



LINEAR PROGRAMMING SERVICE OF STATISTICS

REDUCTION OF AN AUTOMOTIVE CRASH MODEL

MARCH 24, 2016

THUY VUONG, CIFRE RENAULT

YVES LE GUENNEC, IRT SYSTEMX

YVES TOURBIER, RENAULT & IRT SYSTEMX



- 01** INTRODUCTION
- 02** MODEL REDUCTION
- 03** CUR METHOD
- 04** REGRESSION CUR
- 05** CONCLUSION

01 INTRODUCTION

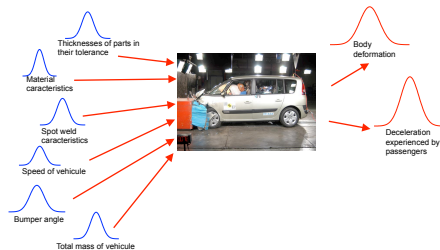
Context

Example of classical study

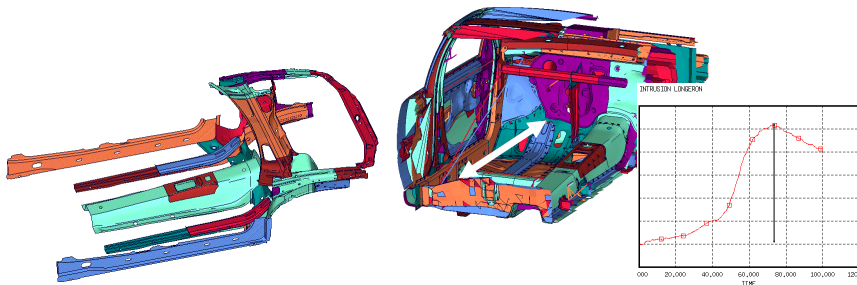
Standard studies with DOE

Conclusion on DOE studies

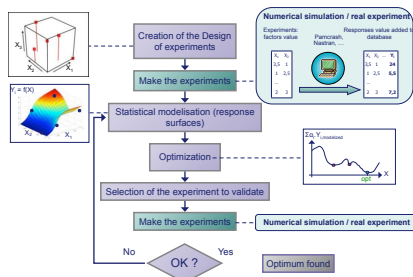
- ◆ The objective is optimization or modelisation (the objective concerns the outputs)
- ◆ The system is a black-box (we don't know how it works inside)
- ◆ Each evaluation of the black-box is very costly
- ◆ One cannot choose directly the outputs, just fix the inputs then run the black-box to measure outputs



- ◆ The list of parts to vary is limited but can be long
- ◆ Frontal crash \approx 20 criteria \Rightarrow 20 constraints
- ◆ Up to 100 parameters (thicknesses, materials, reinforcements, shapes, spot welds...)



1. Define the parameters, responses, optimization problem, reproducibility...
2. Build a DOE
3. Perform tests
4. Make a statistical model for each response (LP can be used here)
5. Use the models to optimize, propose one solution (or more)
6. Validate the solution(s) with new test(s)
7. If necessary, go back to 1, 2 or 4



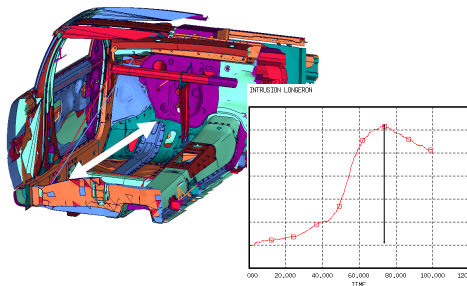
- ◆ Total cost = Number of crash simulations $\in [3, 10]$. Number of parameters
- ◆ Can be fully automatic with EGO like methods
- ◆ Number of parameters can be greater than 100 with standard DOE method
- ◆ BUT:
 - ◆ User must analyze a lot of solutions
 - ◆ One cannot use all the criteria (too numerous, scenario & subjective criteria are only used as final selection)
 - ◆ Number of crash simulations is a bottleneck
 - ◆ The surrogate model use less than 1% of data produced by crash simulations

02 **MODEL REDUCTION**

Replace the entire crash simulation by a surrogate
A simple crash simulation generates Gbytes

