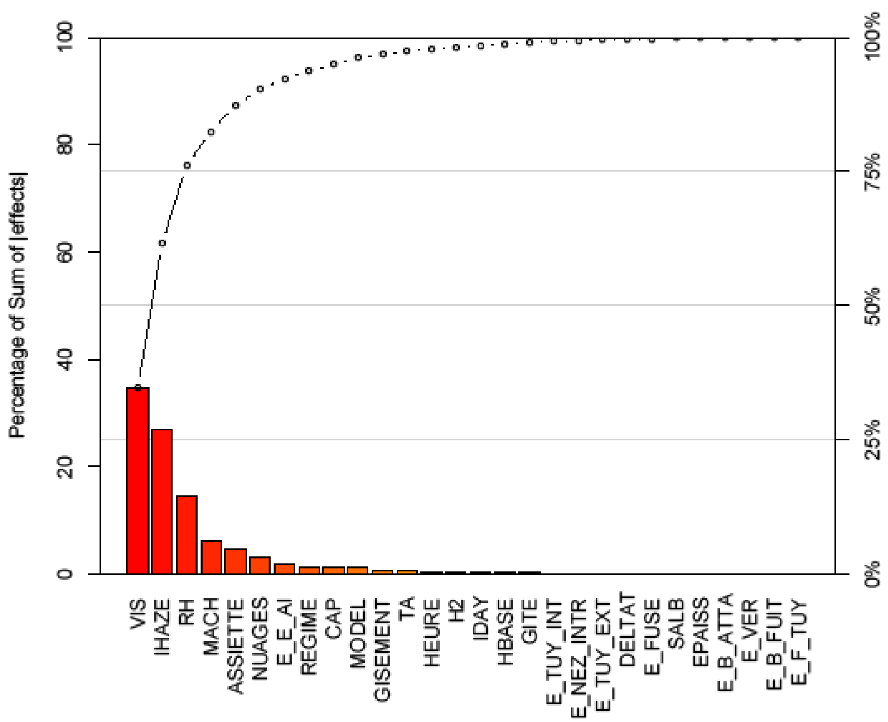
28 input data – 2048 exp – resolution VI

Application to a typical air-to-ground attack example

Daytime air-to-ground attack, in France, at low altitude

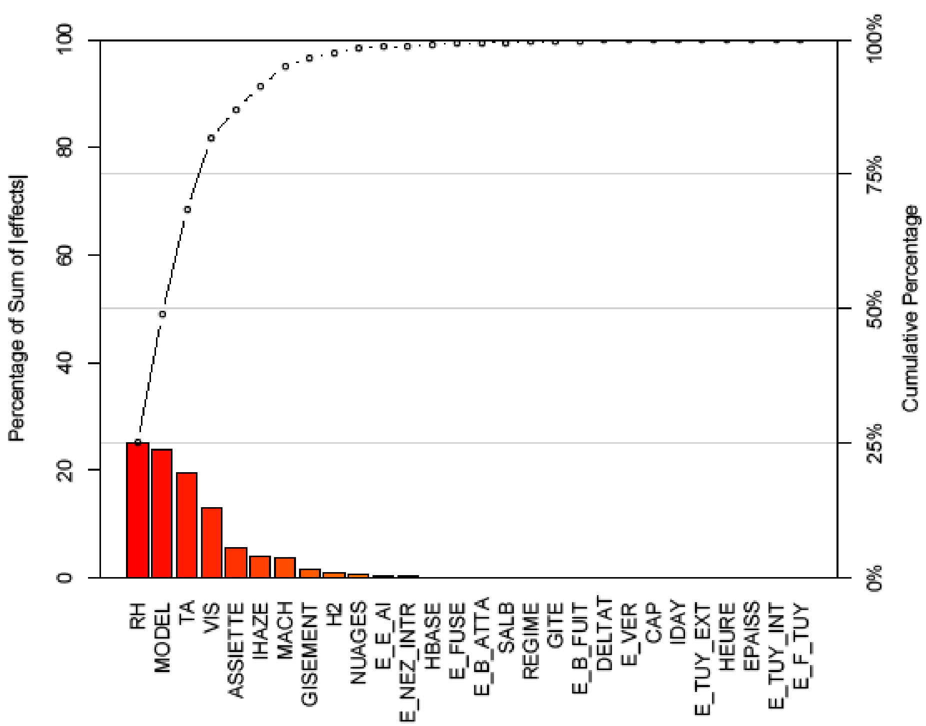
Pareto plot: factors sorting / main effects only

B II



7 related to atmosphere background
5 to flight conditions - 1 to characteristics of aircraft

B III



7 related to atmosphere background
4 to flight conditions - 2 to characteristics of aircraft

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13 Factors that mostly contribute to IRS variability

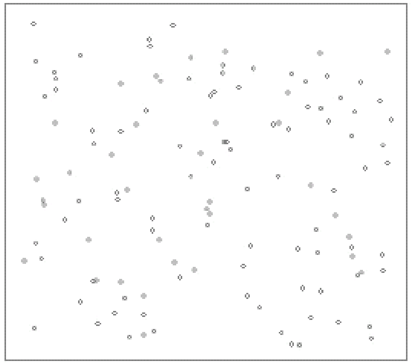
Quasi Monte Carlo estimation of the IRS dispersion

