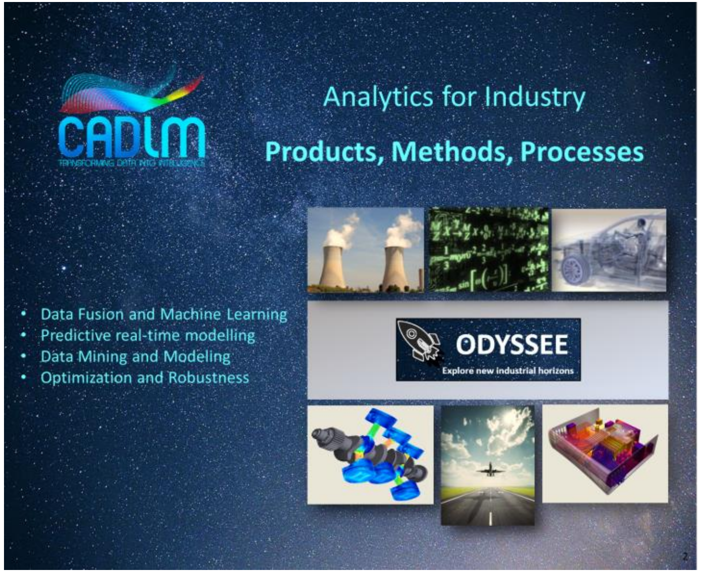
ODYSSEE

Machine Learning (ML) based ROM for Real-Time Optimization
With applications for engineering (and everything else)



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CTO, CADLM

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CADLM
TRANSFORMING DATA INTO INTELLIGENCE

CADLM - Transforming data into intelligence

ODYSSEE
Explore new industrial horizons

“CADLM accelerates product design and development via real-time parametric simulations with our optimization, machine learning and AI tools”

ODYSSEE - Explore new industrial horizons

Optimal **D**ecision **S**upport **S**ystem for **E**ngineering and **E**xpertise

- AI & Data Mining
- Machine Learning
- Model Reduction
- Optimization
- Risk and reliability
- Robustness

Engineering services

- Simulations
- Training

Customizations

ODYSSEE applications

Our customers

arianespace
arianeGROUP
THALES
SAFRAN
TOYOTA
BOMBARDIER
HONDA
DAIHATSU
Toyota Motor North America
faurecia
inspiring mobility
Ford
PSA
GROUPE
TOYOTA
Toyota Industries
JFE
TOYOTA
Autoliv
OPEL
Seiko Epson Corporation
EPSON
YAMAHA
Revs Your Heart
Schlumberger
ULVAC
Kubota
azbil
Nikon
TOYOTA BOSHOKU
AsahiKASEI
nexter
A COMPANY OF
KNDS
TOYOTA
Toyoda Iron Works
TOYODA GOSEI
DAIMLER
mazda
Panasonic
ArcelorMittal
Technetics
GROUP
トヨタ車体
TOYOTA AUTO BODY
INSTITUT VEDECOM

Which came first: Data or Computers ?

Which came first: Data or Computing ?

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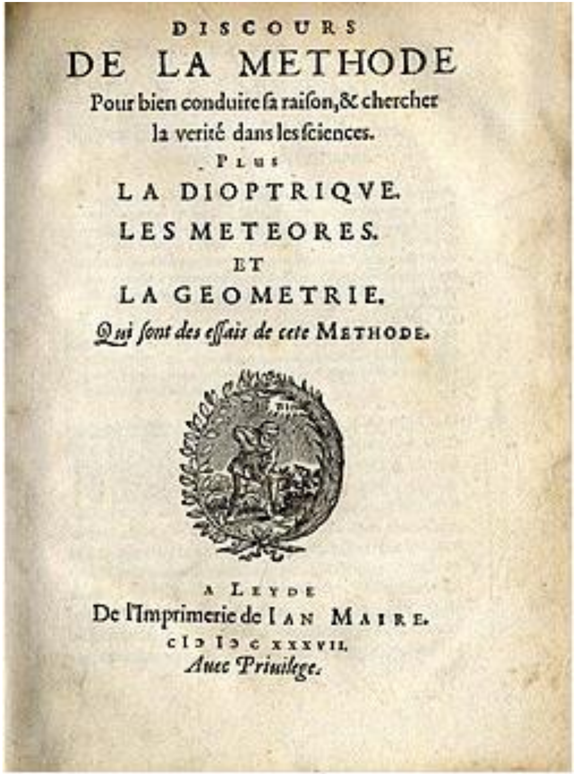
Machine Learning (ML) with CAE will greatly impact the product development process.

Focus Areas:

- Creating Predictive Models with Machine Learning
  - Avoid long, complex and costly (pre/solve/post) simulation process.
  - **Simulation can provide the training data**
- Support Controller / Sensor Learning providing additional training data
  - Will replace the costly analysis process.
  - Enable the creation of autonomous systems.



DISCOURS
DE LA METHODE
Pour bien conduire ſa raiſon,& chercher
la verité dans les ſciences.
PLUS
LA DIOPTRIQVE.
LES METEORES.
ET
LA GEOMETRIE.
Qui ſont des eſſais de cete METHODE.

A LEYDE
De l'Imprimerie de IAN MAIRE.
CIϽ IϽ C XXXVII.
Auec Priuilege.

Our solutions aim at COST reduction

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Customers' problems (COST)

- Computing (**HW/SW**, CPU, Energy, …)
- Optimization (**Iterations**, **curse of dimensionality,** precision of surrogate models,, parametric studies, stochastics)
- Simulation (**Model size and complexity**, Multi-physics, multi-scale, encapsulation, model transfer without loss of confidentiality)
- Time (**Real-time**, pre/post automation, animations, etc.)

Our Applications

1. **Real-Time** predictive modeling and optimization (CAE or test data)
2. **Image , Sound & Sensors** compression, identification, learning, prediction
3. **Fault** prediction (Sensor data)

Our Technology Positioning

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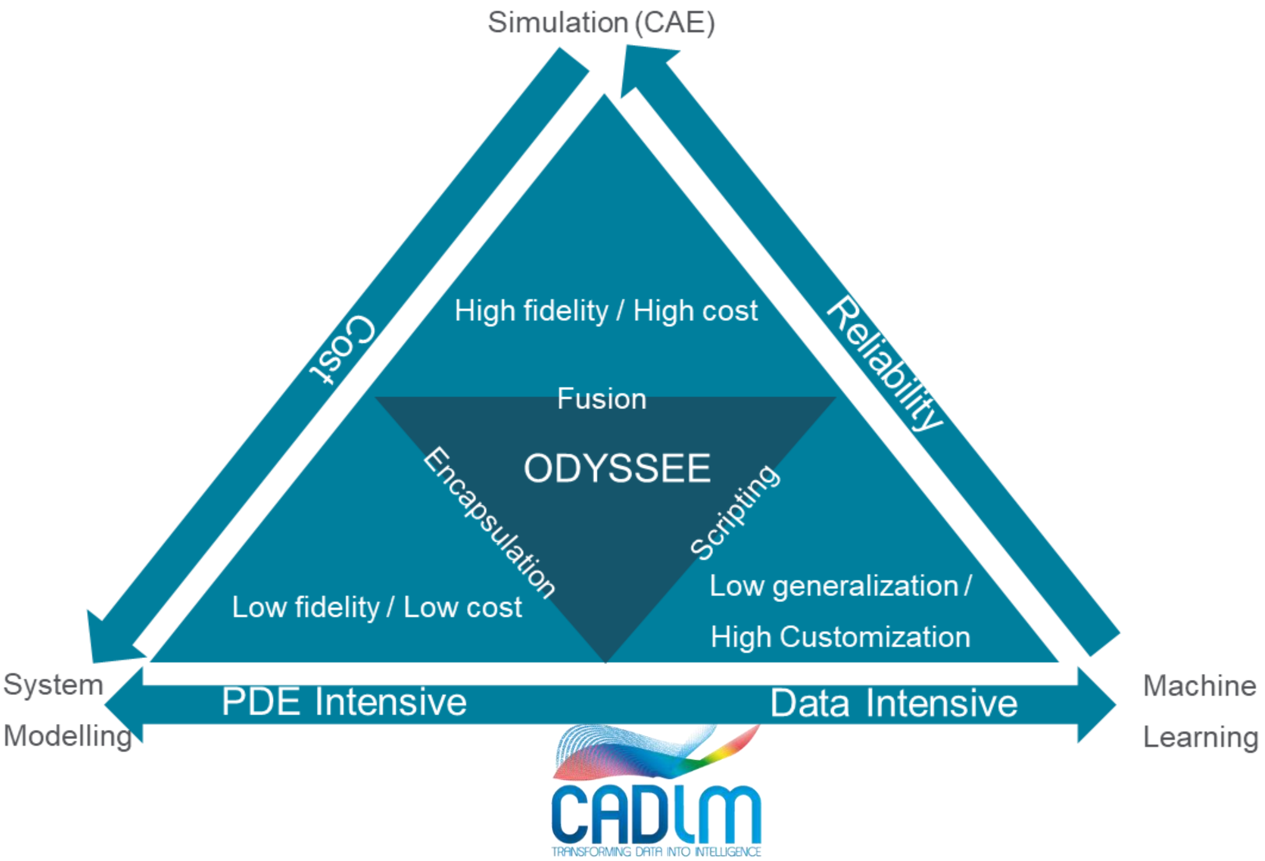

Our Added Value Raises with Design Complexity

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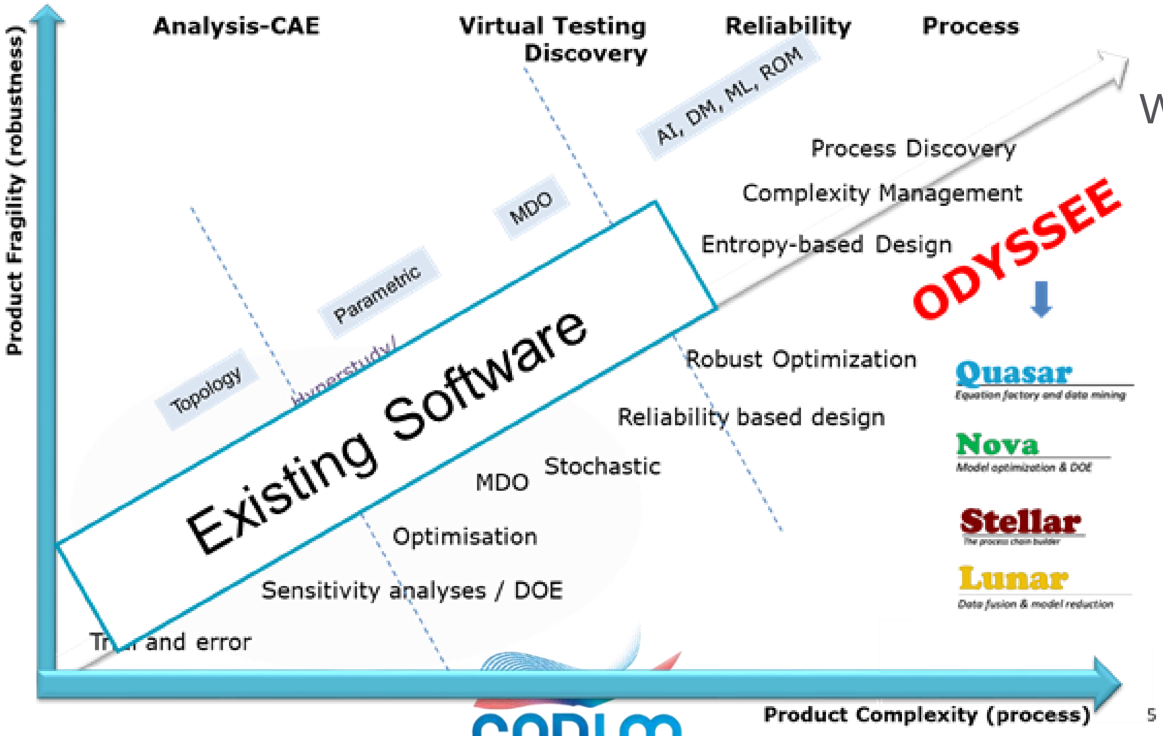
Positioning



We star here

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ODYSSEE Full Package

LUNAR
Model Reduction & Optimization

QUASAR
Machine Learning

NOVA
Optimization

- QuasarOnline, PULSAR, …

ODYSSEE is a modular package:

Lunar
Data fusion & model reduction

Quasar
Equation factory and data mining

Nova
Model optimization & DOE

Current Design process

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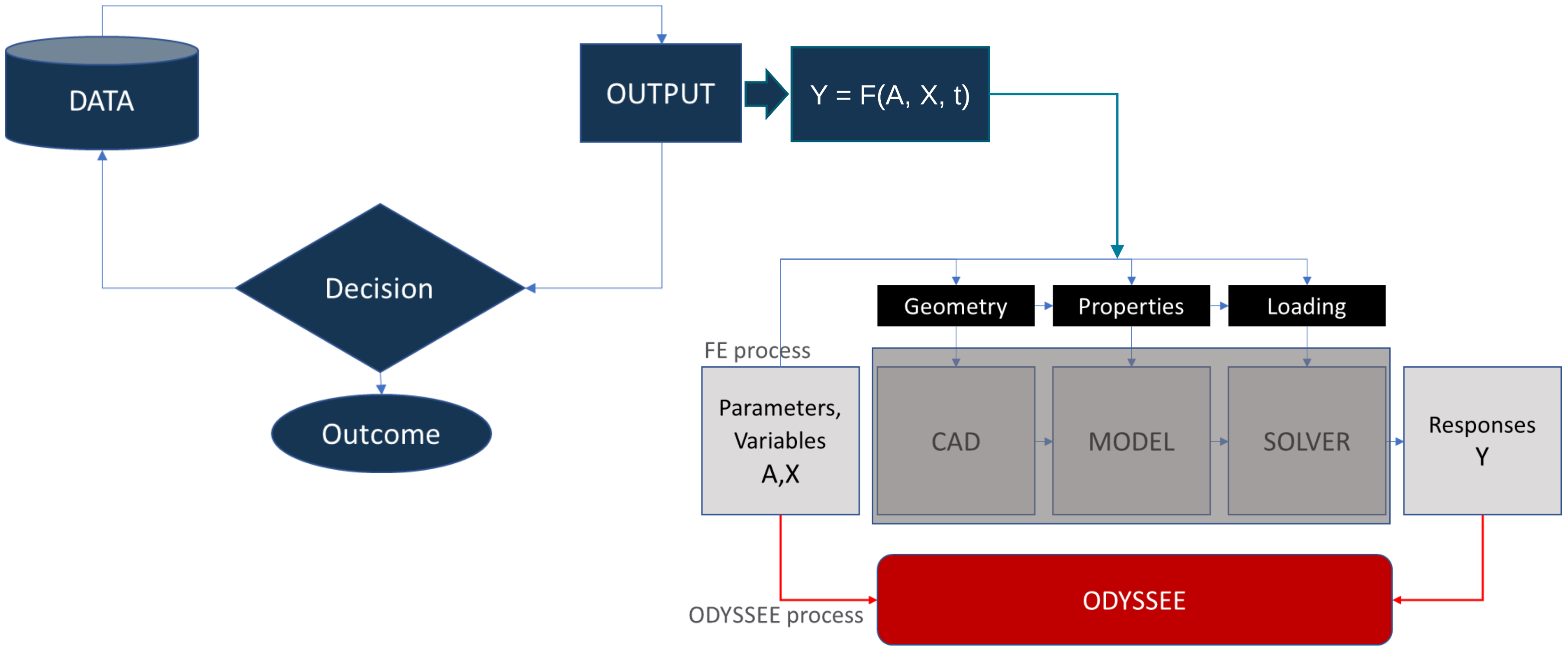
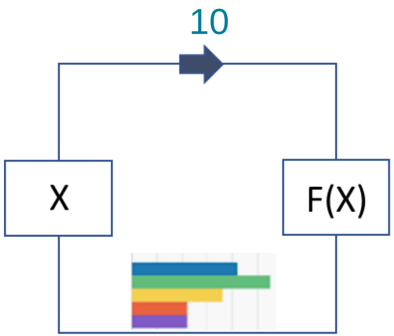
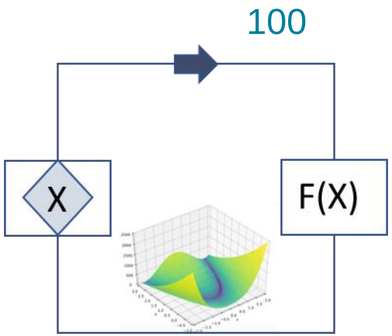


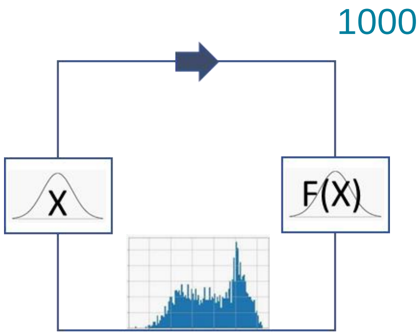
Why LUNAR?



