SIMUREX 2018 scientific school
Aussois, France, 15-19 October 2018

Uncertainty and global sensitivity analysis

on building performance simulation (BPS)

Jeanne Goffart

Univ. Savoie Mont-Blanc, LOCIE, CNRS

Goals

Aims of this workshop

- Acquire the concept and the basis of uncertainty and sensitivity analysis
- Understand some key point for the management of uncertainties in building simulation (or other complex model) and the use of uncertainty and sensitivity analysis
- Overview of the capabilities of these statistical methods

→ Advantages and limits of the most known methods (SOBOL, MORRIS, etc.)

- **Means**

  Applications and case studies in building performance simulation to illustrate the purpose
  References to **simplify research** on each aspect of the methods
  Advice and **good practice** in the presentation

  At the end: demonstration of the capabilities of the library on Sensitivity Analysis **SALib in Python** by Nicolas Cellier (15 min) **[Jupyter Notebook]**
  → **Performing easily SA** with Morris, Sobol, RBD-FAST, etc…

Structure of the presentation

- **Introduction :** Building Performance and uncertainty
- **Warning : Avoid the One factor At the Time technique !**
- **Methodology** :The 6 steps to perform Uncertainty and Sensitivity Analysis
- **Application :** Methods for Building Performance Simulation

→ Understand the differences between Morris and RBD-FAST

→ Presentation of RBD-FAST Method

Introduction

Building Performance Simulation and Uncertainties

Deterministic versus statistic

- Uncertainty and sensitivity analysis → statistical methods
- Explore the model over different combinations of values for the uncertain inputs
- → bring a statistical approach from the deterministic model

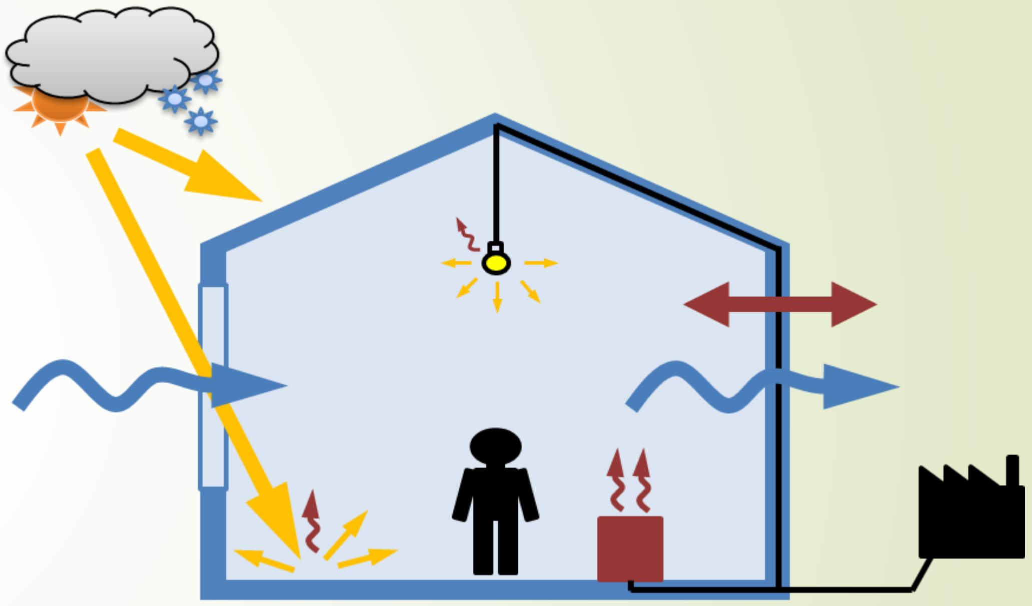
→ deterministic result
→ N evaluation with the same inputs → N same result

→ Building performance simulation

Building performance simulation (BPS)

- Annual simulation with a hourly timestep

  - Modelling of the physical phenomena
  - Energy transfer in a zone
    - combined heat and mass transfer, ventilation, infiltration, phase change, radiation, daylighting, ...
  - Generation of energy
    - Internal gain: people equipement, lighting, HVAC sytem, etc... Etc.



- Performance indicator
  - Energy need
  - Consumption (equipement and use as scenarios and occupant)
  - Thermal, visual comfort, ventilation, air quality, mould risk, ...

A need of reliability

- BPS: Complex model, not transparent, modular (choice of sub model depending on the building case), no linear, no monotonic with a lot of **uncertain inputs**
- More and more used in consulting → Guaranteed building performance?

  → Reliability, risk assesment on the result

  → Uncertainty at each step of the BPS

SOFTWARE USER

Inputs

Building description, close environment, sollicitation

→ Models Computing core →

Outputs

Performance indicator

Lack of knowledge of the inputs, intrinsic characteristic of a physical quantity

Approximation of the reality

Interpretation, depend on the model and the inputs

The albedo

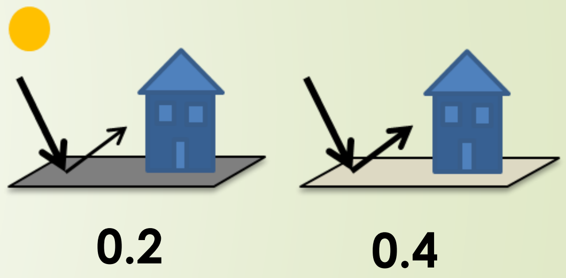
The ratio between the incident solar part and the reflected part (value between 0 and 1)

The value commonly used : concrete ground : **0.2**
Close Environment of the real buidling studied : white concrete : **0.4**

In situ measure

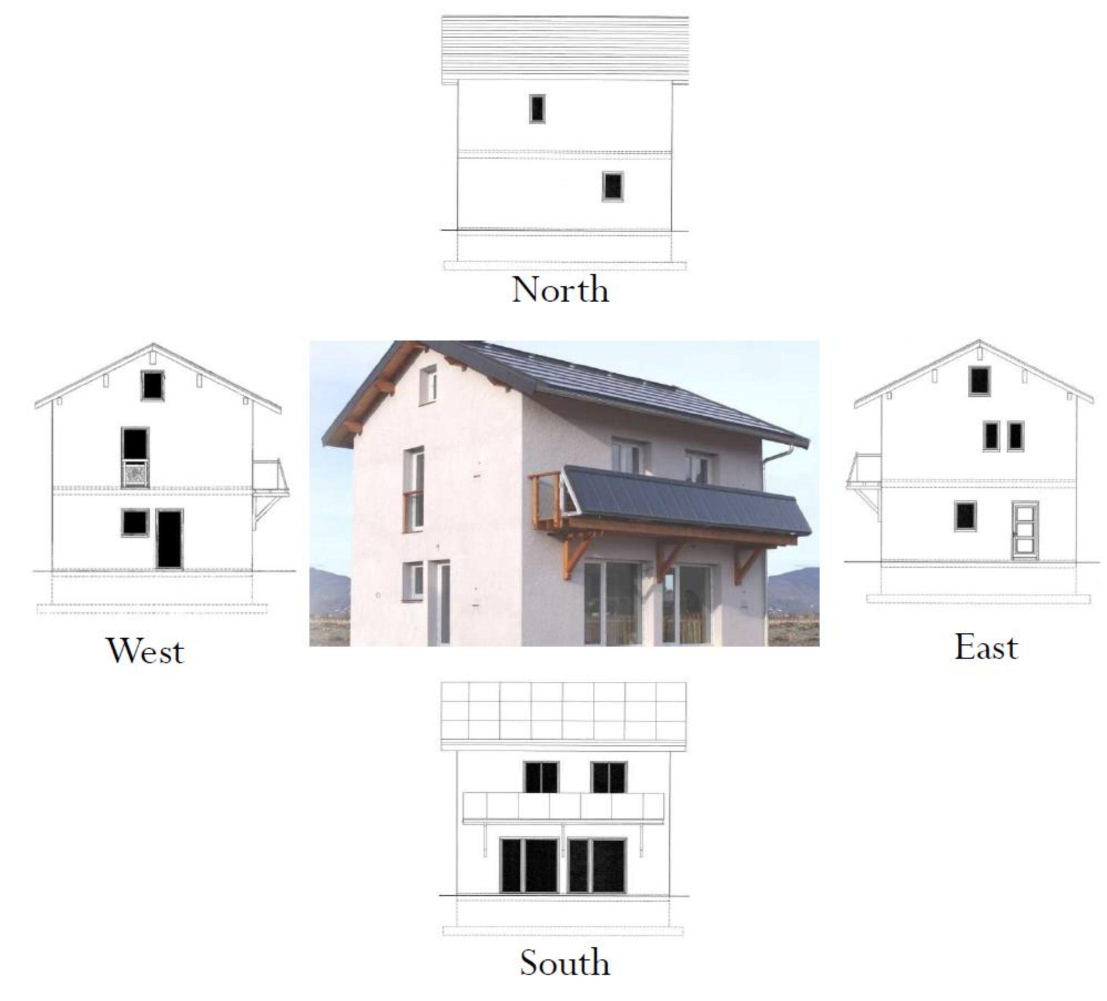
Variability during the day: temporal dependence
Short campaign measure (2 weeks in april) :
order of magnitude

Type d'information	Valeur
Moyenne	0,39
Max	0,43
Min	0,25



Impact of the underestimation of the albedo during the summer ?

Case study : uncertainty on a assumption



Goffart 2013 (in french)

Bio-climatic insulated building in France
→ improve free energy gain

- Increase solar gain in winter and reduce energy loss
  →Huge window at south facade vs tiny window in north
- Decrease solar gain in summer : reduce internal temperature
  →Overhang : balcony at the south façade

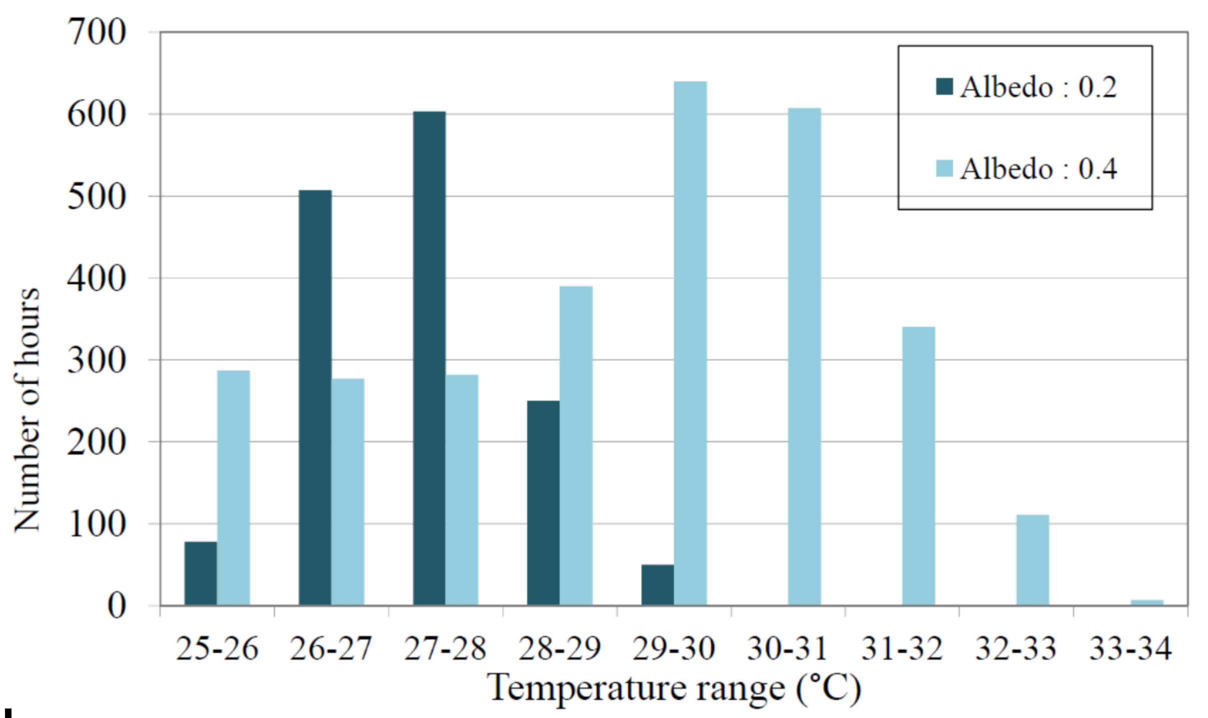
Impact of an assumption, an approximation of the solar part ?

impact of the albedo on summer discomfort

Evaluation of the indoor air temperature during july and august

Output: number of hour T_{in} > 27 °C
Equivalent of the day of discomfort

Albedo 0.2	Albedo 0.4
40 days	99 days



Goffart et al. 2011

Significant impact in a particular case :
Involve different kind of uncertainty :

- **Variability of the input**
- **Constant value assumption : the model**
- **Difference between the design stage and the real building (change of the close environment ground)**

Different kind and level of uncertainty

A need of methodology to identify how important are the individual inputs for the prediction
And to acquire more knowledge on the most important input

Sensitivity and uncertainty analysis techniques in order to gain into transparence in building simulation

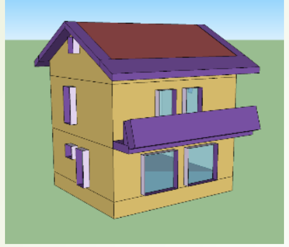
- Sensitivity analysis: determine the most influential input
  - Point the weaknesses of the model, the reduction of the uncertainty of some inputs,...
  - Simplification of the model (no influential inputs)
  - Prioritizing research effort (modelling, instrumentation)
  - Prioritizing input estimation, measure
- Uncertainty analysis: evaluate the uncertainty of an output model from the input uncertainty : confidence bound
  - Variation of the uncertain inputs→ output variation
  - Confidence bound → Risk analysis, **Model ROBUSTNESS**

Stability of the response model under an uncertain environment

the ability of tolerating perturbations

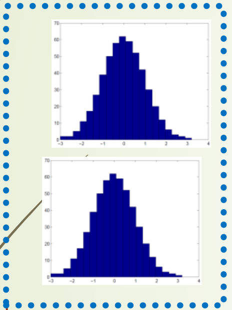
Procedure

- Sample generation
- Propagation through model
- Output analysis



Geometry
Thermo-physical
Environment (Albedo)
…

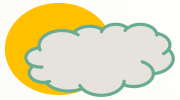
Inputs



Static

hundreds

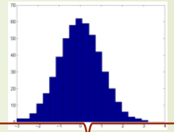
Time series



Deterministic Models

Output

Dynamic (temperature)
Scalar (energy need, consumption)
Threshold (discomfort, mould risk)



Input uncertainty:
What is an uncertainty ?
How to determinate ?
Different kind ?

Extract, determine which input is the most responsible for the uncertainty input
→ Sensitivity analysis

Estimate confidence bound
→ Uncertainty analysis

GLOBAL Sensitivity Analysis: both UA and SA

« Uncertainty » workshop : Antoine Caucheteux [Tuesday]

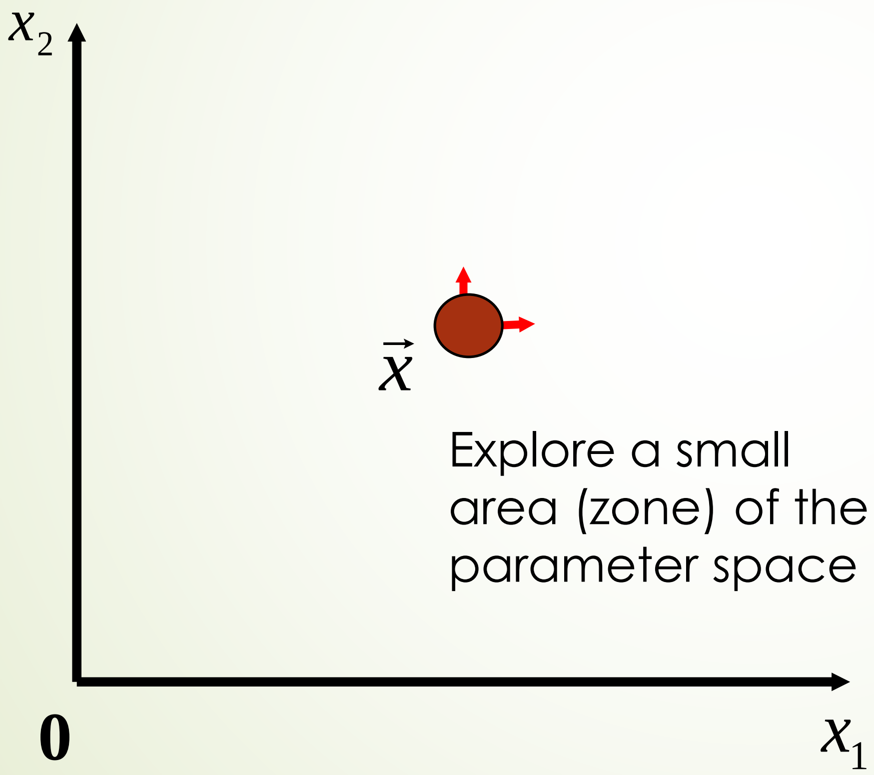
Why **GLOBAL** sensitivity Analysis ?

