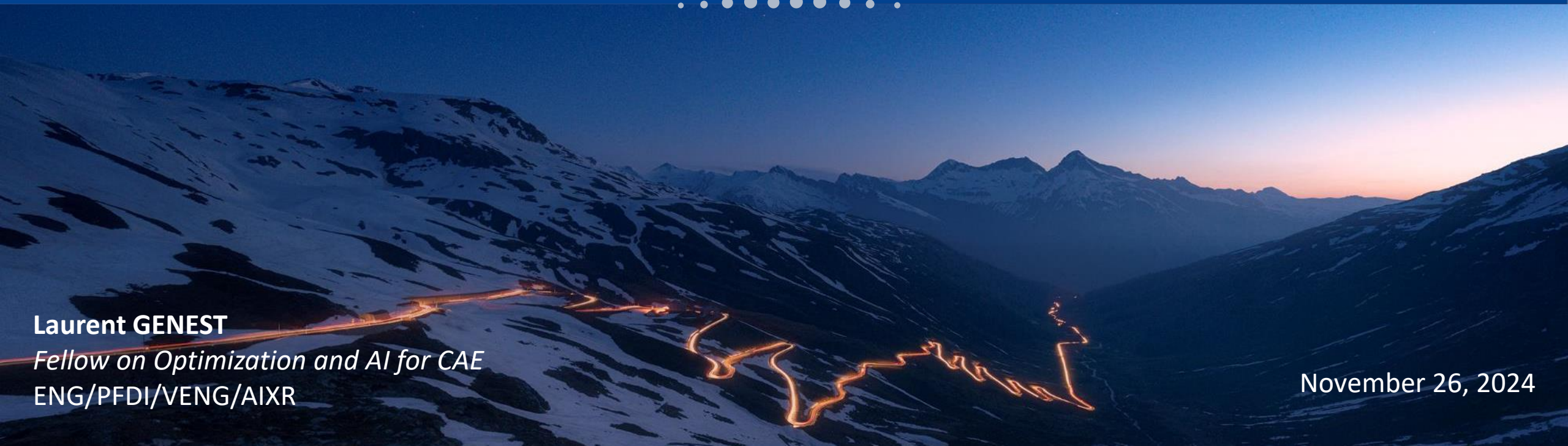
Black-Box Optimization in automotive design
Journée Francilienne de Recherche Opérationnelle



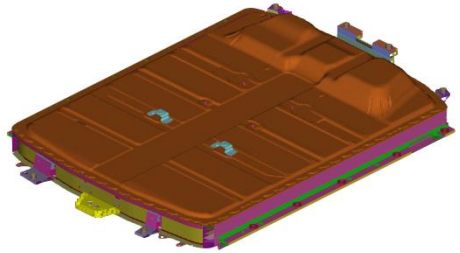
Laurent GENEST
Fellow on Optimization and AI for CAE
ENG/PFDI/VENG/AIXR

November 26, 2024

AGENDA

- Black box optimization problems for automotive design
- Optimization process
- Outlooks

PROBLEM DEFINITION – V CYCLE DESCENT



Synthesis

Sub-system

Part

- Mass
- Cost
- Aerodynamics

- Crashworthiness

- Acoustics

- Durability/Fatigue
- …

PROBLEM DEFINITION – BLACK BOX

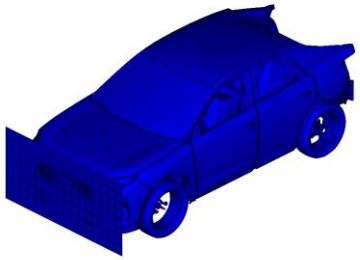
Inputs variables
Integer, discrete or continuous

Parts thickness
Steel grade
Materials
Shape
Reinforcements presence/absence
Alternatives
Architecture
Spotwelds location
…

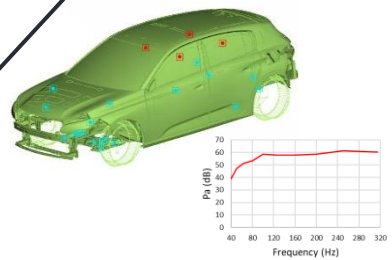
CAE Simulations

Extracted scalar outputs
Objectives or constraints

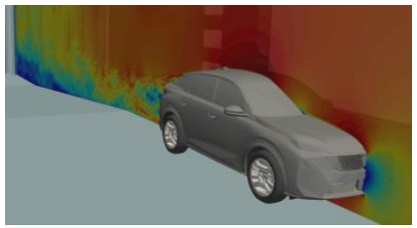
Mass
Cost
Manufacturing constraints
Assembly constraints
Drag coefficient CdA
Maximal intrusions
Accelerations - HIC
Acoustic noise
Stress
…