- Parametric Studies
- Trial and error

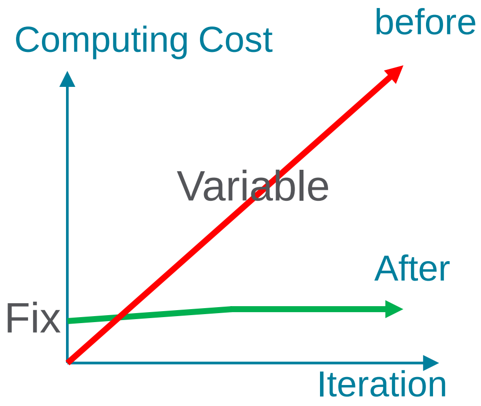


- Optimization
- Model Fitting

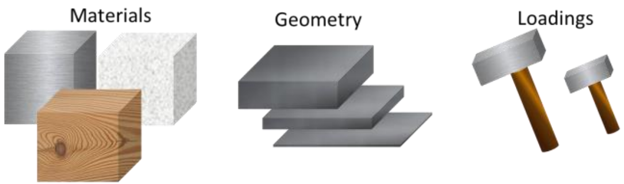


- Reliability Studies
- Robustness

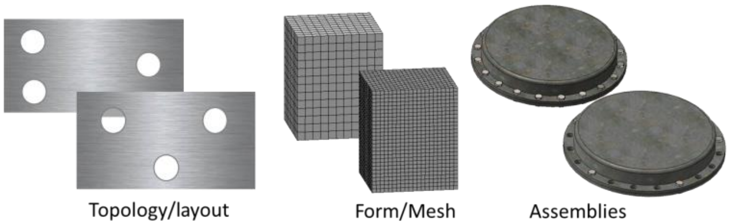
All require numerous solver runs



Lunar for real-time parametric studies



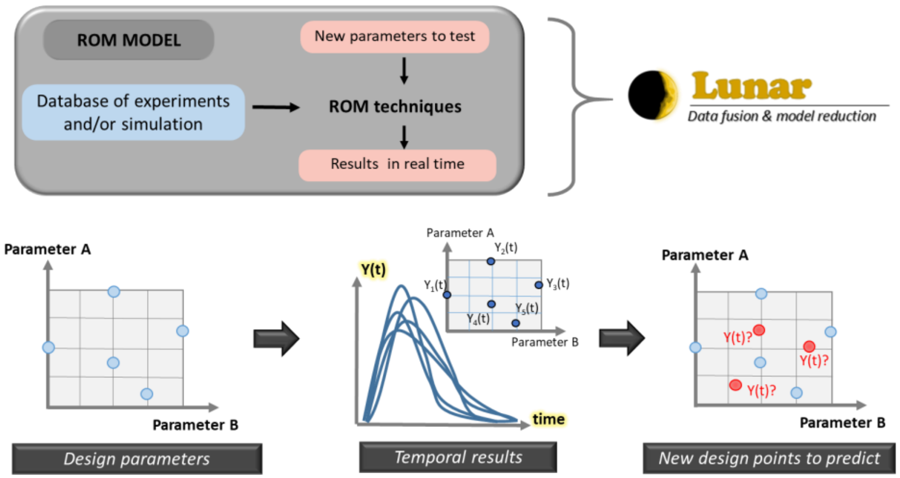
Model parameters may be simple or complex



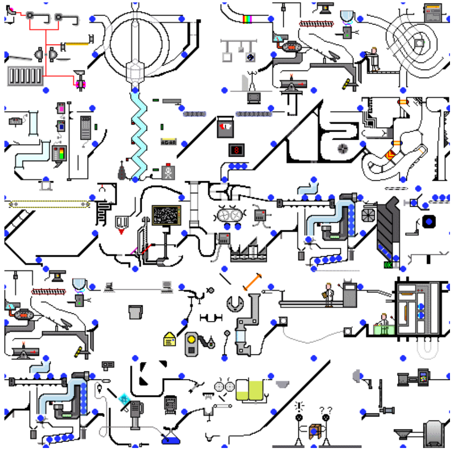
Design Parameters

DOE based data collection

Model Order Reduction (ROM) + ML



Lunar
Data fusion & model reduction



Reduced Order Modelling (ROM) and Real-Time Optimization

ODYSSEE (LUNAR/ QUASAR/ NOVA)

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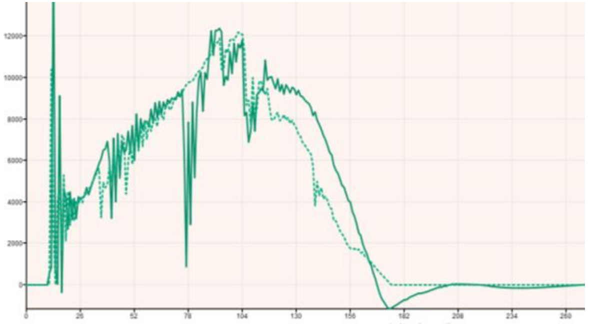
Lunar exploits ROM

Lunar is based on Model Order Reduction techniques

May predict temporal & static responses

May predict bifurcation and non-linear response



Prédiction des réponses temporelle

Note:

- **ROM is not a response surface method**

A response surface uses polynomial or other interpolation functions as « a-priori » applied to scalars (temporal responses are treated as scalars -> long and non repeatable: needs to be re-done for every prediction)

- **ROM predicts complete time responses and is based on physical modes of behavior**

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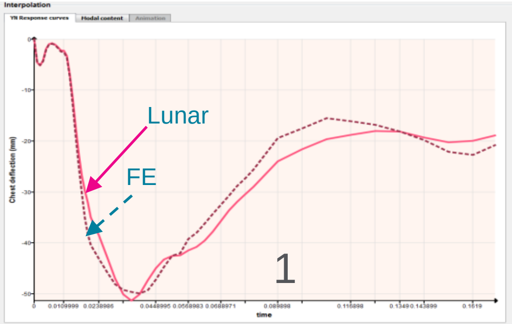
Expected Real-time output

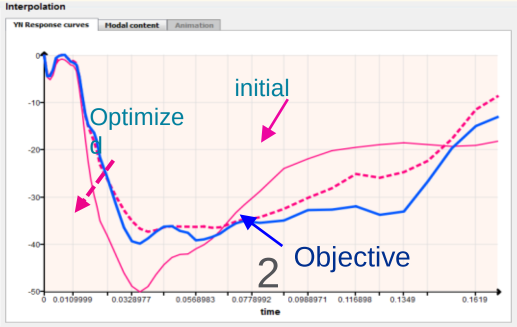
Lunar

Data fusion & model reduction

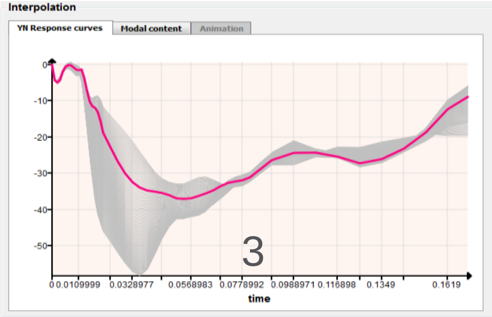
Time responses in real time



Optimization and parameter fitting

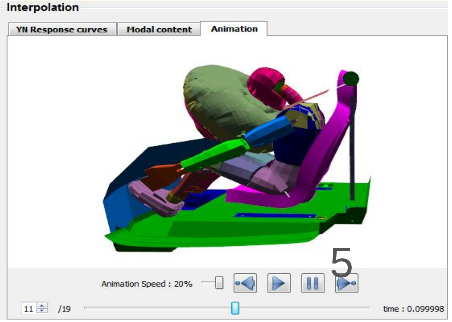


Population studies (corridors)



Sensitivity analysis of parameter effects

Real-time animations



Advantages

Real-time computing

- Zero-computing effort for parametric studies and optimization
- Corridors & Population generation (statistics)
  - Parameter effects
  - DOE's

Software and physics independent

- Works with Structural, Thermal, CFD, Acoustics (Ls-dyna, Radioss, pam-crash, MSC Nastran, Marc, Adams, Cradle CFD, Actran)

Automation/Parser

- Automatic post-preprocessing and rating
  - Multi-channel

Reduces CAE computing effort

- Allows for a few, wisely selected sampling points
- Adaptive learning that allows you to improve as you learn

Precision & completeness

- Full time history output (not only scalars)
- Physical domain decomposition and not fitting (it is NOT a Response Surface Method!)

Can produce 3D animations

- No interpolations but reconstructions
- Stress/displacement iso-value reconstruction

Evaluation tools included

- Quality of parameters • Quality of DOE
- Best method for your application

CADLM offer (AI/ML/ROM based optimization)

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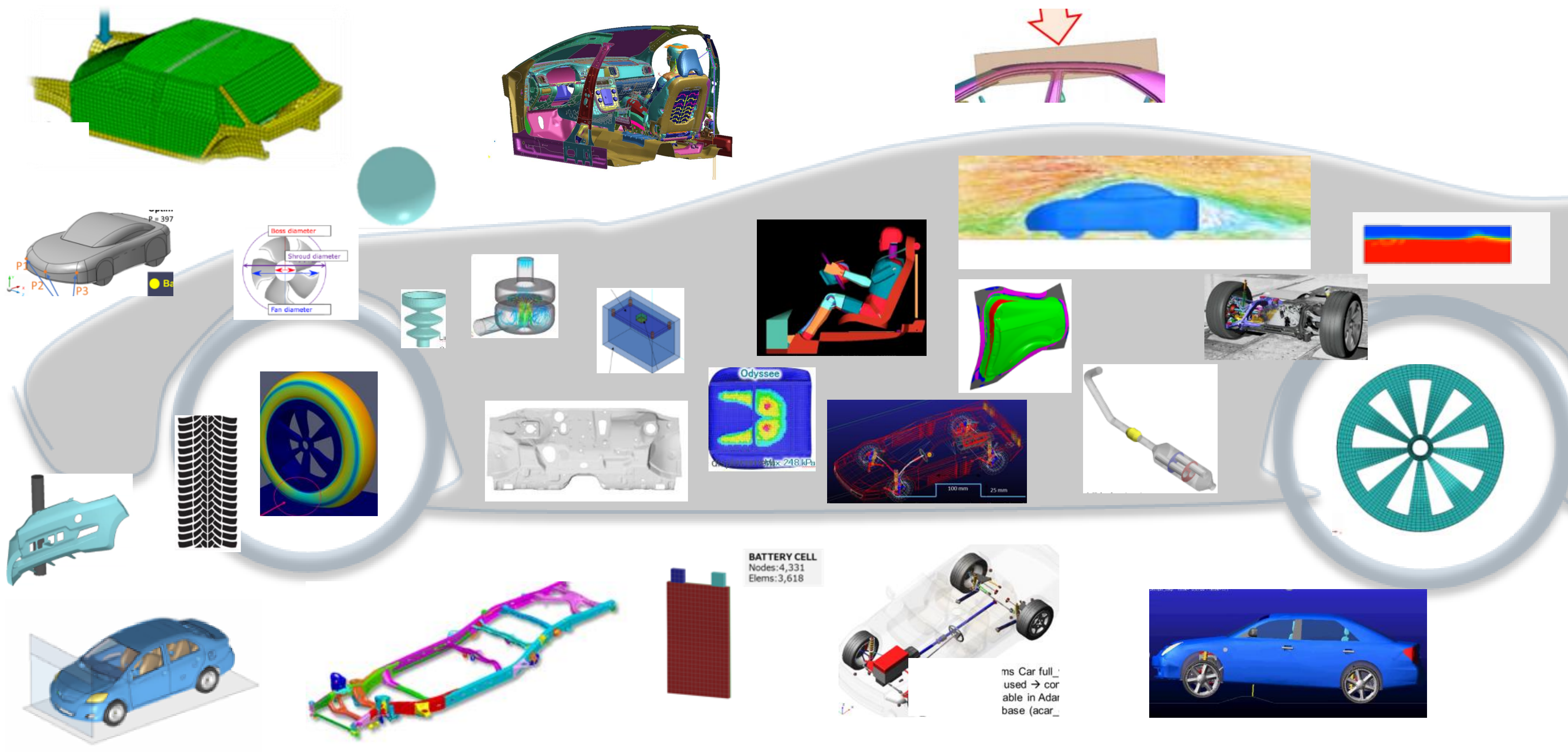
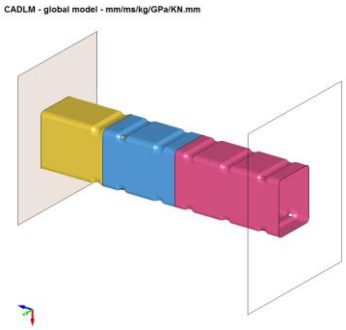
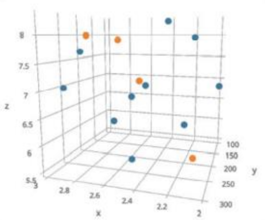
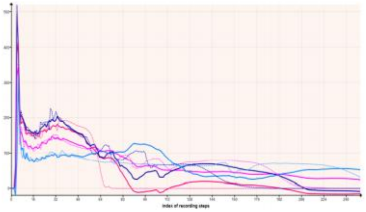


- Aerodynamics
- Aeroacoustics
- Battery
- Crash
- Electric
- Ergonomics
- Exhaust
- Fuel tank
- Heat
- Impact
- Noise
- Safety
- Stamping
- Strength
- Styling
- Tires
- Vibroacoustic

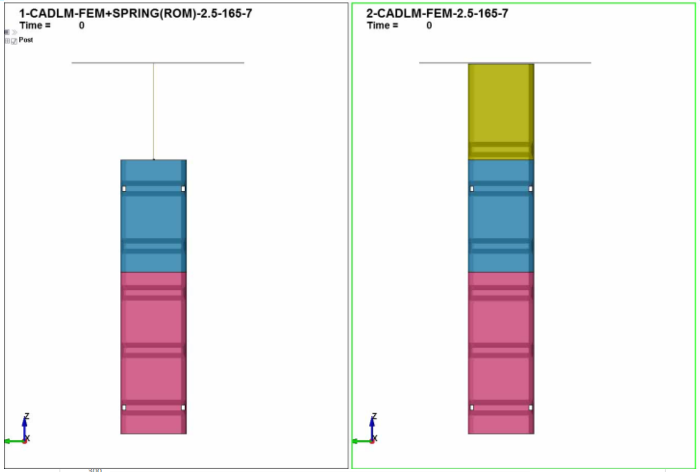
Sub-system encapsulation (*.k include)

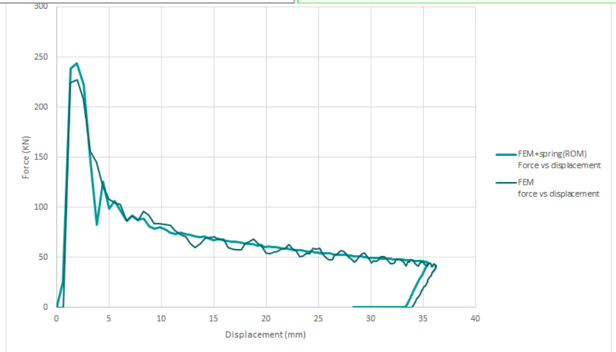




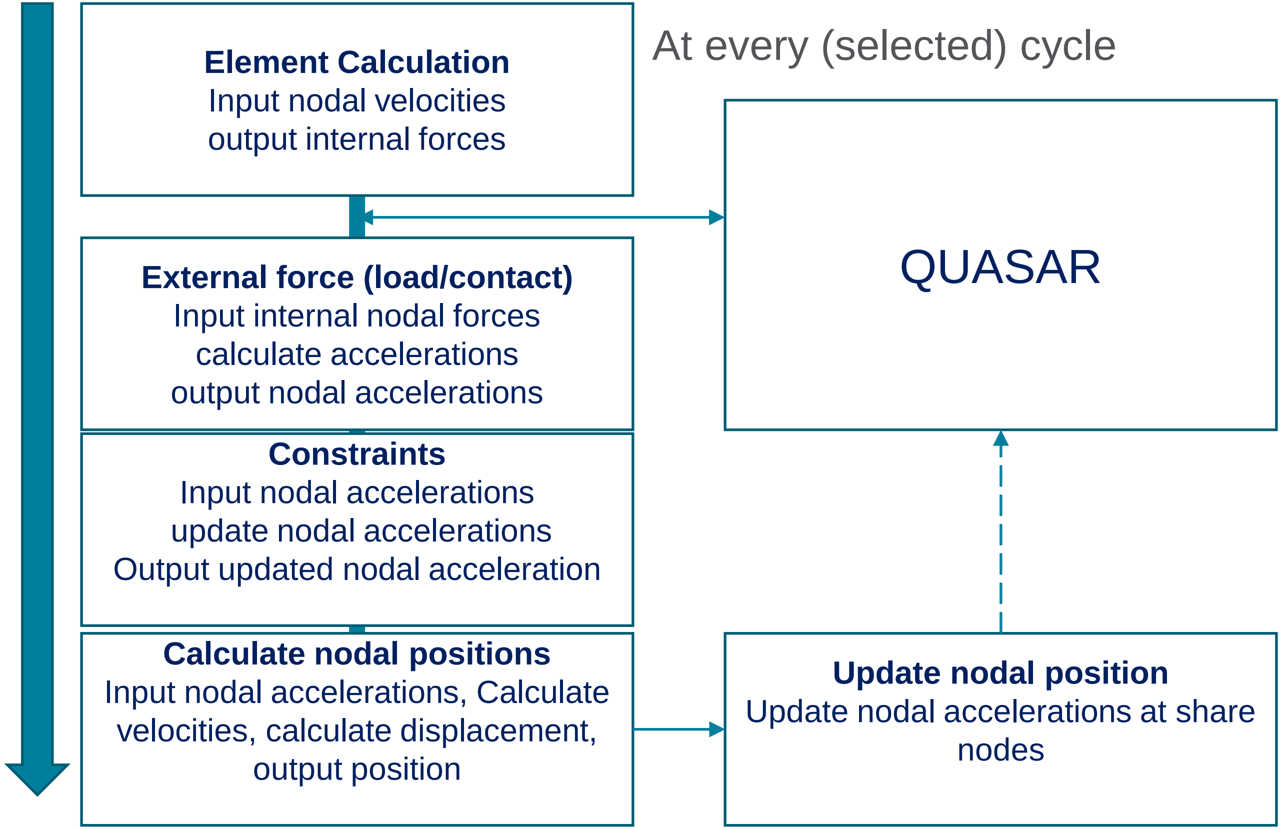


thickness :2.33 mm; mass RW:300. kg; velocity RW:7.22 mm/ms





Quasar-IsDyna coupling



*DEFINE_QUASAR_COUPLING *DEFINE

***DEFINE_QUASAR_COUPLING**

Purpose: Define LS-DYNA node/node set that interacts with Cadlm's QUASAR ROM model. Each coupling needs to have its own keyword card and will not accept multiple entries.

Card 1	1	2	3	4	5	6	7	8
Variable	NODE	TYPE	ROMID	PID	PTYPE	IOPT	CID	EX_ND
Type	I	I	I	I	I	I	I	I

Card 2	1	2	3	4	5	6	7	8
Variable	FILENAME1							
Type	A80							

Card 3	1	2	3	4	5	6	7	8
Variable	FILENAME2							
Type	A80							

Optional card for user defined constants. Eight floating point per card until reach next keyword card.

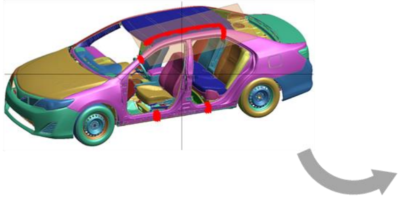
Card 4	1	2	3	4	5	6	7	8
Variable	Variables – ncards							
Type	F							

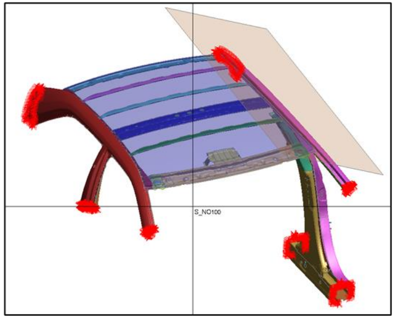
*QUASAR Keyword

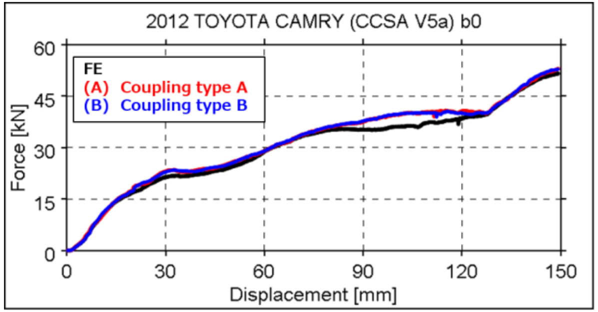
DYNA-QUASAR coupling

- Motivation
  - Want to reduce calculation time by utilizing ODYSSEE
    1. Cut out only the parts you want to evaluate from the full car model
    2. Boundary characteristics are predicted using ODYSSEE

- The calculation stability is greatly improved, and the calculation is possible to the end.
- The calculation speed was also greatly improved and could be reduced to 3 times the target value.