Not LOCAL

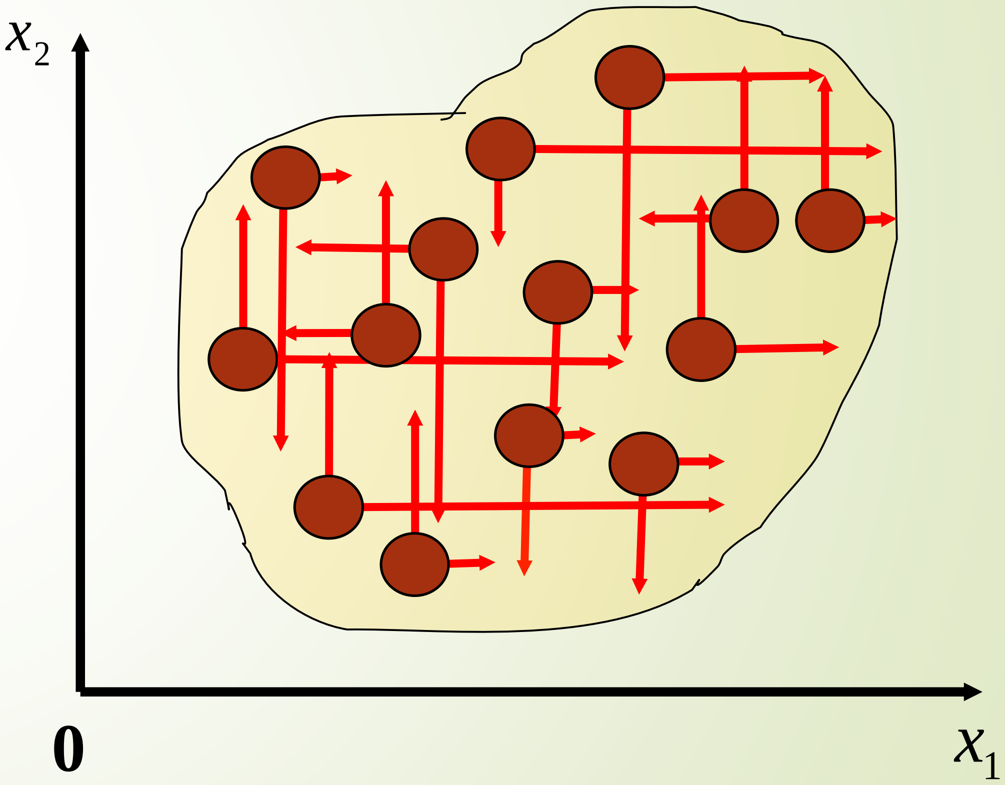
Not « One factor At the Time » (OAT)

Local vs global techniques

Local SA



Global SA



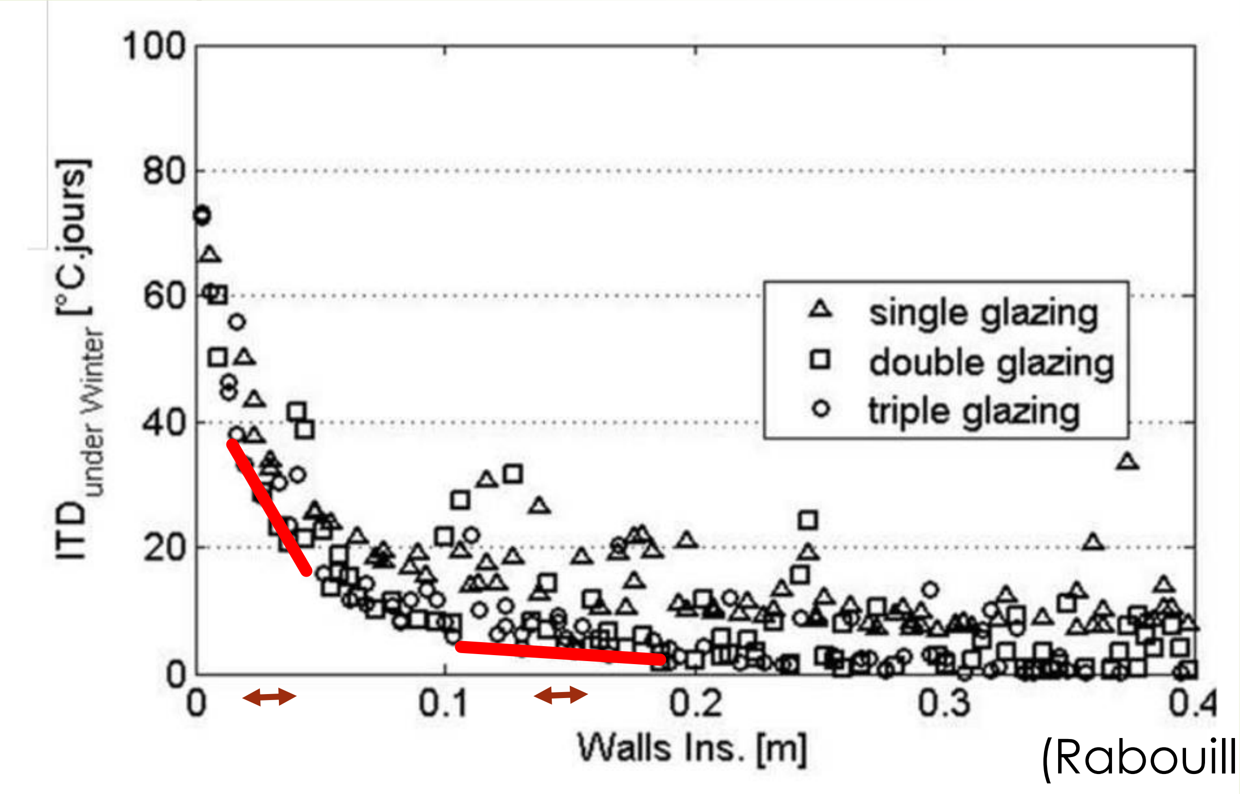
(x_1, x_2) **= space of input** $\vec{x}$ **= nominal value**

Tarantola 2012, SAMO School

Local vs global techniques

- local SA:
  - evaluation of partial derivatives
  - works in the neighborhood of nominal point x_0
  - use of Taylor-like formulas

$$\left.\frac{\partial y}{\partial x_i}\right|_{\vec{x}=\vec{x}_0}$$



(Rabouille, 2014)

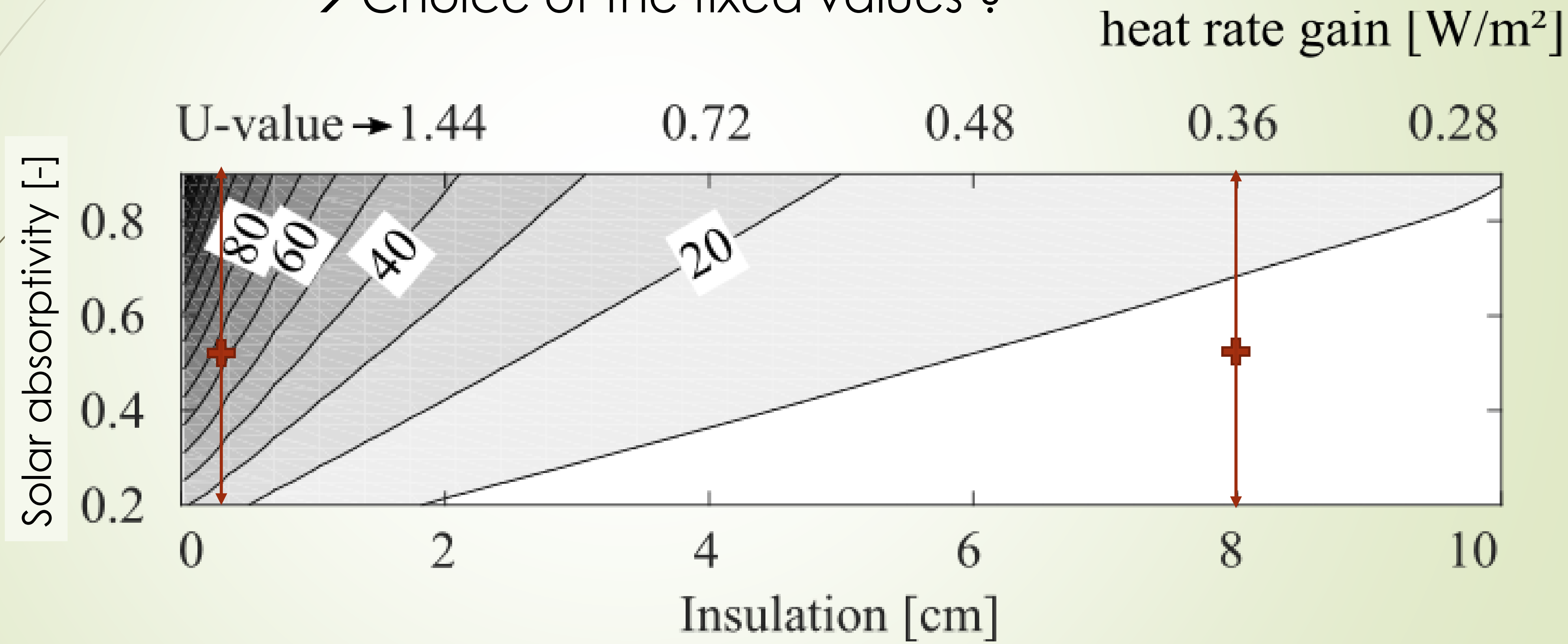
- global SA:
  - full range of uncertainty
  - Monte Carlo methods to generate samples
  - All factors explored simultaneously

Local vs global techniques

Local	Simple to evaluate Require only few model runs	Explore very small area of input space One factor at a time **Until 99 % unexplored space (Saltelli et al. 2010b)**
Global	Explore full range of uncertainty All factors explored simultaneously	Require high number of model runs **Reduced by RBD FAST (Second part of the presentation)**

OAT → Parametric study (not a sensitivity analysis)
Until 99 % unexplored space

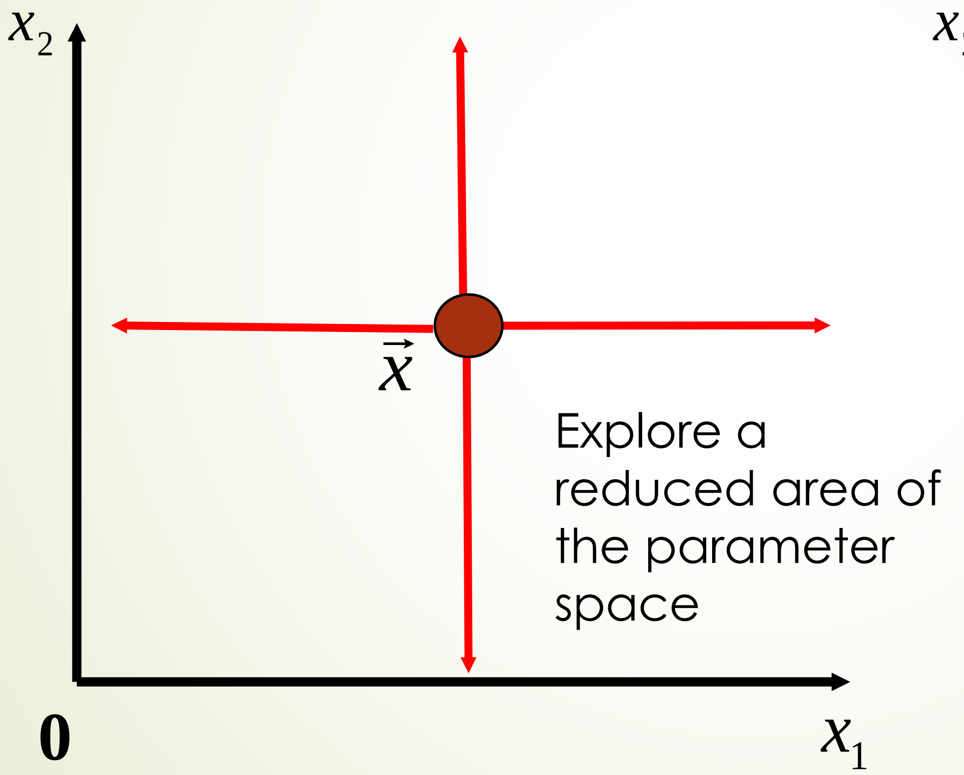
Variation of only one input, the other are fixed
→ Choice of the fixed values ?



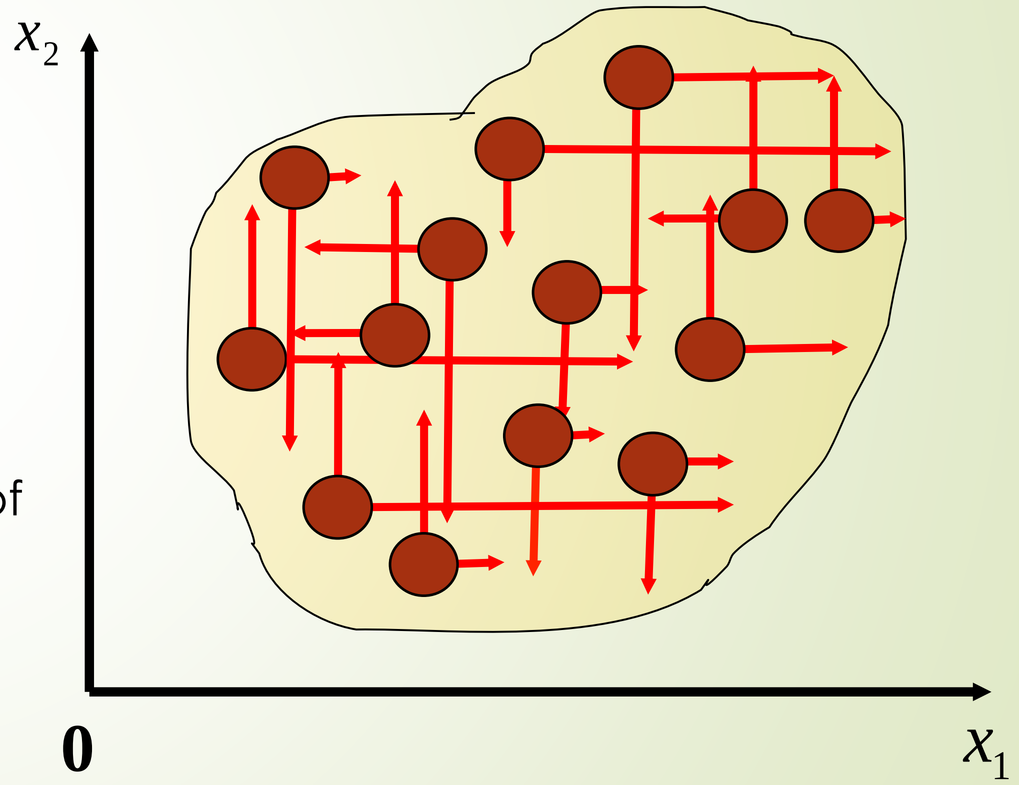
OAT Doesn't Catch the Interactions

One factor at the time

OAT



Global SA



(x_1, x_2) **= space of input** $\vec{x}$ **= nominal value**

Methodology to perform uncertainty and GLOBAL sensitivity analysis

The 6 steps

Steps for a GLOBAL uncertainty and sensitivity analysis

As Lilburne et al. 2009, a global SA follows six steps:

- (1) **Specify** the goal of the study : output of interest ? Question ?
- (2) **Select** the inputs of interest
- (3) **Assign** a range and a statistical distribution to the selected inputs

Important preliminary research work

DEFINITION of the STUDY

Don't start here!

- (4) **Apply** a sampling design to generate a sample of size N from the distributions of the inputs
- (5) **Evaluate** the model for each sample set of input values obtaining N values for the output
- (6) **Use** the results of step 5 for uncertainty analysis and **apply** an estimator of sensitivity to obtain the relative importance of the inputs

Don't start here!

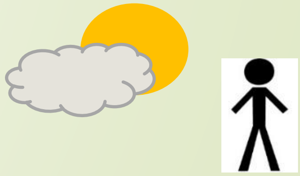
Statistics Methods

Add a step (7): **interpret** the estimator of sensitivity according to the context of the study

(1) **Specify** the goal of the study : output of interest ? Question ?
(2) **Select** the inputs of interest

The most important question is the question ! (Saltelli)

What is the **output of interest, how to quantify my issue** ?
What are the **uncertain inputs** ?
→What are the **fixed inputs**?
→At what value is the fixed input fixed ?
Which **range of variation** ?
Which **distribution law** ?
What model ? (assumptions on the building modelled, etc.)



Add a step (7): **interpret** the estimator of sensitivity according to the context of the study

Step (3): assign range and distribution to inputs

The uncertainty of model inputs can be characterized through a probability density function (pdf).

Characterizing uncertainties is a challenge!

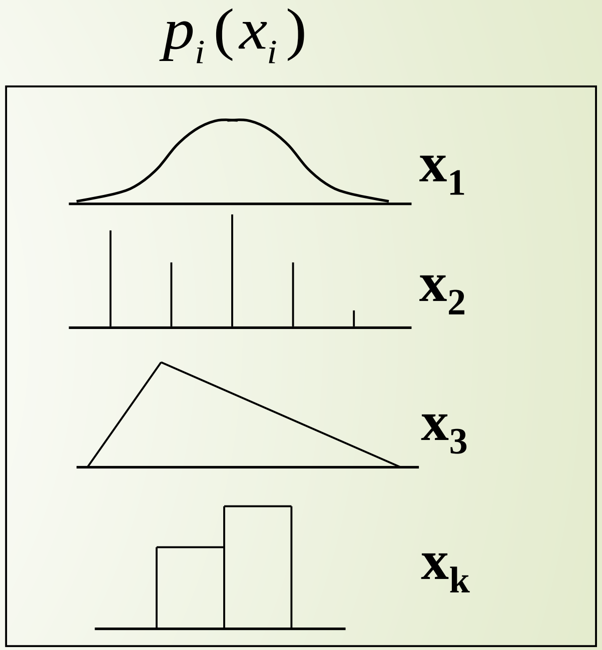
Scientific literature

Physical bounds

Experiments

Expert review processes

Opinion polls, surveys



Helton et al.1993

Underestimate or overestimate the range of the uncertainty may imply different result : coherent with the goal of the study

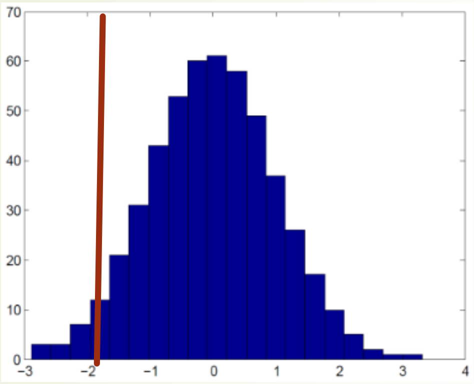
EX: Uncertainties of the conductivity of the insulation : laboratory measure, aging effect , construction defect etc... **It depends on the issue of the study**

(4) **Apply** a sampling design to generate a sample of size N from the distributions of the inputs

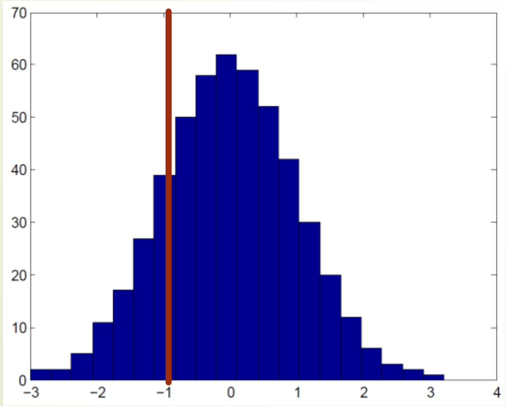
Sample Generation : Monte Carlo

Generation random numbers from the distribution of the model parameters, that is used for the analysis

→ Explore the entire range of variation (Global)

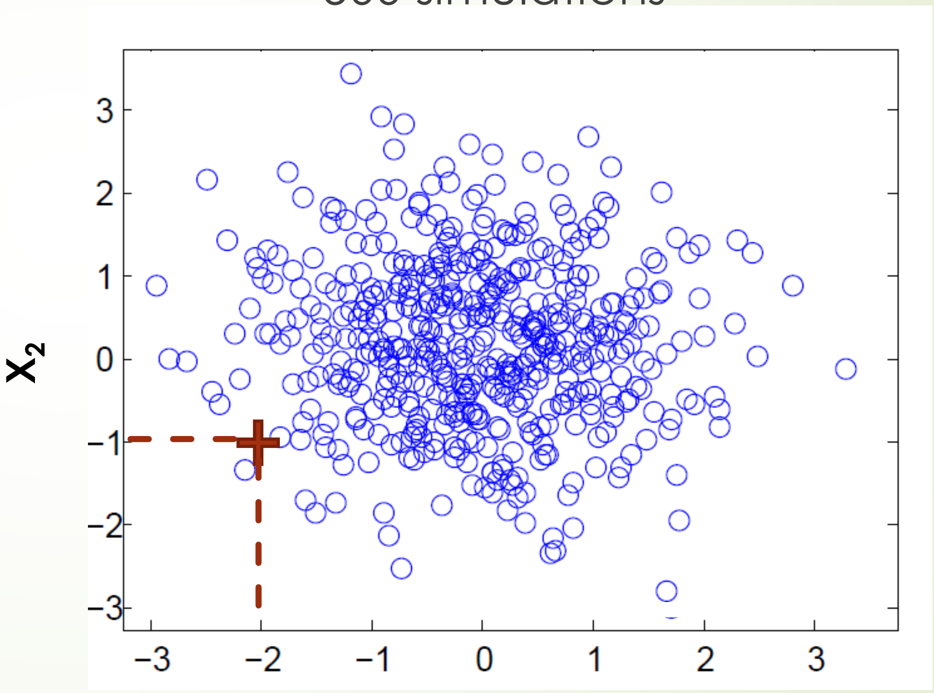


X_1



X_2

500 simulations



X_1

- Optimizing the exploration space
- → LHS, etc.