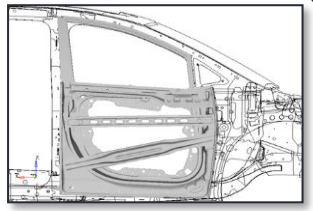
Crashworthiness



Noise



CFD



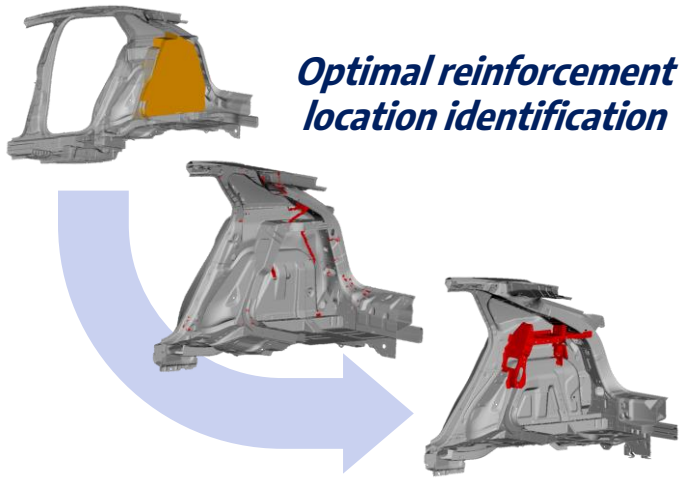
Fatigue

To keep in mind: Computational time,
Numerical scatter, Computation failures

PROBLEM DEFINITION - OPTIMIZATION ACTIVITIES FOR VEHICLE PROJECTS

Load path architecture study

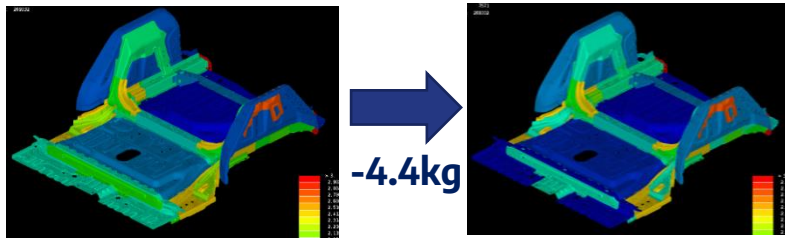
➢ *Topology optimization*



Optimal reinforcement location identification

Lightening and cost savings study

➢ *Multi-Disciplinary Optimization (MDO)*



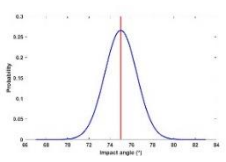
➢ ***Enablers: thickness, material grades, presence/absence of reinforcements...***

➢ ***All disciplines***

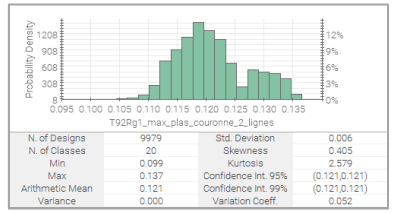
Reliability and robustness assessment

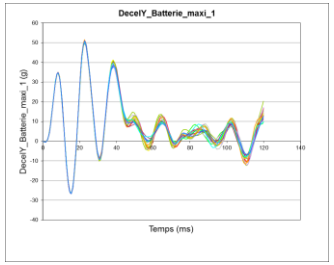
➢ *Stochastics study*

Factor	Target value	Uncertainty	Distribution
Impact speed	64 kph	[0;+1] kph	Gaussian
Side overlap	40%	+/- 20 mm	Uniform
Vertical alignment	-	+/- 25 mm	Uniform
Barrier stiffness	0.342 MPa	-10%/0%	Gaussian
Barrier/Vh friction	0.2	+/-0.2	Uniform



From manufacturing and experiments uncertainties...



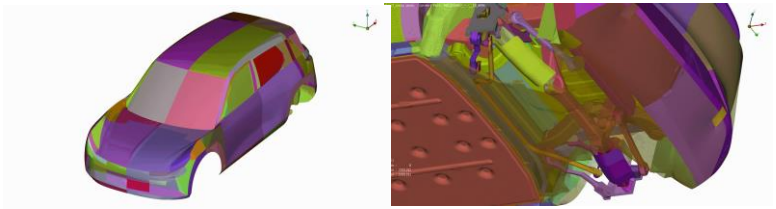


...to performance target violation risk evaluation

Digital concept **Detailed design** **Tooling stage**

Aerodynamics vs Style balance

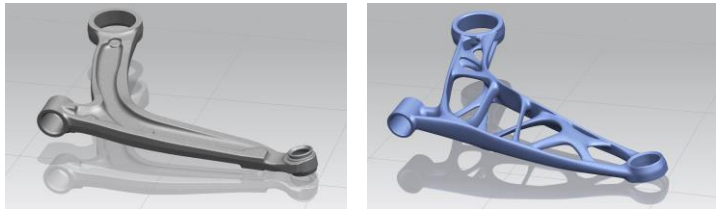
➢ *Parametric shape optimization*



Parameterized CAE model morphing

Disruptive part design

➢ *Topology optimization*



Front control arm (3.4kg > 2.92kg)

PROBLEM DEFINITION – AN EXAMPLE

Find the design configuration dealing with:

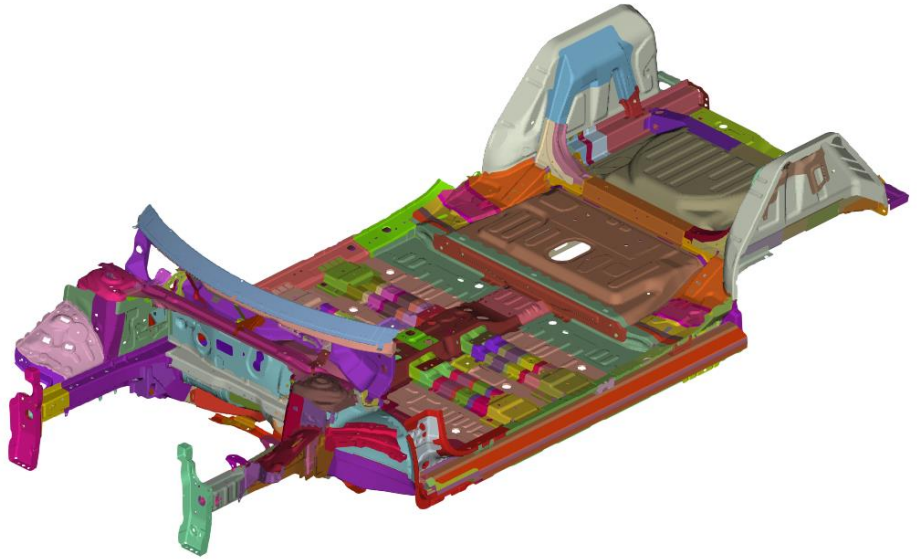
- 80 parts thickness
- 30 parts steel grade

That minimize:

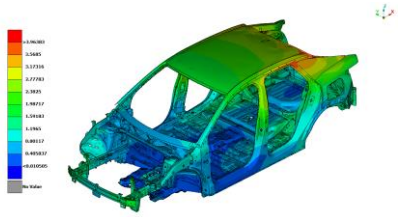
- Mass, total cost

Under following constraints:

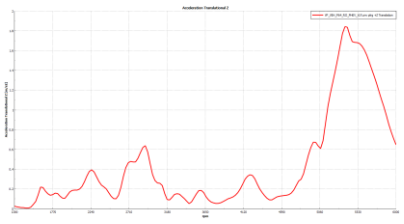
- Modal analysis: 2 criteria
- Structure vibrations: 10 criteria
- Vibroacoustic: 8 criteria
- Static and durability: 10 criteria
- Front crash with several barriers: 80 criteria
- Side crash on several location: 50 criteria