Estimation of P (IRS < threshold)

$$P\left(IRS(X_1,\ldots,X_n) < \alpha\right) = \int_{IR^n} 1_{IRS(X_1,\ldots,X_n)<\alpha}\left(\vec{t}\right) p_{X_1,\ldots,X_n}\left(\vec{t}\right) d\vec{t}$$

- **Monte Carlo**:

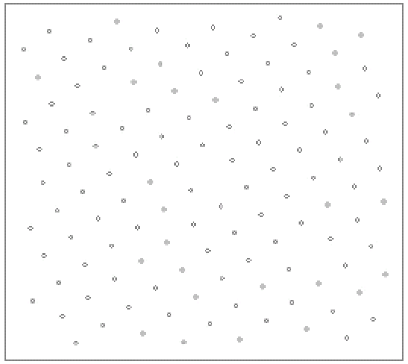
$$P(IRS < \alpha) \approx \frac{1}{N}\sum_{i=1}^{N} I(IRS(u_i) < \alpha)$$



$u_i = (X_i^1, X_i^2, \ldots, X_i^n)$ n = number of input factors

u_i independent – uniform law   cv rate $O(1/\sqrt{N})$

- Alternative: **Quasi Monte Carlo**



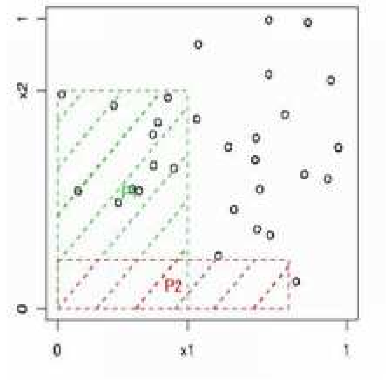
u_i independent   determinist low discrepancy sequence
5 -10 times faster / MC dimension 10 (*Lapeyre et al. 1990*)

discrepancy = characterizes uniformity of sequence distribution

Low discrepancy sequence

$\Gamma = (\xi^j)_{j \in IN}$ sequence n-dim

Discrepancy: $D_N^*(\Gamma) = \sup_{I \in I^*} \left| \frac{A_N(I,\Gamma)}{N} - \mu(I) \right|$ $\quad I^* = \left\{ \prod_{i=1}^{n} [0,\alpha_i); \alpha_i \in [0,1] \right\}$



(a) D1=37%−34%=3%,

D2=14%

$\mu(I)$ = volume of I (theoretical measure)

$A_N(I,\Gamma)$ = nb points ξ^i in I among N first

(empirical measure of volume of I)

Low discrepancy $D_N^* \; O\left(\frac{\log(N)^n}{N}\right)$

Koksma-Hlawka theorem: $\left| \frac{1}{N} \sum_{j=1}^{N} f(\xi_j) - \int_{[0,1]^n} f(u)du \right| \leq V(f) D_N^*(\Gamma)$

Estimation of D_N* and *V(f)* difficult

Large dimension: theoretically cv rate MC better / QMC

but practical studies show better results with QMC / MC (Caflisch et al. 1997 – dimension 360)