Optimizing the exploration space

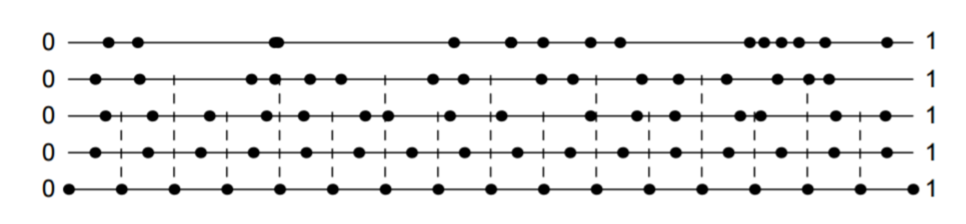


Figure 2.2 Different ways of distributing points from 0 to 1

[Saltelli 2008]

Latin Hypercube Sampling : LHS (Helton 1993)

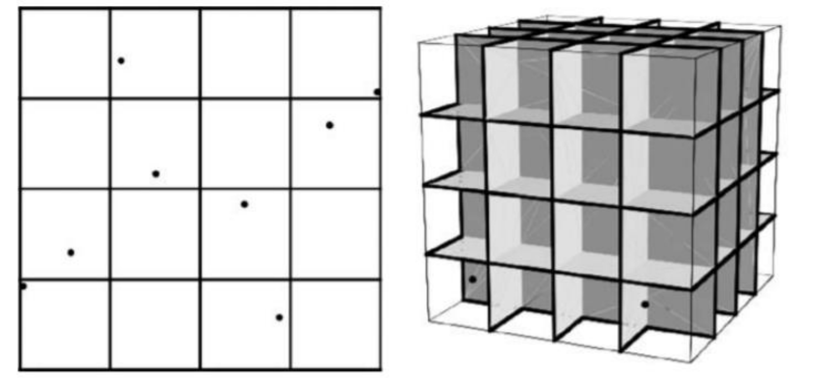
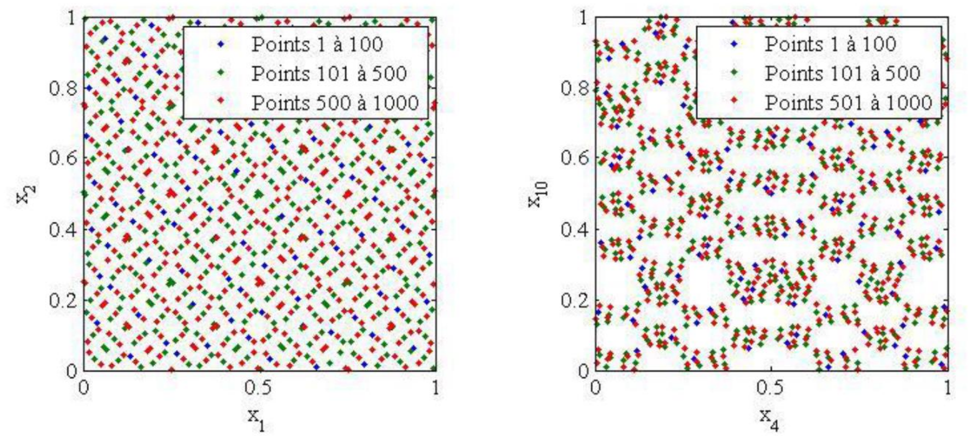


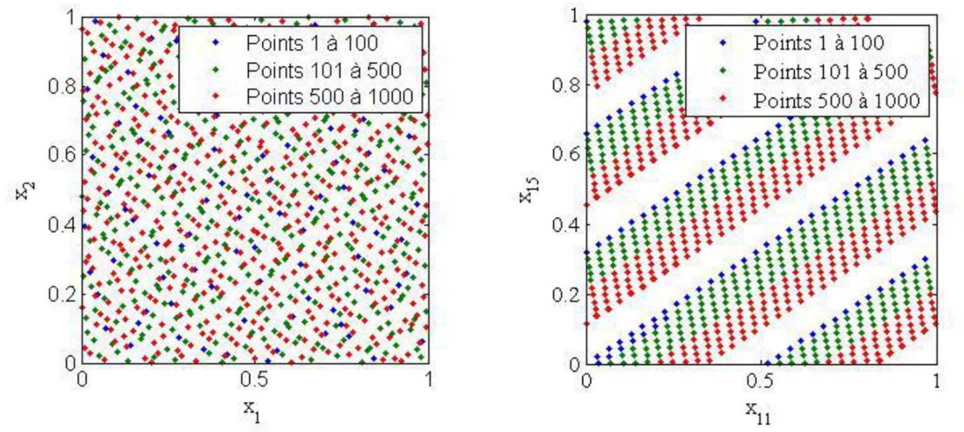
Figure 2.7 Combined fractional factorial – Latin hypercube design

Quasi-Monte Carlo

Sobol Sequence



Halton



[Rabouille 2014]

Less simulation to obtain the same statistical result

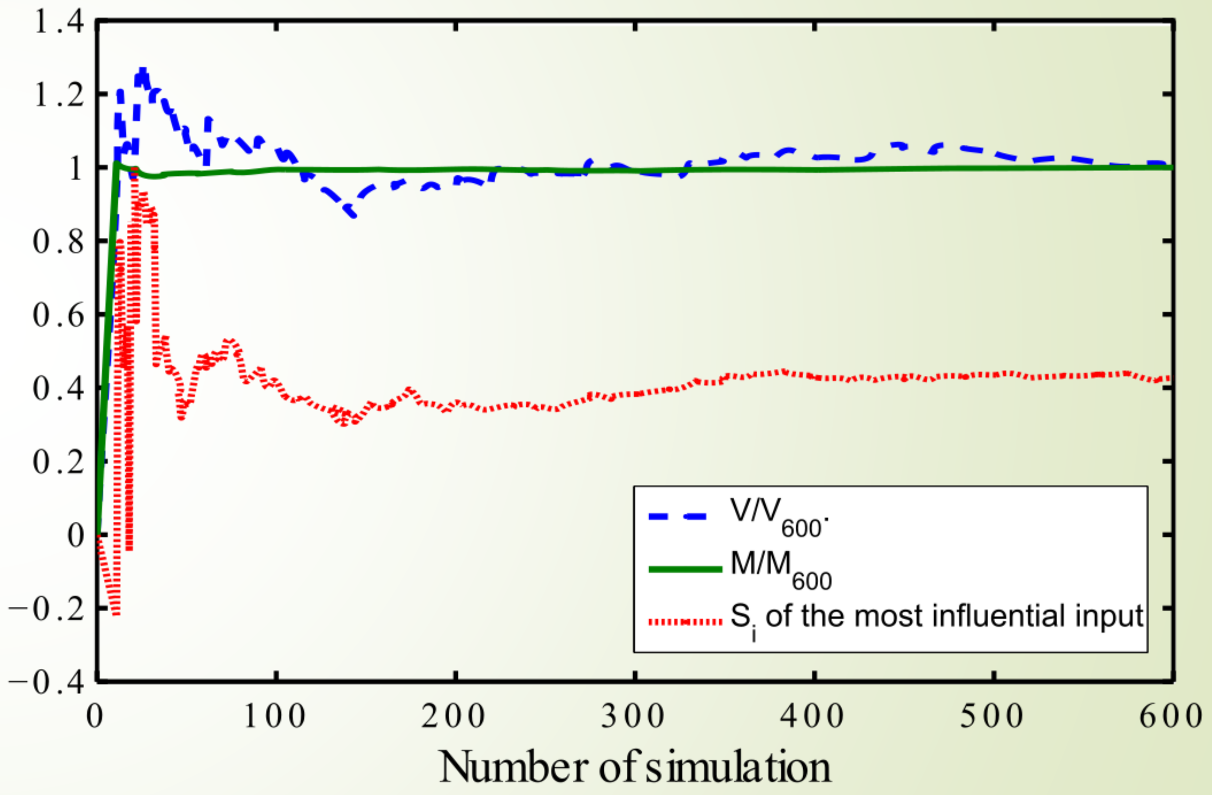
Convergence

- Evolution of statistical quantities according to the number of simulations

Mean, Variance, etc.

- Sufficient evaluation to obtain a stable result

→ representative sample

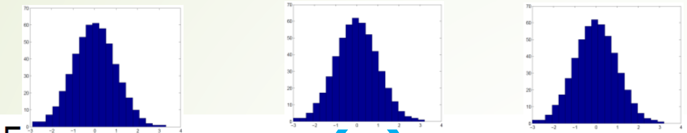


(Goffart,2015)

(5) **Evaluate** the model for each sample set of input values obtaining N values for the output

Propagation

$$\mathbf{Y} = f\left(\mathbf{X}_1, \ldots, \mathbf{X}_i, \ldots, \mathbf{X}_p\right)$$



N simulation

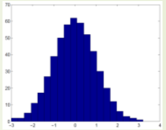
$$\begin{bmatrix} X_{1,1} & \cdots & X_{1,i} & \cdots & X_{1,p} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ X_{j,1} & \cdots & X_{j,i} & \cdots & X_{j,p} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ X_{N,1} & \cdots & X_{N,i} & \cdots & X_{N,p} \end{bmatrix}$$