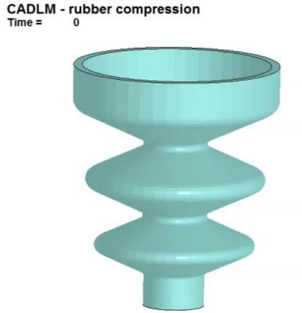


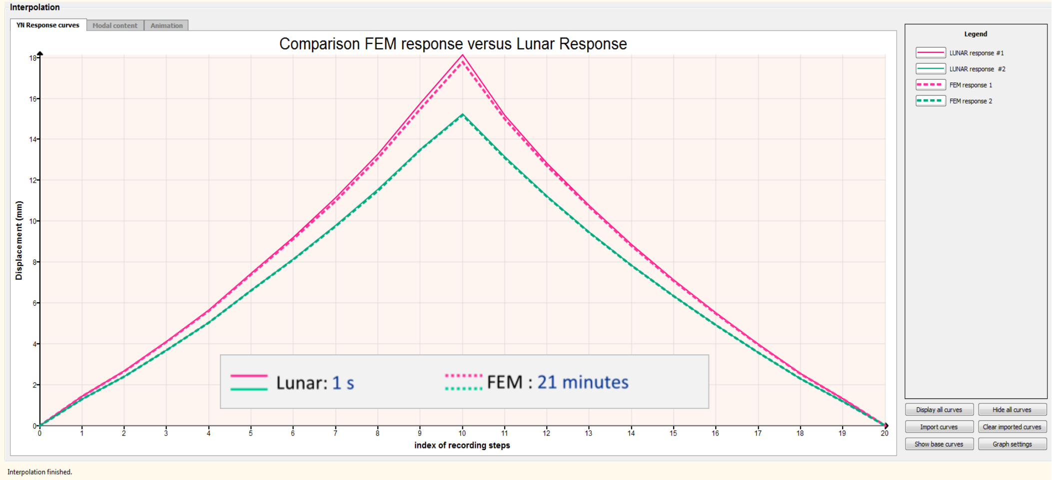
	sec./cycle		
	Total	Quasar	Dyna
FY2019	13.49	13.48	0.01
FY2020	0.05	0.03	0.02
Ideal (20% of Full FE)	0.02	0.01	0.01

1

Courtesy of JSOL

Rubber joint (ls-dyna) – Material Nonlinearity





15 runs, 3 parameters

Mass => X1

Mooney Rivlin parameters => X2, X3

Output Channel

Displacement at extremity of joint => Y1

Elapsed Time

FE = 21 minutes
LUNAR = 1 sec

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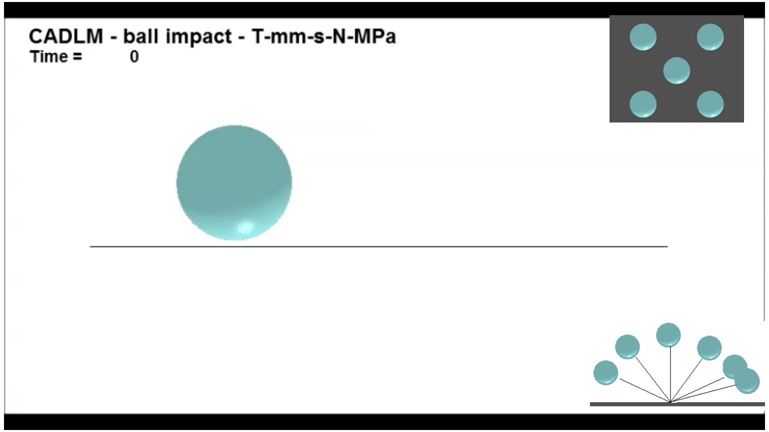
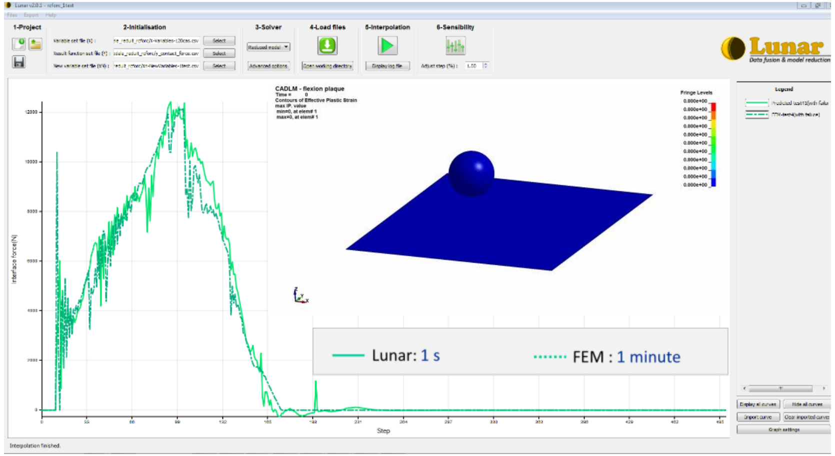
Ball impact with rupture (ls-dyna)

ODYSSEE
Explore new industrial horizons





15 runs, 4 parameters

Position X,Y => X1, X2

Ball speed at impact => X3

Impact angle => X4

Output Channel

Contact force => Y1

Elapsed Time

FE = 1 minute

LUNAR = 1 sec

CADLM
TRANSFORMING DATA INTO INTELLIGENCE

Plate flexion (Influence Lines)

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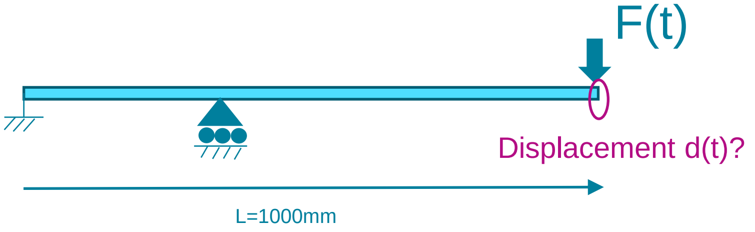
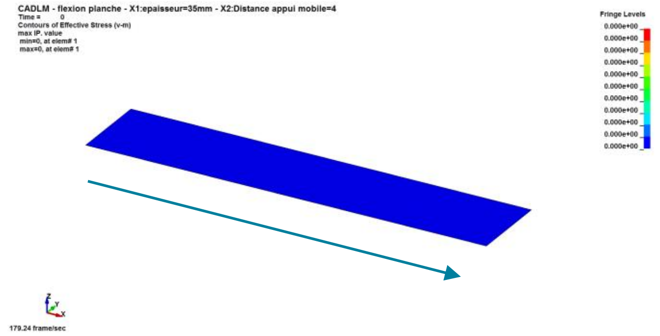
Explore new industrial horizons



Influence Lines



2 model parameters
Plate thickness => X1
Mobile support distance=> X2

Output channels:
displacement-time over the complete spatial domain => Y1

15 DOE runs

Finite Elements	Lunar
1 minutes / simulation	1 second

Plate flexion (Influence Lines)

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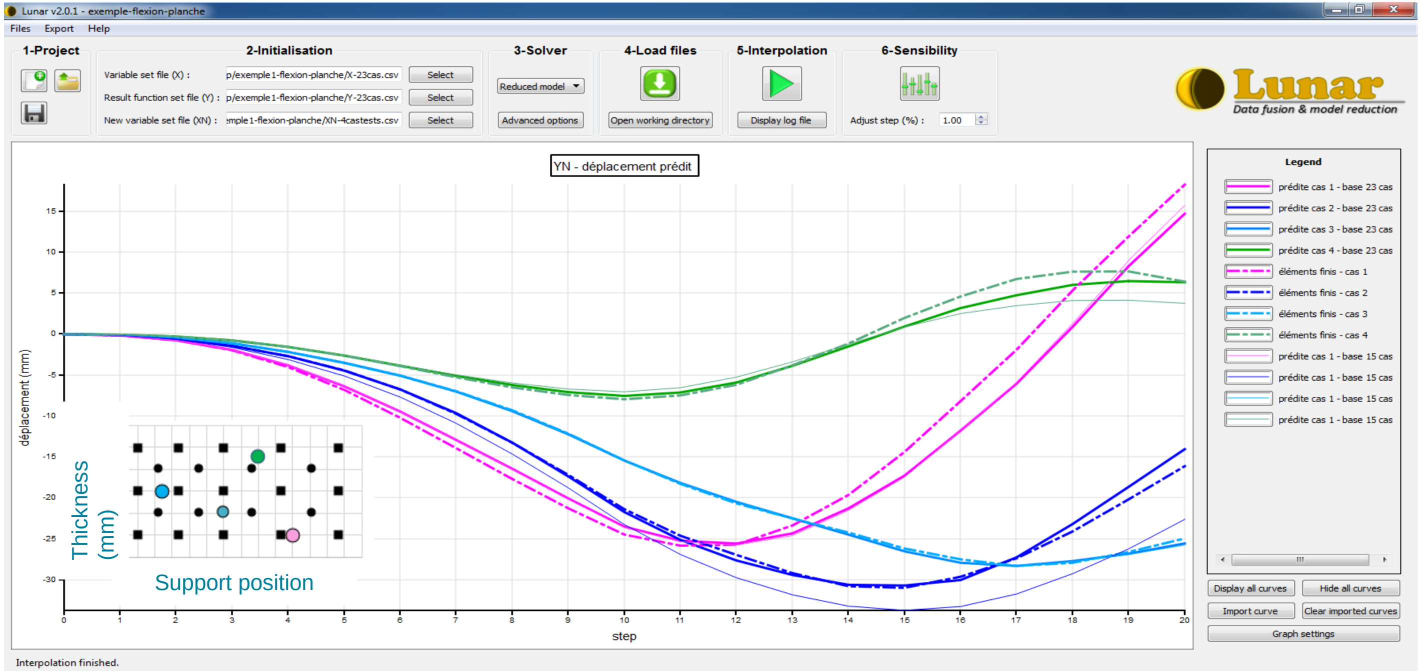
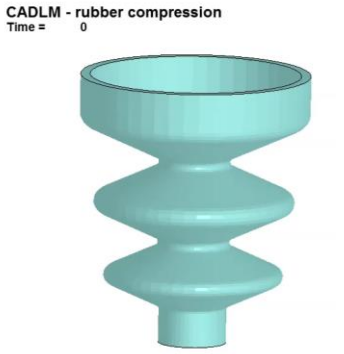


Lunar: 1 s
DOE ■ + ●

Lunar: 1 s
DOE ■

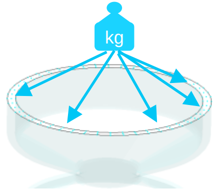
FEM : 1 minutes

Example – Rubber Compression Joint



3 model parameters
Mass => X1
Mooney Rivlin parameters (A, B) => X2, X3

Output channels:
Displacement at extremity of joint => Y1

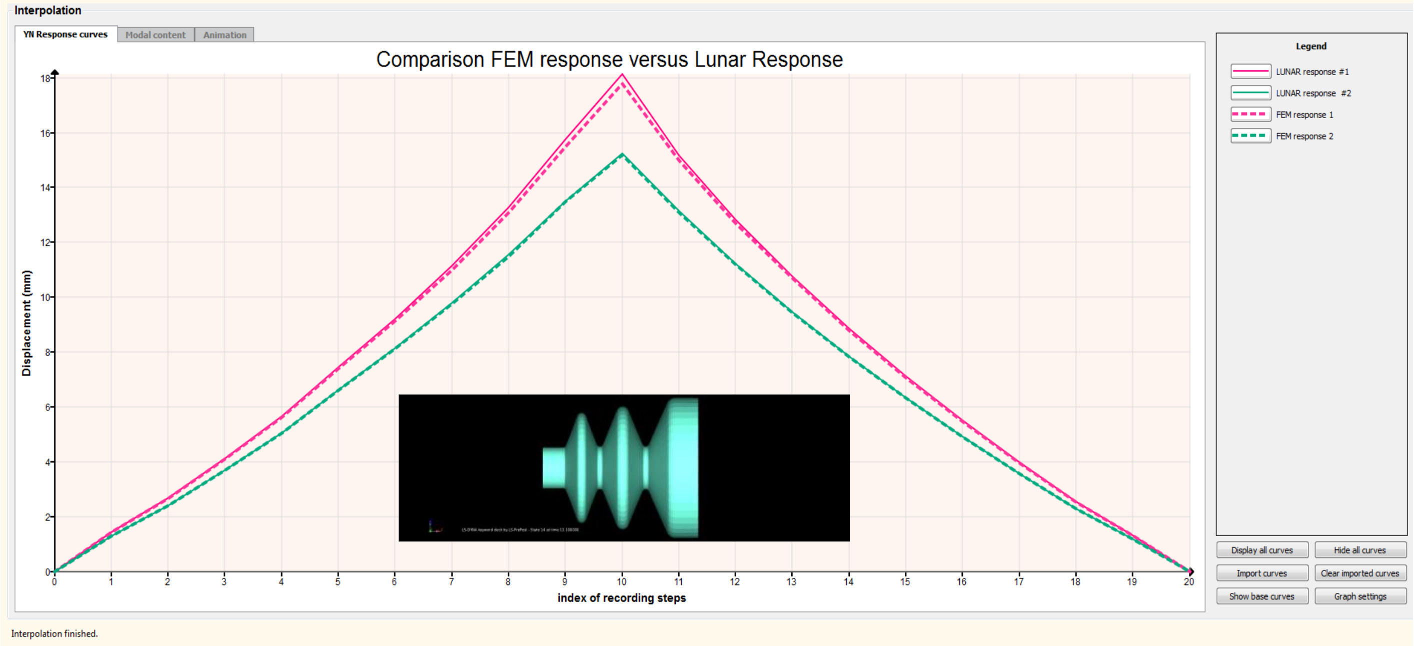


13 DOE runs

Finite Elements	Lunar
21 minutes / simulation	1 second

Rubber Joint Compression

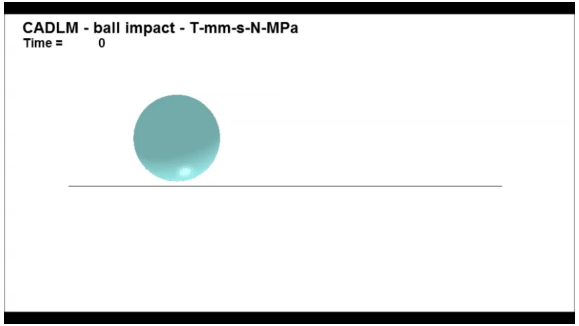
ODYSSEE
Explore new industrial horizons



Lunar
Data fusion & model reduction

Lunar: 1 s   FEM : 21 minutes

Example: Ball impact on plate

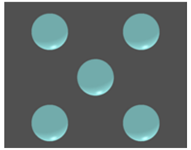


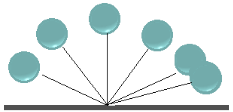
4 Model parameters:

Position X,Y => X1, X2
Ball speed at impact => X3
Impact angle => X4

Output Channel:

Contact force => Y1





15 DOE runs

Finite Elements	Lunar
1 minute / simulation	1 second

Ball impact on plate

ODYSSEE
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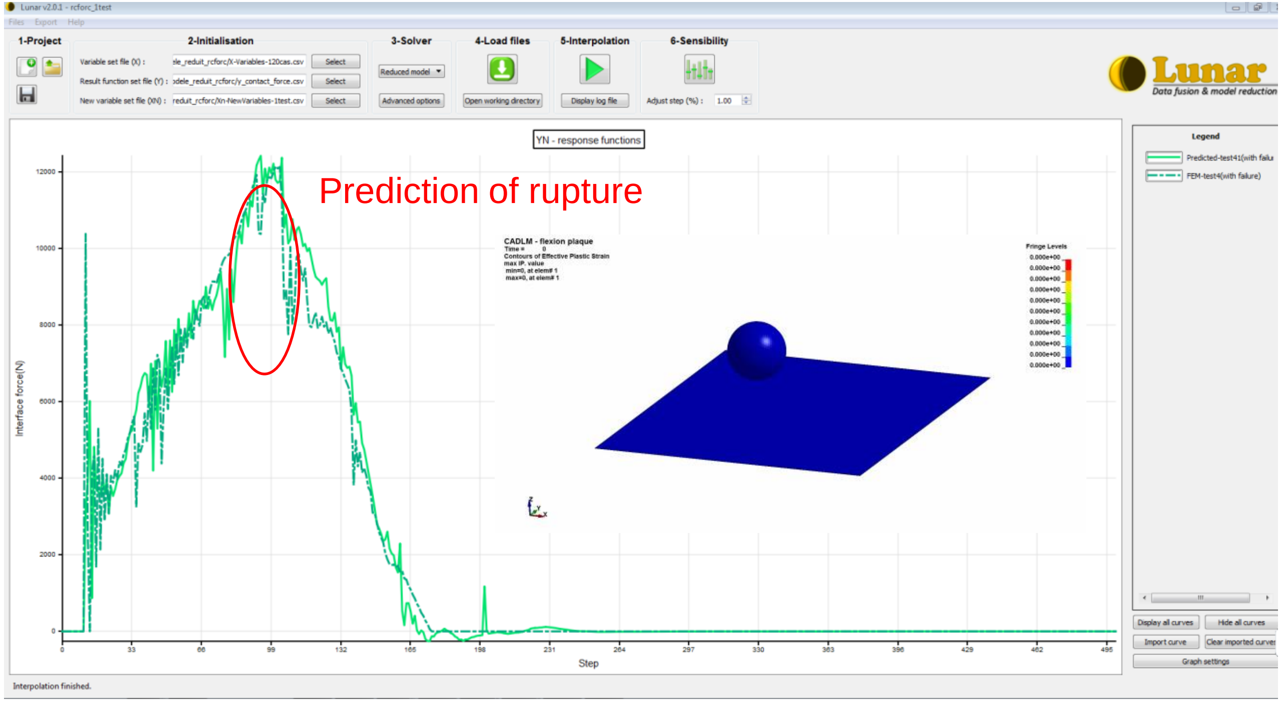
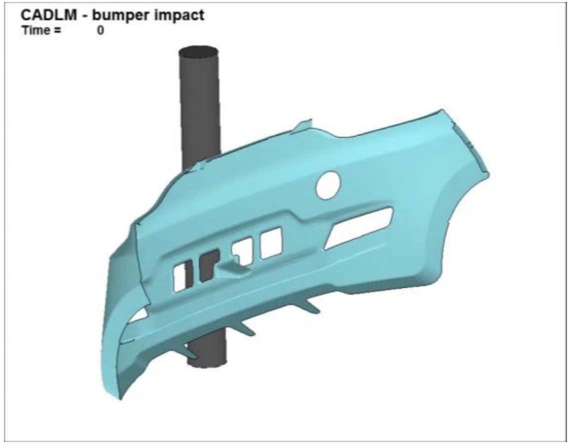


