

# Complexity based design robustness analysis

Application to mechatronic component (vehicle hatchback )

Damien BORDET & Kambiz KAYVANTASH  
k.kayvantash@cadlm.fr



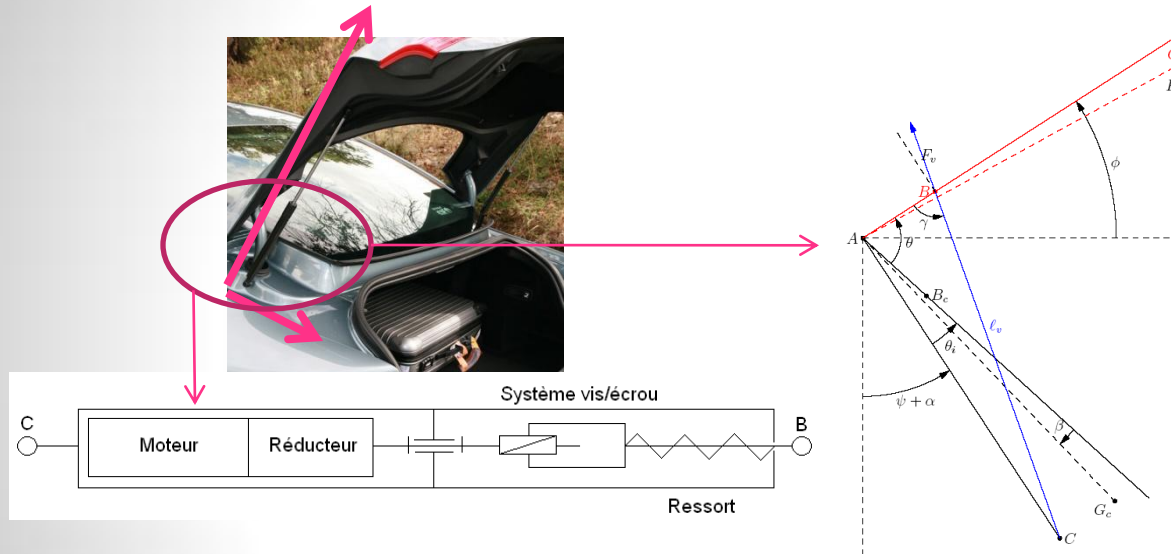
8<sup>th</sup> European LS-DYNA Users Conference, Strasbourg -  
May 2011

# Definitions

- Let Model be  $f=f(\mathbf{A},\mathbf{X})$ 
  - Let  $\mathbf{A}$  = Model parameters
  - Let  $\mathbf{X}$ = Model Variables
- Parametric analysis -> variations of  $\mathbf{A}$
- Sensitivity analysis -> variations of  $\mathbf{X}$
- Optimization -> best choice of  $\mathbf{X} = \mathbf{X}_o$
- Model dispersion -> Stochastic analysis ->  $\sim\mathbf{A}$
- Robust optimization -> best choice  $\mathbf{X}_{ro} \rightarrow F(f, \sigma(\mathbf{X},\mathbf{A}))$
- Complexity based robust optimization ?

# Objectives

- Establish robustness indicators for the optimal design of electric motor



MOVEO/O2M project:  
Courtesy of Valéo and  
SupMéca

- Expected results:
  - Establish optimal design variables subject to given model parameters
  - Identify optimal layout solution taking into account the robustness of the solution
  - Identify impact of uncertainty in model parameters on optimal design

# Criteria and constraints

- Minimize the maximum motor power needed:  $\text{Min}(\text{MaxPm en W})$

- Subject to:

- $\text{cstr0} \geq 0$  (minimum lever length)  $l_v^{\text{init}} \geq l_{\text{min}}$

- $\text{cstr1} \geq 0$  (maximum lever path)  $l_v^{\text{max}} - l_v^{\text{init}} \leq l_v^{\text{init}} - l_{\text{mr}}$

- $\text{cstr2} \geq 0$  (Minimum spring length)  $l_v^{\text{init}} - l_{\text{mr}} \geq dn + Sa$

- $\text{cstr3} \geq 0$  (Opening time)  $p_v r \geq \frac{2\pi(l_v^{\text{max}} - l_v^{\text{init}})}{t_m \omega_m}$