⇒ Effective dimension

⇒ PhD S. Varet – effective discrepancy: joint property of sequence + integrand

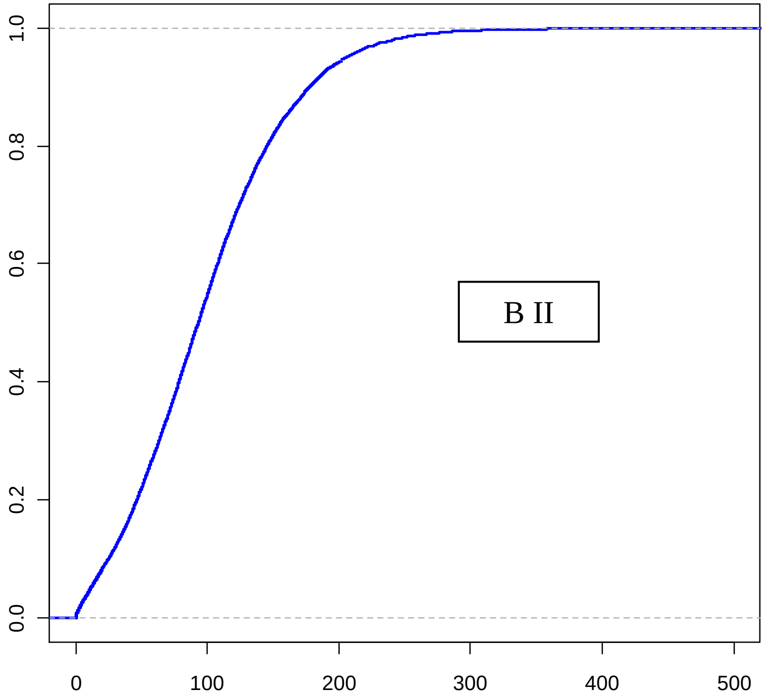
Results: IRS dispersion

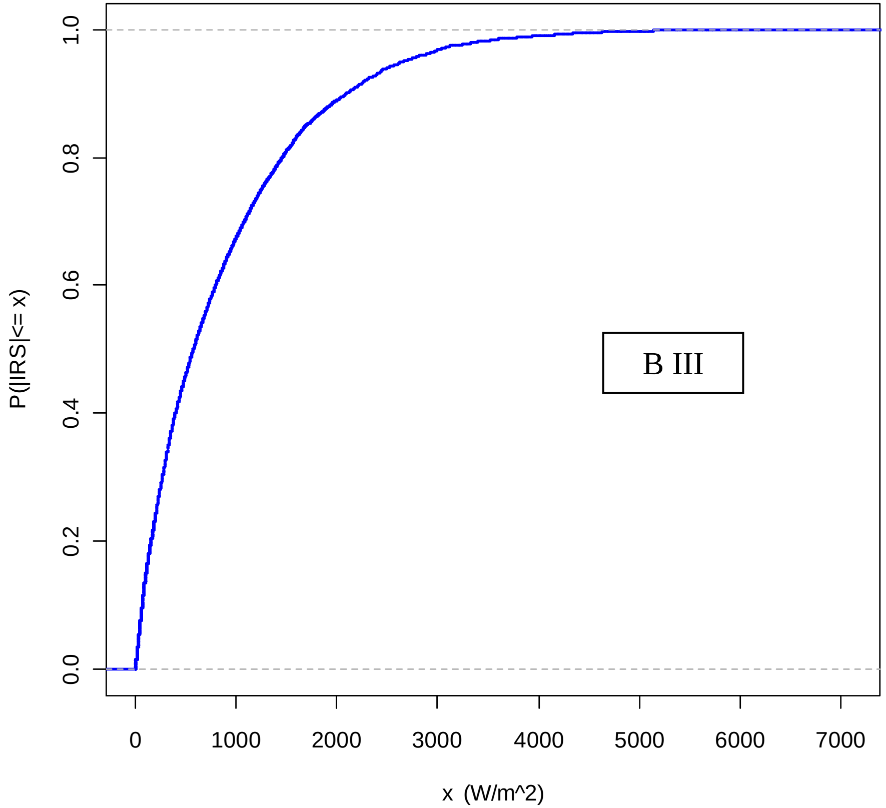
10240 computations

- 8 Variables related to weather conditions: bootstrap in statistics database   web site *meteo.infospace.ru*
- Other variables: - 14 unimportant: constant

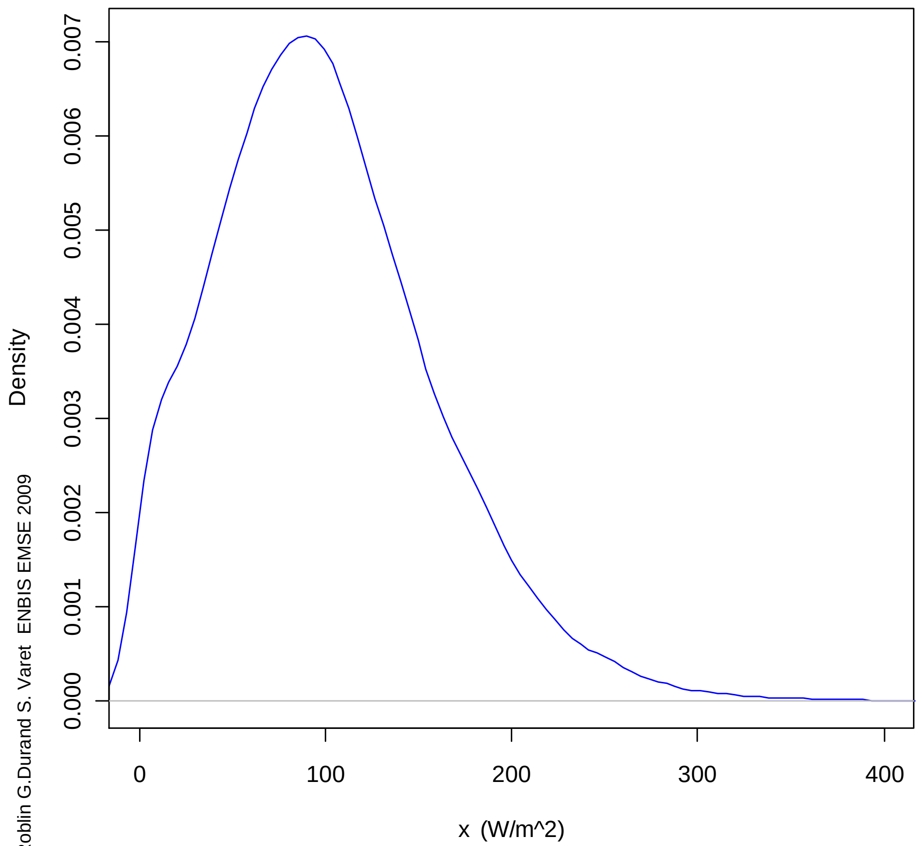
  - 6 important: Faure low discrepancy sequence with scrambling (Owen 1995 – Tuffin 1997 – Faure tezuka 2003)
  Randomization methods modify the decomposition on prime number basis used in sequence building

  They preserve the low discrepancy, add randomness, useful to estimate CI, and decrease projection irregularities on small dimension subspaces