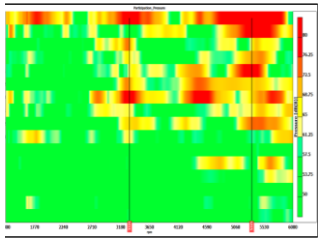
Studied perimeter



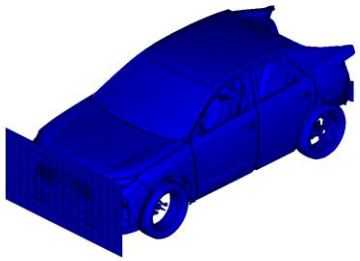
Modal analysis
~ 1 CPU.h



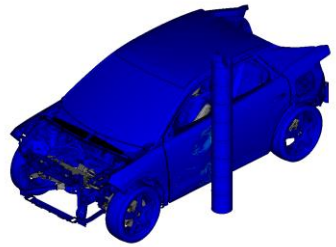
Vibrations
~ 10 CPU.h



Vibroacoustic
~ 10 CPU.h

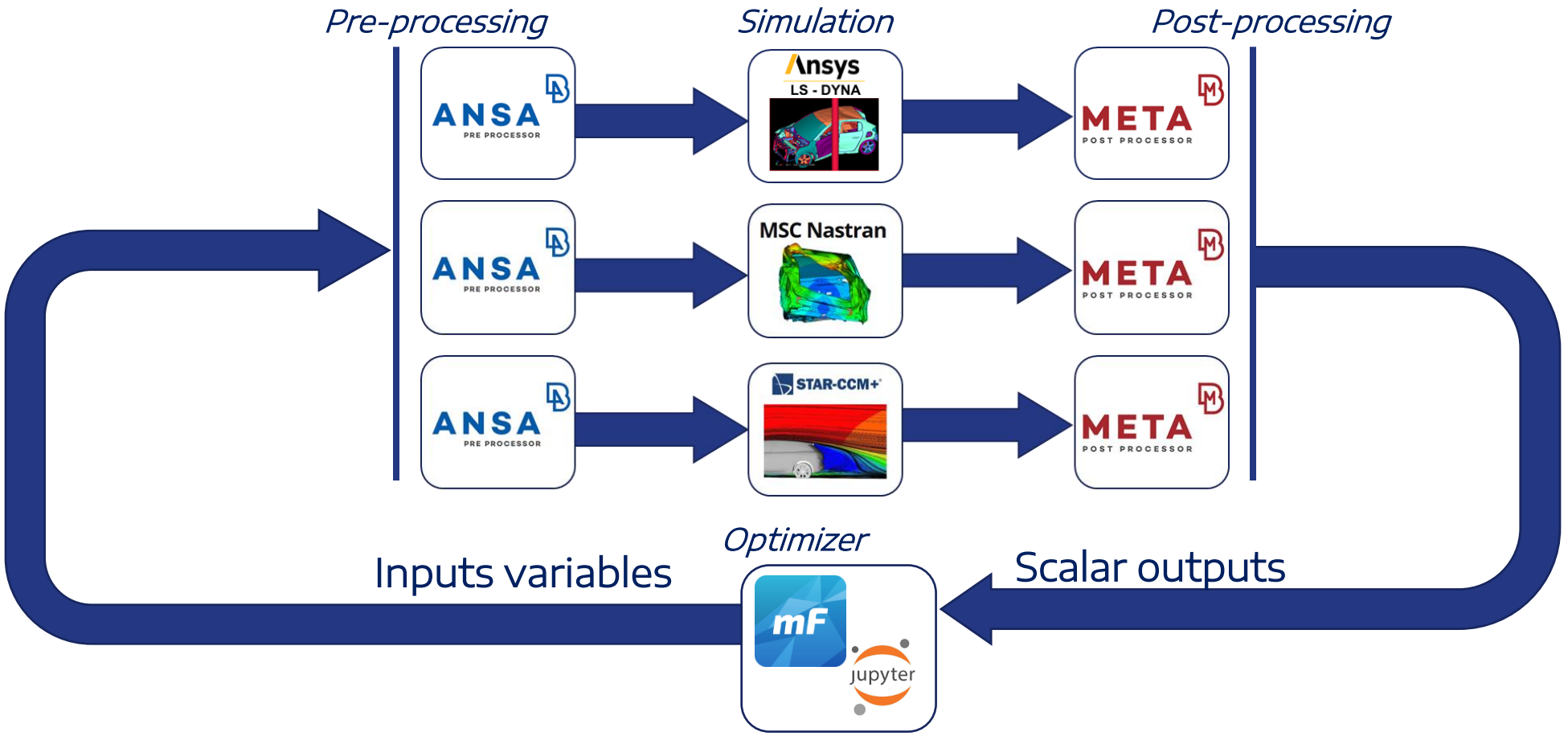


Front crash
~ 10^3-10^4 CPU.h

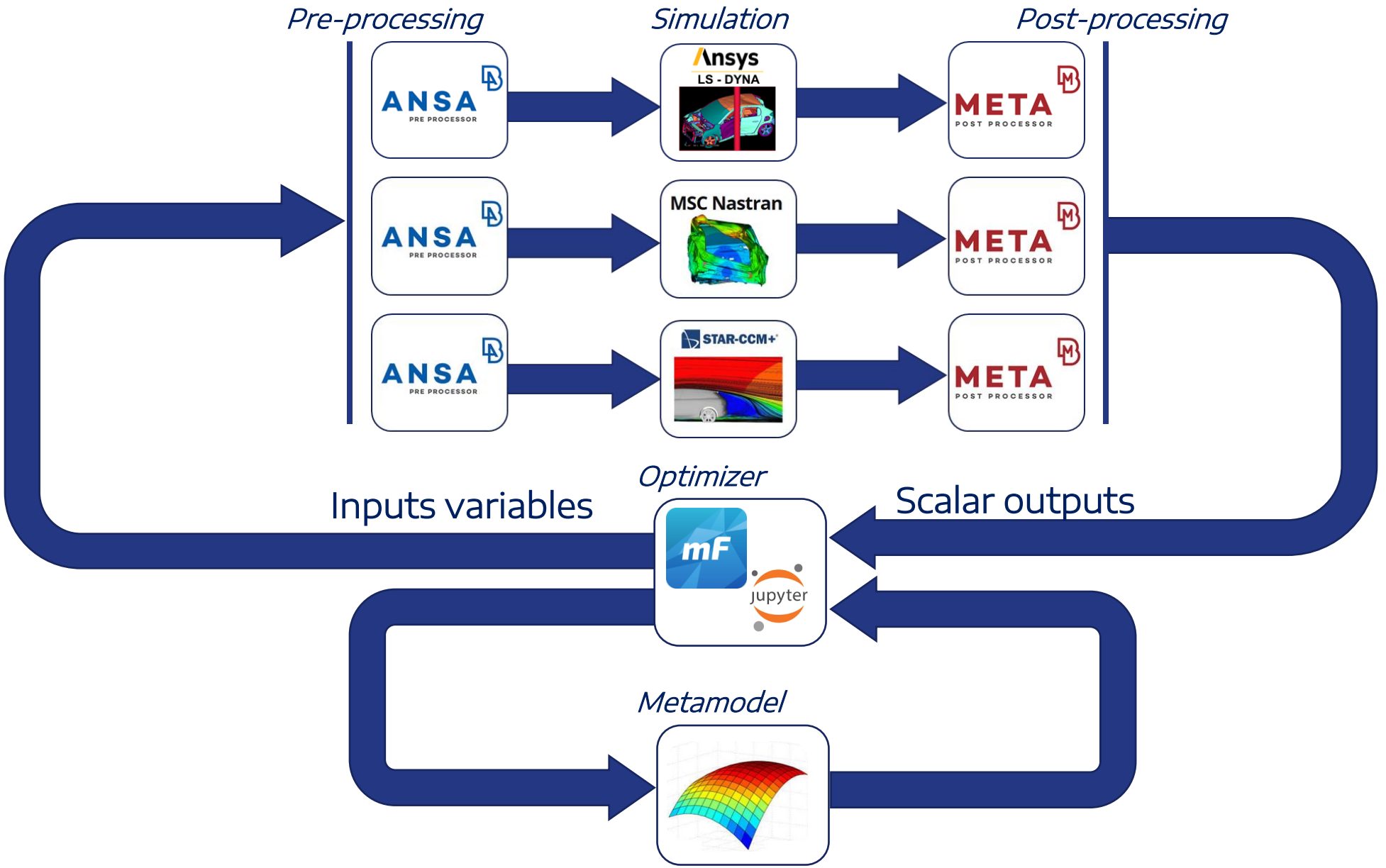


Side crash
~ 10^3 CPU.h

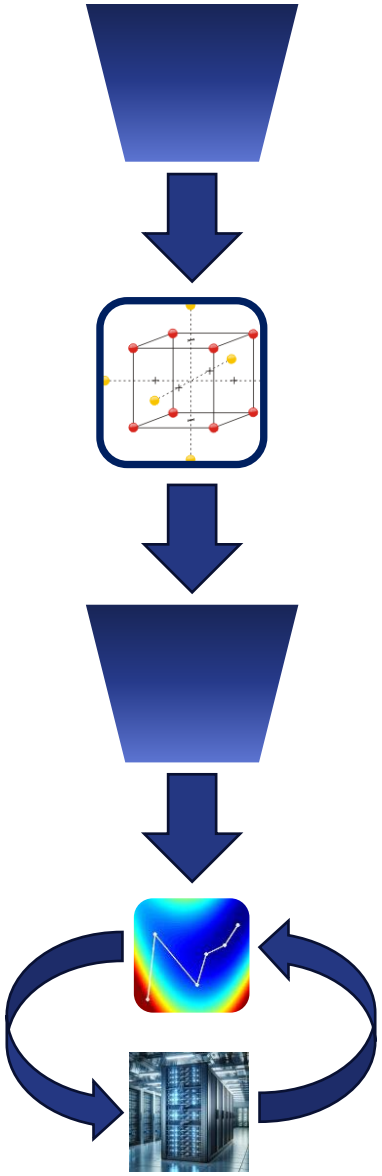
OPTIMIZATION PROCESS – AUTOMATED WORKFLOWS



OPTIMIZATION PROCESS – AUTOMATED WORKFLOWS



OPTIMIZATION PROCESS – ALGORITHM



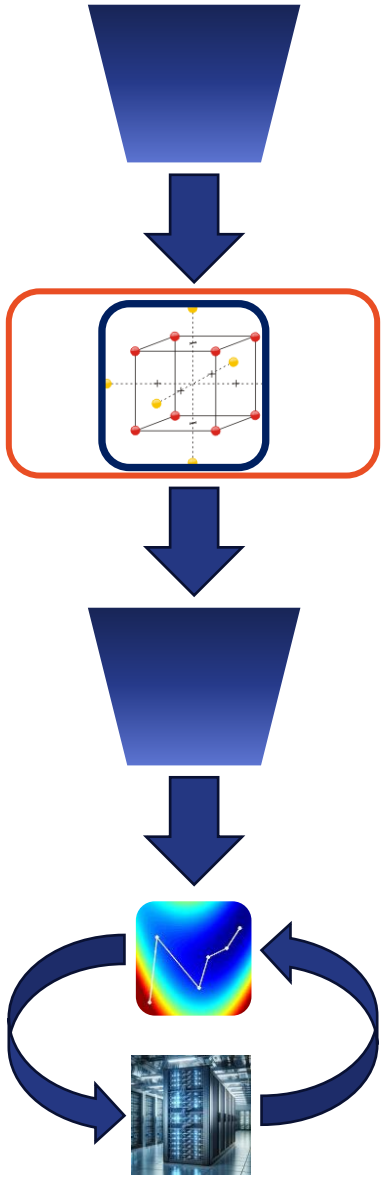
Knowledge based dimension reduction