- $\text{cstr4} \geq 0$  (Spring internal diameter)  $D - d \geq 0.02$

# « Optimal Design » process

- Optimization of electric hatchback motor (NLPQL)
  - Define and determine optimal design variables
  - Define criteria related to vehicle cost and performance
  - Define vehicle and environment parameters (assumed fix)
- Monte Carlo Analysis (LH)
  - Variables set to optimum
  - Variation of vehicle parameters
  - Variation of environmental parameters
- Robustness analysis
  - Identification of system fragility (complexity based robustness)

# Model variables

## ▪ Variables of motor model

- $\omega_m$  : angular velocity (tr/min)
- $G_{\text{ressort}}$  : spring shear module (Pa)
- $L_{V_{\text{min}}}$  : minimum arm length of jack (m)
- $L_{\text{mr}}$  : length of (geared) motor (m)
- $\eta_1$  : motor efficiency (S-U)
- $\eta_2$  : geared motor efficiency (S-U)
- $\eta_3$  : efficiency of screw system (S-U)
- $n$  : Number of spring coils (S-U)
- $d$  : spring cable diameter (m)
- $D$  : mean spring diameter (m)
- $p_r$  : spring increment (m)
- $p_v$  : screw increment (m)
- $\text{Inv}_r$  : Transmission ratio (S-U)

## • variable min/max bounds:

- $\omega_m = 3209.09 \text{ tr/min}$   $2700 < \omega_m < 3300$
- $G_{\text{ressort}} = 8.27575 * 10^{10} \text{ Pa}$   $8.0 * 10^{10} < G_{\text{ressort}} < 8.3 * 10^{10}$
- $L_{V_{\text{min}}} = 0.20141 \text{ m}$   $0.18 < L_{V_{\text{min}}} < 0.22$
- $L_{\text{mr}} = 0.15561 \text{ m}$   $0.135 < L_{\text{mr}} < 0.165$
- $\eta_1 = 0.7525$   $0.7 < \eta_1 < 0.9$
- $\eta_2 = 0.7626$   $0.7 < \eta_2 < 0.9$
- $\eta_3 = 0.8475$   $0.7 < \eta_3 < 0.9$
- $n = 48$   $40 < n < 55$
- $d = 0.003828 \text{ m}$   $0.003 < d < 0.004$
- $D = 0.023535 \text{ m}$   $0.022 < D < 0.03$
- $p_r = 0.010798 \text{ m}$   $0.009 < p_r < 0.011$
- $p_v = 0.011818 \text{ m}$   $0.006 < p_v < 0.012$
- $\text{Inv}_r = 27$   $9 < \text{Inv}_r < 36$

- **Note** : Model Variables **X** => (assume known if not use model reduction techniques based on machine learning techniques developed by CADLM)

# Model parameters

## ■ Vehicle parameters

- $X_a ; Z_a$  : point A (axis X et Z) (m)
- $X_b ; Z_b$  : point B (axis X et Z) (m)
- $X_c ; Z_c$  : point C (axis X et Z) (m)
- $X_g ; Z_g$  : point G (axe X et Z) (m)
- $t_m$ : maximum opening time (s)
- $\theta$ : hatchback opening angle ( $^\circ$ )
- Masse: hatchback mass (kg)
- $\delta_{LB}$  : distance variation B1/B2 (m)
- $\delta_{LC}$  : distance variation C1/C2 (m)

## ■ Environnement parameters

- $\alpha$ : angle of hatchback to horizontal ( $^\circ$ )
- $g$ : gravity ( $m/s^2$ )