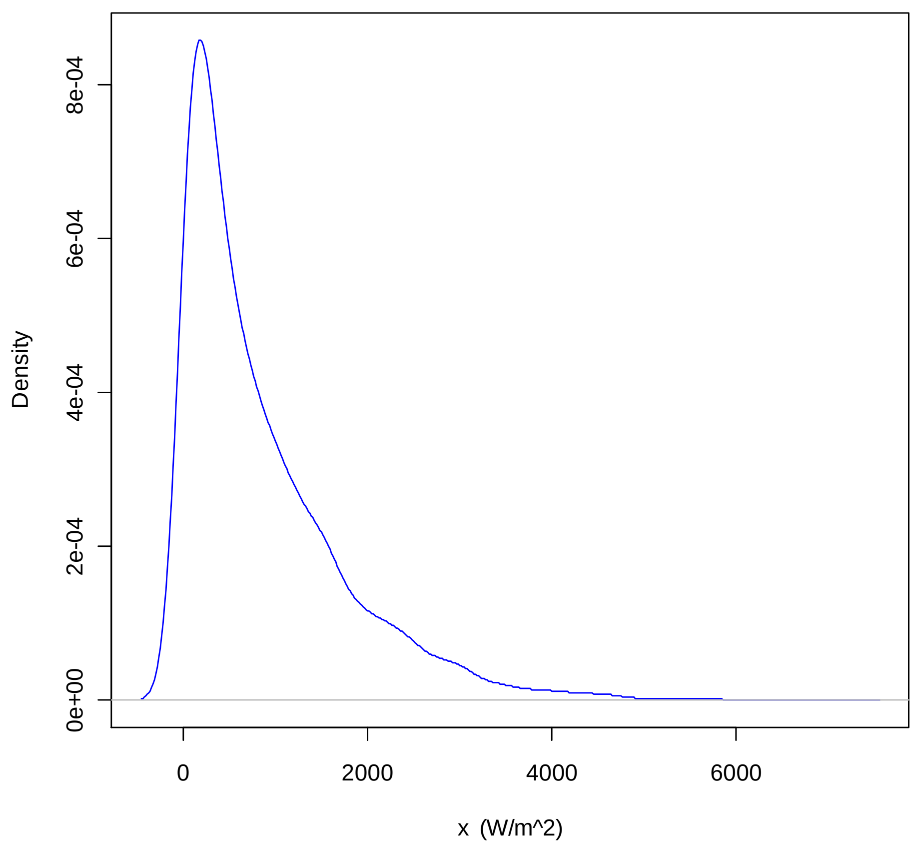




Empirical cumulative distribution function = > estimation of P(IRS < threshold)


Density
0.000
0.001
0.002
0.003
0.004
0.005
0.006
0.007
0
100
200
300
400
x (W/m^2)

B II


Density
0e+00
2e-04
4e-04
6e-04
8e-04
0
2000
4000
6000
x (W/m^2)

B III

Quantiles estimation

Realistic thresholds for non-detection probabilities depend a lot on the optronics sensor we want to size

=> estimation of three quantiles β, which correspond to typical non-detection probabilities

1 %, 5 % and 25 %

Empirical estimator: $\inf\{y, F_N(y) > \beta\} = y_{\lceil \beta N \rceil}$ after IRS reordering (F_N ecdf)

	1 %	5 %	25 %
250	[1.63, 1.71]	[11.36, 11.56]	[54.8, 55.2]
500	[1.57, 1.62]	[11.44, 11.6]	55
1000	[1.34, 1.38]	[11.12, 11.24]	55
2000	[1.23, 1.26]	[11, 11.08]	55
5000	[1.18, 1.2]	[10.94, 10.98]	55
10000	[1.16, 1.17]	10.92	55

95% confidence level bootstrap estimations based on 5000 draws among the 10240 IRS values, for different sample sizes

Good evaluation of 5 % and 25 % quantiles with 2000 values

Set-up of a Neural Network Metamodel

Neural Network

Linear Regression => poor predictions in our case

Multilayer feedforward neural network = universal approximator (Hornik et al. 1989)

Single output

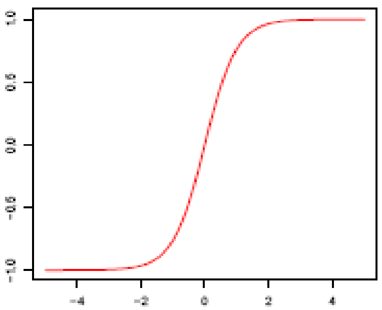
Linear activation function

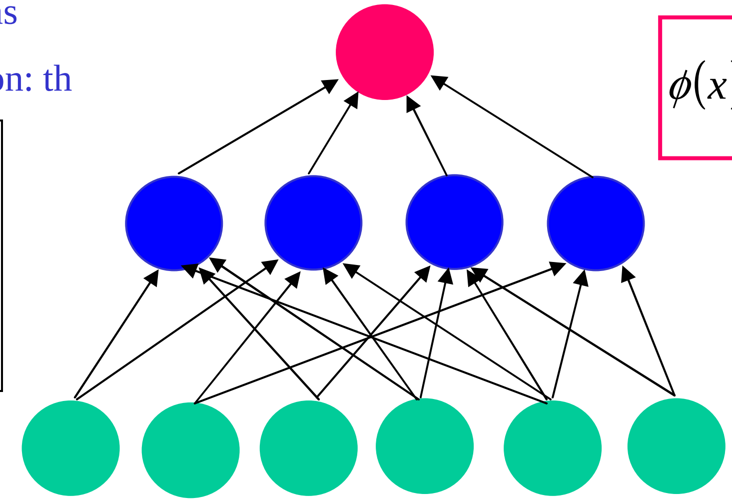
$$\phi(x) = \sum_{i=1}^{n_c} w_{n_c+1,i}\, th\left(\sum_{j=1}^{n} w_{ij} x_j + w_{i0} \right) + w_{n_c+1,0}$$