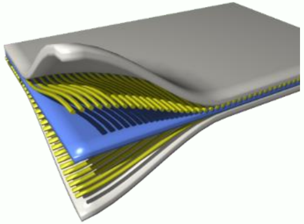
Lunar: 1 s

FEM : 1 minute

Pole impact of composite bumper panel



Model parameters:
Fiber orientations in:
- Layer 1: X1
- Layer 2: X2
- Layer 3: X3
- Layer 4: X4

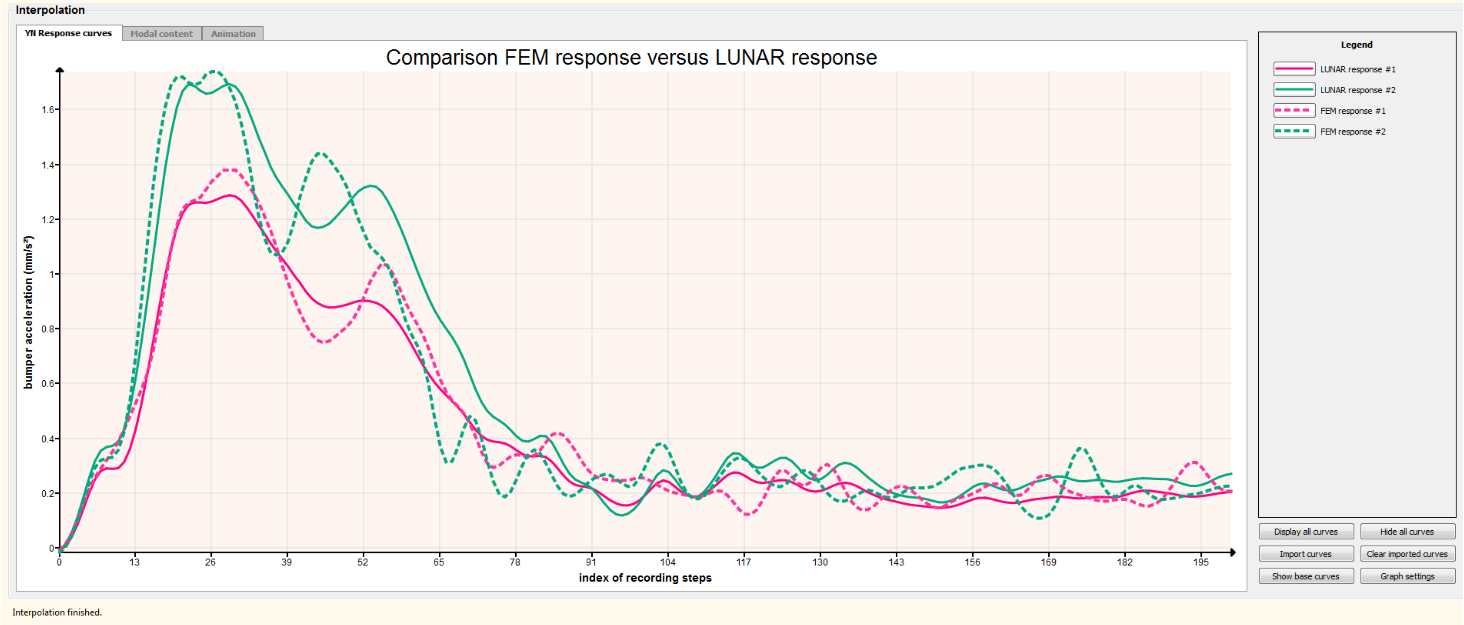


output channel:
Y : Bumper deceleration

15 DOE runs

Finite Elements	Lunar
6 hours/ simulation	1 second

Crash composite bumper panel



Lunar
Data fusion & model reduction

Lunar: 1 s

FEM : 6 hours

Example - Fluid blood flow model

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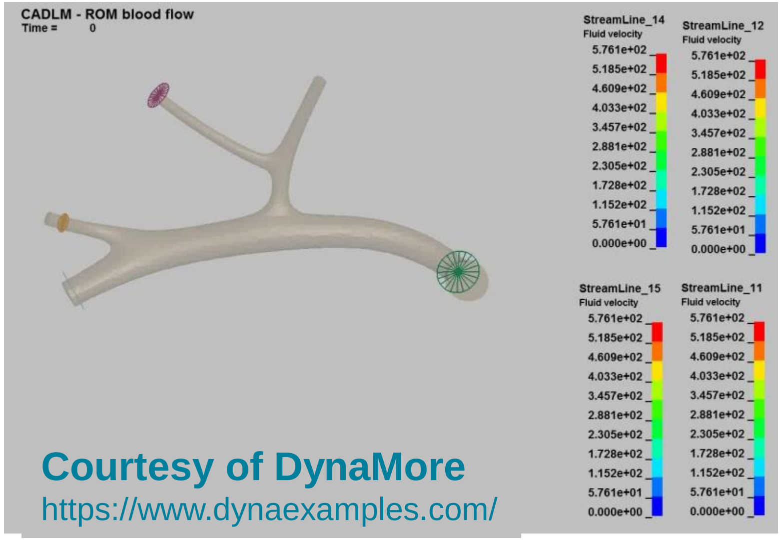
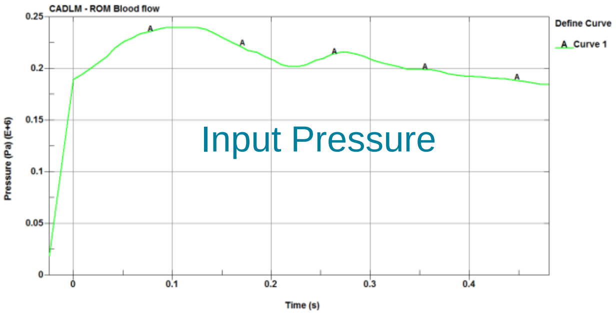
2 Model parameters:
Blood pressure injected in input surface => X1
Blood pressure in one output surface => X2

Output channels:
Flow rate measured at the input/output surfaces



Courtesy of DynaMore
https://www.dynaexamples.com/

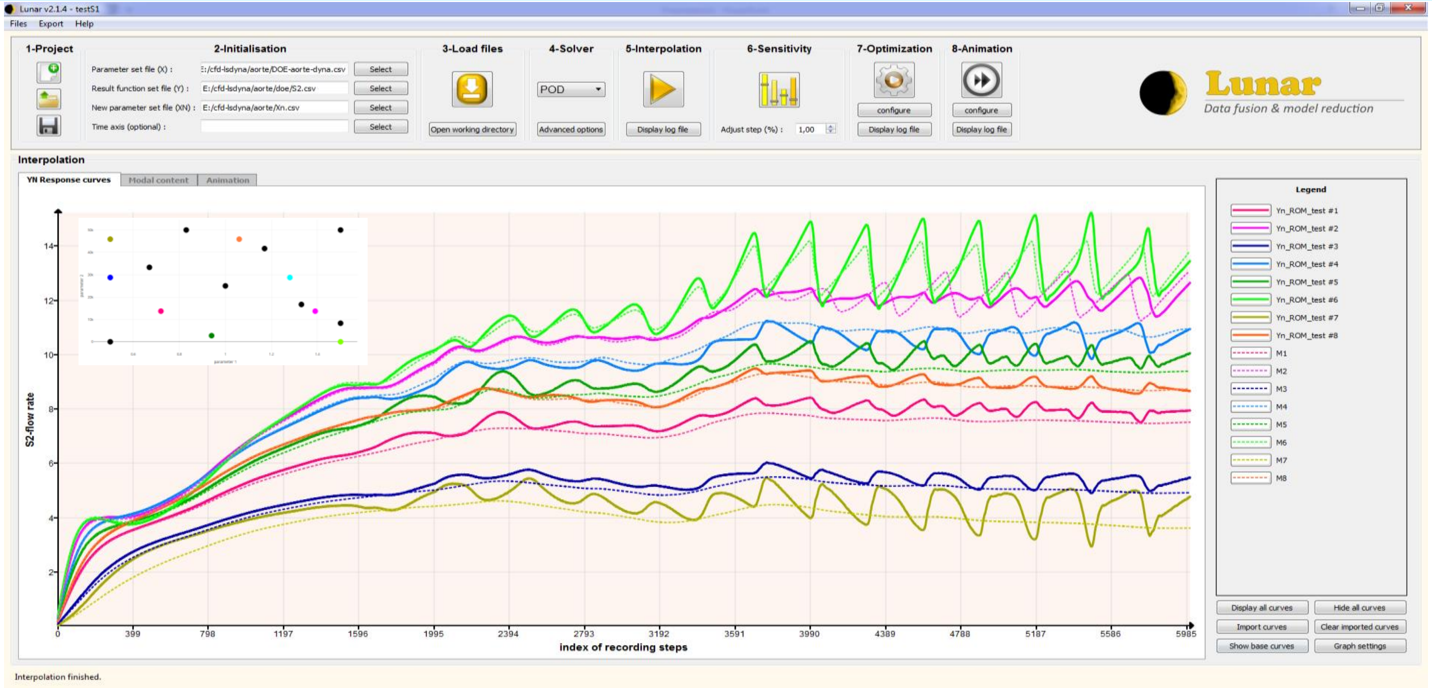


DOE 8 runs

Finite Elements	Lunar
2.5 hours per simulation	2 seconds

Example - Fluid blood flow model

ODYSSEE
Explore new industrial horizons



Lunar
Data fusion & model reduction

Lunar: 2 s

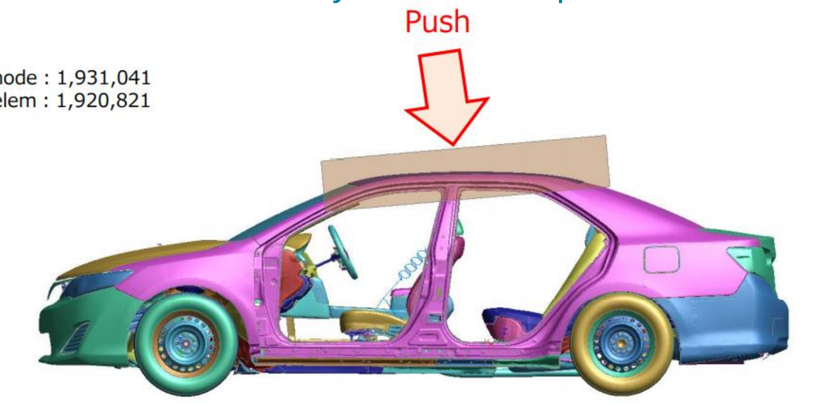
FEM : 2.5 hours

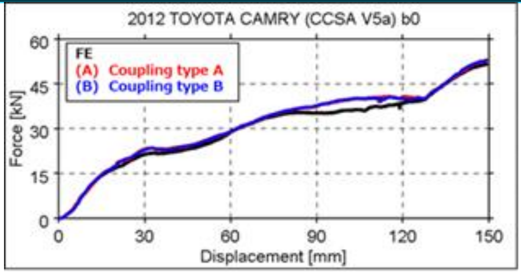
Crash – sub-modelling

ODYSSEE
Explore new industrial horizons

Courtesy of JSOL Corporation

Num. of node : 1,931,041
Num. of elem : 1,920,821





	sec./cycle		
	Total	Quasar	Dyna
FY2019	13.49	13.48	0.01
FY2020	0.05	0.03	0.02
Ideal (20% of Full FE)	0.02	0.01	0.01

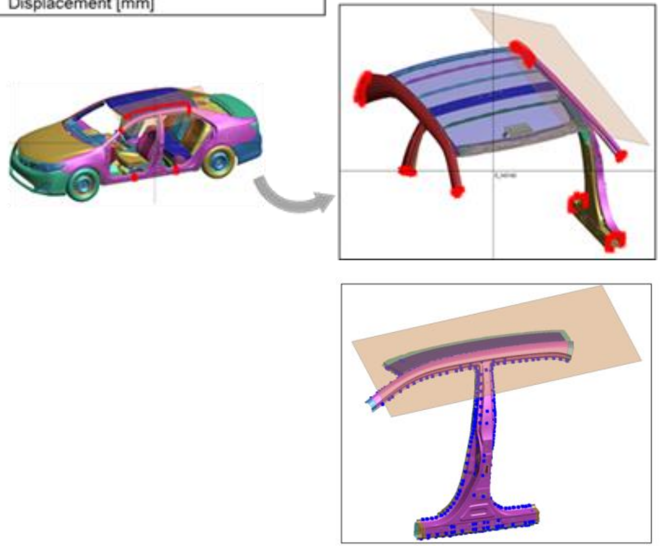
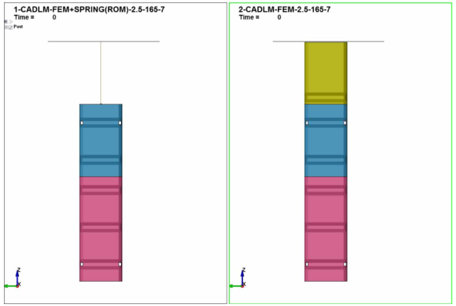
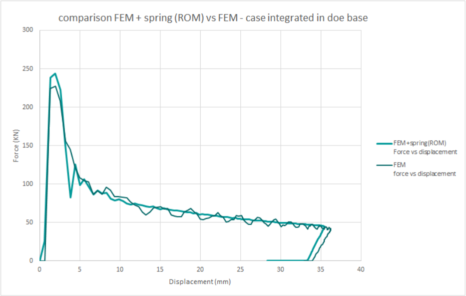


Fig1. Coupling model





Sub-modelling of crash box-beam

Example - Sled test

ODYSSEE
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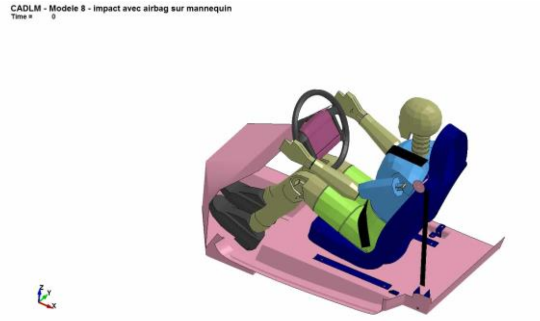
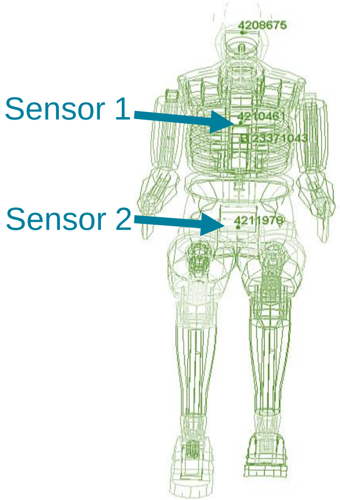


3 Model parameters:
Deceleration (breaking speed)
=> X1, X2
Airbag mass debit
=> X3

Output channels:
Thorax compression => Y1
Pelvis acceleration => Y2

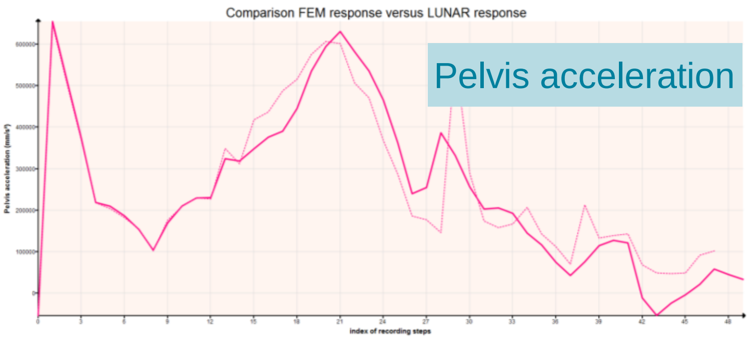


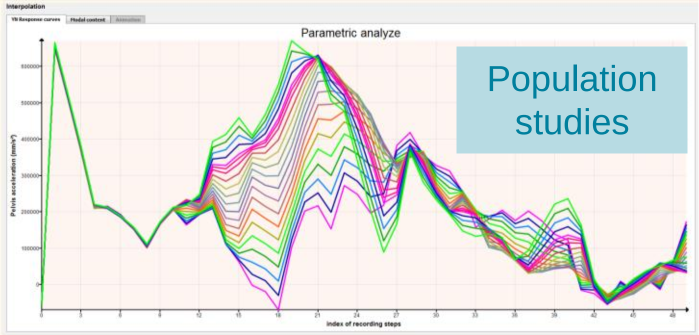
15 DOE runs

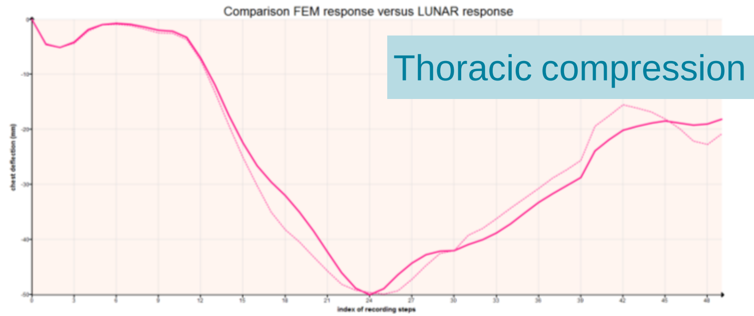
Finite Element solution per run	Lunar
1 hour/ simulation	1 second