## • Vehicle:

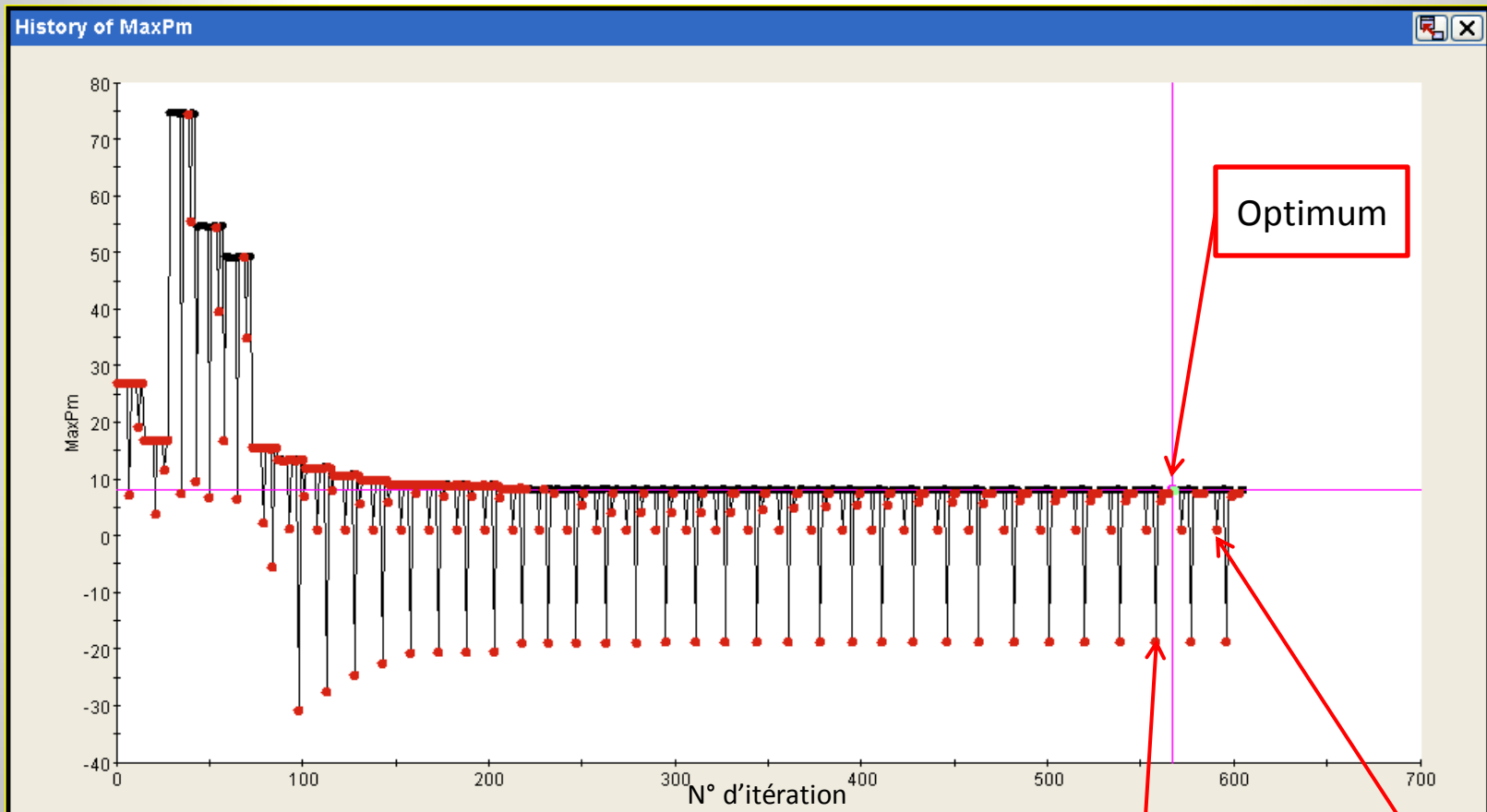
- $X_a = 0.34135$  m ;  $Z_a = 1.68229$  m
- $X_b = 0.44169$  m ;  $Z_b = 1.59108$  m
- $X_c = 0.65209$  m ;  $Z_c = 1.20849$  m
- $X_g = 0.73909$  m ;  $Z_g = 1.26679$  m
- $t_m = 7.08$  s
- $\theta = 83.72^\circ$
- Masse = 31.9 kg
- $\delta_{LB} = 0.008601$  m
- $\delta_{LC} = 0.02$  m

## • Environnement :

- $\alpha = 0.0^\circ$
- $g = 9.81$   $m/s^2$

# Optimization process

- Minimize (MaxPm) :



Cstr2 < 0  
MaxPm < 0

Cstr3 < 0



# Optimal layout

- System optimal variables:

- $\omega_m = 3290.71$  tr/min
- $G_{\text{ressort}} = 8.3 \cdot 10^{10}$  Pa
- $L_{v_{\text{min}}} = 0.22$  m
- $L_{mr} = 0,165$  m
- $\eta_1 = 0,8411$
- $\eta_2 = 0,84$
- $\eta_3 = 0,84$
- $n = 55$
- $d = 0.004$  m
- $D = 0,024$  m
- $p_r = 0.011$  m
- $p_v = 0.00635463$  m
- $\text{Inv}_r = 14$

- Optimal output (all constraints >0):

- **MaxPm = 8,05 (W)**
- cstr0 = 0,228432 (m)
- cstr1 = 0,108162 (m)
- cstr2 = 0,0526323 (m)
- cstr3 = 2,52733E-6 (m)
- cstr4 = 4,85723E-17 (m)