$q = n*n_c + 2*n_c + 1$ parameters

Hidden layer n_c neurons

Sigmoid activation function: th





n input data selected thanks to Fractional Factorial Design sensitivity analysis

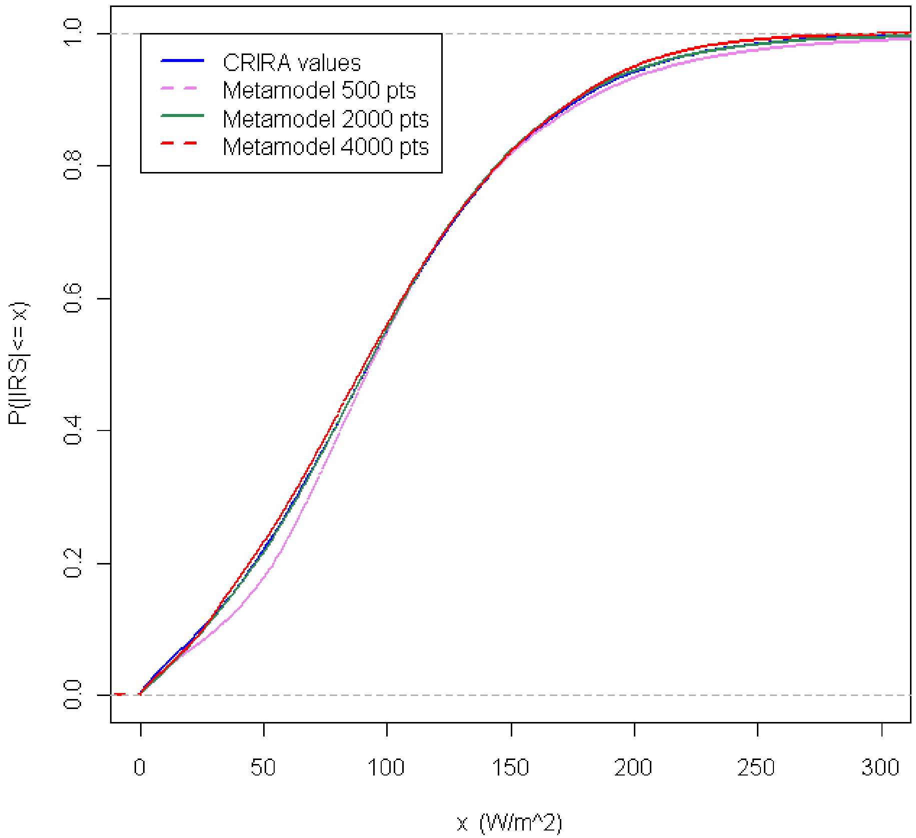
Weight decay: cost function

$$J(w) = \frac{1}{2} \sum_{i=1}^{N} \left\| y_i - \varphi(x_i, w) \right\|^2 + \frac{\alpha}{2} \sum_{j=1}^{q} w_j^2$$

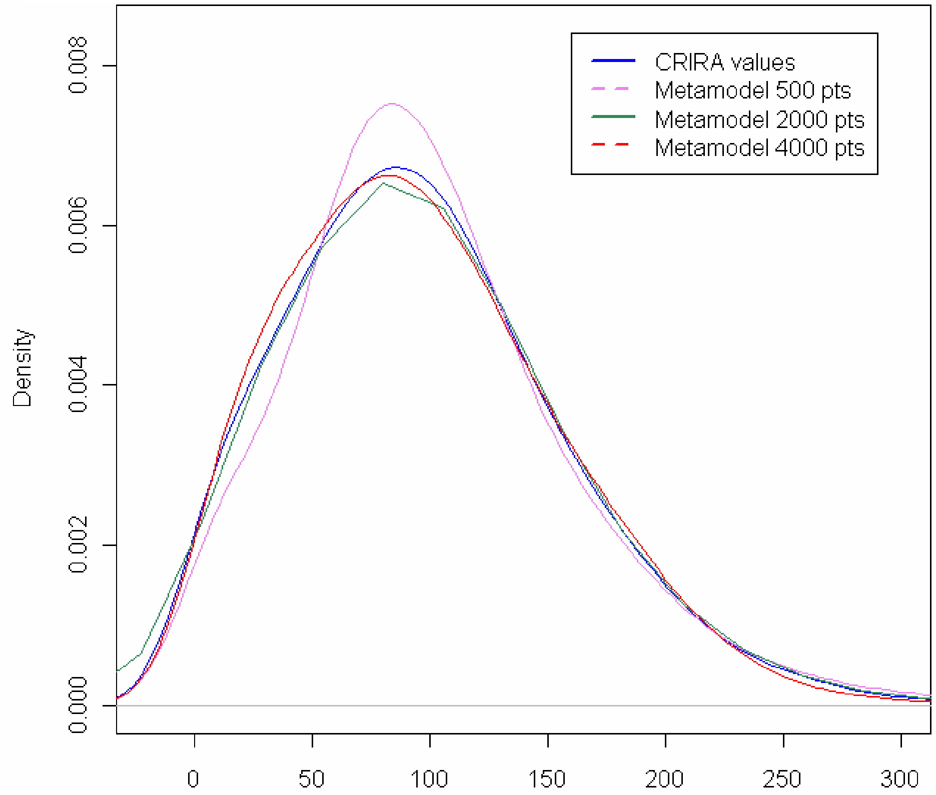
Neural Network Metamodel – Band II

13 input data　　7 hidden neurons　　decay 0.01

Learning: first 500/2000/4000 points among 10240 QMC + bootstrap　　Test: 10000 MC + bootstrap