- Splitting perimeter in several studies (e.g., front, rear…)

Design of Experiments
- Plackett-Burman with fold over
- Latin Hypercube Sample with maximization of minimum distances (maximin)

ANOVA
- Sensitivity analysis
- P-value computation for dimensionality reduction

Optimization loops
- Human-assisted optimization
- Metamodel-based optimization (Gaussian Processes, Radial Basis Functions)
- Enrichment strategies for constraints

OPTIMIZATION PROCESS – ALGORITHM



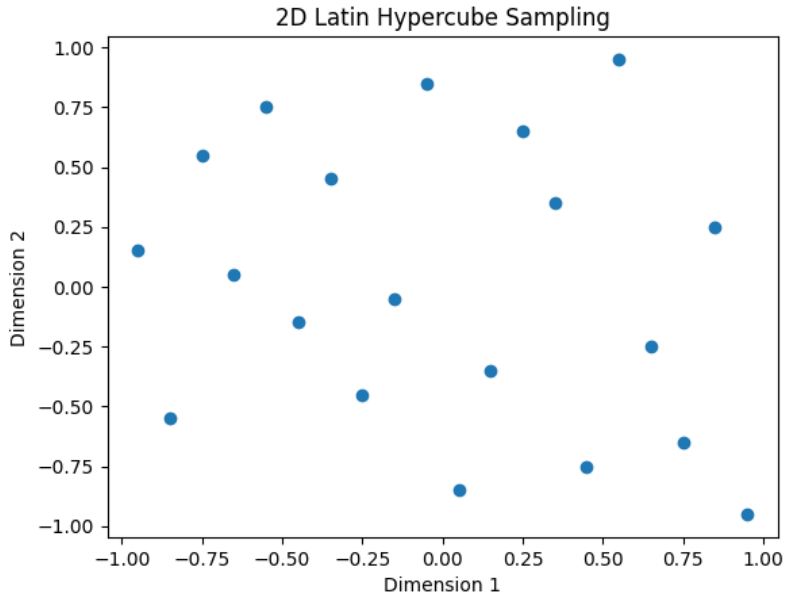
Design of Experiments combination

- Plackett-Burman with fold over
- Latin Hypercube Sample with maximization of minimum distances (maximin)