Insulation conductivity

Infiltration rate

p statics inputs

Model
$f(\ldots)$



VARIANCE
Analyse of the output spread

$$\begin{bmatrix} Y_1 \\ \vdots \\ Y_j \\ \vdots \\ Y_N \end{bmatrix}$$

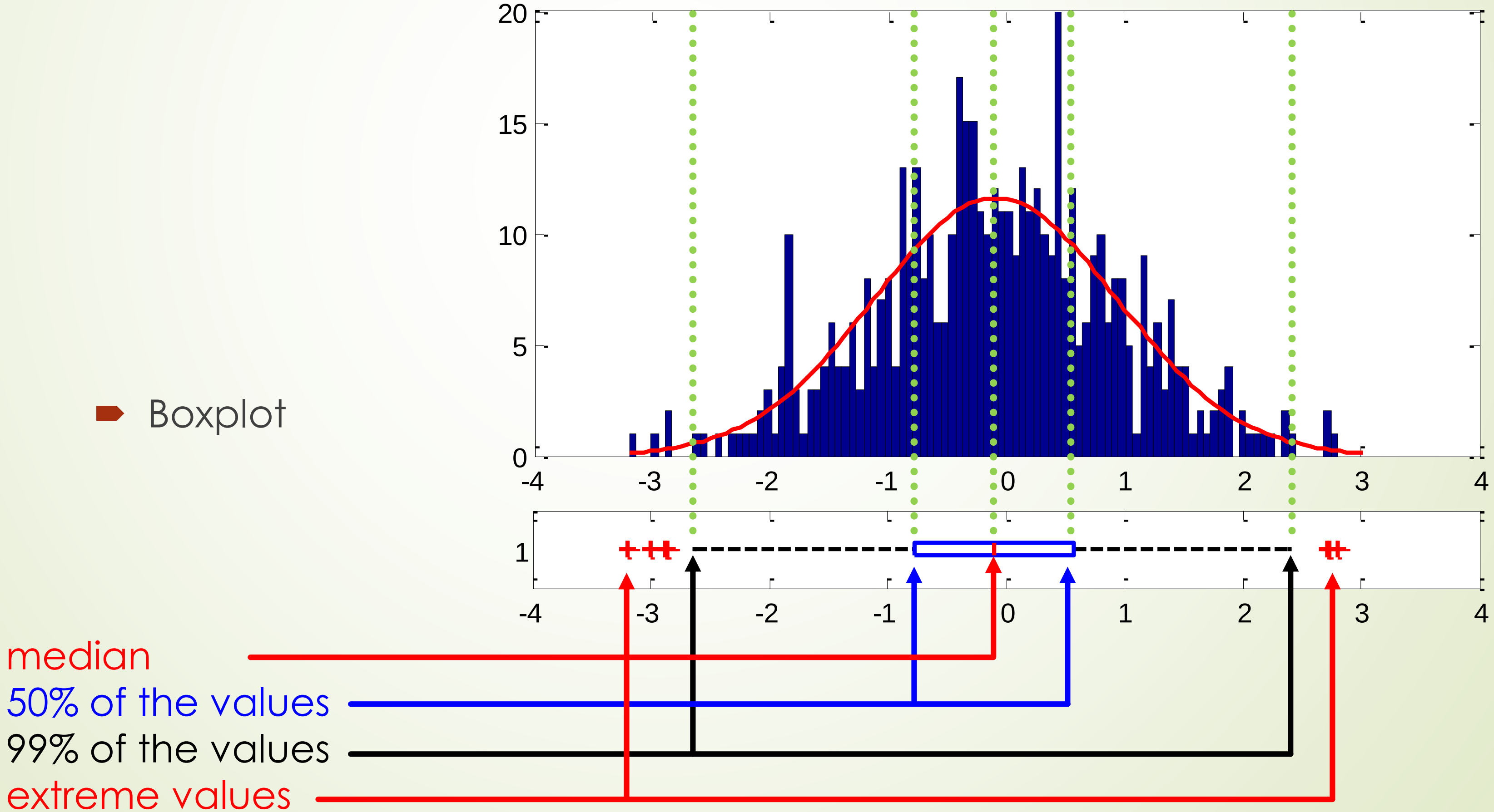
N value of the output

Energy heating, cooling needs
Degree day of the discomfort
…

- N value of Y → Confidence bound
- Input variation → Output variation

Representation and interpretation of output uncertainty

- Histogram
- Boxplot



Boxplot
→ Convenient for asymmetric distribution

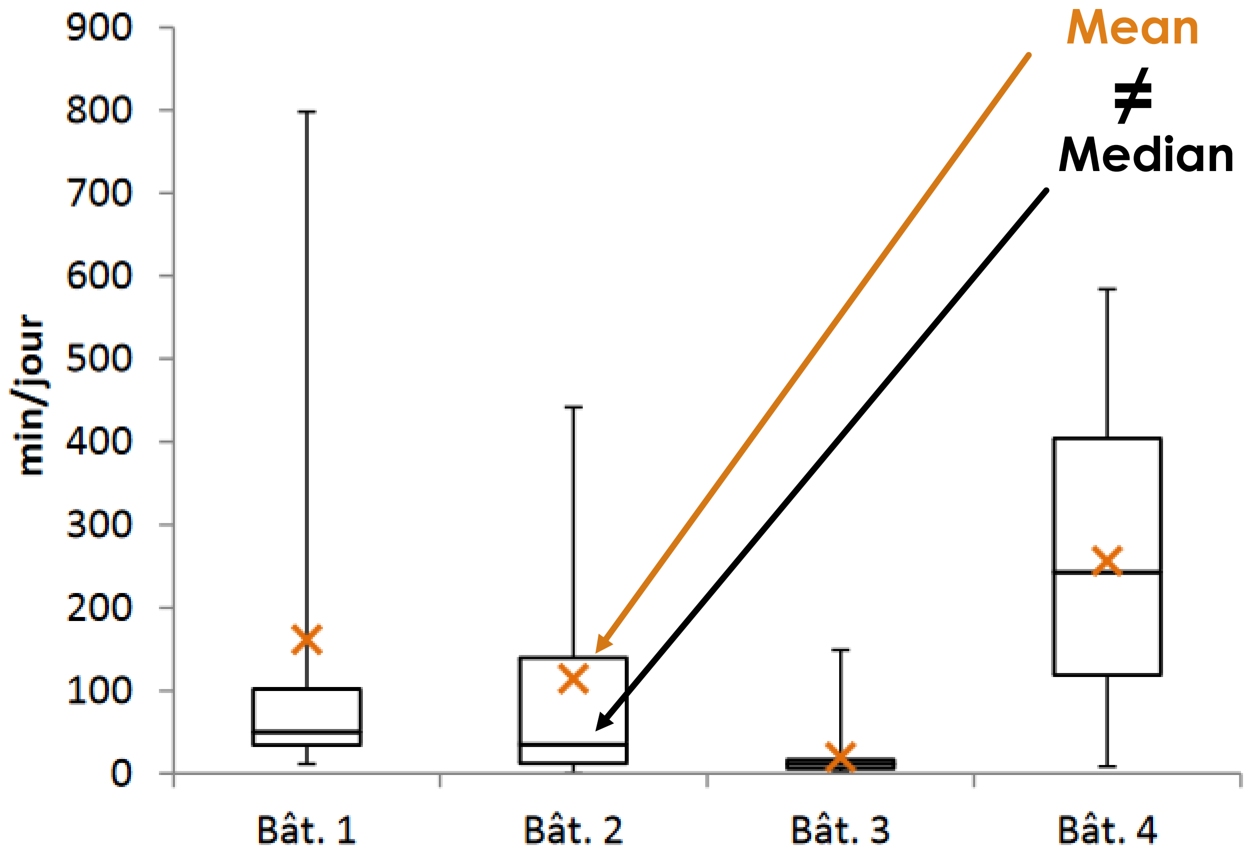
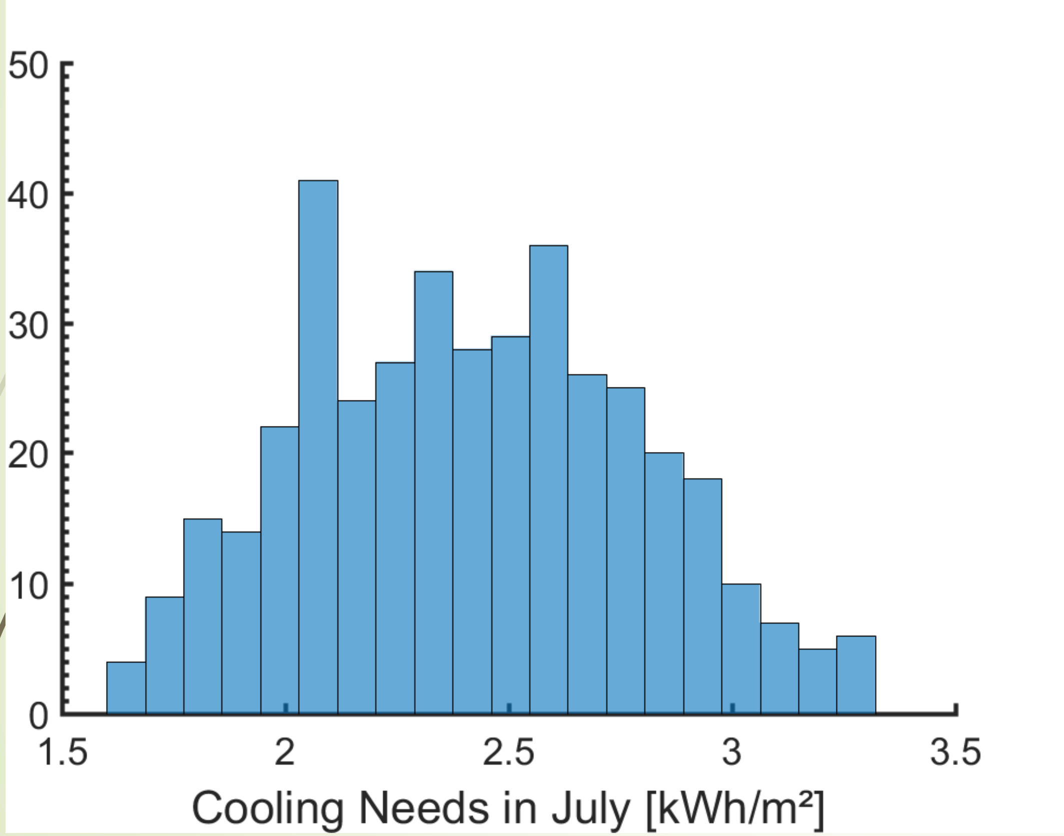


Figure 101 : Boxplots des durées d'ouvertures des fenêtres pour les quatre bâtiments instrumentés. Les moyennes sont représentées par les croix oranges.

(Vorger, 2014)

First Result: Output Uncertainty



- N value of Y → Confidence bound
- Input variation → Output variation

→ 39 uncertain inputs

→ 400 Simulations

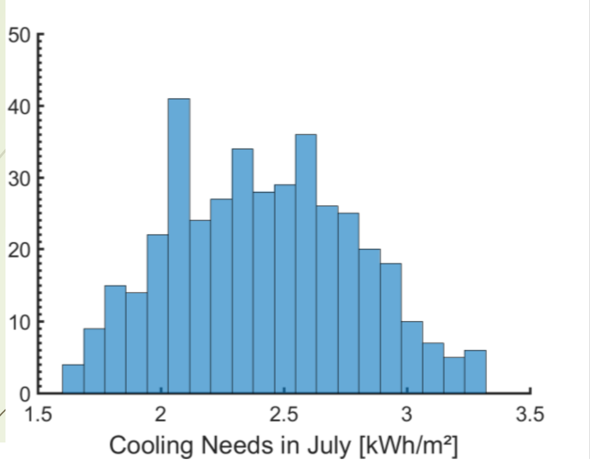
And Then ?

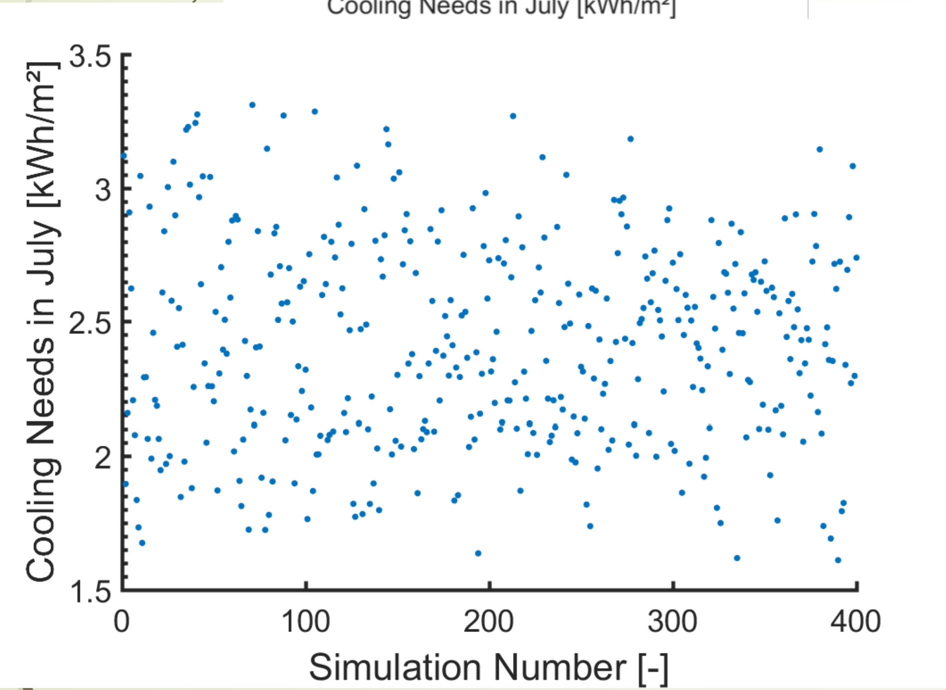
Reducible ? Manage the main input responsible? By measure etc..

Input(s) responsible(s) for this dispersion ?

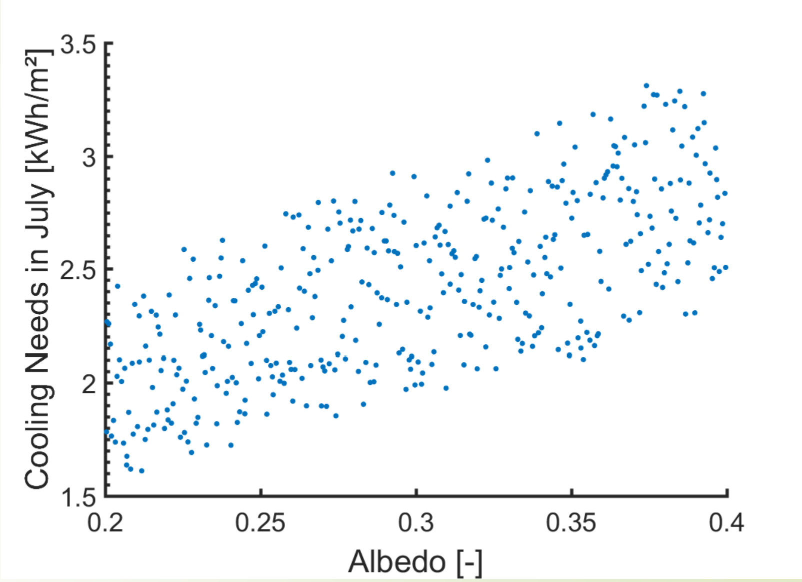
→ **Sensitivity Analysis**

Scatterplot : Output dispersion VS Input Variation

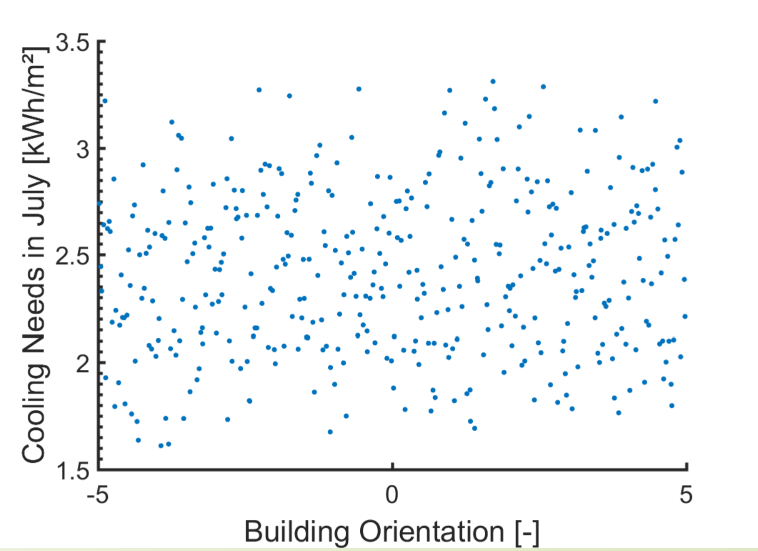


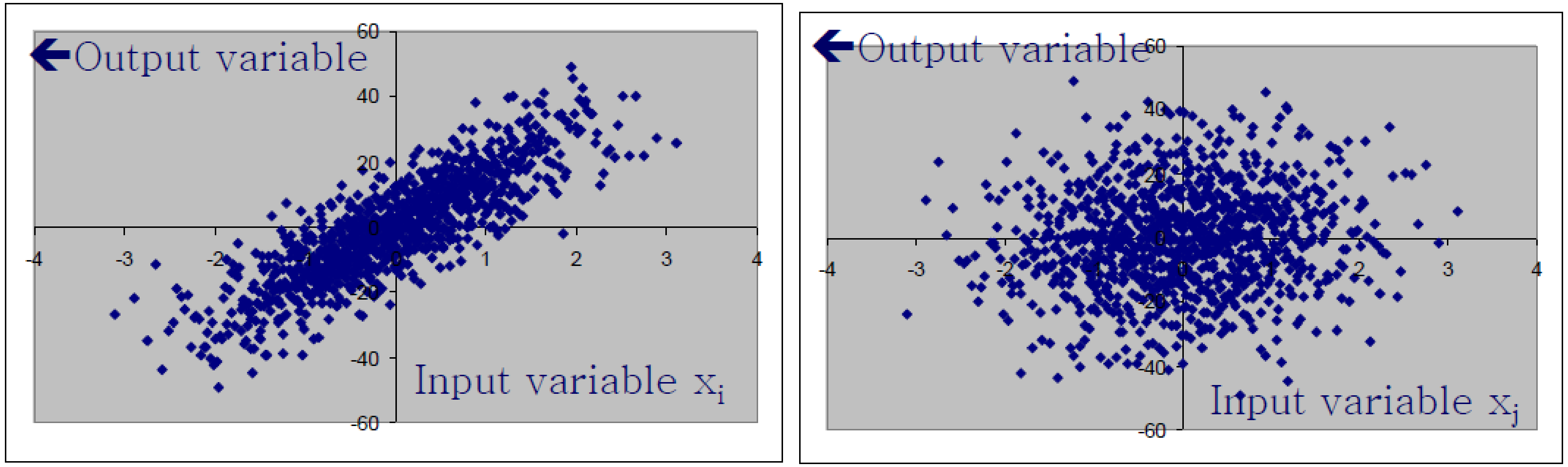


According to the albedo variation



According to the orientation variation

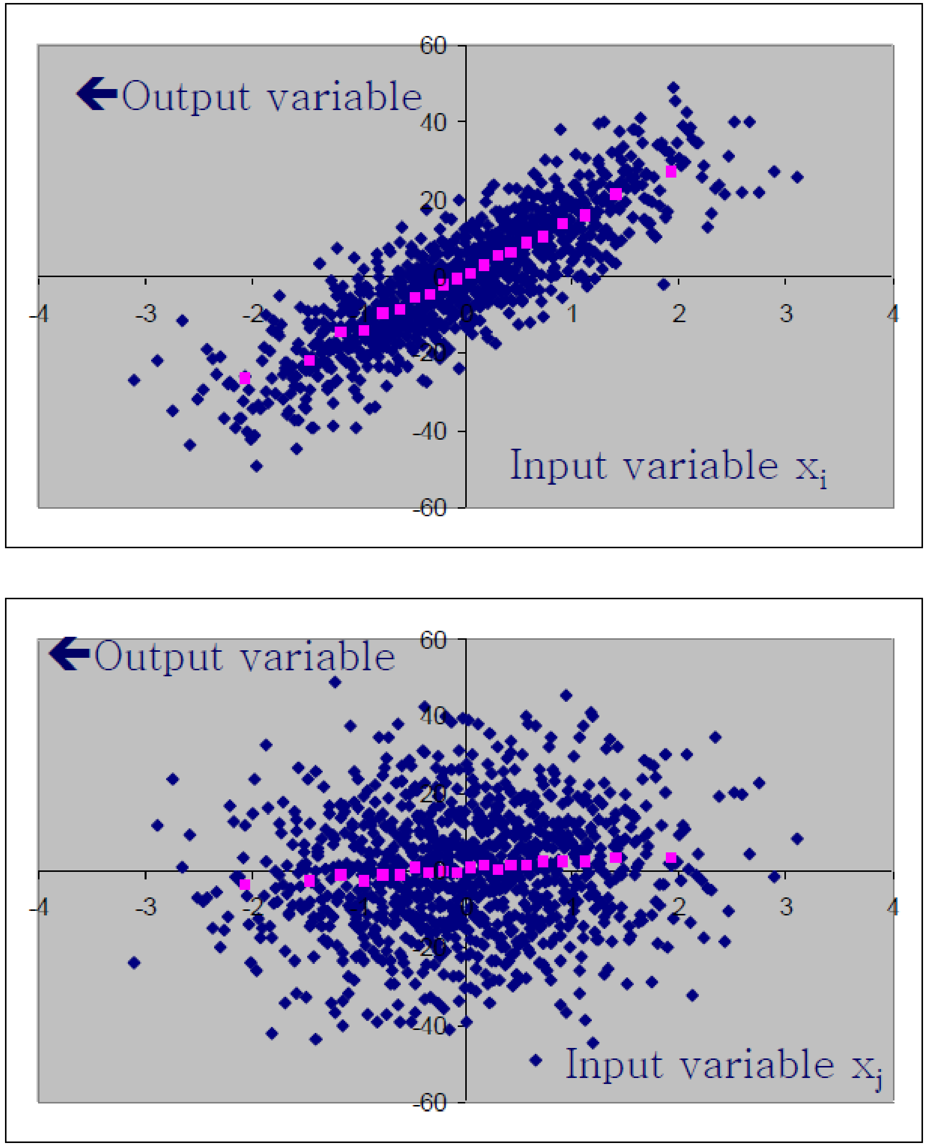




Which factor is more important?

Why?

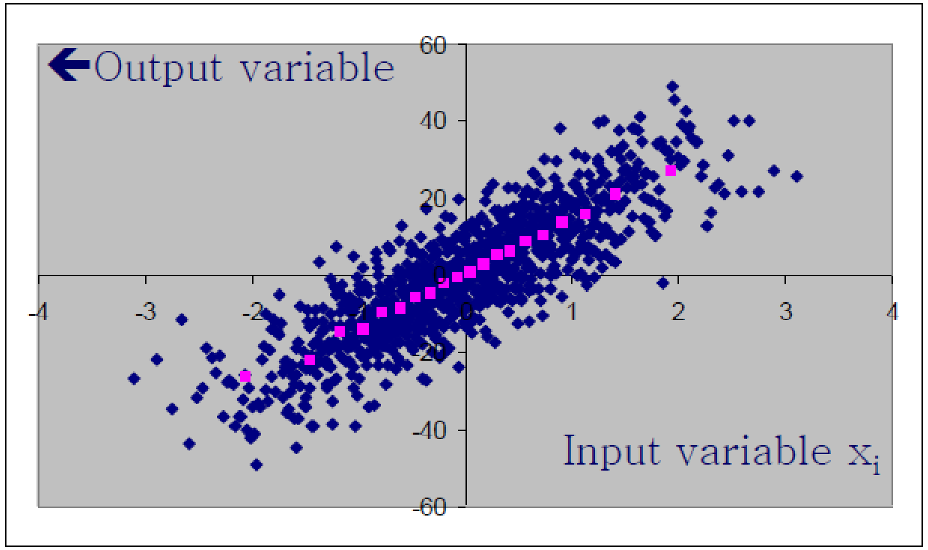
From Saltelli's presentation :
http://www.andreasaltelli.eu/file/repository/Berkeley_ensalada1.pdf



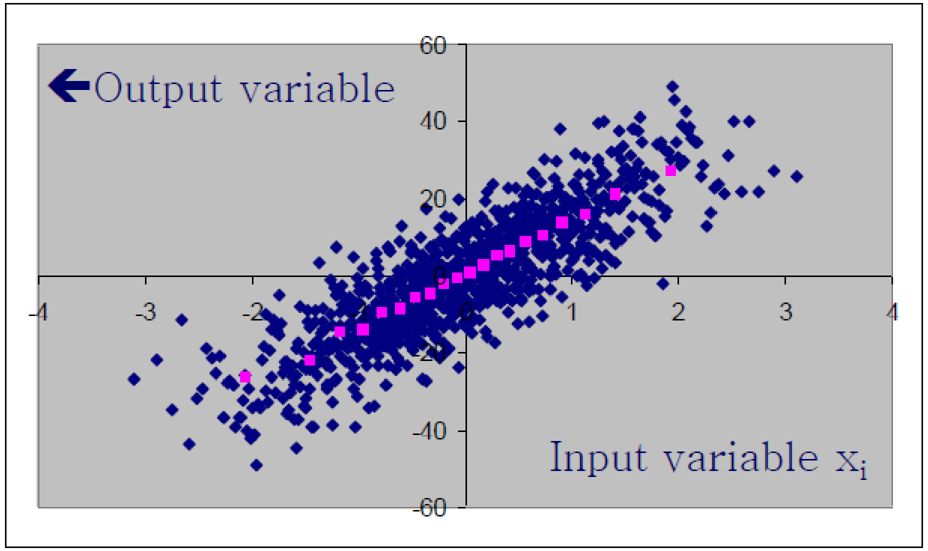
~1,000 blue points

Divide them in 20 bins of ~ 50 points

Compute the bin's average (pink dots)