Empirical cumulative distribution function



Empirical probability density function

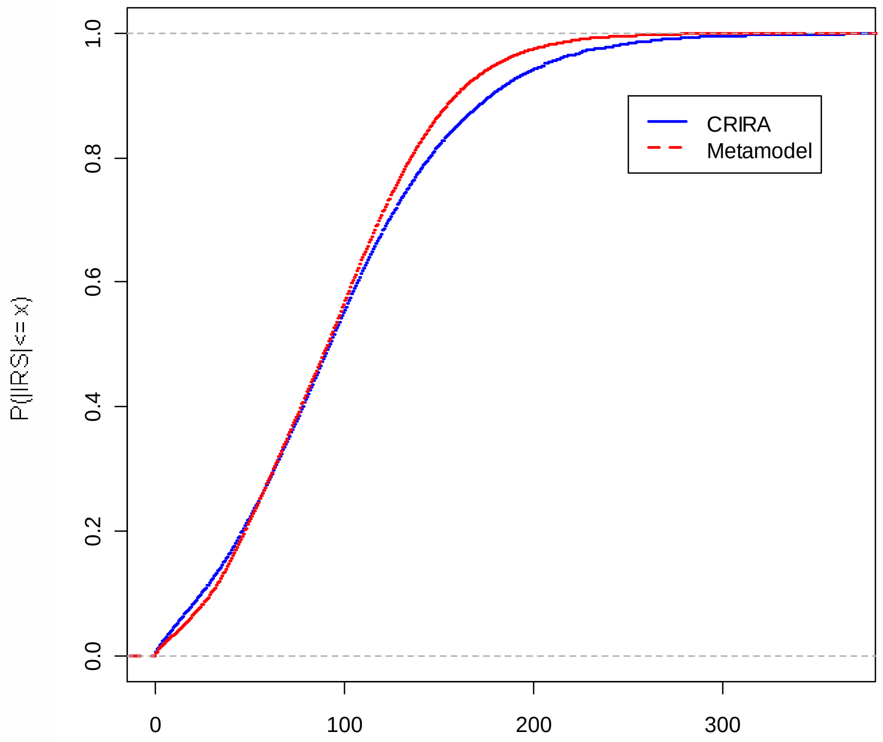
Very good agreement between real and predicted cdf and pdf

4000 pts neural network metamodel

Neural Network Metamodel – quantiles

13 input data 7 hidden neurons

Learning: random sampling of 4000 points among 10240 QMC + bootstrap Test: 10240 MC + bootstrap



Empirical cumulative distribution function

(worst prediction / 2000 sampling + metamodel)

Bootstrap estimations of three quantiles of the metamodel

1 %	5 %	25 %
[1.42, 1.44]	[13.5, 13.6]	[53.9, 54]

The metamodel gives a very good prediction of non-detection probability:

difference < 1 %

Best choice of learning points ?

Downsize learning database ?

=> Adaptive metamodel

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Adaptive construction (Gazut, Martinez et al. 2008)