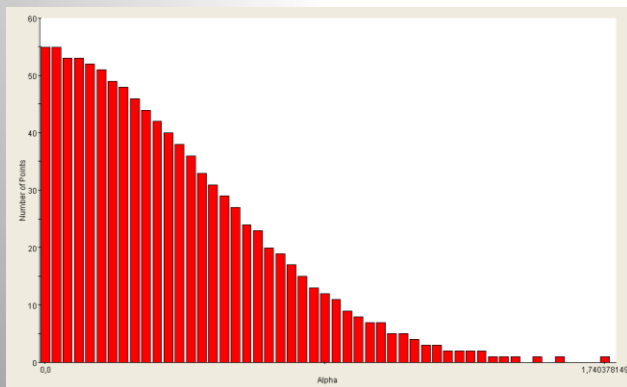
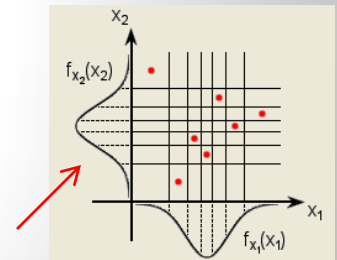
- Iterations: **605**

# Analyse Monte Carlo

- « Destabilize » system around optimal
- Assume normal distribution of model parameters around given bounds:

- |   |  |                                  |
|---|--|----------------------------------|
| ▪ $\alpha_{\text{nominal}} = 0.0^\circ$   | $0.0^\circ < \alpha < 1,74^\circ$                  | ( $\approx$ slope of 3%)         |
| ▪ Masse <sub>nominal</sub> = 31,9 kg      | $29,8 \text{ kg} < \text{Masse} < 34,0 \text{ kg}$ | $\Rightarrow \pm 2 \text{ kg}$   |
| ▪ $\theta_{\text{nominal}} = 83,72^\circ$ | $83,706^\circ < \theta < 83,734^\circ$             | $\Rightarrow \pm 0,02^\circ$     |
| ▪ Xg <sub>nominal</sub> = 0,73909m        | $0,734 \text{ m} < \text{Xg} < 0,744 \text{ m}$    | $\Rightarrow \pm 5 \text{ mm}$   |
| ▪ Zg <sub>nominal</sub> = 1,26679m        | $1,264 \text{ m} < \text{Zg} < 1,269 \text{ m}$    | $\Rightarrow \pm 3 \text{ mm}$   |
| ▪ tm <sub>nominal</sub> = 7,08s           | $7,01 \text{ s} < \text{tm} < 7,15$                | $\Rightarrow \pm 0,07 \text{ s}$ |