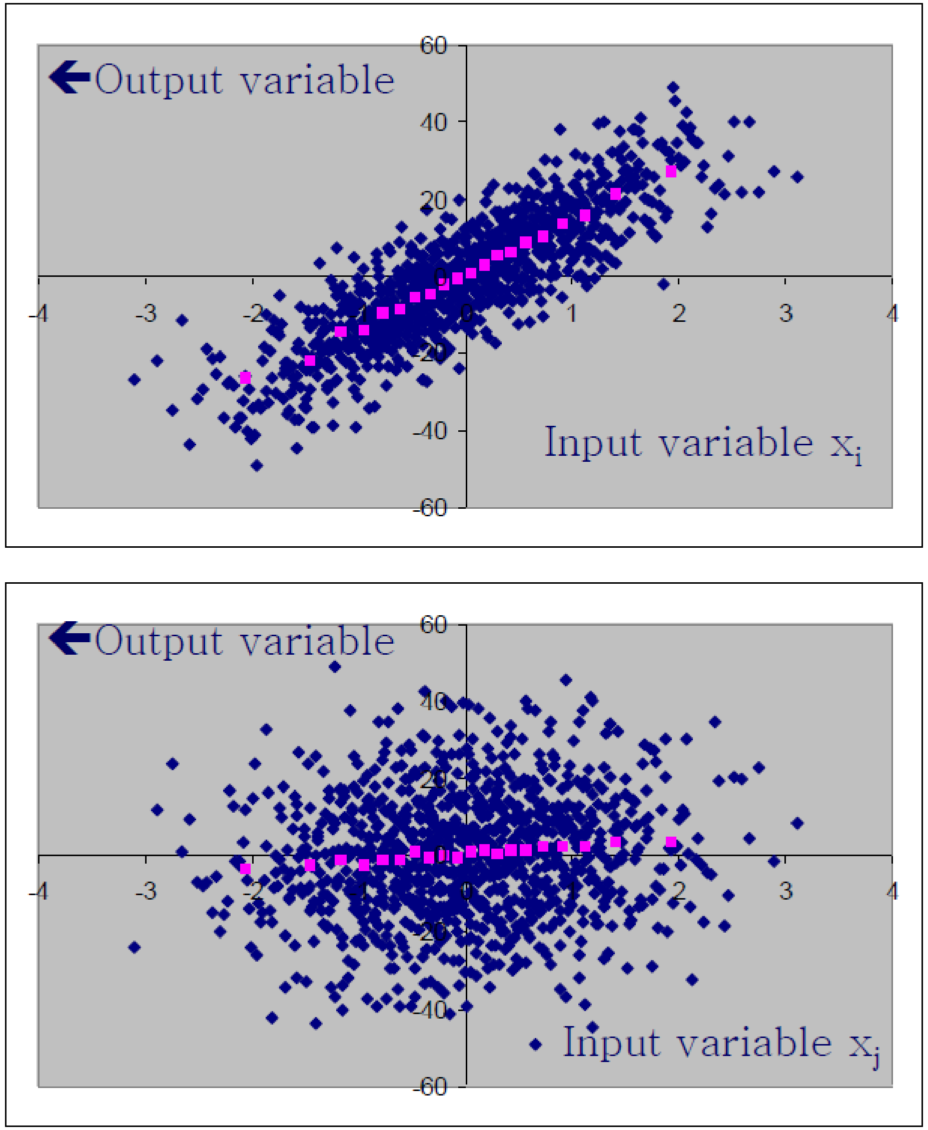


Each pink point is ~ $E_{\mathbf{X}_{\sim i}}\left(Y \middle| X_i\right)$



Take the variance of the pink points and you have a sensitivity measure

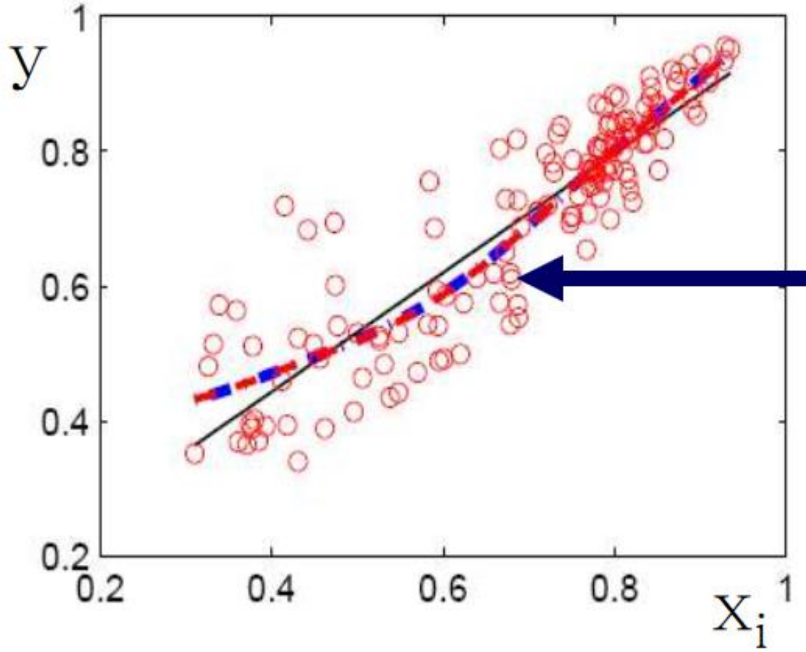
$$V_{X_i}\left(E_{\mathbf{X}_{\sim i}}\left(Y \middle| X_i\right)\right)$$



Which factor has the highest $V_{X_i}\left(E_{\mathbf{X}_{\sim i}}\left(Y \mid X_i\right)\right)$?

(6) **Use** the results of step 5 for uncertainty analysis and **apply** an estimator of sensitivity to obtain the relative importance of the inputs

$$S_i \equiv \frac{V\left(E\left(Y \middle| X_i\right)\right)}{V_Y}$$



Smoothed curve:

$$E_{\mathbf{x}_{\sim i}}\left(y \mid x_i\right)$$

First order sensitivity index:

$$\frac{V_{x_i}\left(E_{\mathbf{x}_{\sim i}}\left(y \mid x_i\right)\right)}{V\left(y\right)}$$

Pearson's correlation ratio

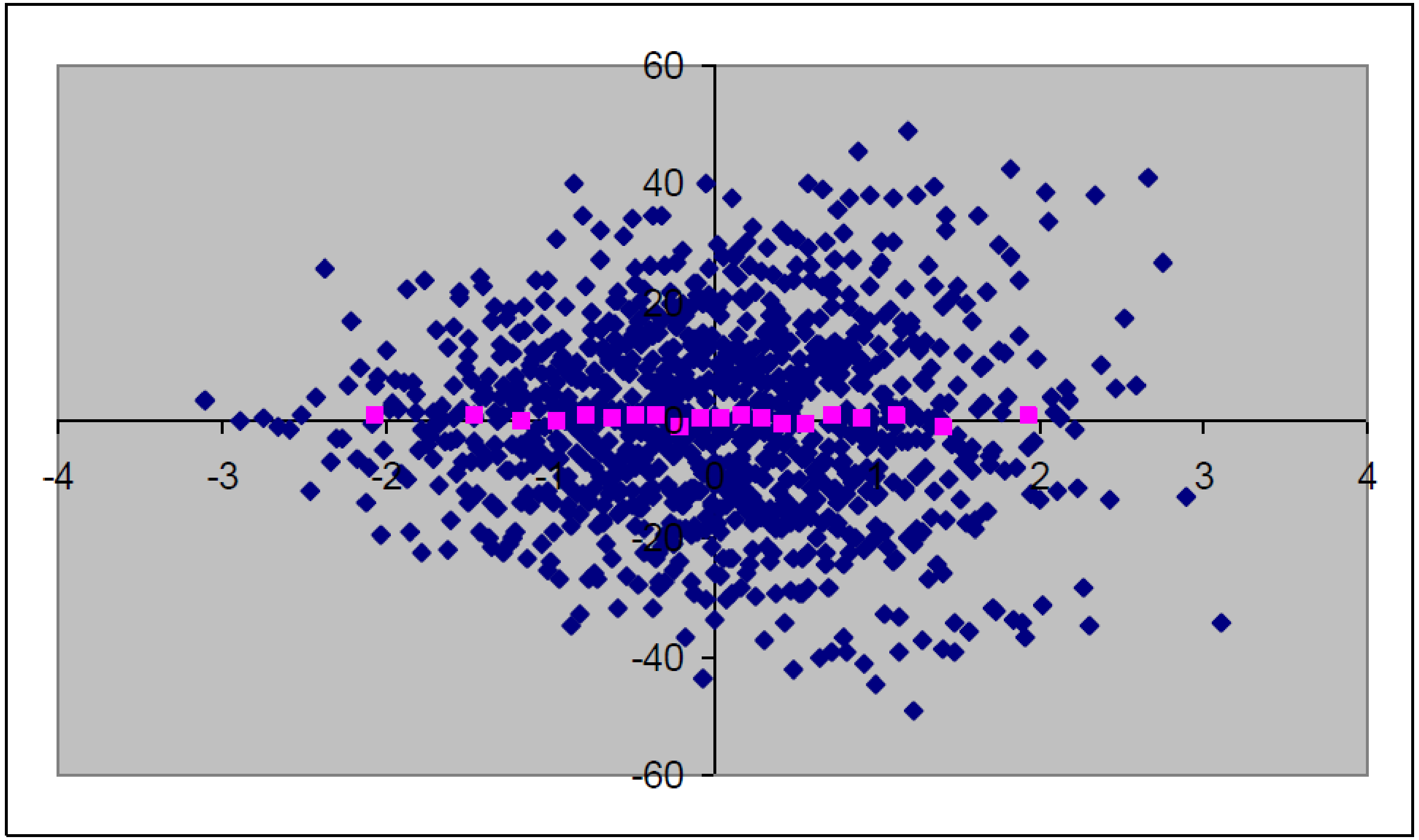
Smoothed curve

$$S_i \equiv \eta_i^2 := \frac{\mathrm{V}_{x_i}\left(\mathrm{E}_{\mathbf{x}_{\sim i}}\left(y \mid x_i\right)\right)}{\mathrm{V}\left(y\right)}$$

First order sensitivity index

Unconditional variance

Is S_i =0? Is this factor non-important?



High order effect

Variance decomposition (ANOVA)

$$V(Y) = \sum_i V_i + \sum_{i,j>i} V_{ij} + \ldots + V_{123\ldots k}$$

First order effect

Second order effect

k order effect

Variance-based sensitivity indices

Sobol's Sensitivity indexes of the **first order** (Sobol, 1993)

$$S_i = \frac{V\left(E\left[Y \mid X_i\right]\right)}{V\left(Y\right)}$$

→ Part of the Y variance due to the input X_i
→ Input responsible

Sobol's Decomposition of the variance (**Independent p input**) (Sobol 1993)

$$V = \sum_{i=1}^{p} V_i + \sum_{1 \le i < j \le p} V_{ij} + \ldots + V_{1\ldots p}$$

Sobol indices for the second and third order

$$S_{ij} = \frac{V_{ij}}{V} \qquad S_{ijk} = \frac{V_{ijk}}{V}$$

- **Robust, intuitive (between 0 and 100 %), independent of the model complexity**
- Highlighting interactions among uncertain inputs
- Applicable to any kind of model

Interactions

$$V = \sum_{i=1}^{p} V_i + \sum_{1 \le i < j \le p} V_{ij} + \ldots + V_{1\ldots p}$$

Divide by the total Variance V

$$\frac{V}{V} = \frac{\sum_{i=1}^{p} V_i}{V} + \frac{\sum_{1\le i<j\le p} V_{ij}}{V} + \cdots + \frac{V_{1\ldots p}}{V}$$

$$1 = \boxed{\sum_{i=1}^{p} S_i} + \sum_{1\le i<j\le p} S_{ij} + \cdots + S_{1\ldots p}$$

$$S_i = \frac{V_i}{V} \quad S_{ij} = \frac{V_{ij}}{V}$$

$$S_{ijk} = \frac{V_{ijk}}{V}$$

Very often: all the output dispersion explained by the first order

VERIFICATION If $\sum_{i=1}^{p} S_i \neq 1$ ⇒

INTERACTIONS
→ Second , third and/or higher effect to compute

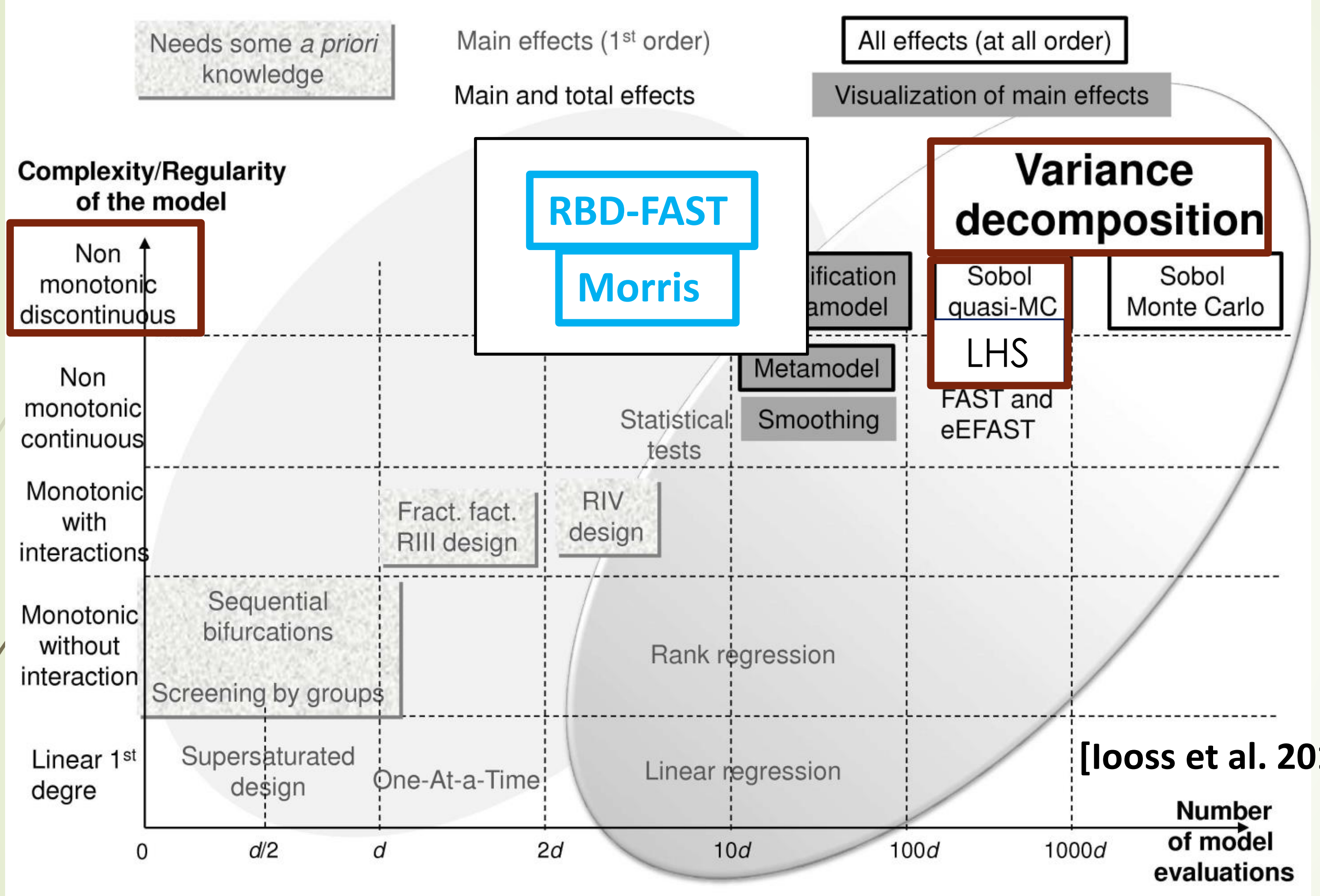
Sensitivity analysis : methods for Building Performance Simulation

Presentation of RBD-FAST

-> most suitable method for BPS

Sensitivity Analysis Methods

BPS



[Iooss et al. 2015]

- **Functional Variance decomposition**

→Sobol's Method (Saltelli *et al.* 2010a)

  – ☺ Quantity and quality of the extractable information
  – ☹ Simulation Cost

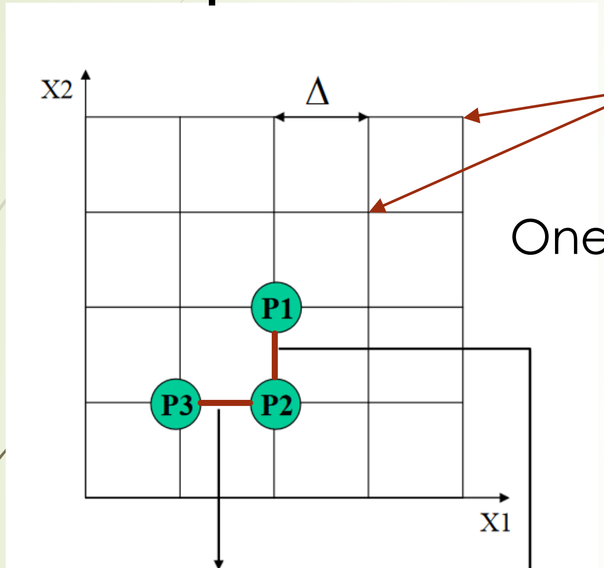
- ***Morris' Screening***
  – ☹ Rank estimation (qualitative)
  – ☺ Simulation Cost (Divide by 100 until 1000 compared to Sobol)

- **RBD FAST : Variance decomposition with low cost simulation (compute S_i)**
  – ☺ Quality and quantity of the extractable information
  – ☺ Simulation cost

