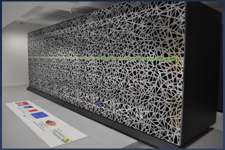

Optimization of a forming process under uncertainty

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User ROMEO conference

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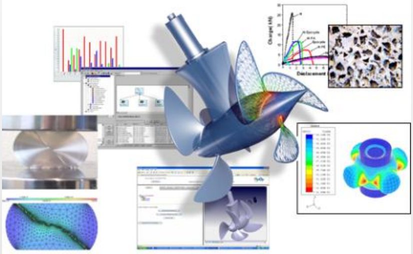
Uncertainty in virtual engineering

In earlier phase of product life cycle development, we need to take into account uncertainty to

- maximize performance of product and garanty stability of performances
- reach necessary level of reliability and safety

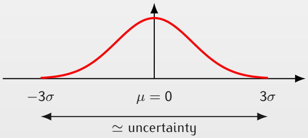
Take into account uncertainties in virtual engineering is still an issue:

- Uncertainty are not easy to model...
- Propagation of uncertainty through complex simulation model requires a great number of model evaluation.



Modelling uncertainty

- Uncertainties are usually represent by aleatory variables.
- A probability density function for each variable (normal distribution,uniform distribution, ...)



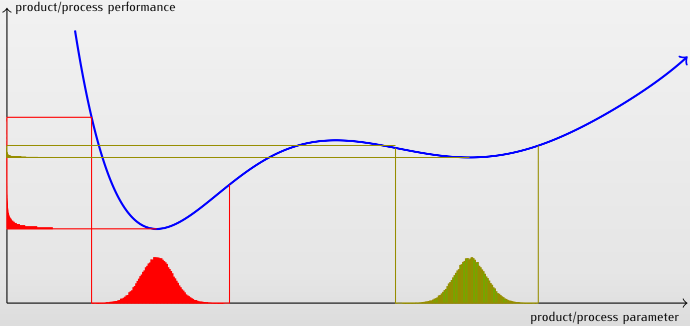
Example a normal distribution of probability. Notation :

- σ: standard deviation of the variable.
- μ: mean of the variable.

Effect of uncertainty

Uncertainty (small inherent variation) produce variation of performances :

- A non robust solution: larger performance variation for a given uncertainty.
- A robust solution : minimal performance variation for the same uncertainty.

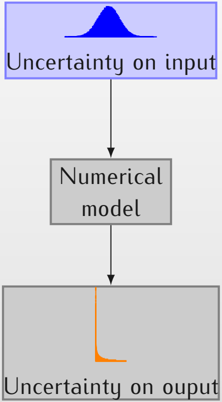


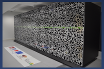
Quantifying Effect of uncertainty

Propagation of uncertainty:

- sampling (monte carlo, latin hypercube ..) the probabilty distribution of input variables
- evaluate each sample to obtain the output probability distribution.

Time consumming with heavy numerical model, need for metamodel or reduced model

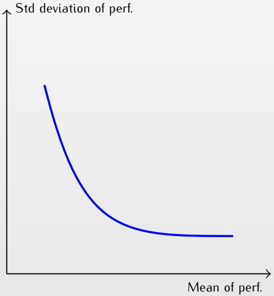


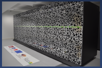


Introduction to robust optimization

Robust optimization aims to maximize performance and to maximize "stability" of performance under uncertainty.

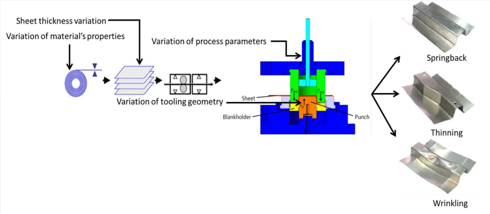
- In practice it isn't possible, designers need to find the best compromise by solving a multi objectif optimization problem.
- For actuel robust optimization problem, standard deviation of performance and (σ) mean of performance (μ) are antagonistic.

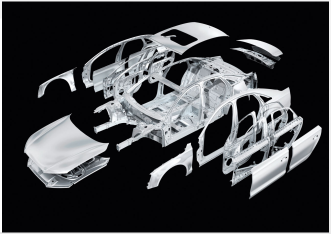




Industrial context

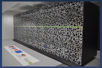
- The main manufacturing process to produce car body "body in white".
- High performance steel and aluminium are used to lighten car body.