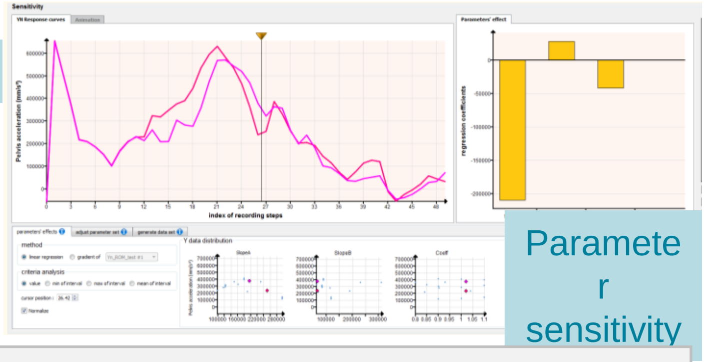
Example - Sled test

ODYSSEE
Explore new industrial horizons







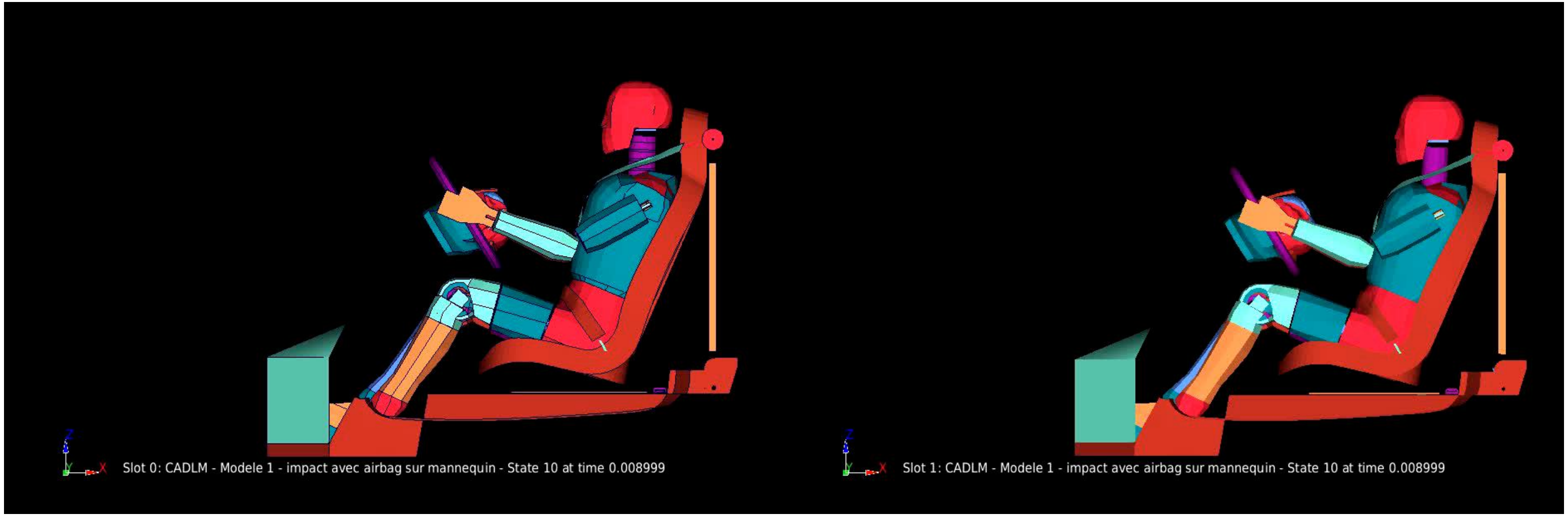


Lunar
Data fusion & model reduction

Lunar: 2 s

FEM : 1 hour

Example - Sled test

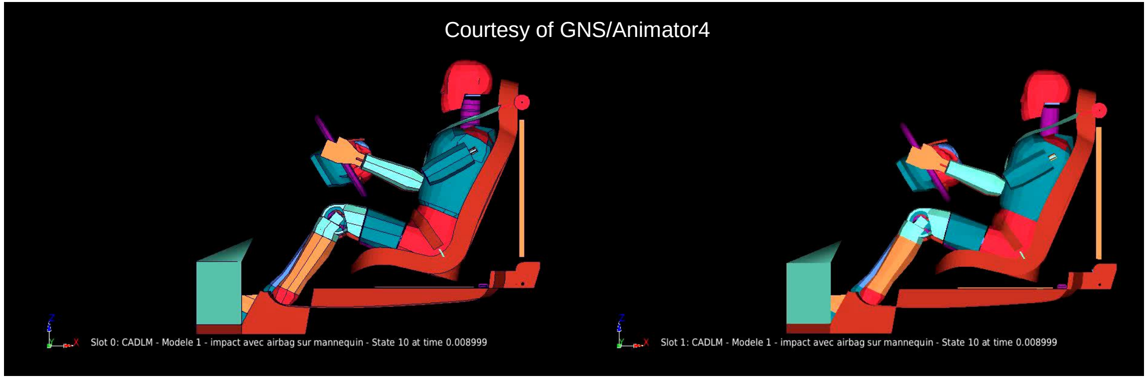


Animation obtained by EF (1h)

Animation obtained by Lunar (2s)

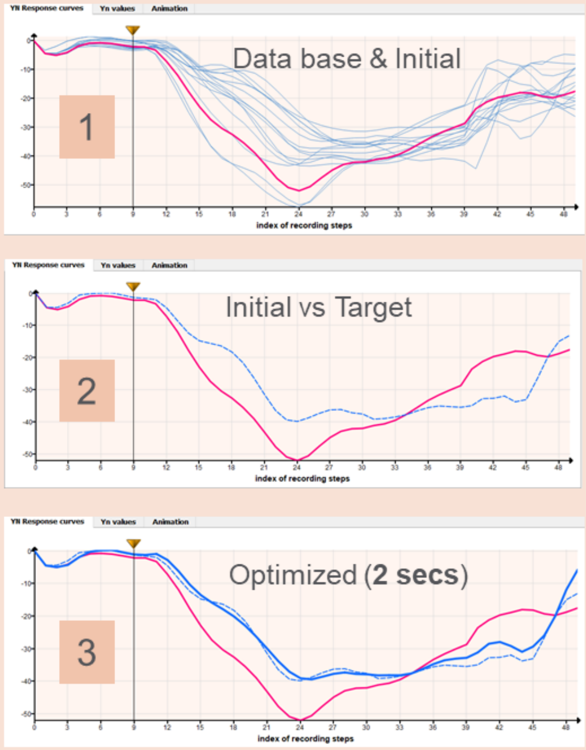
SLED TEST + AIRBAG (Optimization)

ODYSSEE
Explore new industrial horizons



Lunar: 2 s   FEM : 1 hour

Optimization



15 runs, 3 parameters

Deceleration (breaking speed) => X1, X2

Airbag mass debit => X3

Output Channel

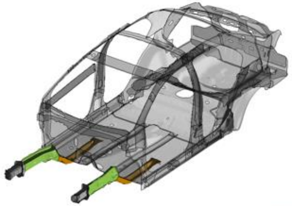
Thorax compression => Y1

Pelvis acceleration => Y2

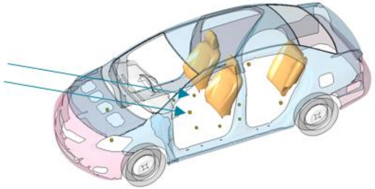
CADLM
TRANSFORMING DATA INTO INTELLIGENCE

Example – ‘Yaris Front crash’

3 Model parameters:
Rail inner thickness => X1
Floor support thickness => X2
Velocity => X3



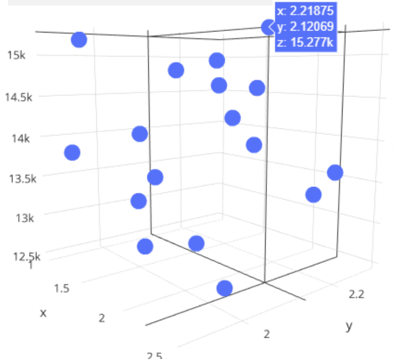
Output channels:
Driver seat acceleration=> Y1
Rigid wall Force => Y2
Gravity center acceleration => Y3

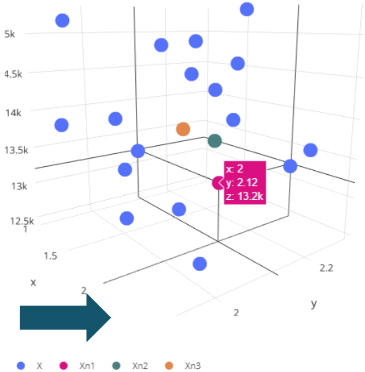


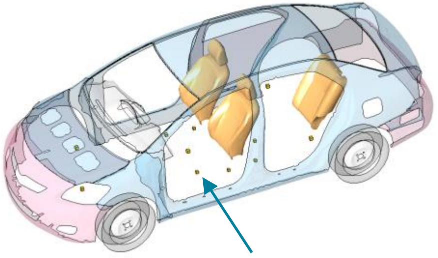
Finite Elements	Lunar
3h per simulation	2 seconds

	Rail inner thickness (mm)	Floor support thickness (mm)	Velocity (mm/s)
Validation 1	2,00	2,12	13200,00
Validation 2	1,60	2,20	13500,00
Validation 3	1,70	2,10	13800,00

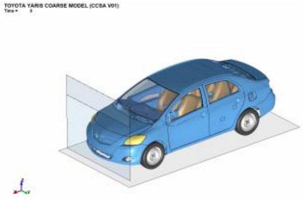
DOE of 17 runs







Driver seat accelerometer

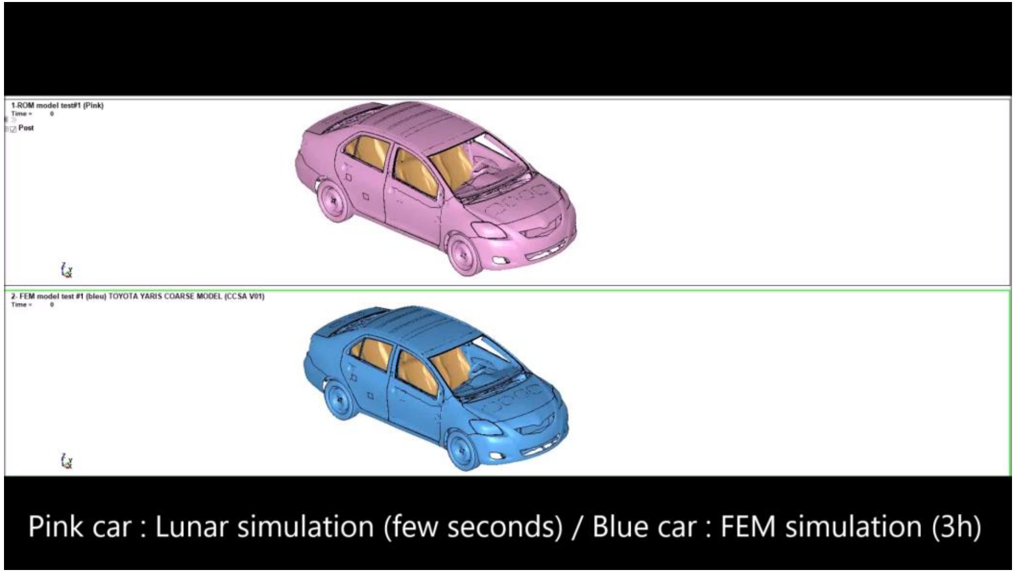


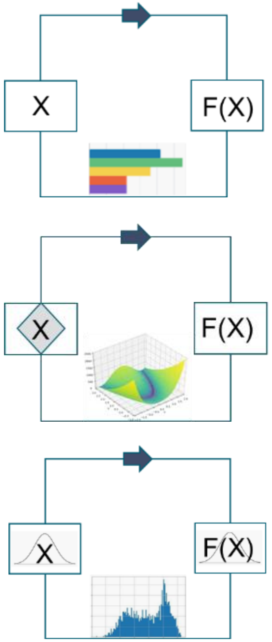
393329 Nodes
378470 Elements

Example – ‘Yaris Front crash’

ODYSSEE
Explore new industrial horizons

Driver seat acceleration





Lunar: 1 s

FEM : 3h

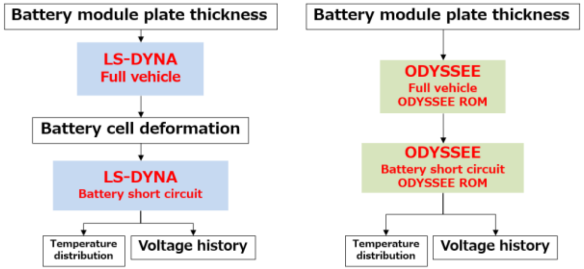
Battery short circuit analysis

Multi-scale & multi-physics analysis by ROM

- Require considering two phenomena with different spatial scales
- Multiphysics analysis by structure, Thermal and electromagnetic field

	Full vehicle crash	Battery short circuit	
Solver	explicit	Explicit （structure）	Implicit （Thermal + EV）
DT(sec.)	1.0E-6	9.0E-6	1.0E-3
Phenomenon time (sec.)	0.4		0.1
Num. of step	399,681	11,112	100
COST	2h7m@128core		5min@4core

Flow of coupling analysis



Model specifications

TOYOTA YARIS
Nodes:1,073,273
Elems:1,036,485

https://www.nhtsa.gov/crash-simulation-vehicle-models

BATTERY CELL
Nodes:4,331
Elems:3,618

Variables

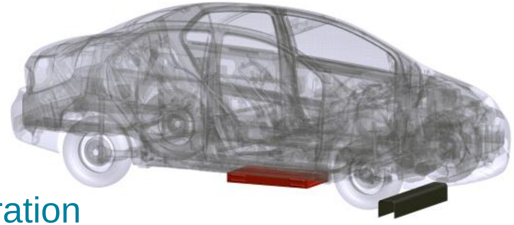
- IN : Module plate thickness
- OUT : Battery cell deformation

Datasets

- Thickness 0.4 - 2.0 mm, 5 sampling

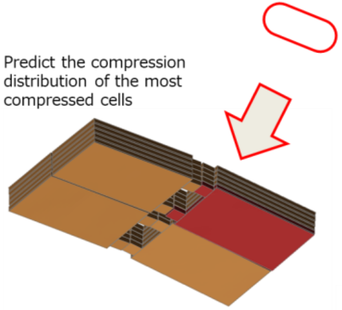
Costs

- Learning : 0.3 sec
- Predict : 0.4 sec



Courtesy of JSOL Corporation

Predict the compression distribution of the most compressed cells



Solver	Location (Node ID)	Compression (mm)
LS-DYNA	43800015	0.88
ODYSSEE	43800015	0.86 (**2.1%**)

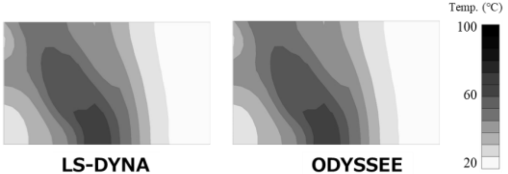
LS-DYNA(t=1.2mm) ODYSSEE (t=1.2mm)

Variables
- IN : Battery cell deformation (**Picture**)
- OUT : Temperature distribution

Datasets
- 15 sampling

Costs
- Learning : 96 sec
- Predict : 0.3 sec

Solver	Location (Node ID)	Max. Temperature (℃)
LS-DYNA	43800104	89.3
ODYSSEE	43800104	89.1 (**0.2%**)



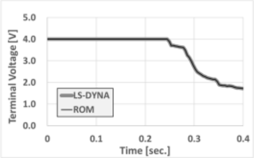
LS-DYNA ODYSSEE

Variables
- IN : Battery cell deformation (**Picture**)
- OUT : Terminal voltage

Datasets
- 15 sampling

Costs
- Learning : 96 sec
- Predict : 0.3 sec

Solver	Terminal voltage (V)
LS-DYNA	1.71
ODYSSEE	1.72 (**0.1%**)



- It is possible to dramatically reduce the simulation COST by using ODYSSEE ROM.
- Coupling between different solvers becomes easy by focusing on input / output only.

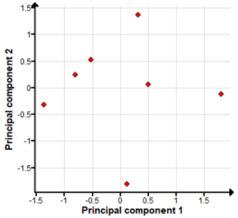
Solver	Full vehicle Analysis (Structure)		Battery short circuit (Structure+Thermal+EM)	
	COST (sec/core)	Error (%)	COST (sec/core)	Error (%)
ODYSSEE (Learning)	0.3	2.1	96	0.2
ODYSSEE (Predict)	**0.4**		**0.3**	
FEM	975,360	-	1200	-

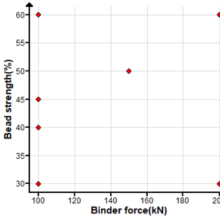
Courtesy of JSOL Corporation

Stamping

ODYSSEE
Explore new industrial horizons

	Input (X)		Output (Y)		
	Binder Force (kN)	Bead Strength (%)	Crack Elements %	Crack area%	No Of elements
M1	100	30	0.0342	0.051	22
M2	200	30	0.0996	0.169	64
M3	100	60	0.948	4.45	609
M4	200	60	0.898	5.08	577
M5	100	40	0.263	0.625	169
M6	100	45	0.336	1.157	216
M7	150	50	0.455	2.195	292
M8	117	53	0.486	2.494	312

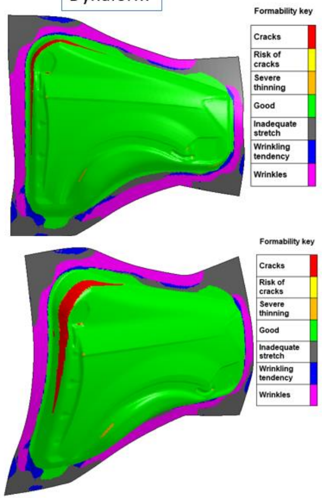




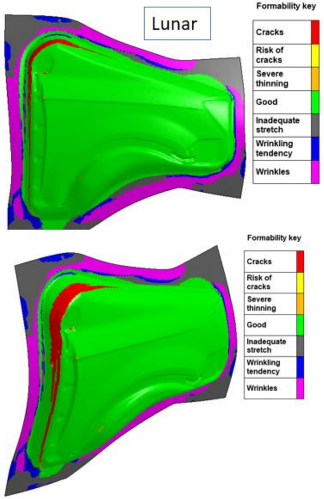
Animation Comparison

XN =117kN, 53%	Crack Elements %	Crack area%	No Of elements
Dynaform Animation	0.486	2.494	312
Lunar prediction - POD	0.554	2.61	356

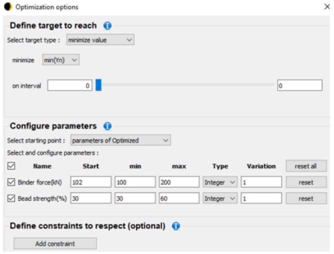
Dynaform

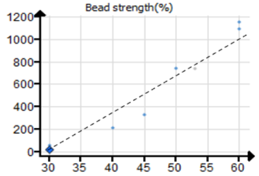


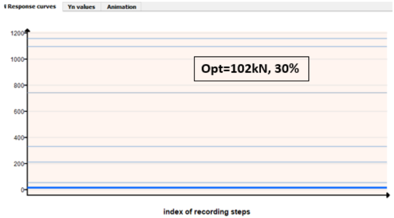
Lunar

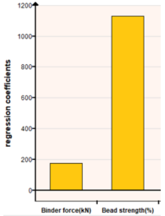


Formability Optimization



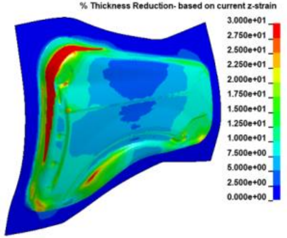


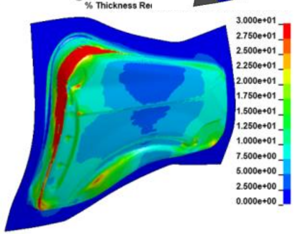




Dynaform

XN =117kN, 53%	Thinning Elements(>30 %)
Dynaform Animation	599
Lunar prediction - POD	740