Principle of Morris Screening and Improvements

- **Morris: A "one factor at a time" method improved**

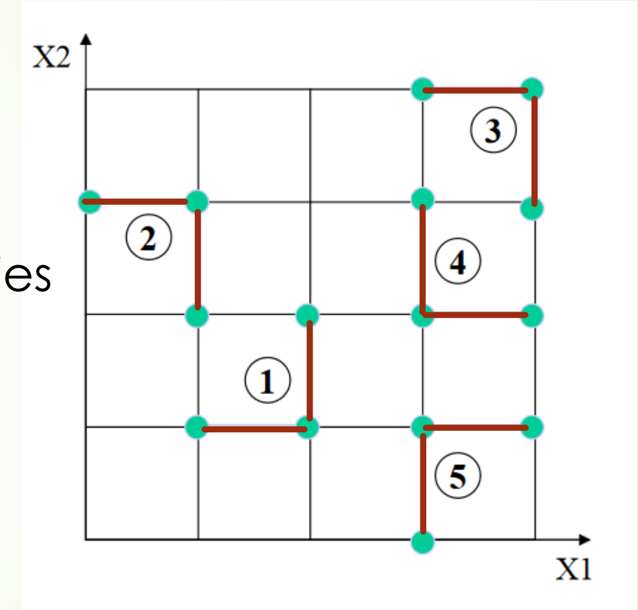
→ Grid: Space discretization (Δ)



$$d_{X_1} = \frac{f(P3)-f(P2)}{\Delta} \qquad d_{X_2} = \frac{f(P2)-f(P1)}{\Delta}$$

→ Estimation of the local elementary effect in several points of space

[Iooss 2009]



→ 2 indicators for the classification of the effects

– **μ* : average of the absolute values of the effects**

Estimate the influence of each variable

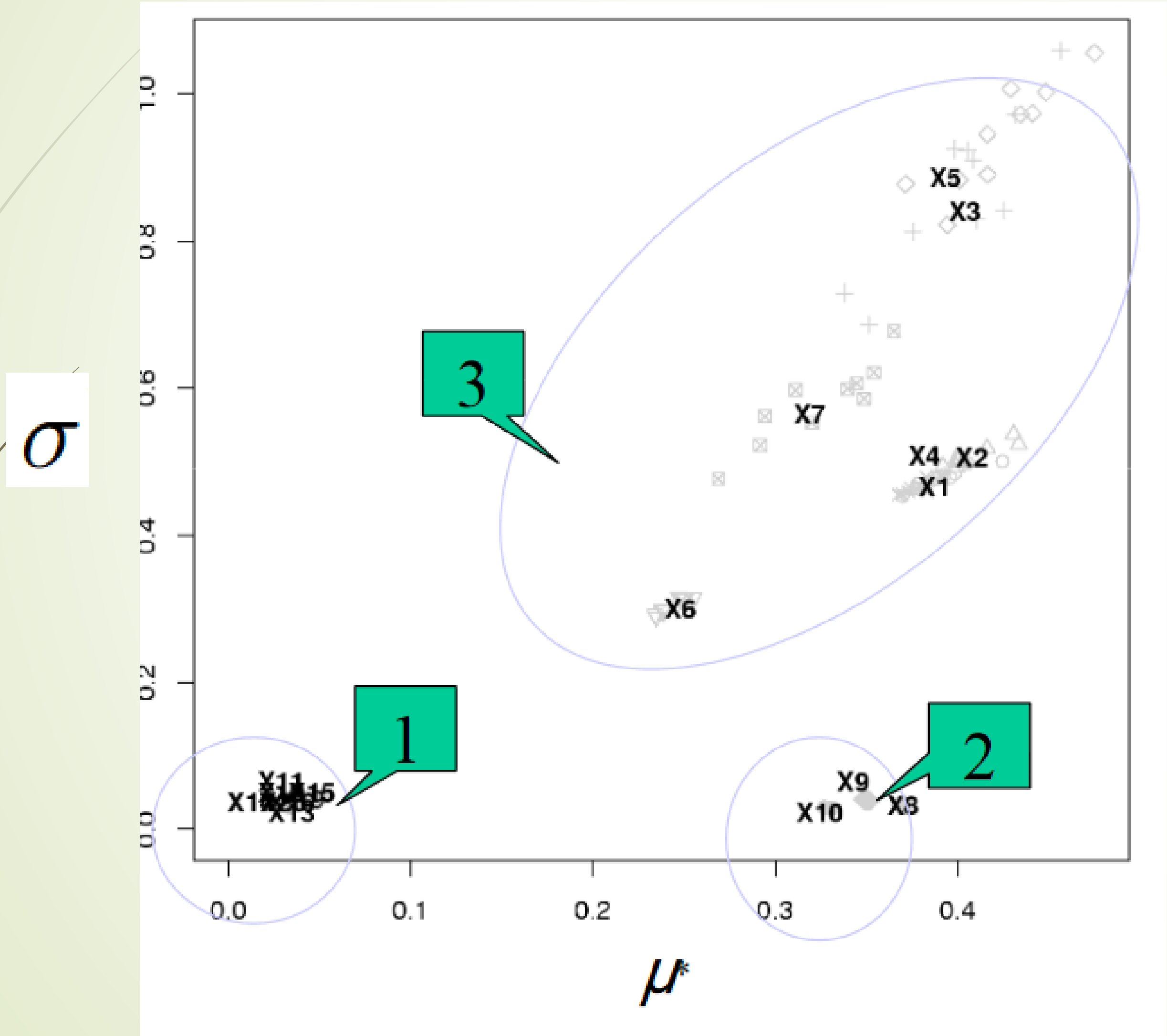
– **σ : standard deviation of the effects**

Estimate the non-linearity of the variable itself and/ or the interactions with other variables

→ Choice and number of trajectories

Optimisation of the space parameter [Campolongo *et al.* 2007]

Principle of the Morris Plot



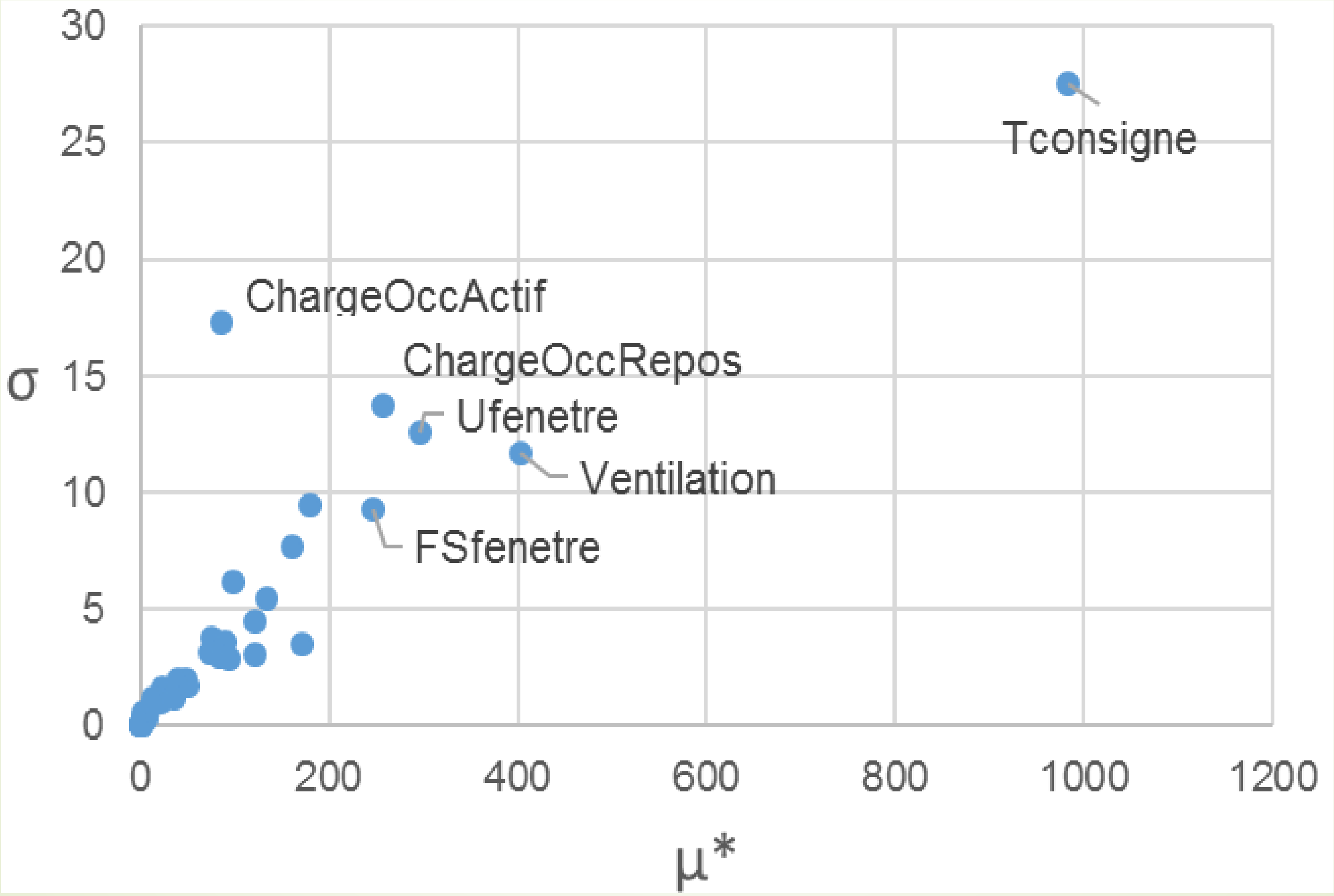
Example: [Iooss 2009]
20 inputs
210 simulations
→ Plot (mu*, sigma)

3 groups:
1. Negligeable effects
2. Linear Effects
3. Non-linear effects and/or with interactions

BPS example : 50 inputs, 306 simulations [Goffart, 2018]

MORRIS

→ 306 simulations (6 optimised trajectories)



$$d^* = \sqrt{\mu^{*2} + \sigma^2}$$

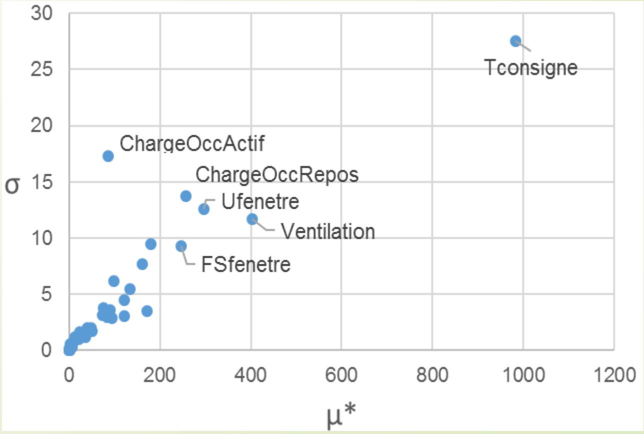
BPS example : 50 inputs, 306 simulations [Goffart, 2018]

MORRIS

$$d^* = \sqrt{\mu^{*2} + \sigma^2}$$

Paramètres	Variation du paramètre dans l'AS	Distance d^* Morris	Rang Morris
Température de consigne [°C]	**20 ± 1**	**984**	**1**
Ventilation [$m^3/(s.m^2)$]	**2,05.10^{-4} ± 10 %**	**404**	**2**
Conductance Fenêtre [$W/(m^2.K)$]	1,3 ± 10 %	298	3
Charge interne occupant au Repos [W]	63 ± 20	257	4
Facteur solaire Fenêtre [-]	0,49 ± 10 %	246	5
Albédo [-]	0,3 ± 0,1	179	6

Rank estimation : Qualitative



BPS example : 50 inputs, 306 simulations [Goffart, 2018]

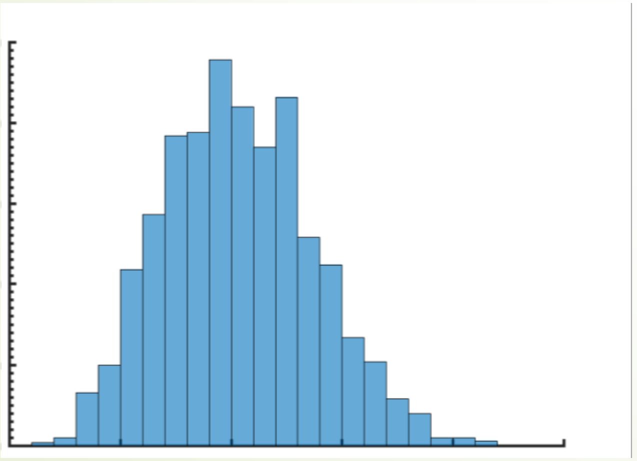
RBD-FAST (First order sensitivity indices)

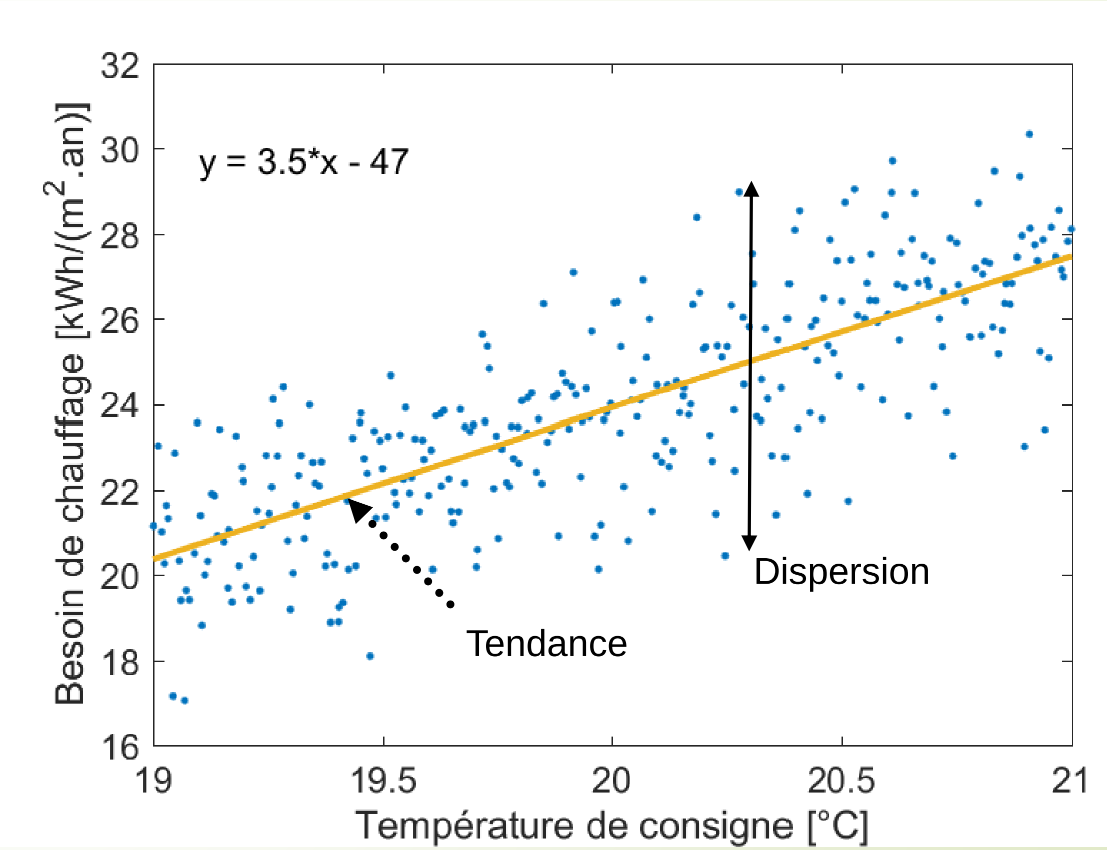
Paramètres	Variation du paramètre dans l'AS	Indice de sensibilité RBD-FAST	Distance d^* Morris	Rang Morris
Température de consigne [°C]	**20 ± 1**	**60 %**	**984**	**1**
Ventilation [m³/(s.m²)]	**2,05.10⁻⁴ ± 10 %**	**11 %**	**404**	**2**
Charge interne occupant au Repos [W]	63 ± 20	8 %	257	4
Conductance Fenêtre [W/(m².K)]	1,3 ± 10 %	7 %	298	3
Albédo [-]	0,3 ± 0,1	7 %	179	6
Puissance équipement le matin de 6 h à 8 h [W]	200 ± 200	5 %	162	8
Facteur solaire Fenêtre [-]	0,49 ± 10 %	< 4 %	246	5

$$\sum_{i=1}^{p} S_i \simeq 1$$

No interaction effect

BPS example : 50 inputs, 306 simulations [Goffart, 2018]
RBD-FAST (First order sensitivity indices)



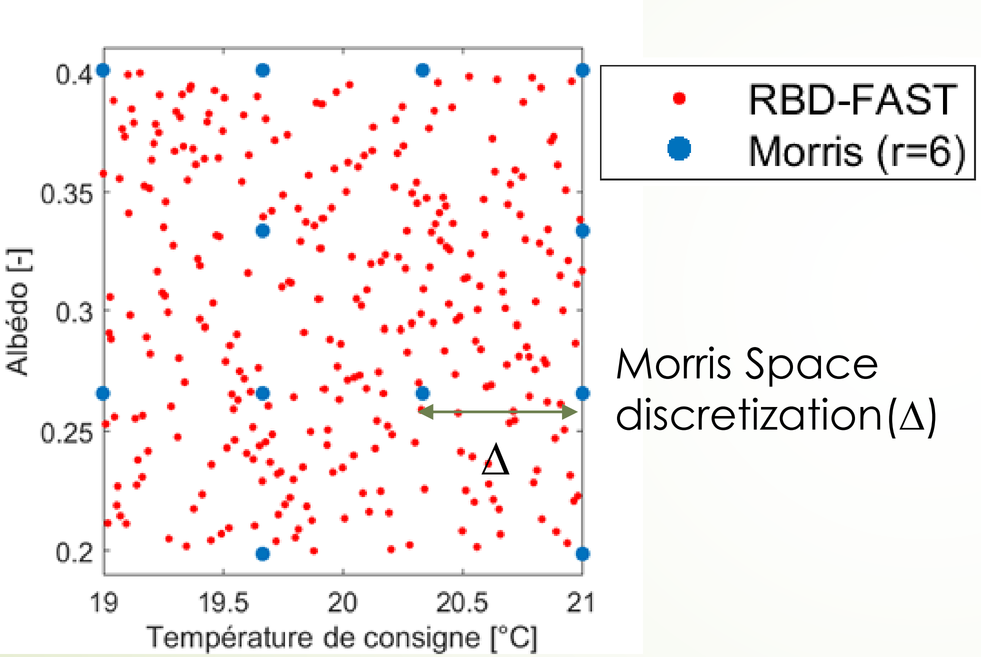


Principle of RBD-FAST

- **RBD FAST : Low cost variance based method** [Tarantola *et al.* 2006]