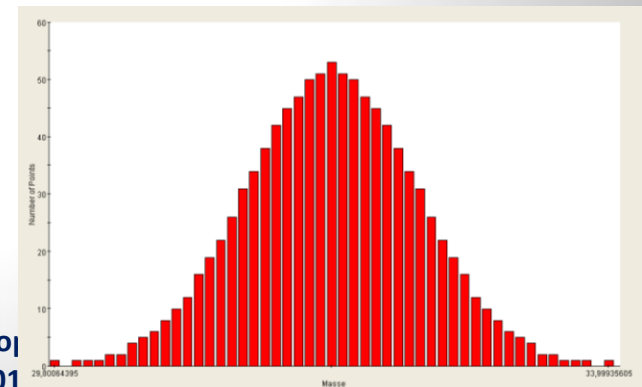
• 1001 points



Variation de  $\alpha$



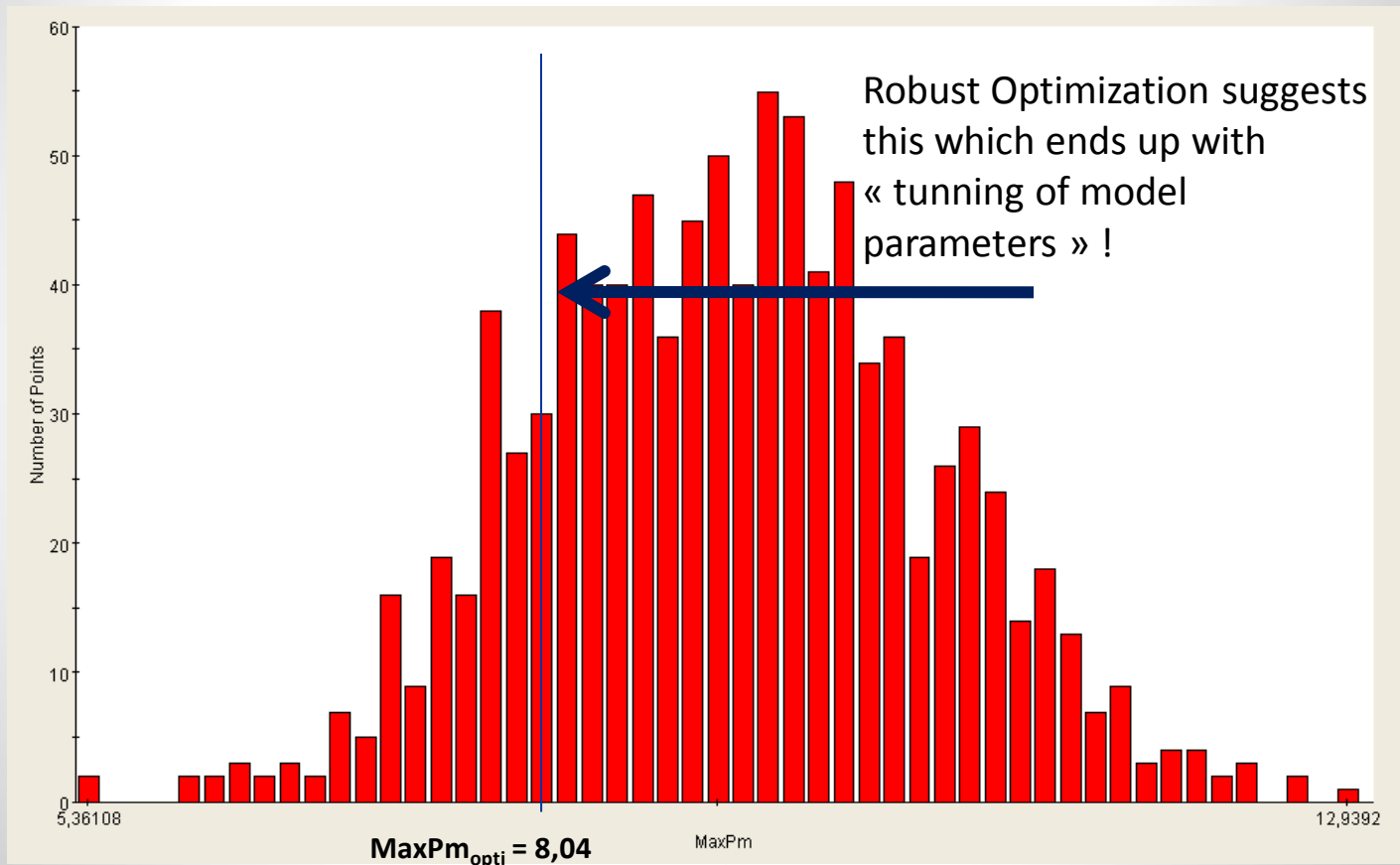
8<sup>th</sup> EuroJ  
May 201



Variation de Masse

# Monte Carlo based dispersion

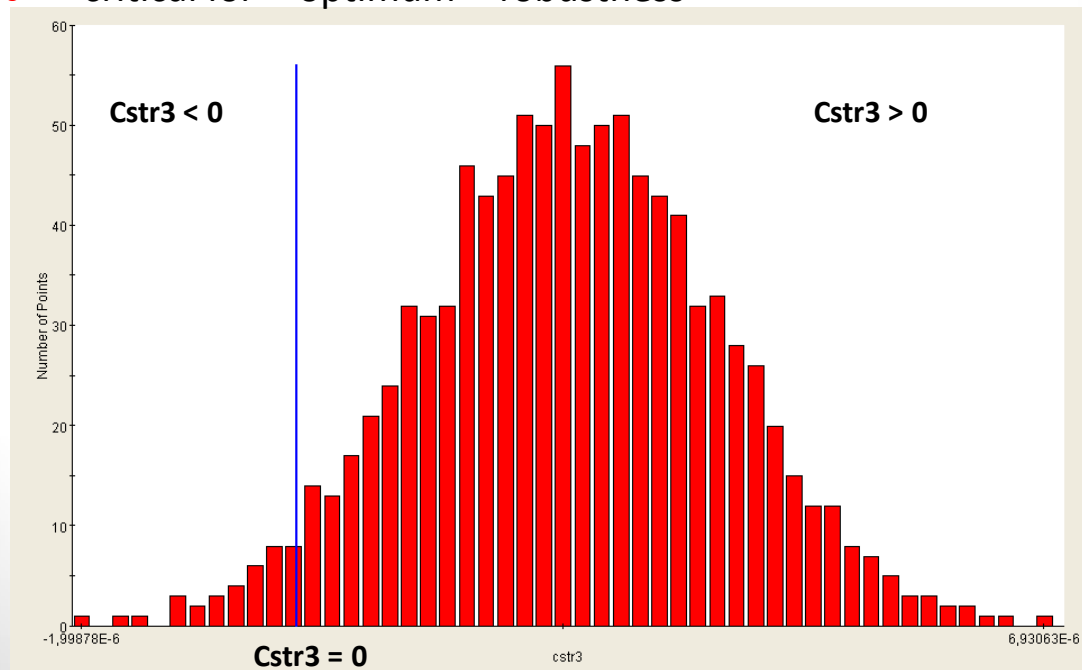
- Motor power variation (970 points / 1001 satisfy constraints)