Numerical simulation :

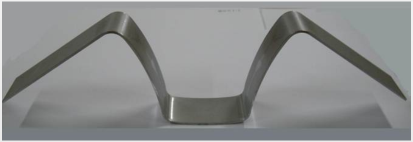
Play a key role in industrial competitivness, for designing theses processes.
Help designers to predict defecs (springback, wrinkling, thining, ...)



U shape bending

U shape draw bending process from Numisheet 2011 BenchMark

- Quantity effect on uncertainty of material and geometry of the blank, and on process paramters
- Optimize process parameter to fit requirement specification on the final U shape.



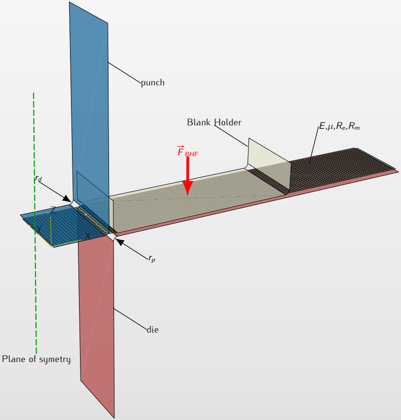
Finite element modelling

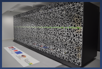
- Blank : 2709 shell elements with 7 integration points.
- Material : DP780 steel, Swift model $\bar{\sigma} = K\left(\varepsilon_0 + \bar{\varepsilon_p}\right)$, Hill48 yield function.
- Tools : analytical rigid surface, friction with Coulomb law, penalty contact enforcement.

Two steps simulation with Abaqus:

1. Forming with explicit dynamics algorithm.
2. Springback with static implicit algorithm.

About 2h30 for one simulation

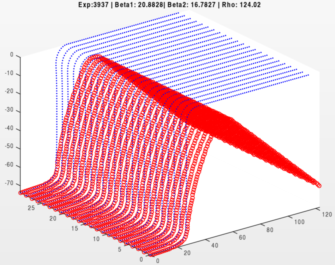


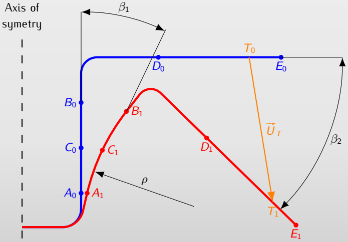


Parameters of the shape after springback

Shape defect due to the springback :

- Two angles $\beta 1_1$ and β_2 between the shape after forming and the shape after springback. : 2709 shell elements with 7 integration points.
- The radius ρ side wall curl.
- The displacement $\vec{U}_T$ of the position of a fictive hole (for assembly requirement)

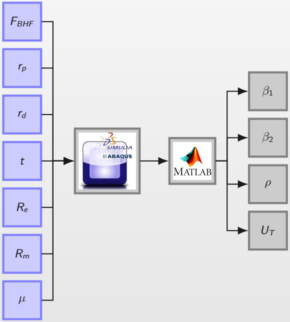


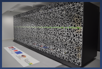


Simulation paremeters and wokflow

7 parameters to control the simulation.

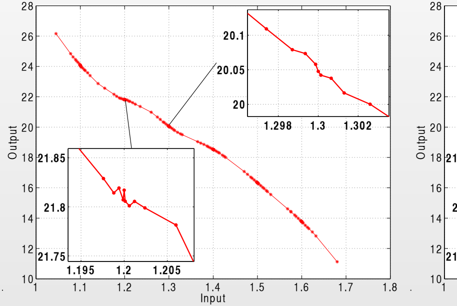
- 4 parameters related to the process :
  - $\vec{F}_{BHF}$: Blank holder force.
  - r_p : Punch radius.
  - r_d : Die radius.
  - μ : Friction coefficient.
- 3 parameters related t blank and its material
  - t : Blank thickness.
  - R_e : Yield stress limit.
  - R_m : Ultimate stress limit.