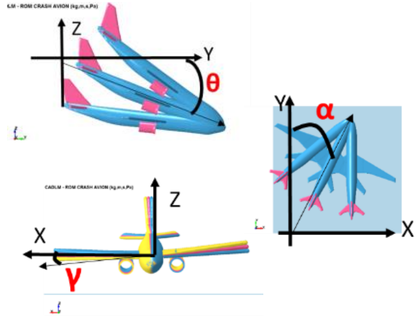
Courtesy of ETA

Bender force, Bender strength
7 runs only

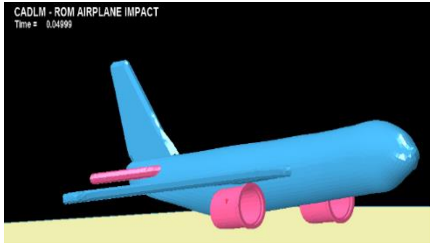
Initial:
XN =117kN, 53%

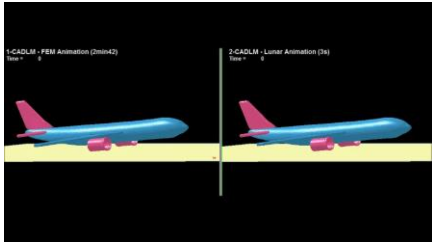
Optimal:
Xopt=102kN, 30%

Flight Simulator (landing conditions)



https://www.youtube.com/watch?v=oNQ0wT0WFng





15 runs, 3 parameters

- Angle θ => X1
- Angle α => X2
- Angle γ => X3

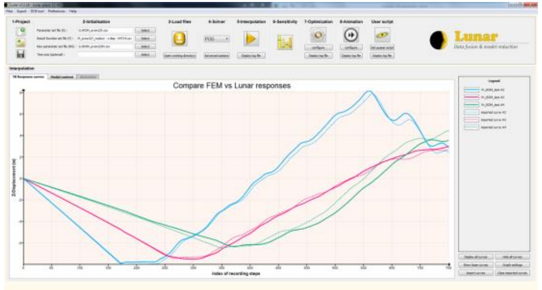
Output Channel

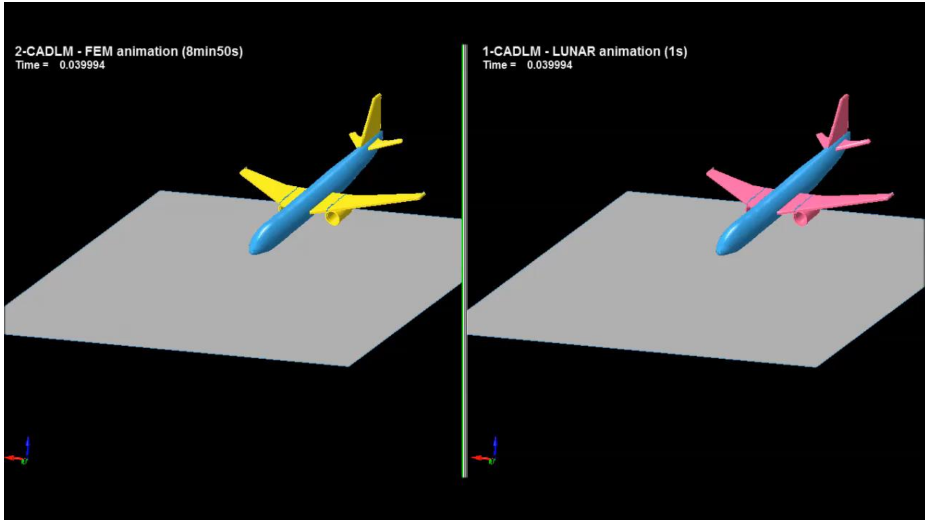
- Nose z-displacement => Y1

Elapsed Time

- FE => 9 minutes
- LUNAR => 1 sec

Flight Simulator (landing conditions)



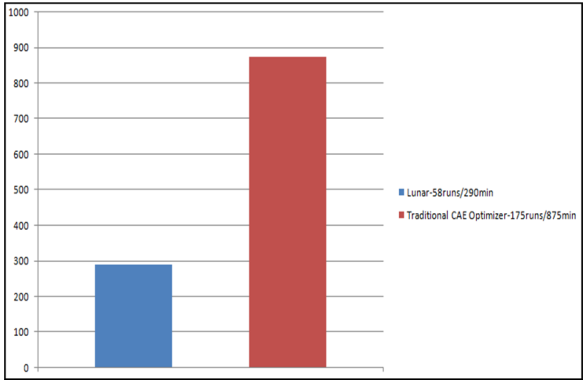


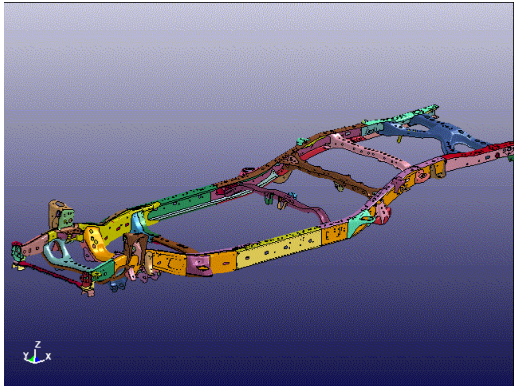
Chassis Frame Optimization for Natural Frequency

- Lunar enabled to reduce the DOE size by 67% (58 runs against 175 runs)and still predict response with good accuracy.
- The CPU time in this case is 33% of the traditional optimization approach.
- For a problem involving more design variables and multiple loadcases, Lunar offers more substantial time and CPU cost savings.
- Once the predictions are validated, Lunar's ROM approach can replace the CAE method to calculate response for any design combination and save significant process time.

Design	First Natural Frequency	Total mass	Rear Stub Mass	Mass Saving (%)
Baseline	11Hz	245	112	
Lunar Optimization	10Hz	224.4	91.4	18.4%
CAE Validation	10.3Hz	223.3	90.3	19.3%

CPU time
(min)





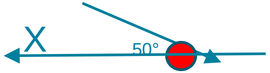
Courtesy of ETA

Fusion for image processing – Automotive head Impact analysis

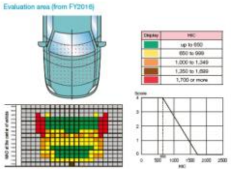
Child head Impact on bonnet

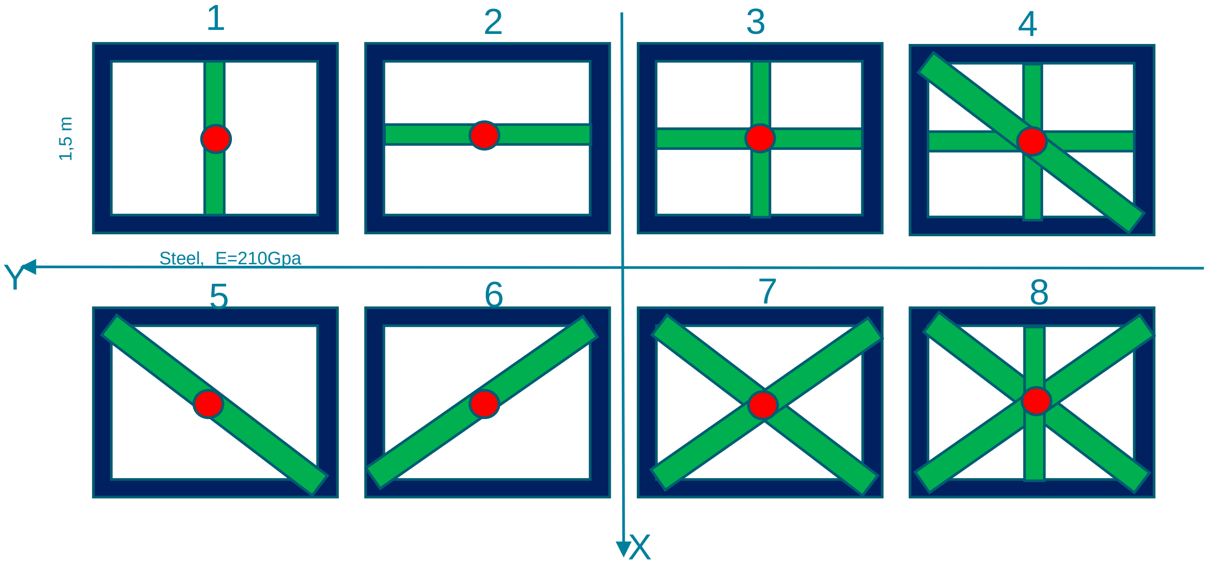
Frame- Steel E=210 Gpa; Blue part 3mm; green part 10 mm

Fixed on 4 corners ; Impactor mass=3.5kg, Vx=40 km/h



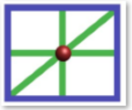
Child head (sphere; Diameter ~25 cm ?



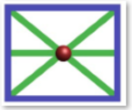


ODYSSEE Reduced Order Modeling for image processing - Accelerations

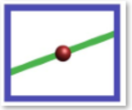
Explore new industrial horizons



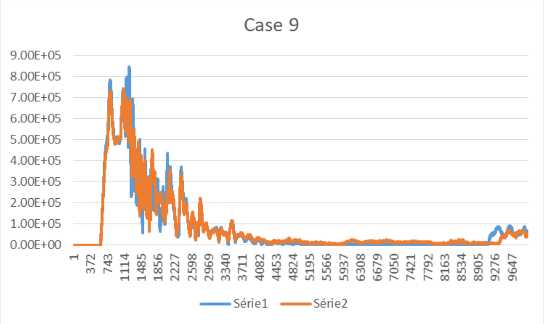
Case9.jpg

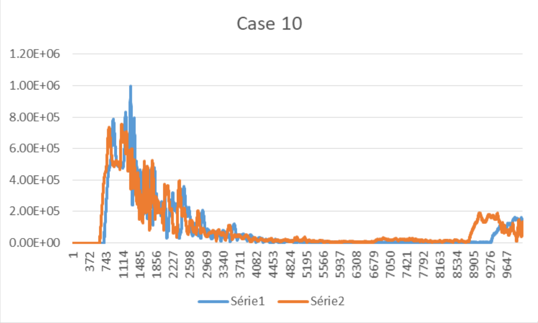


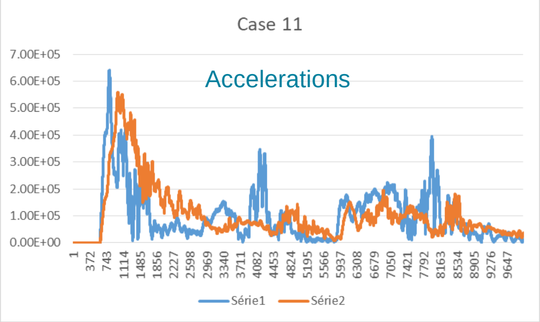
Case10.jpg

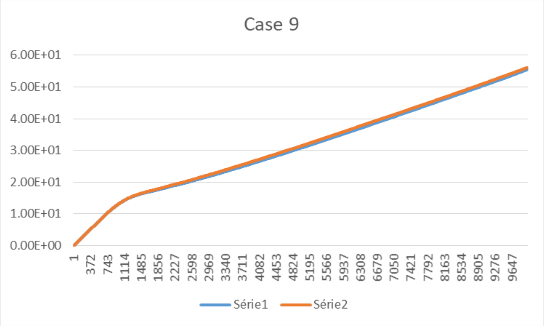


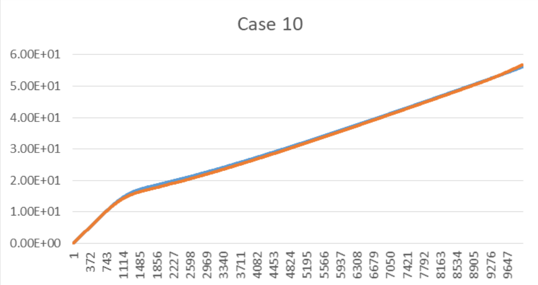
Case11.jpg



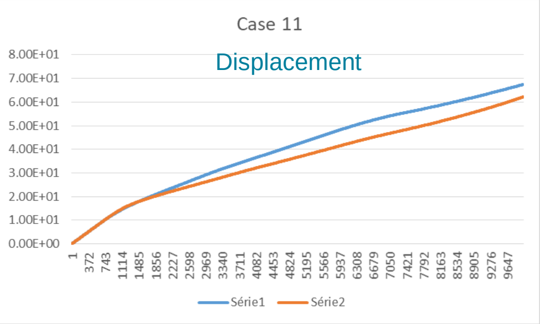






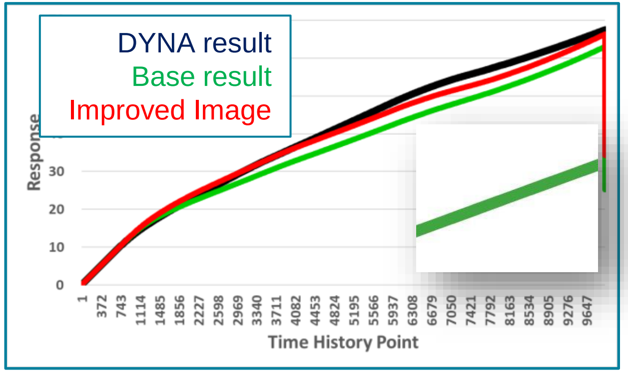


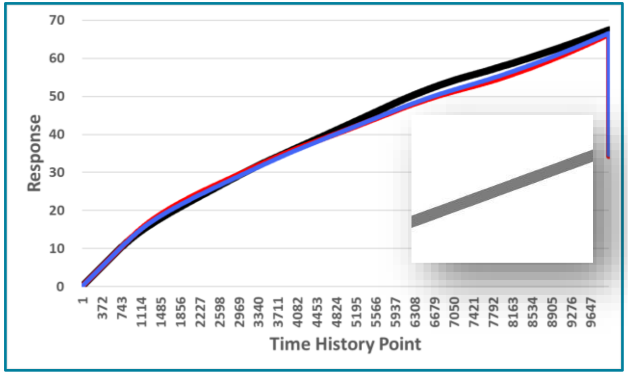
Blue = Isdyna ; Brown = Quasar

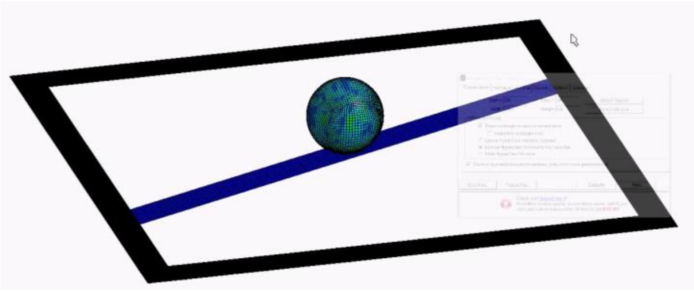


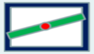
Reduced Order Modeling for image processing – Displacements

Influence of image boundaries







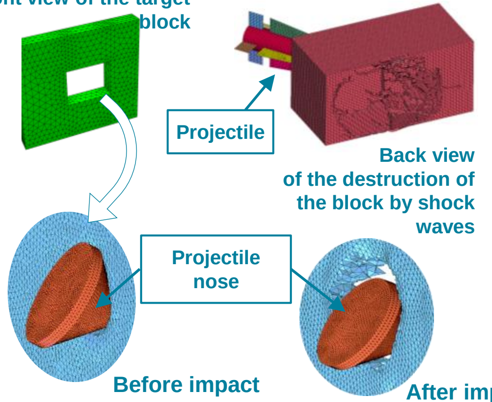
	Error [%]	Max Relative Error [%]
	5.63	9.69
	2.08	4.5
	1.70	3.67

Courtesy of Masahiro Takeda, JSOL

Ballistic impact with ALE simulations
(Defense sector)

mecasif

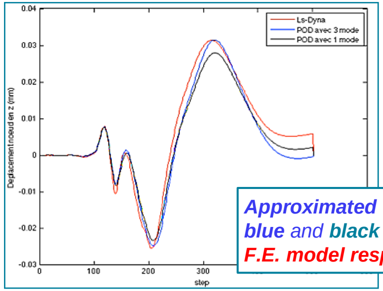
Costly to run a complex dynamic and non linear model like ballistic impact



CADLM

Methodology for ALE based reduced model
Real time solution for simulators based on FE
Reduced CPU cost by reducing the need for finite element solutions

- **Reduced model** of ALE model (fluid/structure interaction)
- Application for real-time predictive **training simulator**
- **Combine reduced model** with a finite model using domain decomposition techniques

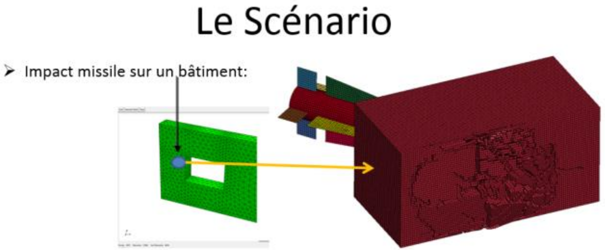


Approximated response in blue and black
F.E. model response in red

Ballistic impact with ALE simulations

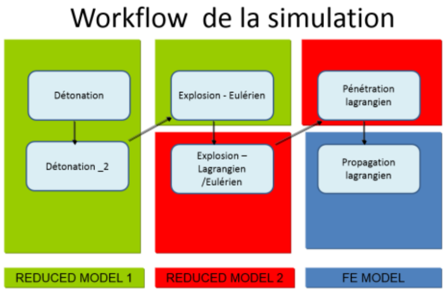
(Defense sector)