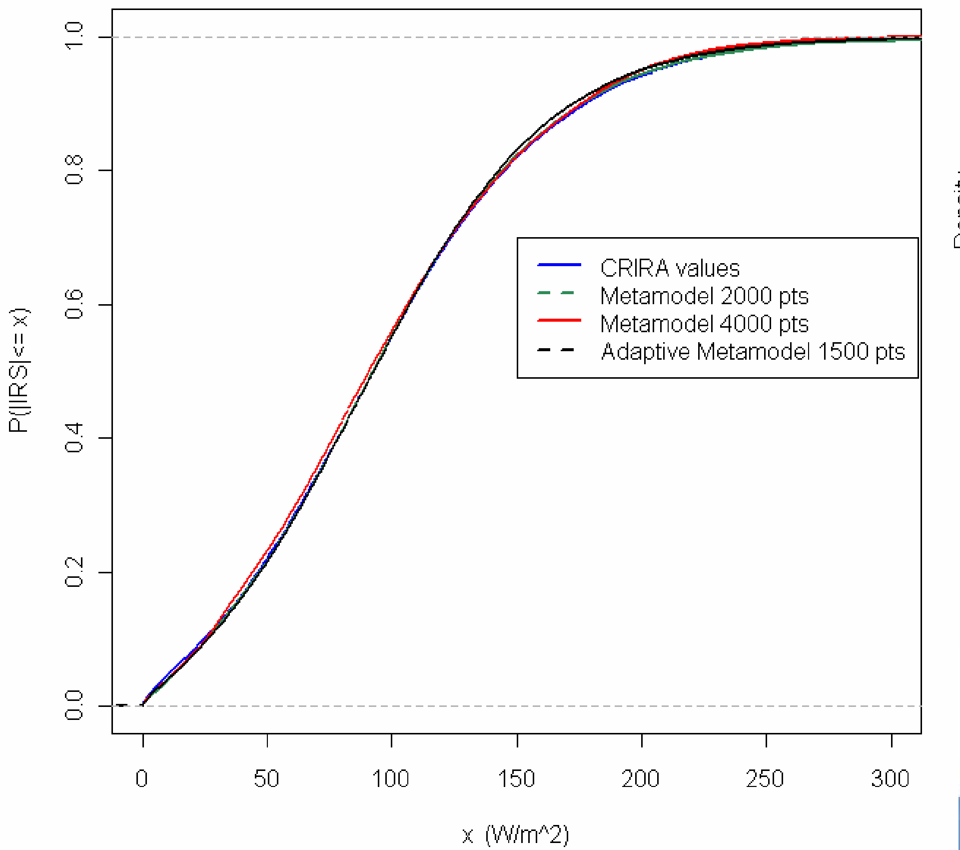
1. N_0 = 500 first pts Faure sequence

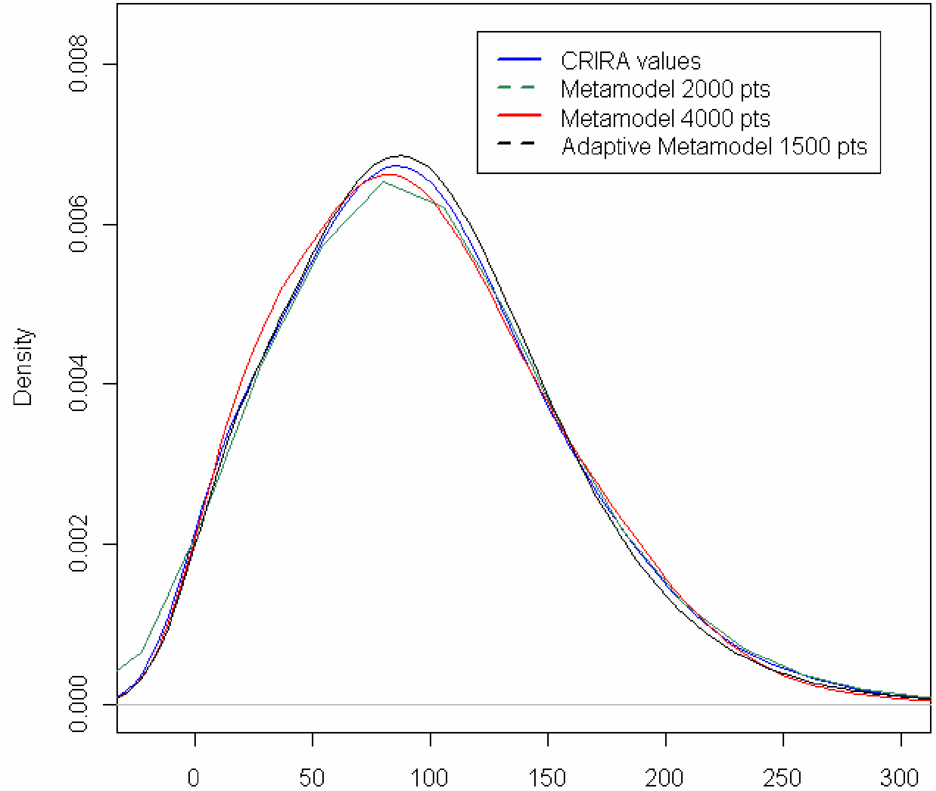
2. 100 bootstrap on set of N_n pts => learning of neural network 7 hidden neuron

3. estimation of mean and variance of the 100 predictions for a 50000 pts database