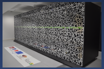




Qualification of the numerical model

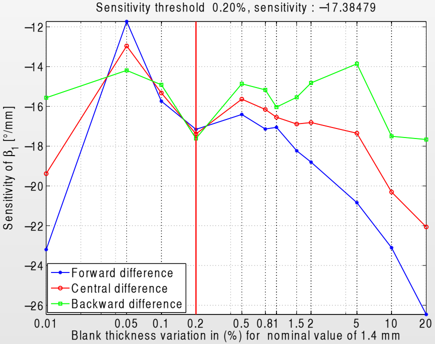
- Numerical experimentation shows that there exists a thresold below which variations around a nominal value are not correctly propagated.
- This thresold must be smaller than 6σ, the "uncertainty interval" of each parameter.

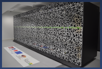




Procedure to determine thresold sensitivity

- Thresolds are determined by the convergence of backward, central et forward finite difference for decreasing value of the step size variation.
- With 25 steps per parameter for 7 parameters for 3 differents values for 3 parameters among 7, we have : $3^3 \times (7 \times 3 + 1) = 4563$ simulations.



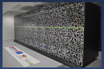


Somes results

Example of thresold sensitivity values :

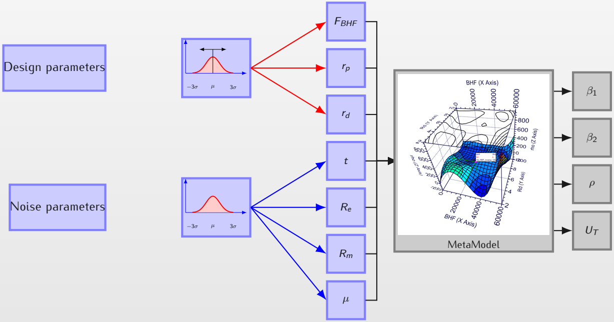
Parameters	$ST_{\beta 1}$ [%]	$ST_{\beta 2}$ [%]	ST_{ρ} [%]	ST [%]	Variation range	$\pm 3\sigma$
F_{BHF}	1.5	5	1.5	5	2940±147 [N]	±2000 [N]
R_d	0.2	5	1	5	7±0.35 [mm]	±0.05 [mm]
R_p	1	5	10	10	5±0.5 [mm]	±0.05 [mm]
t	0.2	0.8	0.1	0.8	1.4±0.0112 [mm]	±0.05 [mm]
μ	1.5	5	5	5	0.1±0.005	±0.01
R_e	1	5	5	5	550±27.5 [MPa]	±50 [MPa]
R_m	2	5	2	5	840±42 [MPa]	±60 [MPa]

- Some sensitivity thresold are larger than the uncertainty of parameter $\Rightarrow$ some precautions are needed to build metamodel

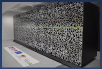


Optimization problem formulation

- Modelisation of uncertainty ⇒ design and noise parameters.



- Meta Model is use for optimization and uncertainty propagation in place of FEM numerical simulation



Optimization problem formulation

- Formulation of the optimisation problem :

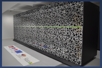
$$\text{Find } \mathbf{x} = \{F_{FBHF}, r_d, r_p\}^T$$

To minimize

$$F_{\text{Obj1}}(\mathbf{x}) = E\left(F_{\text{Perf}}(\mathbf{x}, \mathbf{z})\right) - F_{\text{Perf}}^{\text{Target}}$$

$$F_{\text{Obj2}}(\mathbf{x}) = \sigma\left(F_{\text{Perf}}(\mathbf{x}, \mathbf{z})\right)$$

$$\text{With } \mathbf{y} = \{t, R_e, R_m, \mu\}^T$$

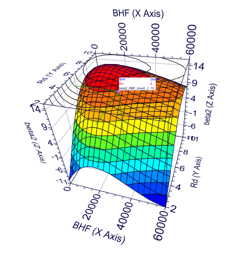


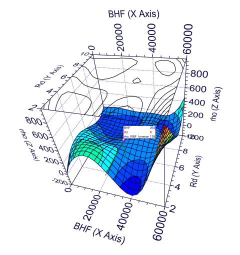
Building metamodels

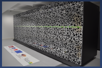
- 3 + 4 parameters and 4 springback parameters, so 4 metamodels (Radial Basis Functions) are needed $MM_i, i = 1 \dots 4$:

$$
\begin{aligned}
\beta_1 &= MM_1(F_{BHF}, r_d, r_p, t, R_e, R_m) \\
\beta_2 &= MM_2(F_{BHF}, r_d, r_p, t, R_e, R_m) \\
\rho &= MM_3(F_{BHF}, r_d, r_p, t, R_e, R_m) \\
U_T &= MM_4(F_{BHF}, r_d, r_p, t, R_e, R_m)
\end{aligned}
$$