A	B	C
+1	+1	+1
+1	-1	-1
-1	+1	-1
-1	-1	+1
+1	+1	-1
+1	-1	+1
-1	+1	+1
-1	-1	-1

Plackett-Burman DOE for 3 factors

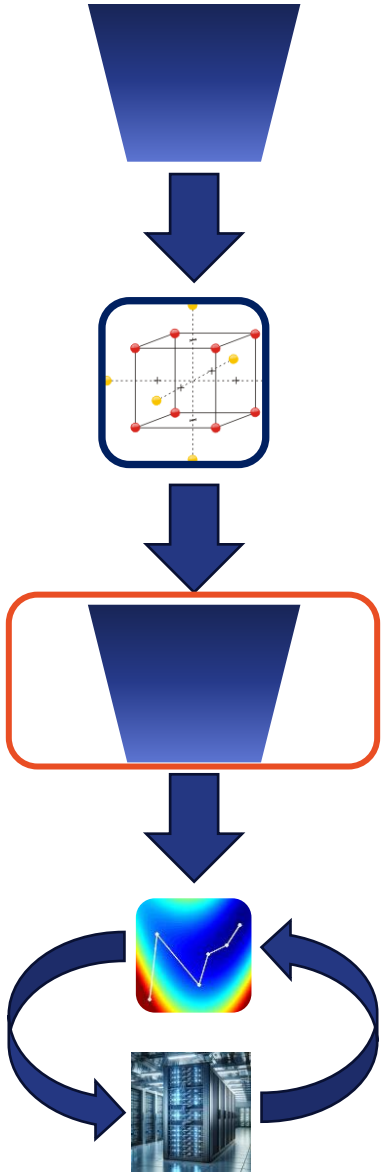
- Based on Hadamard matrices
- Fold over to remove aliases
- Enable global sensitivity analysis



Uniform Latin Hypercube Sample

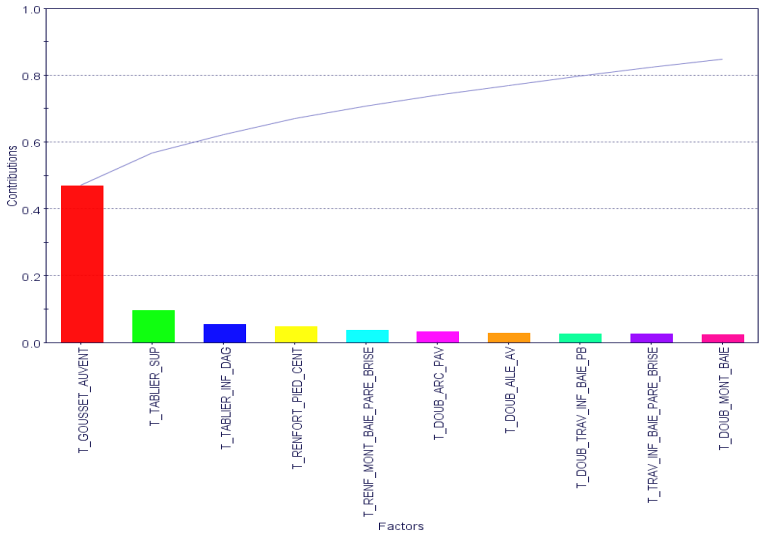
- Maximization of minimal distances to improve the coverage
- Compliant with surrogate modeling

OPTIMIZATION PROCESS – ALGORITHM



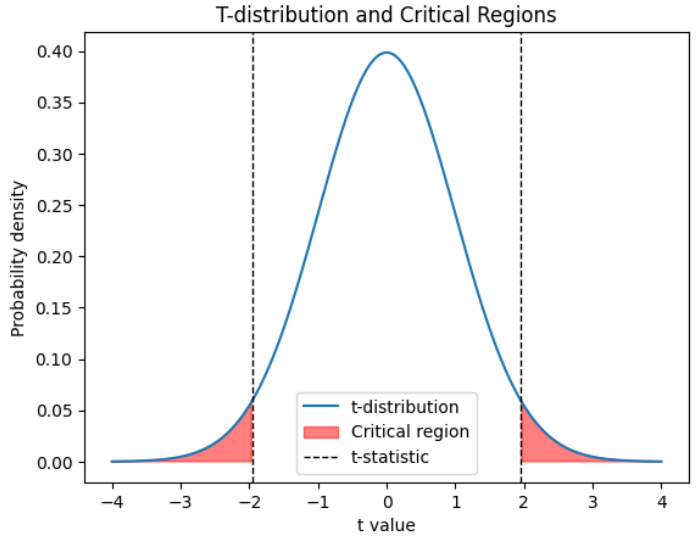
ANOVA

- Sensitivity analysis
- P-value computation for dimensionality reduction before optimization



Sensitivity analysis

- Evaluate most influent factors
- Main trends based on linear (+interactions) polynomial approximation