# Analyse Monte Carlo

- Constraint satisfaction

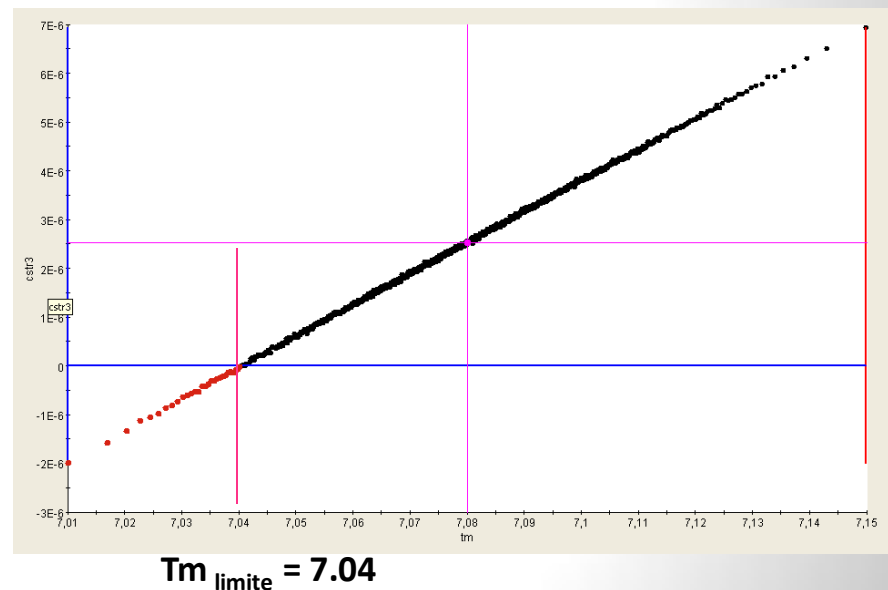
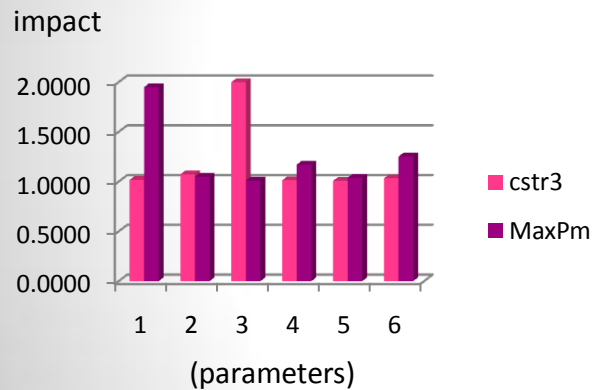
- cstr0 : **100%**
- cstr1 : **100%**
- cstr2 : **100%**
- cstr4 : **100%**
- cstr3 : **97%** => critical for « optimum » robustness



# Conclusion (results)

We observe:

- Constraint cstr3 is violated due to  $t_m$



- Dispersions of MaxPm are due to Masse

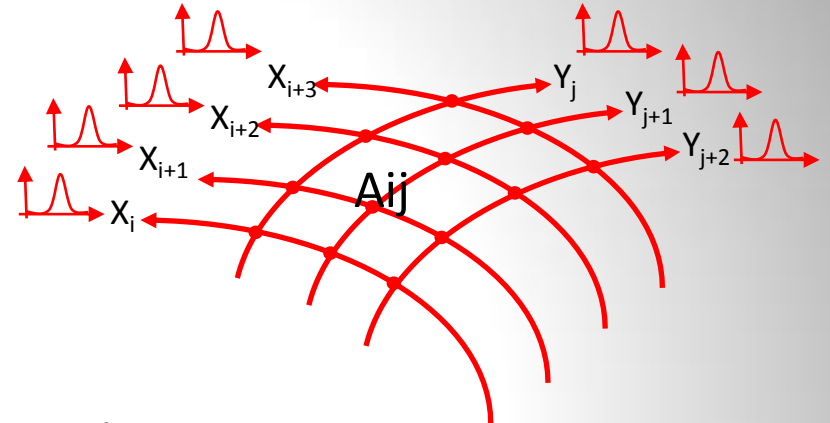
# From stats to robustness?