→ **Both sensitivity and uncertainty**

– Space exploration: optimised and homogeneous (LHS)



Morris Space discretization(Δ)

→ **Quantify the influence of each input**

– Frequential decomposition of the variance by Fourier Transform

– First order sensitivity indices of Sobol

- Part of the Y variance due to the variable Xi
- Intuitive: between 0 and 1

$$S_i = \frac{V\left(E\left[Y \middle| X_i\right]\right)}{V\left(Y\right)}$$

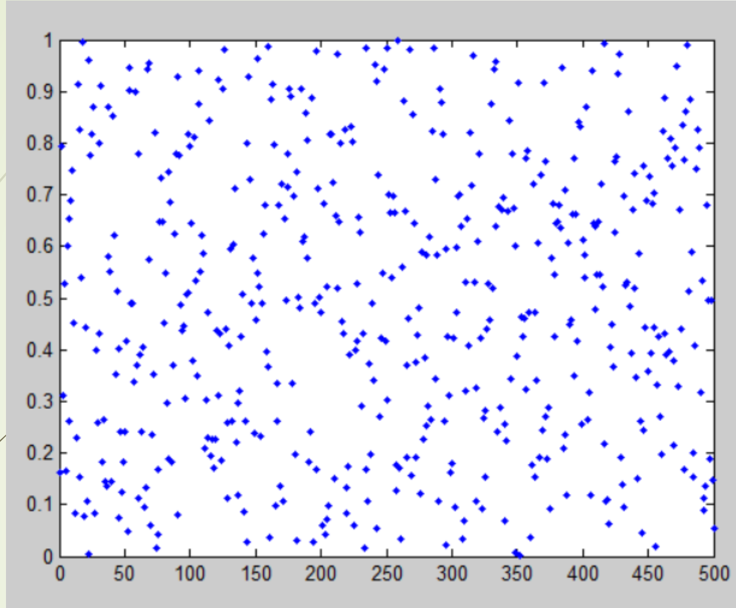
→ **Trick of permutation and reordering the simulations with a frequency**

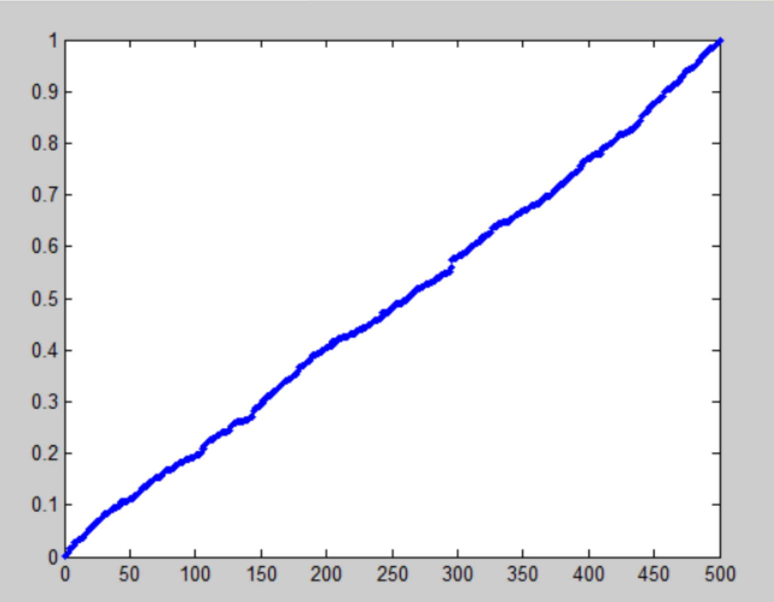
– Compute all the first order sensitivity indices with one set of samples

– EASI : induce triangle shape frequency [Plischke 2010]

Detailed in [Goffart *et al.* 2015]

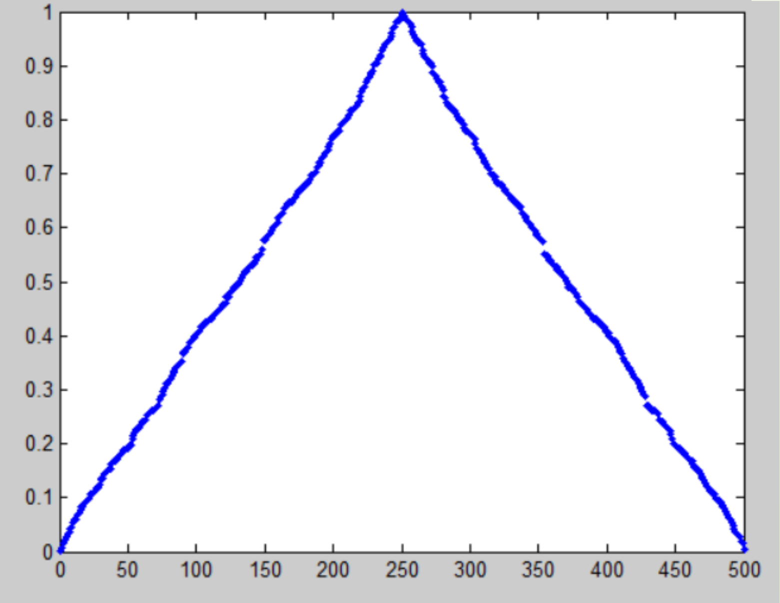
RBD FAST and the pre-processing EASI





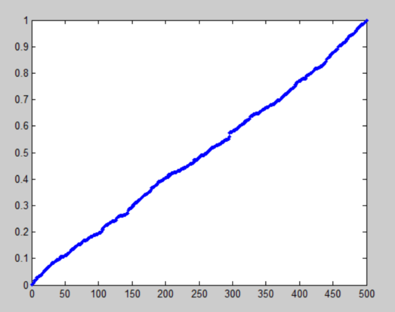
Number of simulation (500)

$$\begin{bmatrix} X_{1,1} & \dots & X_{1,i} & \dots & X_{1,p} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ X_{j,1} & \dots & X_{j,i} & \dots & X_{j,p} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ X_{N,1} & \dots & X_{N,i} & \dots & X_{N,p} \end{bmatrix}$$



$$\begin{pmatrix} 0.0012 \\ 0.0046 \\ 0.0067 \\ 0.0154 \\ 0.0155 \\ 0.0196 \\ 0.0225 \\ \dots \\ 0.9961 \\ 0.9991 \end{pmatrix}$$

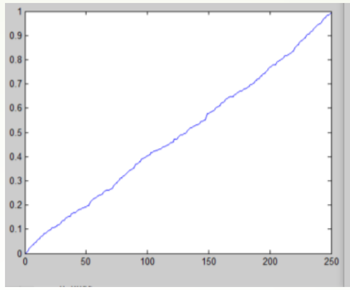
Transformation of the order of simulation



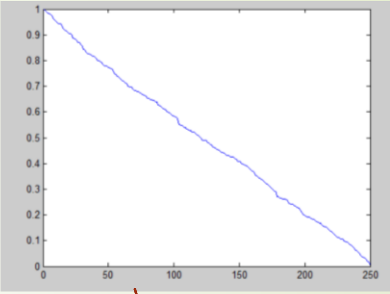
0.0012
0.0046
0.0067
0.0154
0.0155
0.0196
0.0225
…
0.9961
0.9991

0.0012
0.0067
0.0155
0.0225
…

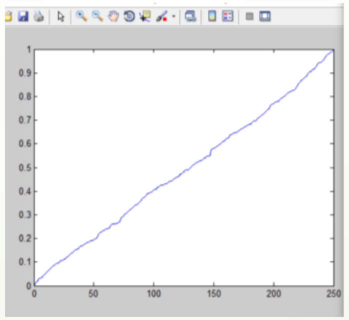
0.9961

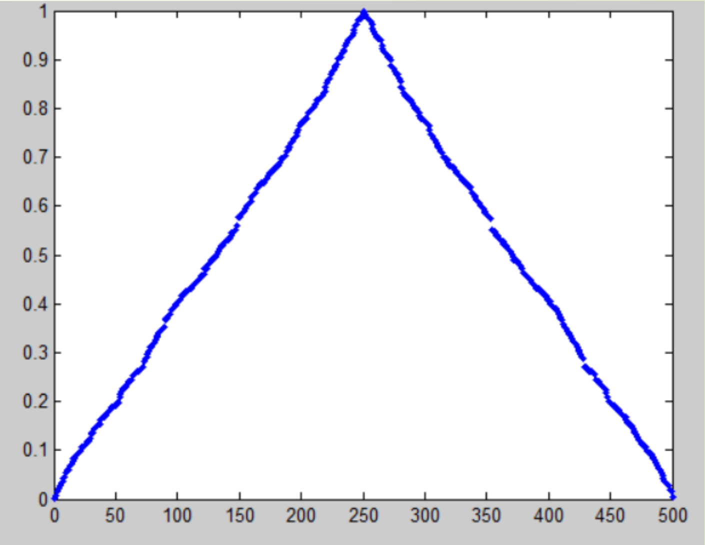


inverse



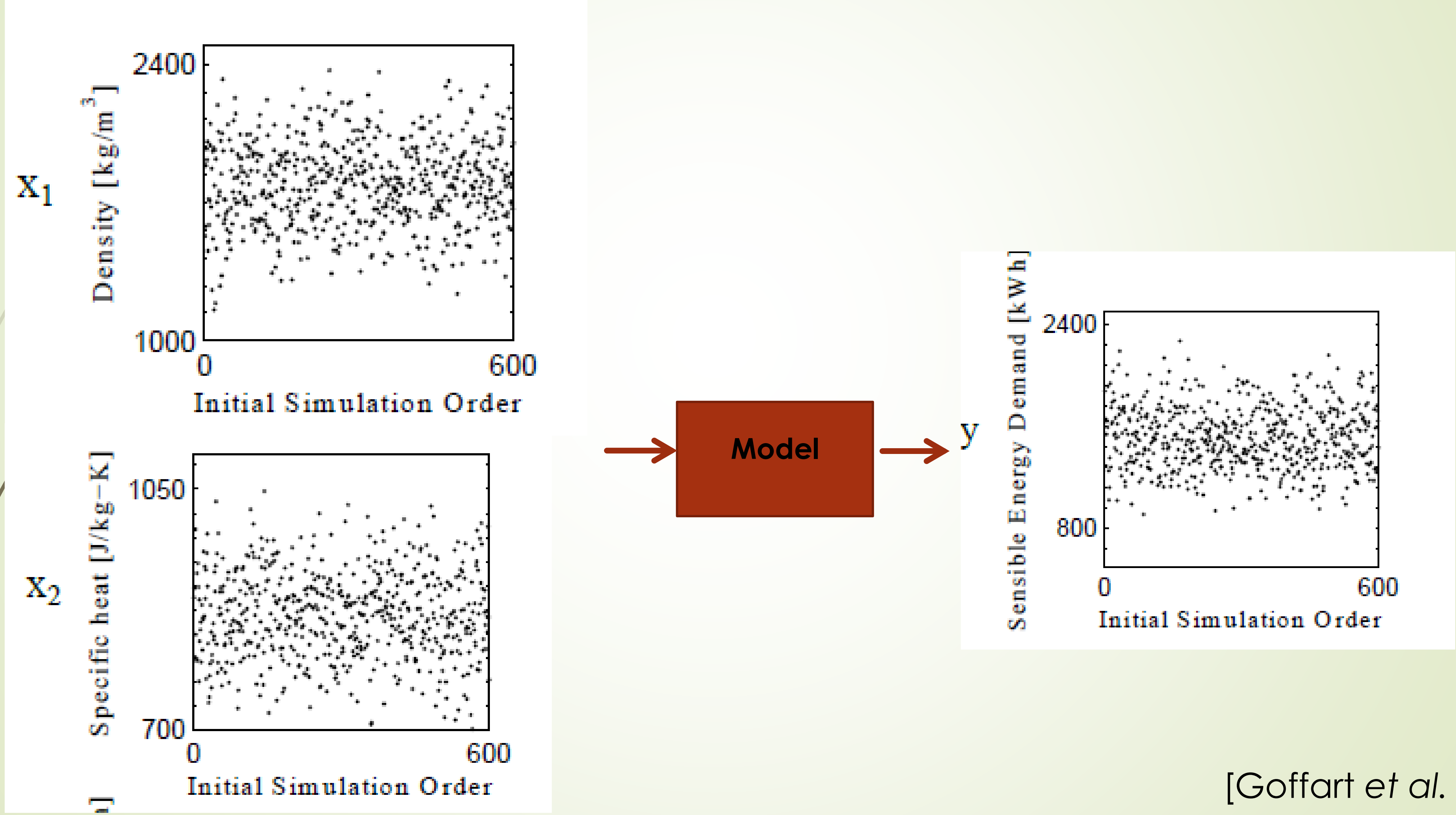
0.0046
0.0154
0.0196
…
0.9961





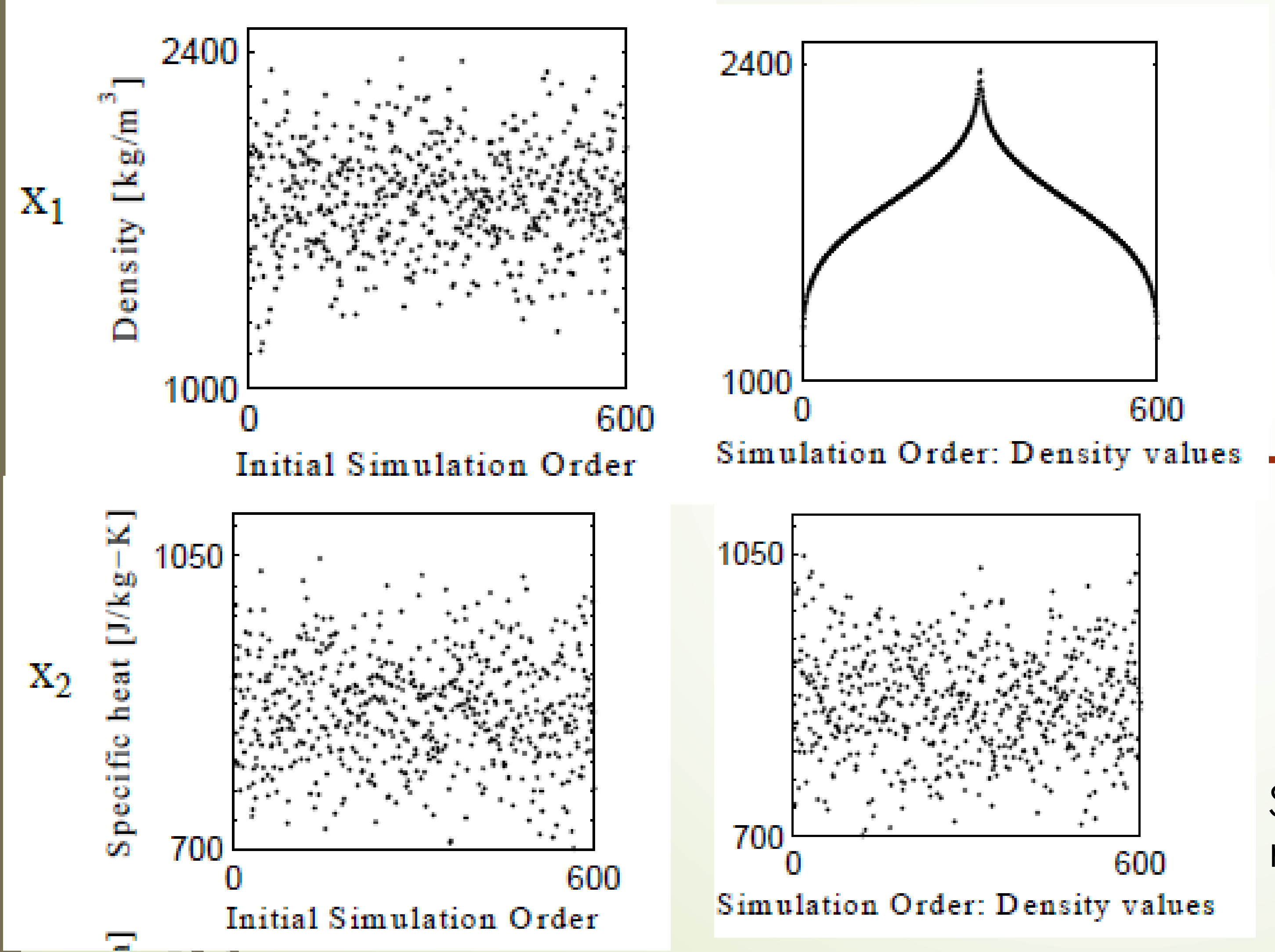
Triangular shaped vector

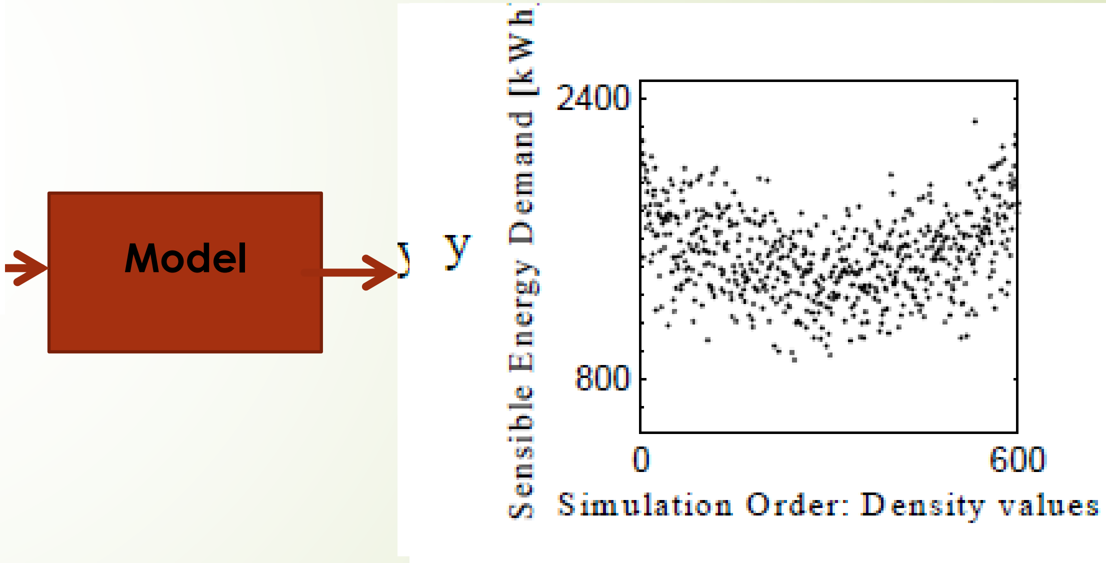
Initial simulation organisation



[Goffart *et al.* 2015]