- A Design Of Experiment (DOE) is set up with :
  - 7 factors and 3 levels per factor $\Rightarrow 3^7 = 2187$ simulations
  - for 2 factors (F_{BHF},μ) 2 intermediairy levels $\Rightarrow 3^5 \times 2^2 = 972$ simulations
- A total of 3159 simulations



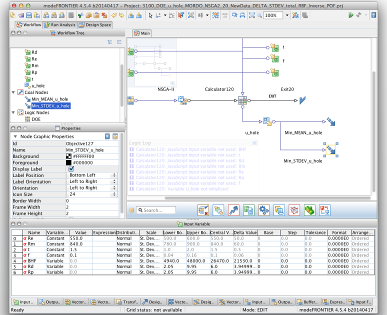


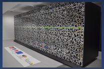


Optimization process

The Multi Objective Robust Design Optimization (MORDO) process is based on :

- An stochastic optimization algorithm (NSGAII).
- A sampling method for aleatory variables (i.e design and noise parameters): Latin HyperCube with 1000 samplings.
- Metamodel to replace the FEM simulation.
- ModeFrontier environnement to run the optimization process



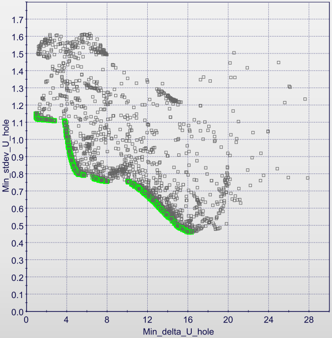


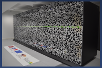
Example of optimization results

With the performance function as the hole displacement (here we want to minimise this performance).

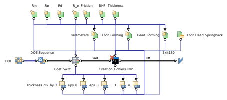
$$F_{\mathrm{Obj1}}(\mathbf{x}) = E\left(U_T(\mathbf{x},\mathbf{z})\right) - U_T^{\mathrm{Target}}$$

Paramètres	Unités	Moyenne	Ecart-type	Min	Max
F_{BHF}	kN	48.000	0.6653	45.929	50.120
r_d	mm	9.950	0.0166	9.897	10.003
r_p	mm	2.446	0.0167	2.3834	2.499
R_e	MPa	549.999	16.703	482.290	604.560
R_m	MPa	840.010	20	777.520	912.390
μ		0.1	3.305×10^{-3}	8.885×10^{-2}	1.119×10^{-1}
t	mm	2	1.668×10^{-2}	1.947	2.052
U_T	mm	0.973	1.131	-2.279	4.639

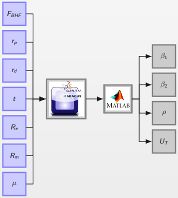




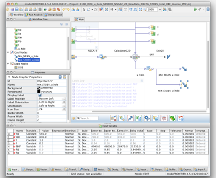
Overview of the complete workflow



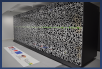
Preparation of files for DEO experiment
Run on laptop comuputer



4563+3159=7722 simulations !
Massive parallelisation on ROMEO
(1600 simulation en parallel)
About 20000 hours of sim. in about 15 hours !



Optimization : about 1 hour on a laptop computer



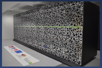
Conclusion

About Robust Optimization :

- Time computation consumming with complex simulation model of forming process.
- Metal modeling technique must be improved to be more efficient.

About numerical simulation :

- For this case, ROMOE makes things possible !! (3 years of calculation in about 1 days !!)
- MetaModelling, offline optimization, typical task that can be highly parallelized.
- Here the number of parallel operations was limited by license of Abaqus.



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- The ROMEO team for his availability and his support.
- Dassault System, lend of a high number of Abaqus license for one week.
- Council of "Champagne Ardenne" for funding the projet "SIMUPROC".