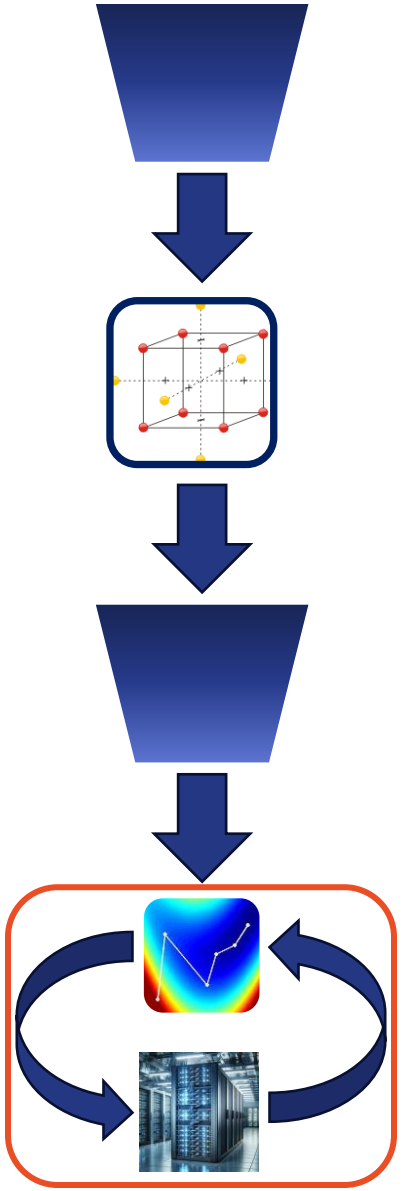


P-Values computations

- Provided by the Student test
- Evaluation of the Null-hypothesis
- Factor rejected when higher than a certain threshold

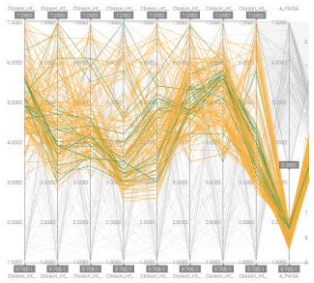
- Other techniques available: Sobol indices, HSIC, confidence regions…

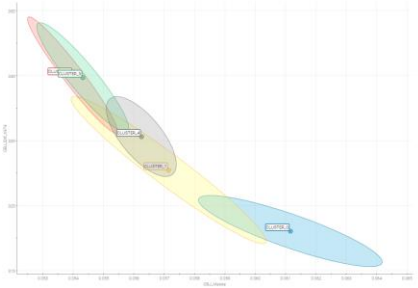
OPTIMIZATION PROCESS – ALGORITHM

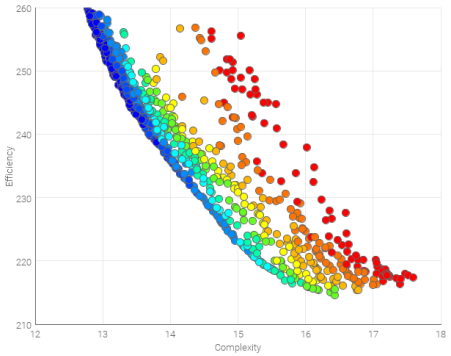


Optimization loops

- Human-assisted optimization through Decision Aid Tool
- Metamodel-based optimization (Gaussian Processes, Radial Basis Functions)
- Enrichment strategies for constraints

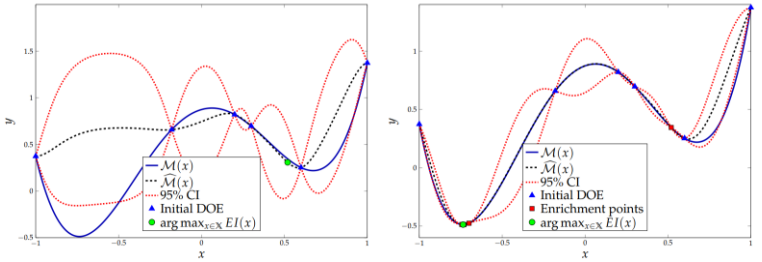




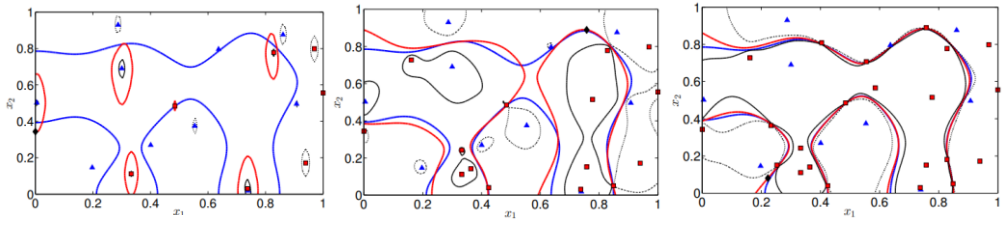


Human-assisted optimization

- Metamodels-based optimization (RBF, GP)
- Clustering of feasible design
- Switch of constraint to objective, constraint target modification, adding new rules…