Initial simulation organisation | **Sorted simulation according to a triangular-shaped vector for x_1**

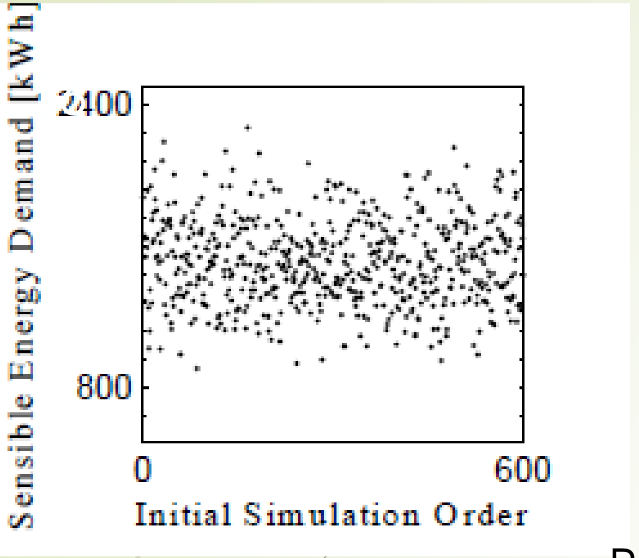




Shuffle for the other variables,
no period involved

[Goffart *et al.* 2015]

y

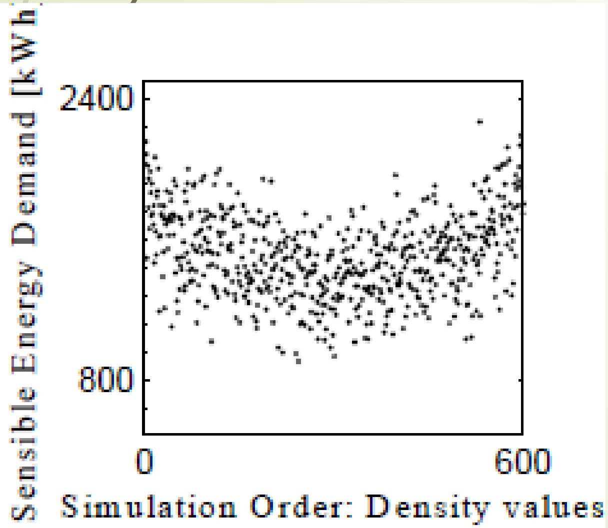


Resorted the output directly according to the vector triangular shaped for X1

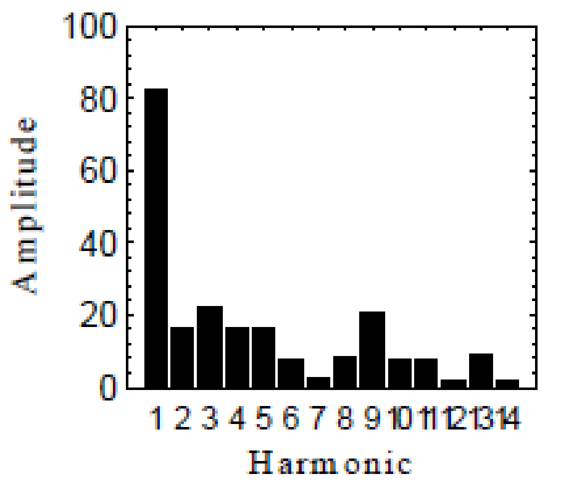
without a reevaluation of the model !

→ **Order of simulation**

y



FFT



Frequency analysis of the sorted output

Effect of X_1

[Goffart *et al.* 2015]

Conclusion on RBD-FAST

RBD-FAST : Obstacle of the variance decomposition is overcomed

- Same number of simulations with Morris and RBD-FAST **or less**

→ HUNDREDS with 50 uncertain inputs (Check the convergence at each study!)

RBD-FAST : high level of extractable information

$$\sum_{i=1}^{p} S_i \simeq 1$$

- First order effect quantification
- Indicate interaction existence
- Both uncertainty and sensitivity analysis with one set of samples
- Visualization of the output according to the input→ tendency

Suitable and Easy to apply on BPS issues

- Free model method (whatever the model complexity, low, high)
- **Implemented by [Team LOCIE] in SALib (Sensitivity Analysis Library) Python** **https://github.com/SALib/SALib [Nico's Jupyter Notebook]**

EnergyPlus Coupling available : IDF modification

https://github.com/santoshphilip/eppy

General Conclusion

Warnings

- Important **work of definition of the study**, the result depends on the fixed input, the variation range, the kind of law, etc..
- Challenge to **define the uncertainties** …
- Have to be aware about the **assumptions** (uncertainty description, and/or assumptions on the input or on the model)
- Understanding of the building model
- Sensitivity methods mastering
  - **Good use of sensitivity** ? → Check with test fonction
  - **Sufficient number of simulations** ?

    → Check the convergence

Not only push on a button … → Expertise

Table Of Contents

This Page

Show Source

Quick search

Go

SALib - Sensitivity Analysis Library in Python

docs failing | build passing | coverage 85% | Code issues | DOI 10.5281/zenodo.160164 | JOSS 10.21105/joss.00097

Python implementations of commonly used sensitivity analysis methods, including Sobol, Morris, and FAST methods. Useful in systems modeling to calculate the effects of model inputs or exogenous factors on outputs of interest.

Supported Methods

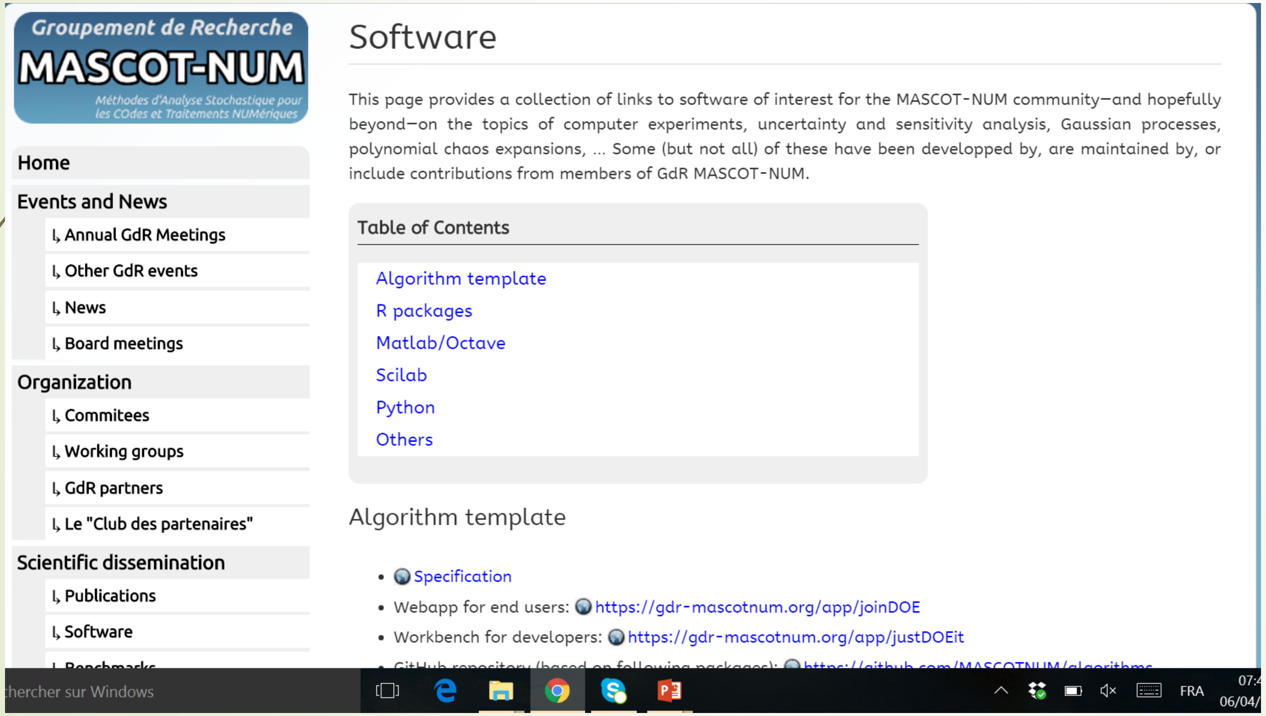
- Sobol Sensitivity Analysis ([Sobol 2001], [Saltelli 2002], [Saltelli et al. 2010])
- Method of Morris, including groups and optimal trajectories ([Morris 1991], [Campolongo et al. 2007])
- Fourier Amplitude Sensitivity Test (FAST) ([Cukier et al. 1973], [Saltelli et al. 1999])
- Random Balance Designs - Fourier Amplitude Sensitivity Test (RBD-FAST) ([`Tarantola et al. 2006 <https://hal.archives-ouvertes.fr/hal-01065897/file/Tarantola06RESS_HAL.pdf`_], [Elmar Plischke 2010], [Tissot et al. 2012])
- Delta Moment-Independent Measure ([Borgonovo 2007], [Plischke et al. 2013])
- Derivative-based Global Sensitivity Measure (DGSM) ([Sobol and Kucherenko 2009])
- Fractional Factorial Sensitivity Analysis ([Saltelli et al. 2008])

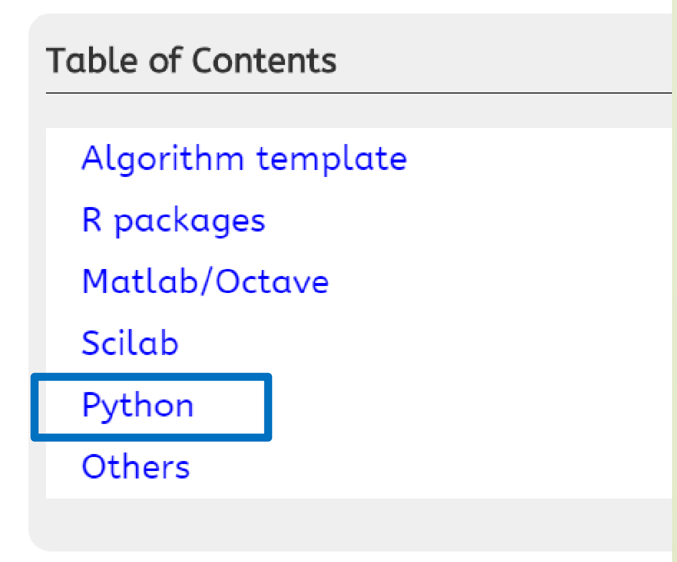
- Getting Started
  - Installing SALib

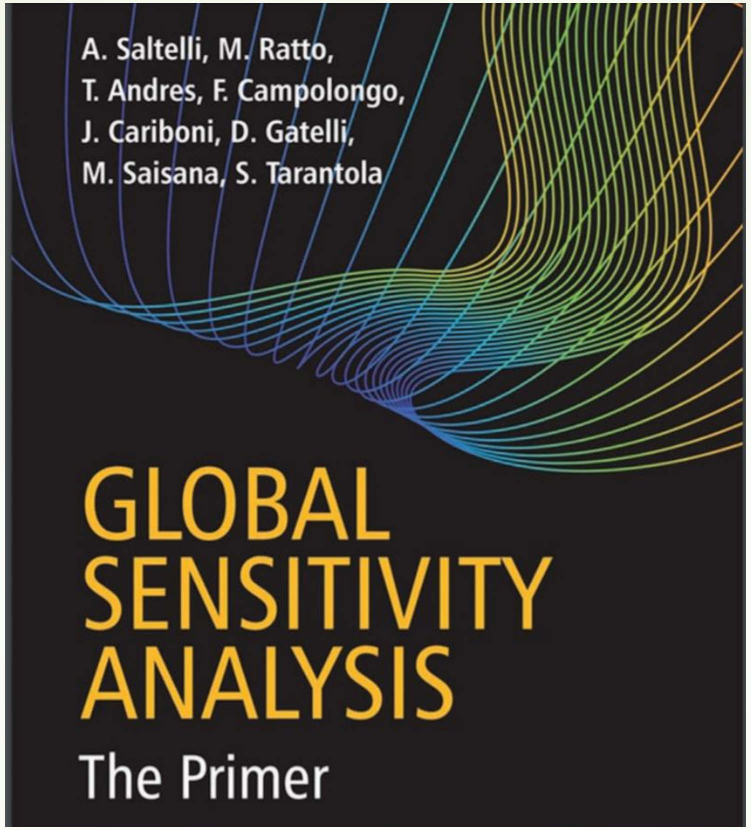
https://salib.readthedocs.io/en/latest/

Ressources

- GDR MASCOT-NUM :
  - http://www.gdr-mascotnum.fr/
  - http://www.gdr-mascotnum.fr/software.html







- http://www.andreasaltelli.eu/file/repository/A_Saltelli_Marco_Ratto_Terry_Andres_Francesca_Campolongo_Jessica_Cariboni_Debora_Gatelli_Michaela_Saisana_Stefano_Tarantola_Global_Sensitivity_Analysis_The_Primer_Wiley_Interscience_2008_.pdf

RESSOURCES (Codes Matlab, R, Python ; Presentation and paper)
Community : GDR MASCOT-NUM http://www.gdr-mascotnum.fr/ (in english)
JRC (SAMO , conferences and schools)

MAIN REFERENCES for the understanding and overview

Saltelli et al. 2008
Andrea Saltelli, Marco Ratto, Terry Andres, Francesca Campolongo, Jessica Cariboni, Debora Gatelli, Michaela Saisana, and Stefano Tarantola. Introduction to Sensitivity Analysis. In Global Sensitivity Analysis. The Primer, pages 1–51. John Wiley & Sons, Ltd, 2008. available in
http://www.researchgate.net/publication/253328104_Global_Sensitivity_Analysis._The_Primer

Iooss et al. 2015
Bertrand Iooss, Paul Lemaître. A review on global sensitivity analysis methods. C. Meloni and G. Dellino. Uncertainty management in Simulation-Optimization of Complex Systems: Algorithms and Applications, Springer, 2015, available in
https://hal.archives-ouvertes.fr/hal-00975701

Jacques 2011
Julien Jacques. Pratique de l'analyse de sensibilité : comment évaluer l'impact des entrées aléatoires sur la sortie d'un modèle mathématique. 2011 available in http://eric.univ-lyon2.fr/~jjacques/

REFERENCES

Campolongo *et al*. 2007
Campolongo, Francesca, Jessica Cariboni, and Andrea Saltelli. 2007. "An Effective Screening Design for Sensitivity Analysis of Large Models." Environmental Modelling and Software 22 (10): 1509–18

Goffart 2018
Goffart, J., Woloszyn, M., «RBD-FAST: une méthode d'analyse de sensibilité rapide et rigoureuse pour la Garantie de Performance Energétique», Conférence Francophone IBPSA, 16-17 Mai 2018, Bordeaux

Goffart et al. 2015
Jeanne Goffart, Mickael Rabouille, Nathan Mendes. Uncertainty and sensitivity analysis applied to hygrothermal simulation of a brick building in a hot and humid climate. *Journal of Building Performance Simulation*, *2015*, https://doi.org/10.1080/19401493.2015.1112430

Goffart 2013
Jeanne Goffart. Impact de la variabilite des donnees meteorologiques sur une maison basse consommation. Application des analyses de sensibilite pour les entrees temporelles. Universite de Grenoble, 2013. French. https://tel.archives-ouvertes.fr/tel-00982150

REFERENCES

Goffart et al. 2011
Jeanne Goffart, Etienne Wurtz, Gerard Sauce, and Timea Bejat. Impact and Source of Uncertainties in High Efficiency Building Simulation : Some Examples. In *Twelfth International IBPSA Conference Proceedings*, pages 2822–2827, Sydney, Australia, 2011.

Helton 1993
Helton J.C. Uncertainty and Sensitivity analysis Techniques for use in performance assessment of radioactive waste disposal, *Reliability Engineering and System Safety*, 42 327-367. 1993

Iooss 2009
Bertrand Iooss. Présentation dans le cadre des rencontres « Maths-Météo » à Toulouse en 2009. Analyse d'incertitudes et de sensibilité de modèles complexes – Applications dans des problèmes d'ingénierie

Lilburne et al. 2009
Linda Lilburne & Stefano Tarantola (2009) Sensitivity analysis of spatial models, International Journal of Geographical Information Science, 23:2, 151-168, DOI: 10.1080/13658810802094995

REFERENCES

Plischke 2010
Plischke, Elmar. 'An Effective Algorithm for Computing Global Sensitivity Indices (EASI).' *Reliability Engineering and System Safety* 95 (4). Elsevier: 354–60. doi:10.1016/j.ress.2009.11.005. 2010

Rabouille 2014
Mickaël Rabouille, recherche de la performance en simulation thermique dynamique: application à la réhabilitation des bâtiments. Universite de Grenoble, 2014. French. http://www.theses.fr/2014GRENA024

Saltelli et al. 2010a
Andrea Saltelli, Paola Annoni, Ivano Azzini, Francesca Campolongo, Marco Ratto, and Stefano Tarantola. Variance based sensitivity analysis of model output . Design and estimator for the total sensitivity index. *Computer Physics Communications*, 181(2) :259–270, 2010.

REFERENCES

Saltelli et al. 2010b
Andrea Saltelli and Paola Annoni. How to avoid a perfunctory sensitivity analysis. *Environmental Modelling and Software*, 25(12) :1508–1517, 2010.

Sobol 1993
I. M. Sobol'. Sensitivity estimates for nonlinear mathematical models. *Math. Mod. and Comput. Exp.*, 1 :407–414, 1993.

Tarantola et al. 2006
Tarantola, S., D. Gatelli, and Thierry Alex Mara. 2006. 'Random Balance Designs for the Estimation of First Order Global Sensitivity Indices.' *Reliability Engineering & System Safety* 91 (6): 717–27. doi:10.1016/j.ress.2005.06.003.

Vorger 2014
Vorger Eric, Étude de l'influence du comportement des habitants sur la performance énergétique du bâtiment, Ecole Nationale Supérieure des Mines de Paris, 2014