- Is this true?
- Can we say anything more?

# Robustness indicators (CADLM)

- Definition:

- **Robustness is a measure of “surprise” or “non-”Gaussian” behaviour of the system**



Let **R** define the robustness of the system defined as  $\Rightarrow 1/R = \text{Fragility}$  Where system fragility is a product (combination) of system **Complexity** x **Uncertainty**

In it's most simple manifestation **complexity is an indicator representing system topology (and cross-correlation).**

Each system parameter **A** includes its uncertainty as well as it's impact on the whole system. Identification of these relations allows us to establish **a complexity map of the system which leads to system « weakest elements »**

In general **entropy based complexity indicators are very good candidates.** However, any other (simplified indicator could already provide a first insight into the problem).

# A simple definition of fragility

- Uncertainty of each parameter/response (around optimum)  $\lambda_j$  may be defined as:

$$\lambda_j = 2 - \frac{Y_{j-opti}}{Y_{j-opti} + \|Y_{j-opti} - Y_{j-moy}\| + Y_{j-max} - Y_{j-min}}$$

- Complexity contribution of **each parameter** may be defined as a function of

- $\alpha_1$  -> parameter correlation with each response
- $\alpha_2$  -> parameter own uncertainty ( $=\lambda_i$ )
- $\alpha_3$  -> Parameter cross-correlation with other parameters

Where each one of the above may be obtained via  $C_{xy}$  = **absolute value of Bravais-Pearson coefficient** :

$$r_p = \frac{\sigma_{xy}}{\sigma_x \sigma_y}$$

$\sigma_{xy}$  = covariance between x et y

$\sigma_x$  et  $\sigma_y$  = standard deviation of x and y



# Robustness analysis

- System correlation matrix

		Xi					Yj						
<b>Matrice de corrélation</b>		Masse	Theta	tm	Xg	Zg	Alpha	cstr0	cstr1	cstr2	cstr3	cstr4	MaxPm
Xi	Masse	2	1.0402	1.0183	1.0077	1.0601	1.0067	1.0000	1.0399	1.0000	1.0173	1.0000	1.9497
	Theta	1.0402	2	1.0555	1.0527	1.0197	1.0048	1.0000	1.9996	1.0000	1.0742	1.0000	1.0489
	tm	1.0183	1.0555	2	1.0151	1.0079	1.0335	1.0000	1.0561	1.0000	1.9998	1.0000	1.0113
	Xg	1.0077	1.0527	1.0151	2	1.0100	1.0132	1.0000	1.0537	1.0000	1.0142	1.0000	1.1714
	Zg	1.0601	1.0197	1.0079	1.0100	2	1.0624	1.0000	1.0196	1.0000	1.0082	1.0000	1.0388
	Alpha	1.0067	1.0048	1.0335	1.0132	1.0624	2	1.0000	1.0045	1.0000	1.0336	1.0000	1.2530
Yj	cstr0	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	2	1.0000	1.0000	1.0000	1.0000	1.0000
	cstr1	1.0399	1.9996	1.0561	1.0537	1.0196	1.0045	1.0000	2	1.0000	1.0747	1.0000	1.0488
	cstr2	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	2	1.0000	1.0000	1.0000
	cstr3	1.0173	1.0742	1.9998	1.0142	1.0082	1.0336	1.0000	1.0747	1.0000	2	1.0000	1.0102
	cstr4	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	2	1.0000
	MaxPm	1.9497	1.0489	1.0113	1.1714	1.0388	1.2530	1.0000	1.0488	1.0000	1.0102	1.0000	2

each value is a measure of coefficient of Bravais-Pearson.