4. add 100 pts largest variance to N_n pts

2. with $N_{n+1} = N_n + 100$

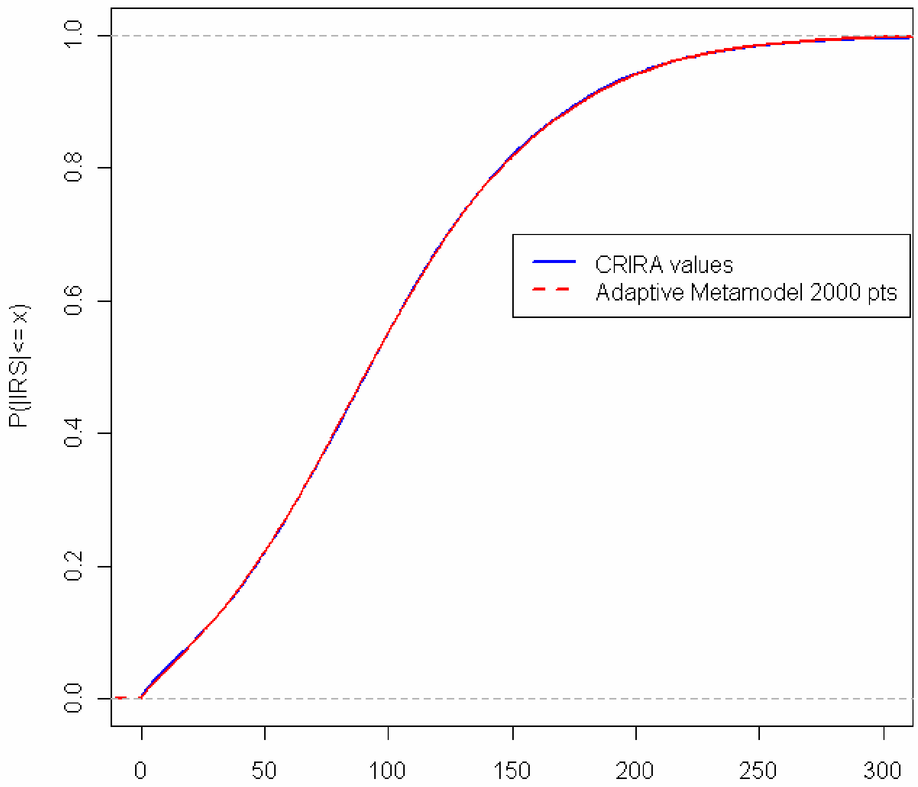


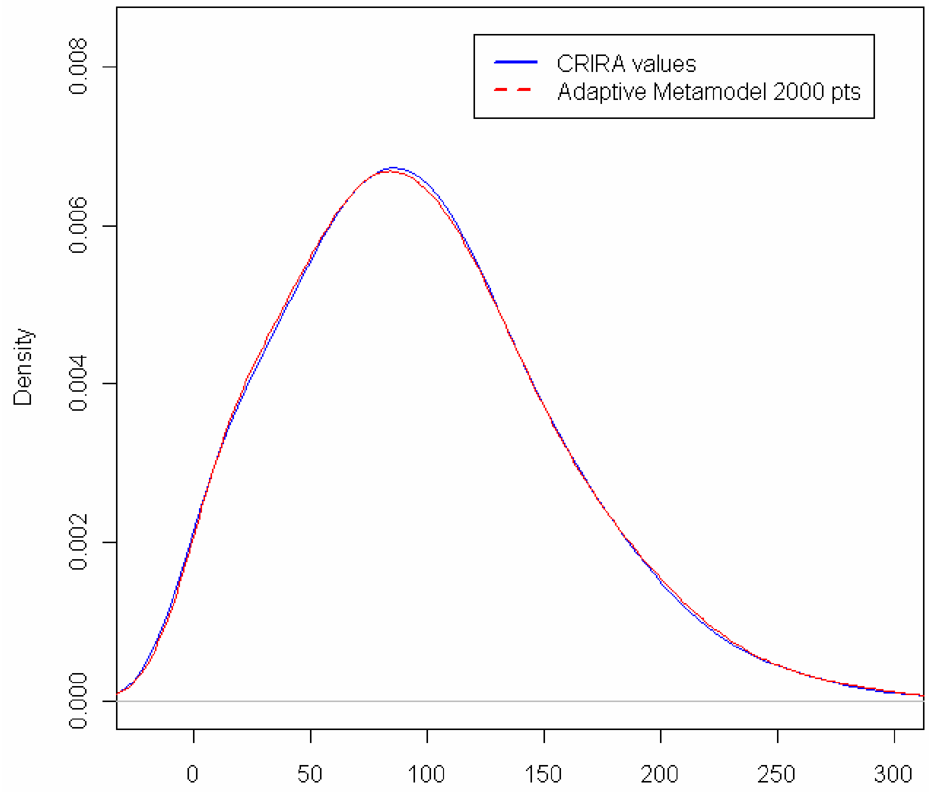


Very good metamodel with 1500 pts

More stable: small impact of choice of N_0 first pts

Adaptive construction





CI 95 % Quantiles	1 %	5 %	25 %
Metamodel 4000 pts (2000 bootstrap)	[1.34, 1.38]	[13.5, 13.6]	54
Metamodel adaptive 1500 pts (2000 bootstrap)	**[1.42,1.46]**	[14.42,14.58]	**[54.23,54.43]**
Metamodel adaptive 2000 pts (2000 bootstrap)	[1.72,1.74]	**[13.32,13.44]**	**[54.95,55.17]**
10000 CRIRA (5000 bootstrap)	[1.16, 1.17]	**10.92**	**55**

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Concluding remarks

- ✓ Sensitivity analysis => Factors that mostly contribute to IRS variability

- ✓ P(IRS < threshold) by Quasi Monte Carlo

- ✓ Metamodel (neural network) => IRS approximation

  => allows much faster sensor properties optimization

- ✓ **Efficient methodology: predicts simulated IRS dispersion of poorly known aircraft**

  can be extended to IRS models of other military objects

Concluding remarks

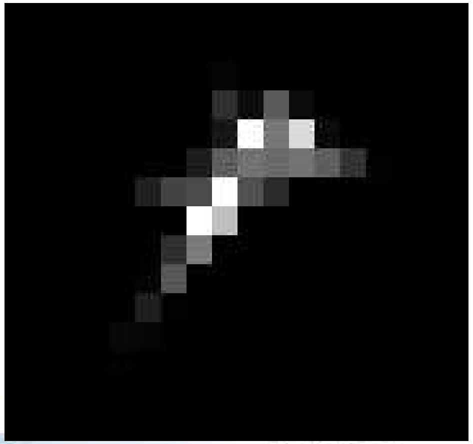
- **Infer the joint density probability of meteorological factors from the database**

  - variance reduction methods => quantiles estimation
  - space filling designs
  - adaptive metamodels

- **Use of S .Varet PhD results: designs which minimize effective discrepancy**

  - estimation of non-detection probabilities
  - metamodel

- **Aircraft spatially resolved: vectorial output (picture 10x10 pixels)**
  new detection and classification algorithms



- sensitivity analysis for a vectorial output ?
- characterization of IRS dispersion ?
- classification algorithm which accounts for IRS dispersion

Different aspect angles of aircraft => very dissimilar pictures

Thanks

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