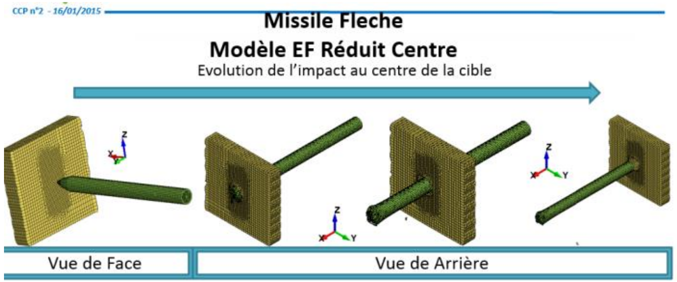
Collaboration SILKAN/CADLM



Complexe

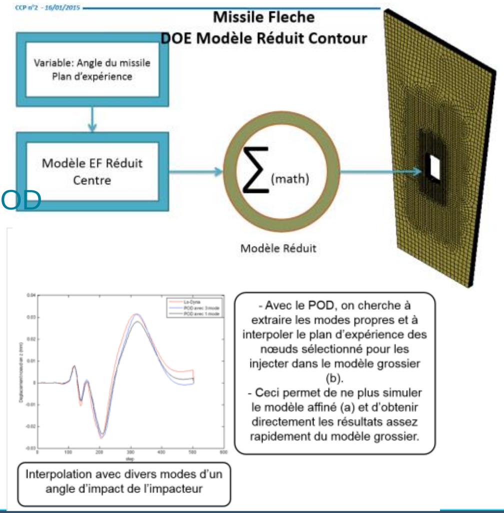
Longue





EF vers base POD

Workflow



Real Time Parametric Design and Optimization

ODYSSEE
Explore new industrial horizons

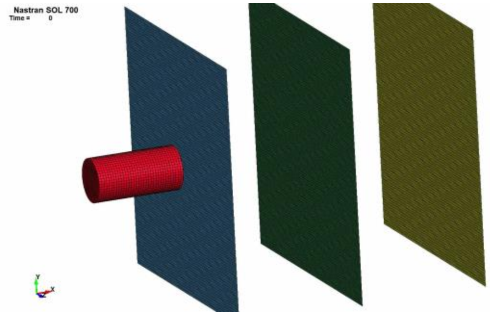
Reduce BIRD strike analysis simulation time using ***LUNAR*** *(ROM) and NOVA (Optimization)*

Target:

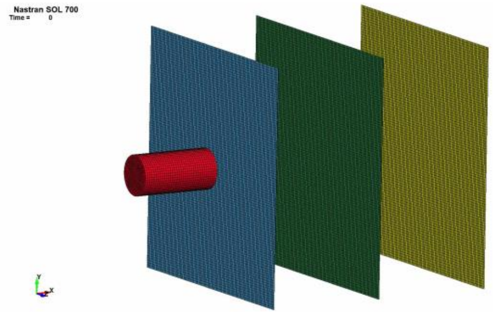
- Find the optimal thickness distribution for plate1, plate2 and plate3

Constraint:

- No elements erosion in plate3



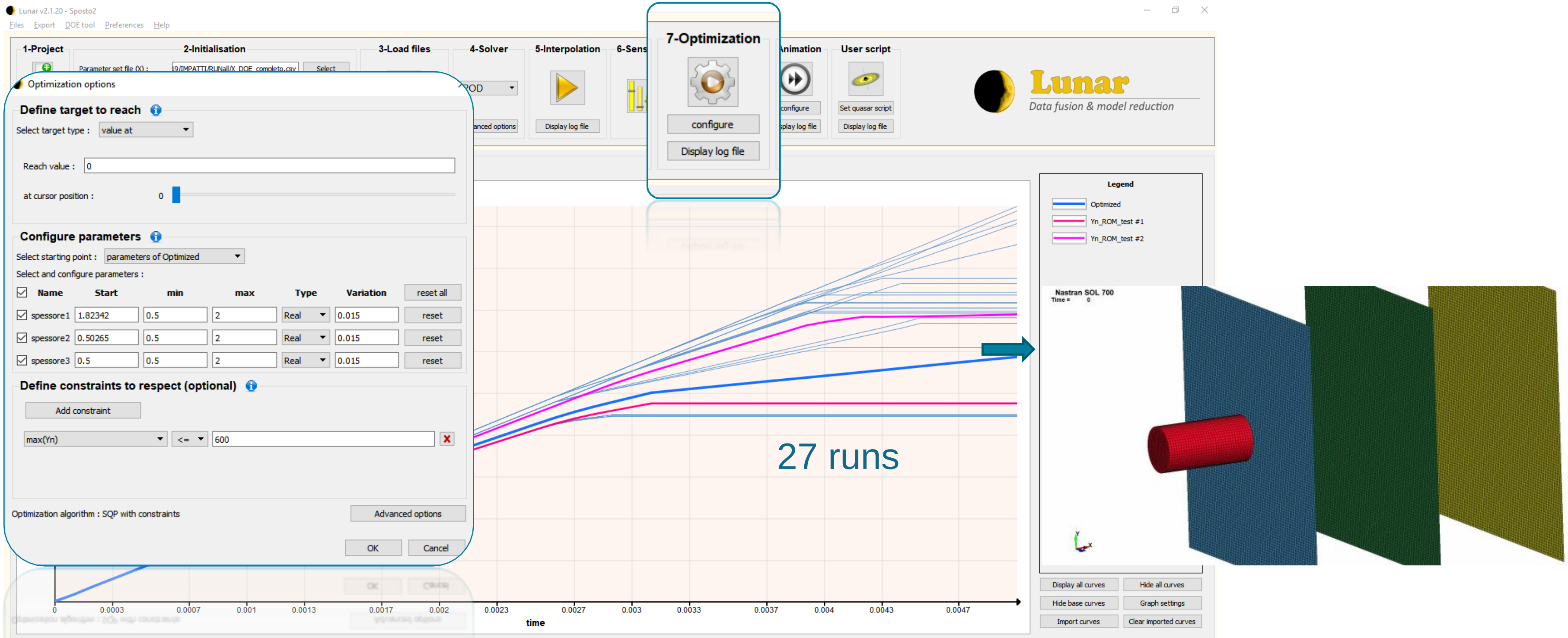
Minimum Thickness 0.5 mm



Maximum Thickness 2.0 mm

CADLM
TRANSFORMING DATA INTO INTELLIGENCE

Lunar : Optimization



ELAPSED time = 15.42 seconds

Chassis Frame Optimization for Natural Frequency

ODYSSEE
Explore new industrial horizons

Frame Rear Stub components were parameterized for Geometry, Grade and Gauge.

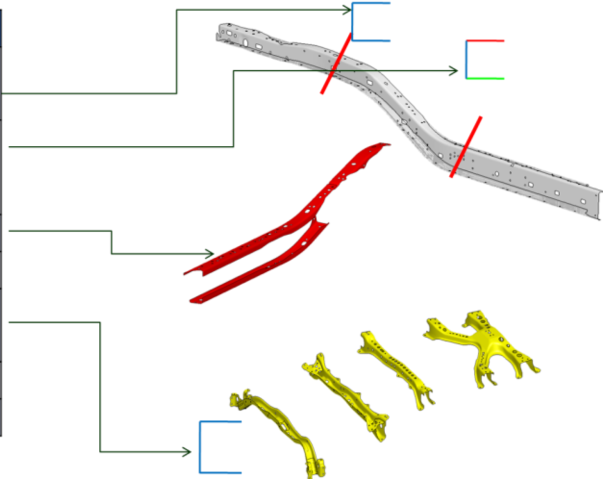
Design details and constraints

- Mass is 245kg
- First Torsional mode is at 11Hz
- Only the rear stub (mass 112kg) needs to be optimized so that the crash performance is not altered.

Rear Stub (to be optimized):
Mass = 112 kg
(of Rail, X Members and reinforcements)

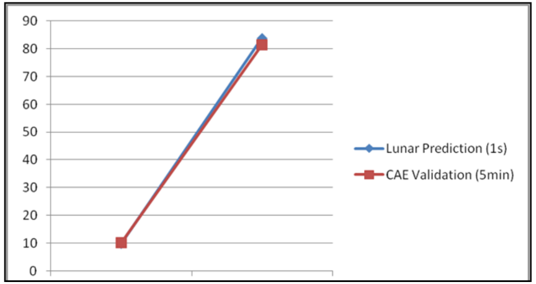
Full Frame Mass
245 kg

Variables
Rail divided into three sections to vary the section individually (Front, middle, rear)
TWB Rail (three)with separate thickness of flanges(Each TWB will have 3 section thickness variable)
TWB Rail (grade)
Reinforcements (gage/grade)
Sections of X-members: Width and height of each member individually (no transition 15%)
4 cross members (gage/grade)
X-member Brackets gage/grade



Optimization Targets

- First Torsional mode should be within 10% limit of Baseline design (>= 10Hz)



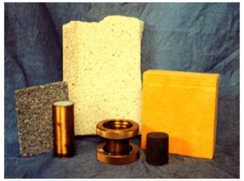
	Frequency	Mass
Lunar Interpolation	9.9Hz	83.8Hz
CAE Validation	10.3Hz	81.5Hz

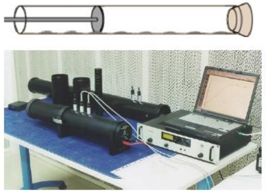
Courtesy of ETA

ACTRAN - Predicting the absorption coefficient of a porous material

ODYSSEE
Explore new industrial horizons

$$\alpha = 1 - \left| \frac{p_{reflected}(\omega)}{p_{incident}(\omega)} \right|$$

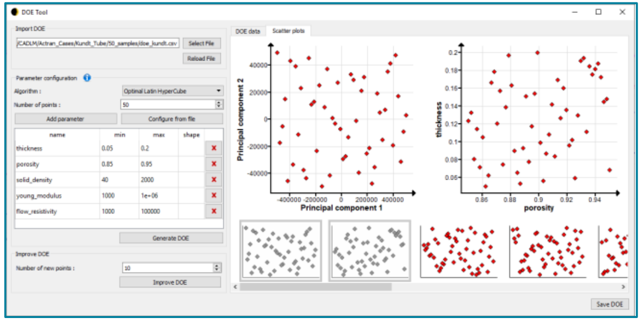


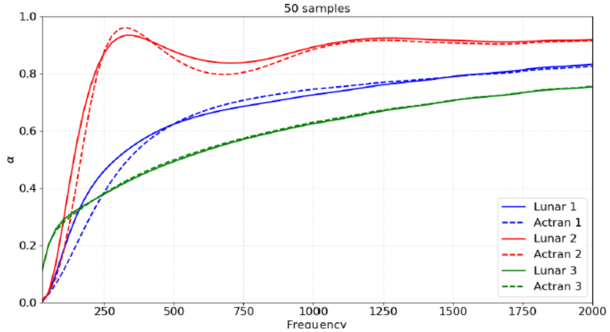


Experimental Setup

Quantity	Min	Max
Thickness [m]	0.05	0.2
Porosity [m]	0.85	0.95
Solid density [kg/m^3]	40	2000
Young's modulus [Pa]	1000	1000000
Flow resistivity [Ns/m^4]	1000	100000

Numerical Setup



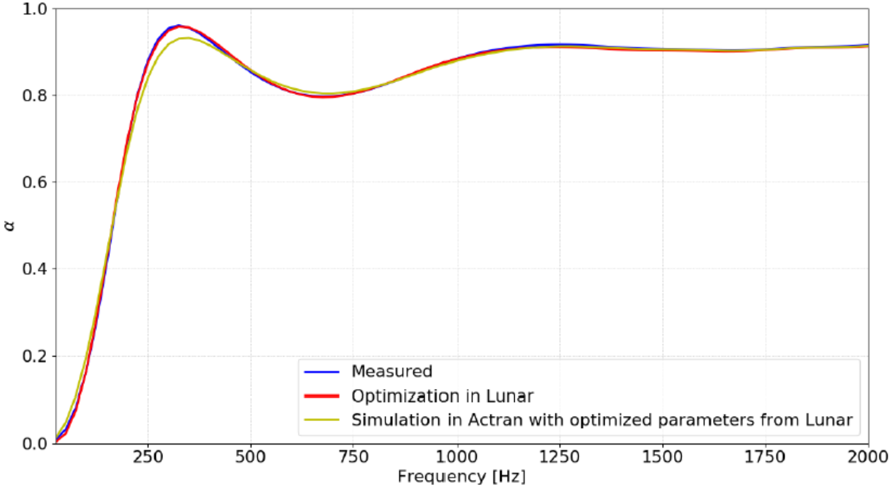


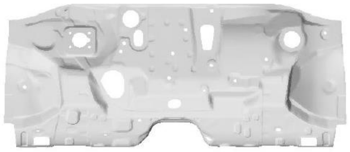
Validation

Courtesy of MSC

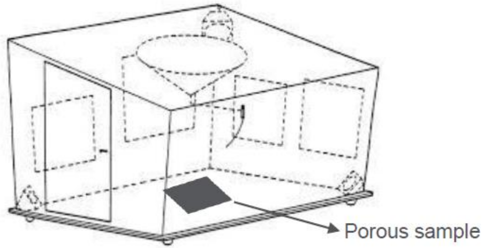
Optimization for finding material properties

- A dummy measured curve is given and the material properties are found via optimization
- Then the optimized parameters are used to create a new Actran model in order to compare the optimized model with reality
- The DOE with the 50 samples is used as a starting point (time taken: 3 min)





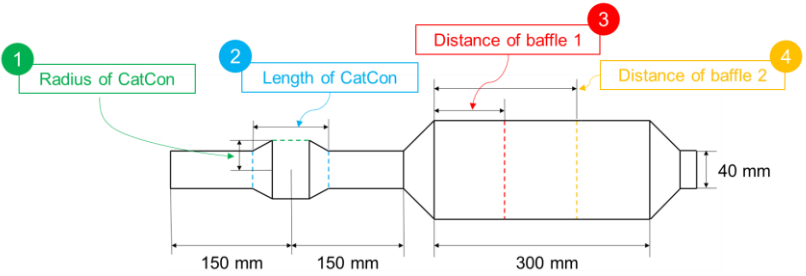
Multi-layer trim component

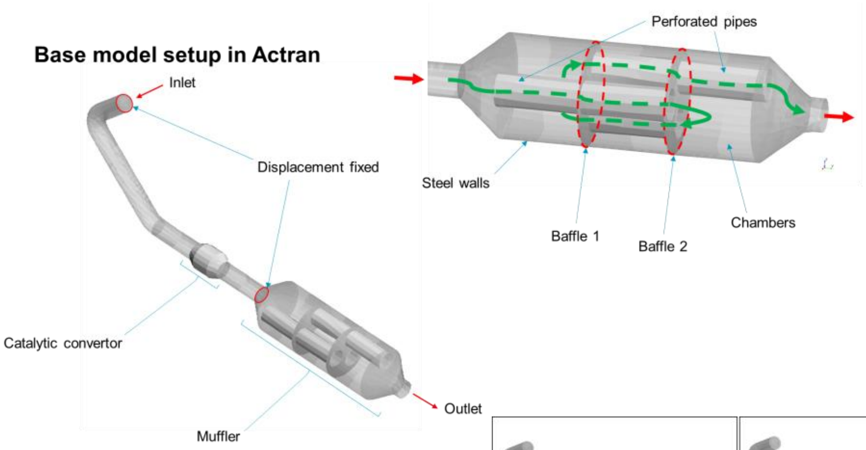


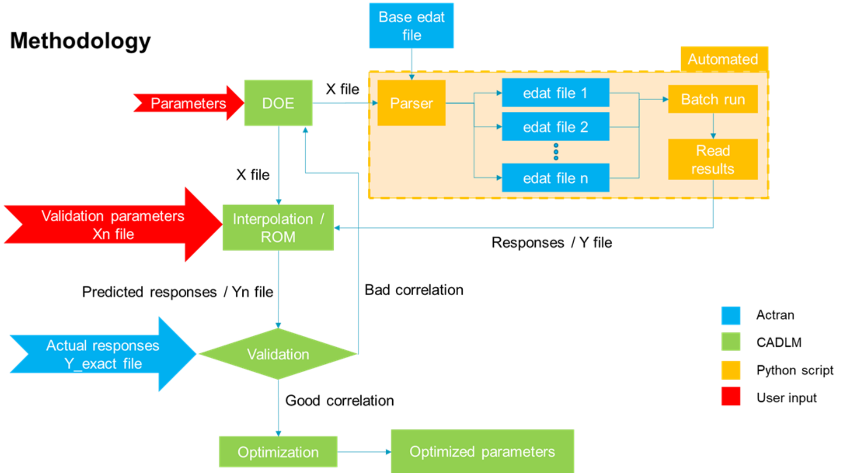
Alpha cabin

Actran : Exhaust System Optimization

ODYSSEE
Explore new industrial horizons

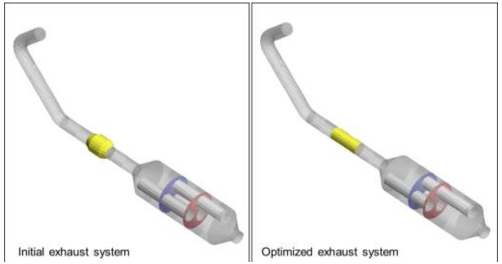


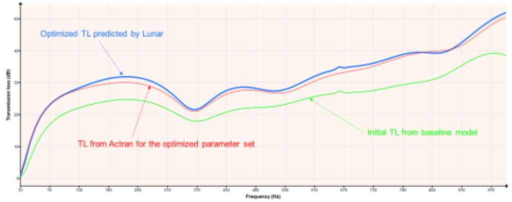




Optimized solution

CADLM
TRANSFORMING DATA INTO INTELLIGENCE

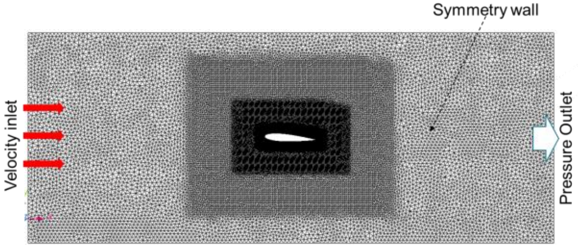




scFlow - Flow around an obstacle

AOA MODEL AND ANALYSIS CONDITIONS

– Tetra Grid settings



Analysis domain

- Domain size
  – 1.5 x 0.6 x 0.015 [m]
- Mesh 정보

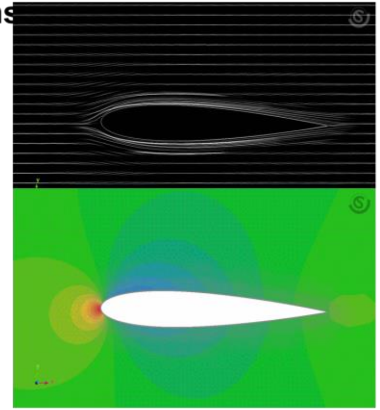
	해석 도메인
Mesh size	0.32 ~ 10 [mm]
Mesh number	3,789,135 개

➢ Reference : *Flying hot wire study of flow past an NACA 4412 airfoil at maximum lift, D. Coles and A.J. Wadcock, AIAA J, 17, 321-328 (1979)

Set AOA model and analysis conditions

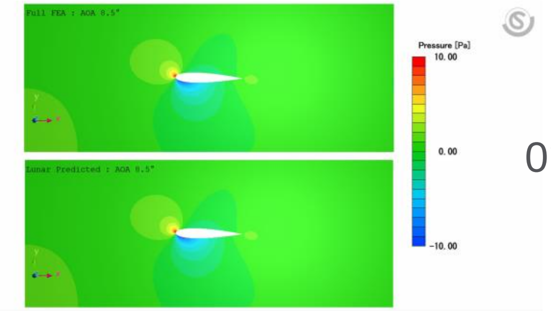
- AOA (Angle of Attack) analysis model
- Analysis conditions