# Robustness analysis

- Parameter/response correlations

$\alpha_1 = C_{ij}$	Masse	Theta	tm	Xg	Zg	Alpha
cstr0	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
cstr1	1.0399	1.9996	1.0561	1.0537	1.0196	1.0045
cstr2	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
cstr3	1.0173	1.0742	1.9998	1.0142	1.0082	1.0336
cstr4	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
MaxPm	1.9497	1.0489	1.0113	1.1714	1.0388	1.2530

- Parameter uncertainty measure

$\alpha_2$	Masse	Theta	tm	Xg	Zg	Alpha
$\lambda_i$	1.1163	1.0003	1.0194	1.0130	1.0033	1.6814

- Vecteur de corrélation de chaque variable avec les autres

	Masse	Theta	tm	Xg	Zg	Alpha
$\alpha_3$	1.0266	1.0346	1.0261	1.0197	1.0320	1.0241

# Robustness analysis

- Parameter complexity contribution

Yj

		Yj					MaxPm
		cstr0	cstr1	cstr2	cstr3	cstr4	
Ai	Matrice de complexité						
	Masse	1.0476	1.0609	1.0476	1.0534	1.0476	1.3642
	Theta	1.0116	1.3448	1.0116	1.0364	1.0116	1.0279
	tm	1.0151	1.0338	1.0151	1.3484	1.0151	1.0189
	Xg	1.0109	1.0288	1.0109	1.0157	1.0109	1.0680
	Zg	1.0118	1.0183	1.0118	1.0145	1.0118	1.0247
Alpha	1.2352	1.2367	1.2352	1.2464	1.2352	1.3195	

- $C_{ij} = 1$       =>      low uncertainty or low correlation with response or other parameters
- $C_{ij} = 2$       =>      large uncertainty / strong correlation with response or other parameters

# Robustness analysis

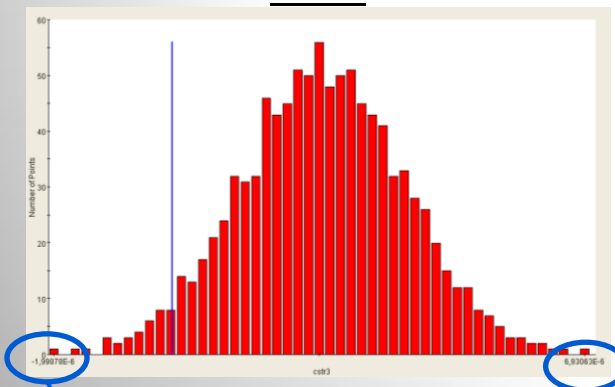
- System response uncertainty

$Y_j$  {

Réponses du système	Incertitude
cstr0	1.000
cstr1	1.001
cstr2	1.000
cstr3	1.779
cstr4	1.000
MaxPm	1.521

Large uncertainty  
( $\lambda_j$  les + proches de 2)

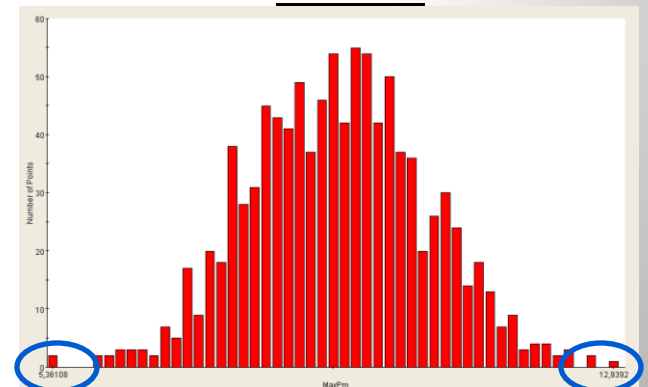
cstr3



-2.00e-6

6.93e-6

MaxPm



5.36

12.94

# Robustness analysis

- Impact factor (influence) of parameters on system fragility

	Vehicle/environment parameters	$0 < \text{Fragility} < 1$
Xi	Masse	0.359
	Theta	0.298
	tm	0.338
	Xg	0.249
	Zg	0.236
	Alpha	0.528

Alpha is the most influent parameter (since it's influence is not symmetric therefore large uncertainty)

Masse follows since MaxPm strongly dependent on it paramètre et MaxPm a une incertitude importante

tm est le troisième plus influent car cstr3 est quasi corrélé qu'avec tm et cstr3 a une incertitude importante

# Conclusion

## AVANTAGES

- Much more practical and less iterations than robust optimization (no specific tools required)
- Complexity based robust analysis is superior since it provide information on uncertainty and topology of the system
- Only MC like analysis, no approximation methods (DOE or RSM, FORM, SORM, etc. )
- Allows for definition of easily measurable real-time (static or dynamic) system complexity indicators
- Simple implementation uses Bayesian statistics

## INCONVENIENTS

- needs distinguish X and A
- needs good knowledge of A (usage, vehicle, environment)
- Full implementation needs introduction of entropy based indicators (information content, etc.)