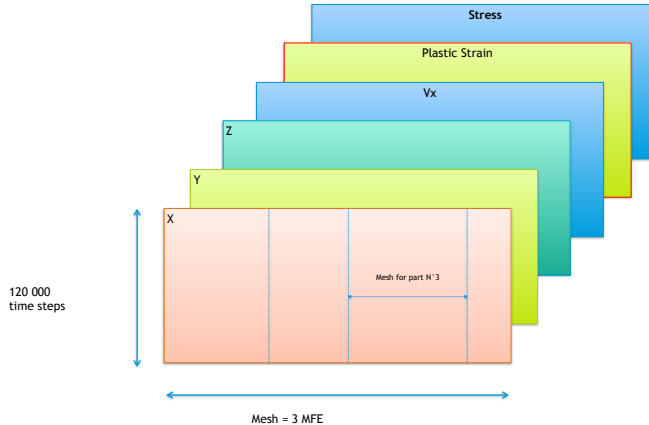
REPLACE THE ENTIRE CRASH SIMULATION BY A SURROGATE

- ◆ Standard DOE \rightarrow surrogate = function(max(Intrusion))
- ◆ Model reduction \rightarrow max(surrogate = function(Intrusion))



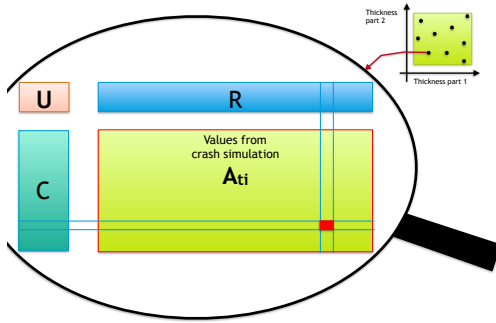
$$HIC = \{ [\frac{1}{t_2 - t_1} \cdot \int_{t_1}^{t_2} a(t) \cdot dt]^{2.5} (t_2 - t_1) \}_{Max}$$

- ◆ > 15 values computed for each node / finite element at each time step
- ◆ > 40 Gb / simulation



03 CUR METHOD

The conventional CUR method
CUR and Linear Regression
CUR and Linear Programming

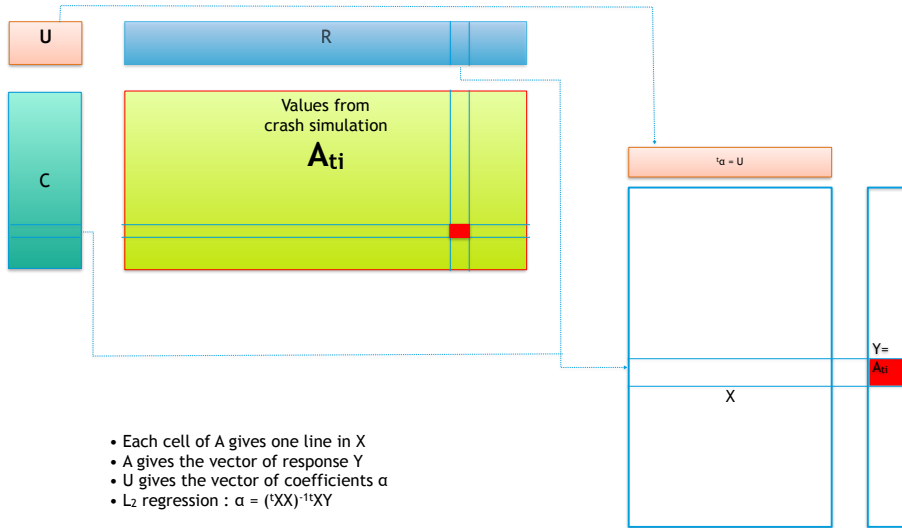


$$A \approx C.U.R$$

- ◆ Each cell A_{ti} is fitted by a linear model:

$$A_{ti} = \sum_{k_C=1}^{d_C} C_{t,k_C} \sum_{k_R=1}^{d_R} U_{k_C,k_R} R_{k_R,i}$$

- ◆ With CUR method, C & R matrices are selected into A
- ◆ U is the matrix of coefficients which minimizes the global error criterion
- ◆ CUR retains important times and locations



L_2 REGRESSION

$$\text{Min} \sum_{t=1, i=1}^{t=\text{Max}_t, i=\text{Max}_i} \epsilon_{t,i}^2$$

Under

$$\forall t, i \quad Y_{t,i} = X_{t,i} \alpha + \epsilon_{t,i}$$

Solution:

$$\alpha = ({}^tXX)^{-1} {}^tXY$$

L_1 REGRESSION

$$\text{Min} \sum_{t=1, i=1}^{t=\text{Max}_t, i=\text{Max}_i} \epsilon_{t,i}^+ + \epsilon_{t,i}^-$$

Under, $\forall t, i$

$$\epsilon_{t,i}^+ \geq 0$$

$$\epsilon_{t,i}^- \geq 0$$

$$Y_{t,i} - \sum_k X_{t,i,k} \alpha_k = \epsilon_{t,i}^+ - \epsilon_{t,i}^-$$

Solution:

Linear Programming

L_∞ REGRESSION

$$\text{Min} \quad \epsilon_{\max}$$

Under, $\forall t, i$

$$\epsilon_{\max} \geq 0$$

$$-\epsilon_{\max} \leq Y_{t,i} - \sum_k X_{t,i,k} \alpha_k$$

$$Y_{t,i} - \sum_k X_{t,i,k} \alpha_k \leq \epsilon_{\max}$$

Solution:

Linear Programming

04 REGRESSION CUR

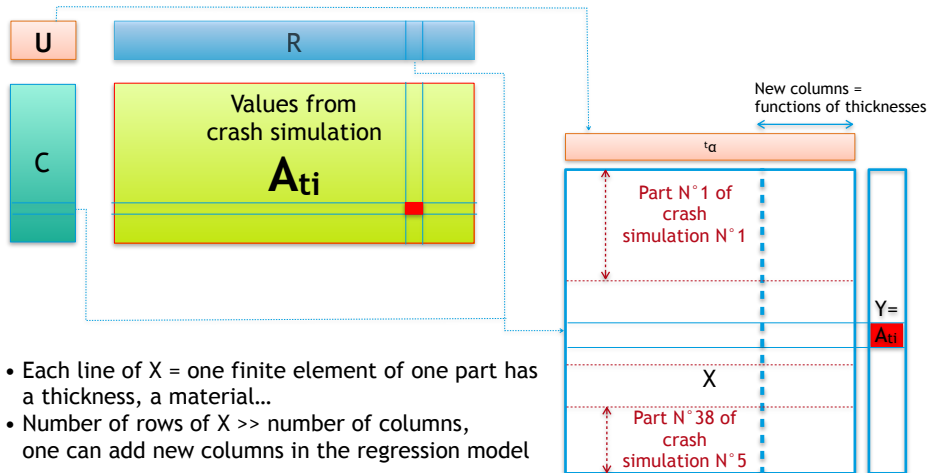
ReCUR, how to interpolate?

ReCUR, small example

ReCUR, big example

Why Linear Programming?

Algorithm (simplified)

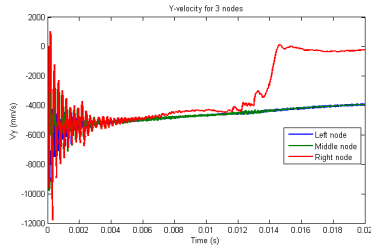


- Each line of X = one finite element of one part has a thickness, a material...
- Number of rows of $X \gg$ number of columns, one can add new columns in the regression model

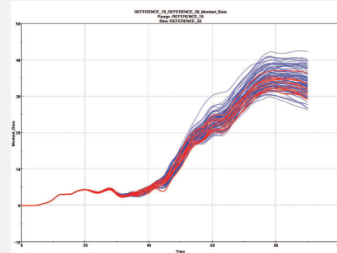




NUMERICAL CONVERGENCE



NUMERICAL DISPERSION



- ◆ Numerical convergence & dispersion \implies robust regression
- ◆ Size of the matrices can vary from one crash simulation to another (if a part is present in one simulation but not in the other)
- ◆ L_∞ allows to detect bad cells
- ◆ Possibility to add constraints, like total volume for the parts during the crash

$List = \{\}$

Do N times

Solve LP

$$\min \quad \gamma \cdot \epsilon_{max} + \sum_j \beta_j^+ + \beta_j^-$$

$$\forall t, i \notin List \quad -\epsilon_{max} \leq A_{ti} - \sum_j (\beta_j^+ - \beta_j^-) \cdot X_{tij} \leq \epsilon_{max}$$

$$\forall j \quad \beta_j^+ \geq 0, \quad \beta_j^- \geq 0$$

If (max absolute error over $A_{ti} \notin List \leq \epsilon_{target}$)

Then

END

Else

Add the K biggest error cells to $List$

Endif

Done

05 CONCLUSION

| Linear Programming service of Statistics

- ◆ Good tools for fast prototyping
- ◆ Accept big problems
- ◆ Parallel computation up to 32 cores without effort
- ◆ Many good solvers available, easily interchangeable, even open source

Perspectives:

- ◆ Continue to add constraints
- ◆ Add rigid body movements and other functionalities
- ◆ Try to apply to other problems like CFD, NVH...
- ◆ At the end, if possible, go back to L_2 with LASSO?

Thank you for your attention.
Q&A



LINEAR PROGRAMMING SERVICE OF STATISTICS

REDUCTION OF AN AUTOMOTIVE CRASH MODEL

MARCH 24, 2016

THUY VUONG, CIFRE RENAULT

YVES LE GUENNEC, IRT SYSTEMX

YVES TOURBIER, RENAULT & IRT SYSTEMX