Objective enrichment



Constraint enrichment

Enrichment strategies

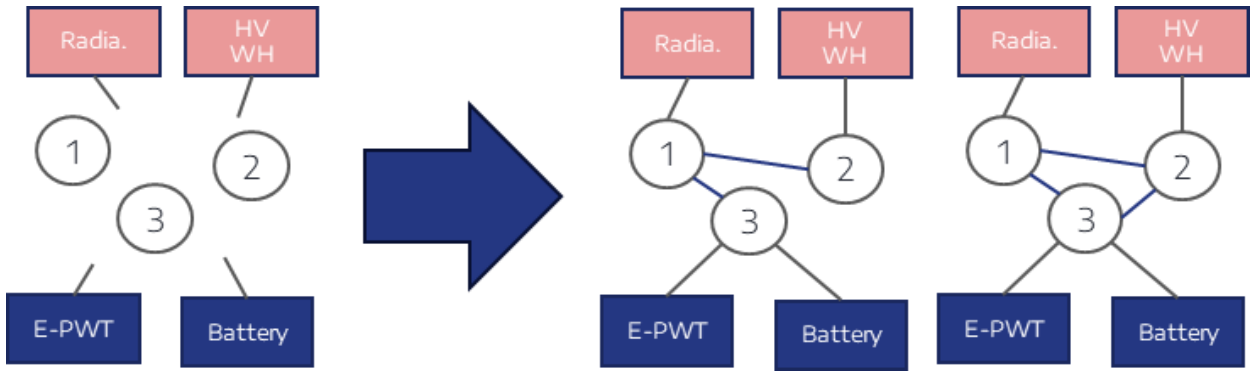
- Gaussian Processes based techniques
- Objectives are quite linear (mass, cost)
- Constraints enrichment through Deviation Number, Expected Feasibility, Expected Violation

Toward Architecture Problems

Low computational time → **High dimension of variables** → **Architecture problems** → ***Toward Operations Research?***

Handling a high number of constraints

Mixed-integer problems and combinatorial optimization



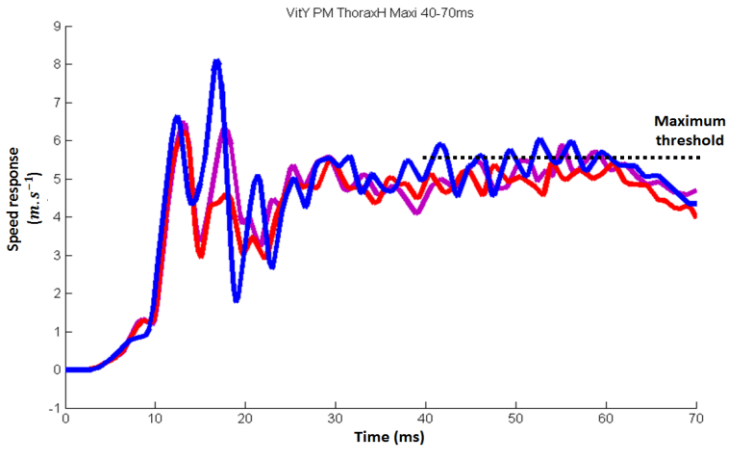
Thermal architecture problem

- 10-100 Billions of possible architectures
- Single evaluation: ~20s

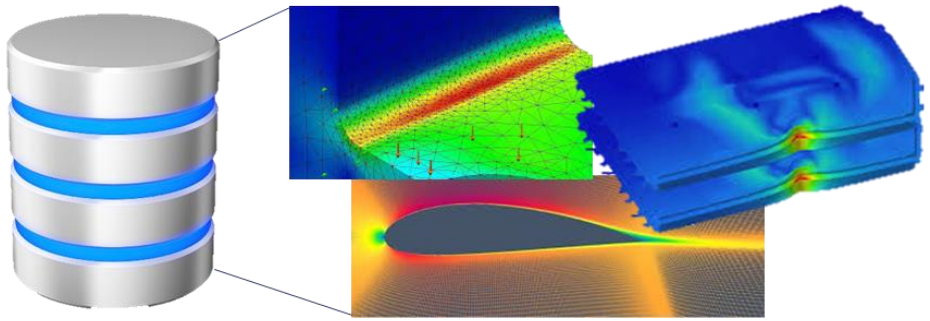
OUTLOOK – DEEP LEARNING SURROGATES

New type of metamodels to predict fields and curves

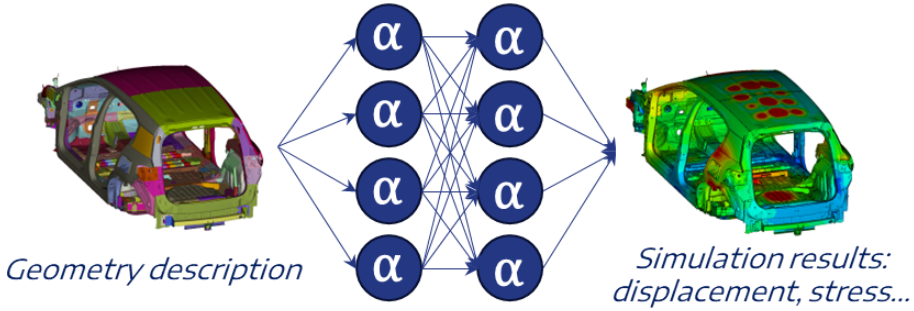
- Reduced Order Models
  - Decomposition based approaches
- Graph Neural Networks
  - Message Passing Neural Network, Graph Convolutional Network
- Physically-Informed Neural Networks/Surrogates
  - Usage of mechanical equations in addition to the database
  - Aim to enhance the predictivity to handle complex non-linear physics



Acceleration results of a safety simulation
Maximum could appear at various time



Database of simulations results
Meshes could be characterized as a graph



Graph Neural Networks
Prediction of the simulation results from geometry description (meshes)

CONTACT

Laurent GENEST
ENG/PFDI/VENG/AIXR
Fellow on Optimization and AI for CAE
laurent.genest@stellantis.com