Setting analysis conditions	
Turbulence Model	SST kω Model
Steady/Transeint	Steady analysis
Density	1.206 kg/m^3
Viscocity	1.83e-05 Pa s
Pressure Correction Method	SIMPLEC
Time Derivative Terms	Second order implicit scheme
Airfoil Model	NACA 4412 airfoil

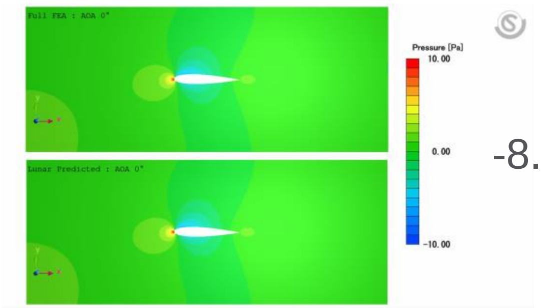


Flow around NACA 4412 airfoil

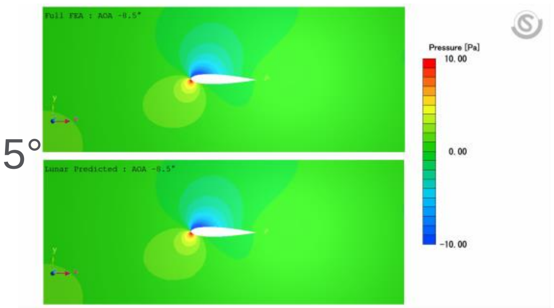
8.5°



0°



-8.5°

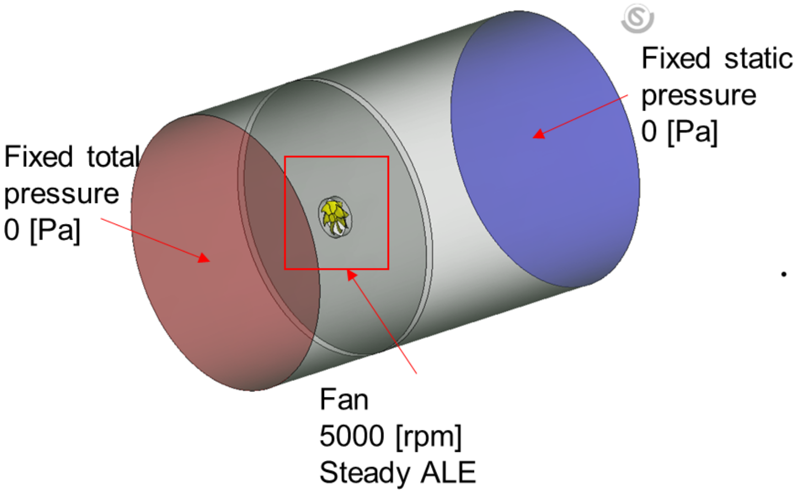


Predictions vs Full CFD

scFLOW – Steady-State analysis

scFLOW Steady-State analysis

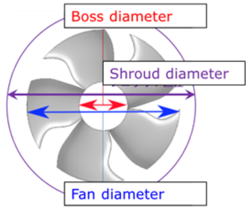
- Prediction of flow rate by fan shape



Courtesy of Tomoyuki Hirabayashi (MSC Japan)

- Prediction of flow rate by fan shape
  - Design Variables and Objective Function

Design Variable	Unit	Min	Max
Number of wings	Sheet	3	10
Shroud diameter	Mm	100	130
Fan diameter	mm	100	120
Boss diameter	mm	30	40



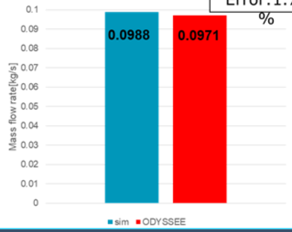
Objective function	Unit
Outlet mass flow rate	kg/s

- Sampling : Optimal Latin Hyper Cube n=30
- Comparing scFLOW and Lunar in some design variable combinations.

- Result
  - Comparing scFLOW and Lunar in some design variable combinations.

Difference between the analyzed value and the predicted value

Error:1.73 %

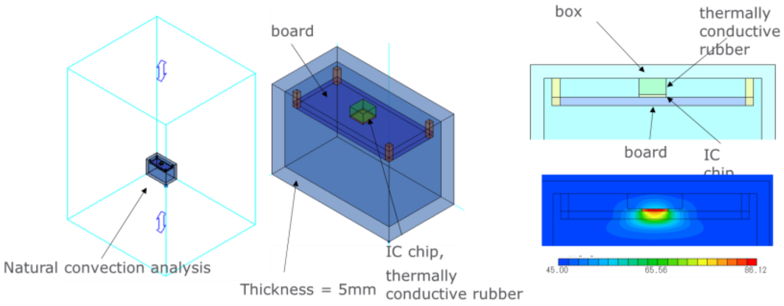


Calculation time
scFLOW :~16min (72Core)
ODYSSEE :Few seconds

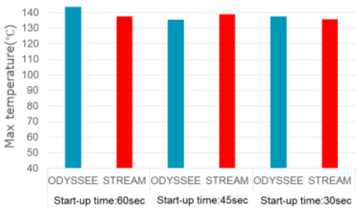
scSTREAM – Transient Analysis

scSTREAM Transient analysis

- Prediction under unsteady heating conditions
  - Predicts the maximum temperature of the IC chip



- Result
  - Max temperature and calculation time



Match in the range of ±6°

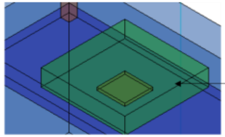
Calculation time
scSTREAM :58 sec (72Core)
ODYSSEE : Few seconds

scSTREAM Transient analysis

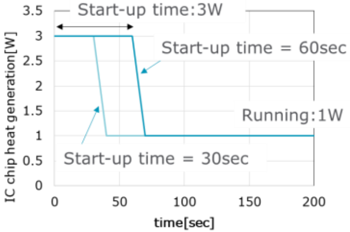
- Prediction under unsteady heating conditions

Design Variable	Unit	Min	Max
Rubber size	mm	10	30
Rubber thermal conductivity	W/(m・K)	0.8	7.3
IC Chip High heat generation Start-up time	sec	30	60

- Objective function: IC chip maximum temperature[℃]
- Sampling：Optimal Latin Hyper Cube n=20



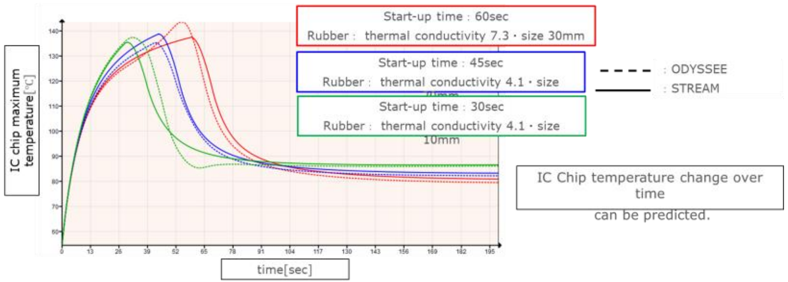
Change the size and thermal conductivity of the rubber



Reduce heat generation by shortening the start-up time.

scSTREAM Transient analysis

- Result
  - Predicting the maximum temperature of an IC chip



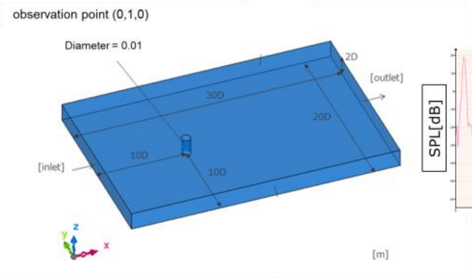
IC Chip temperature change over time can be predicted.

scFLOW - Prediction of aerodynamic sound analysis

ODYSSEE
Explore new industrial horizons

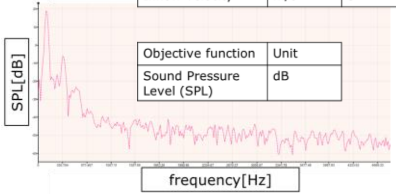
scFLOW Prediction of aerodynamic sound analysis

- Evaluation of aerodynamic sound around a three-dimensional cylinder
  - It predicts the aerodynamic sound when the inflow velocity is changed.



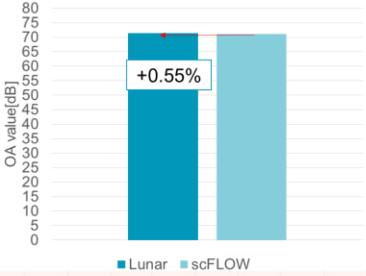
Design Variable	Unit	Min	Max
Inflow velocity	m/s	5	15

Objective function	Unit
Sound Pressure Level (SPL)	dB



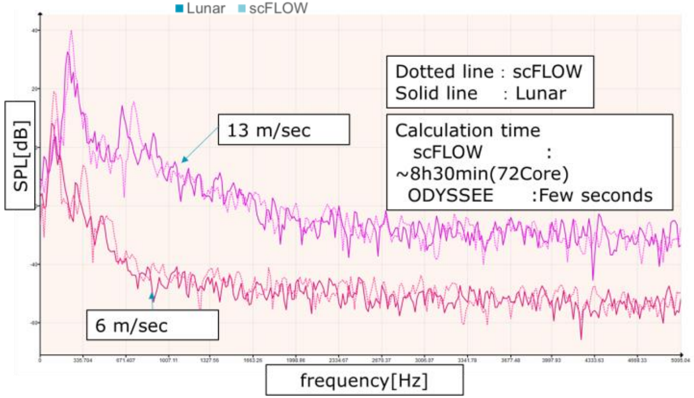
Initial turbulent flow field(LES) Courant Number 5.0 ~3h50min @72Core → Aerodynamic sound analysis(LES) Δt = 2μs ~4h40min @72Core → POST SPL analysis ~1min/data → Lunar Prediction Few seconds

- Result：OA value
  - Comparison of scFLOW and ODYSSEE , with training in OA value(overall value, Total sound pressure)
  - 13m/sec conditions were evaluated.
  - The predicted deviation of OA values was less than 1%, which was highly accurate.



Succeeded in predicting OA values with an accuracy of approximately 99.5%.

Over 3,000 times faster with over 99% prediction accuracy



Dotted line：scFLOW
Solid line ：Lunar

Calculation time
scFLOW ： ~8h30min(72Core)
ODYSSEE ：Few seconds

Courtesy of Tomoyuki Hirabayashi (MSC Japan)

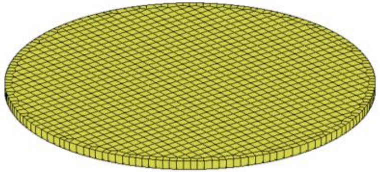
Pump membrane optimization with multi-physics interaction

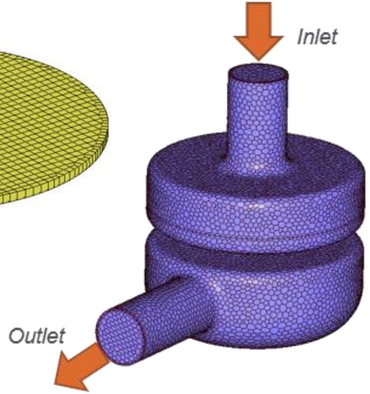
ODYSSEE
Explore new industrial horizons

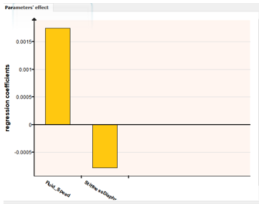
Design of experiments

X: (2 variables)

1. Inlet Fluid Speed
2. Membrane Stiffness

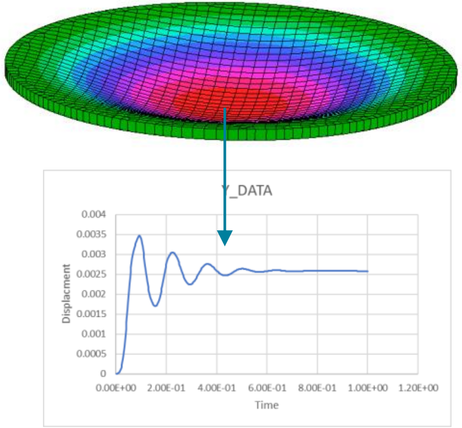


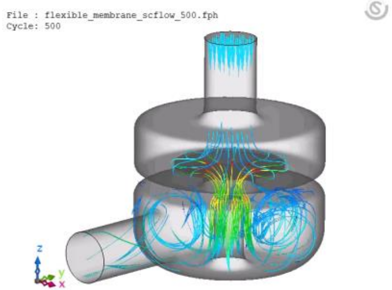




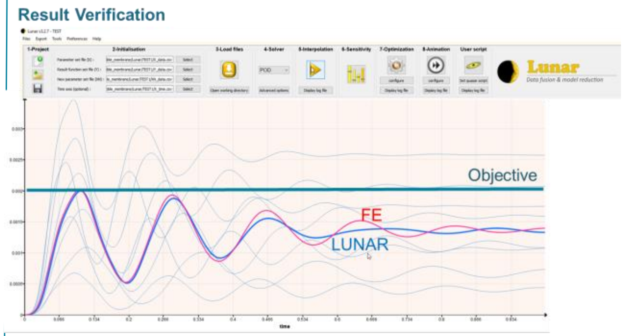
Y:

1. Displacement center of membrane





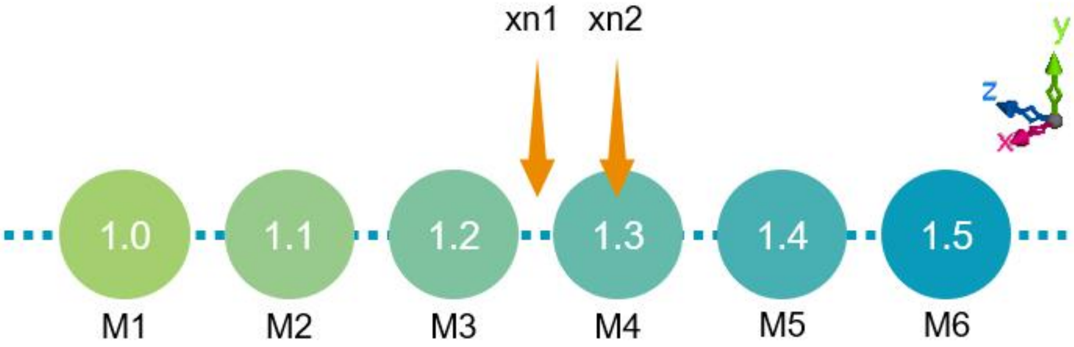
x 8

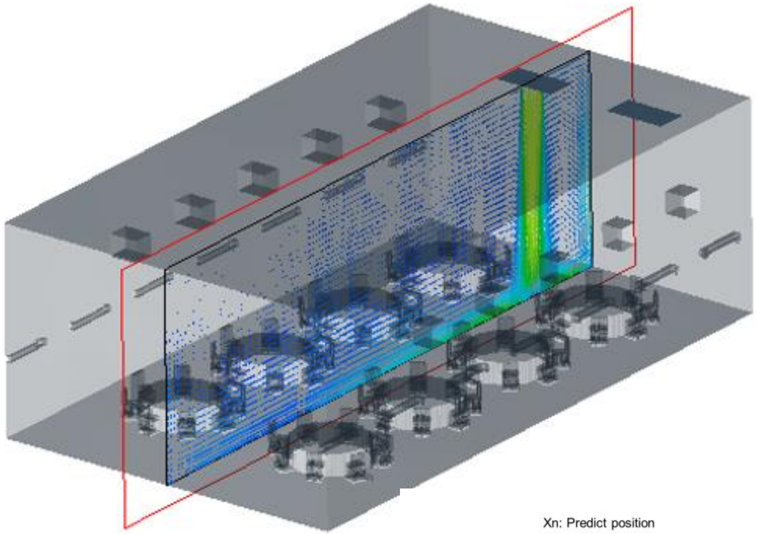


Restaurant Airconditioning

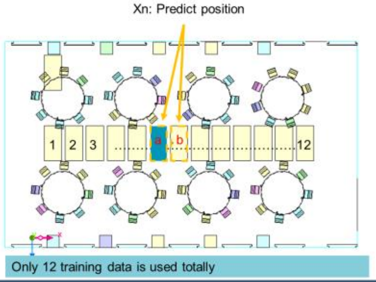
ODYSSEE
Explore new industrial horizons

- Inflow position is constant
- transient analysis: 0~200s
- Design variable: inflow velocity
- Prediction: 1.25, 1.3(=M3), 1.45 m/s
- # sampling: 6 case (1, 1.1, 1.2, … 1.5m/s)





cross section



Restaurant Airconditioning – Optimal positioning

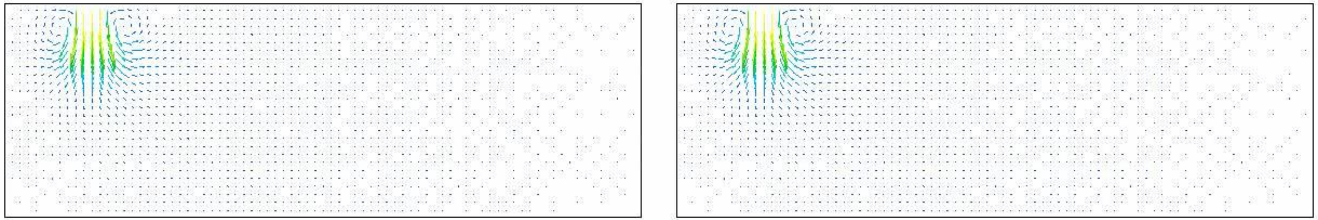
ODYSSEE
Explore new industrial horizons

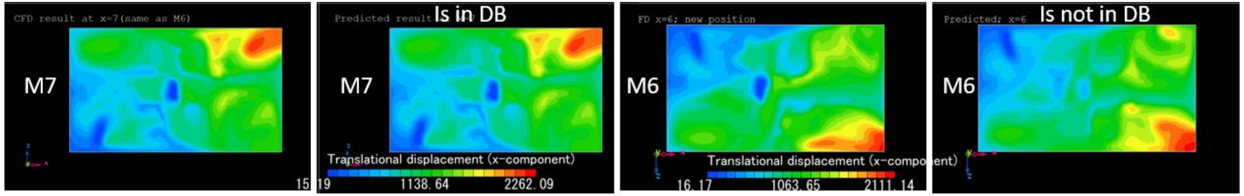
1.0 · 1.1 · 1.2 · 1.3 · 1.4 · 1.5

CFD on xn3 param
Time : 5.000000

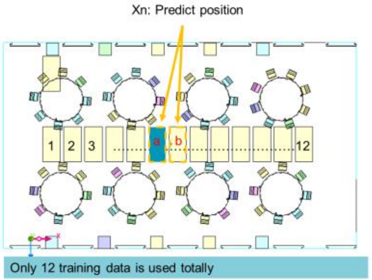
- x=1.45

CFD | LUNAR



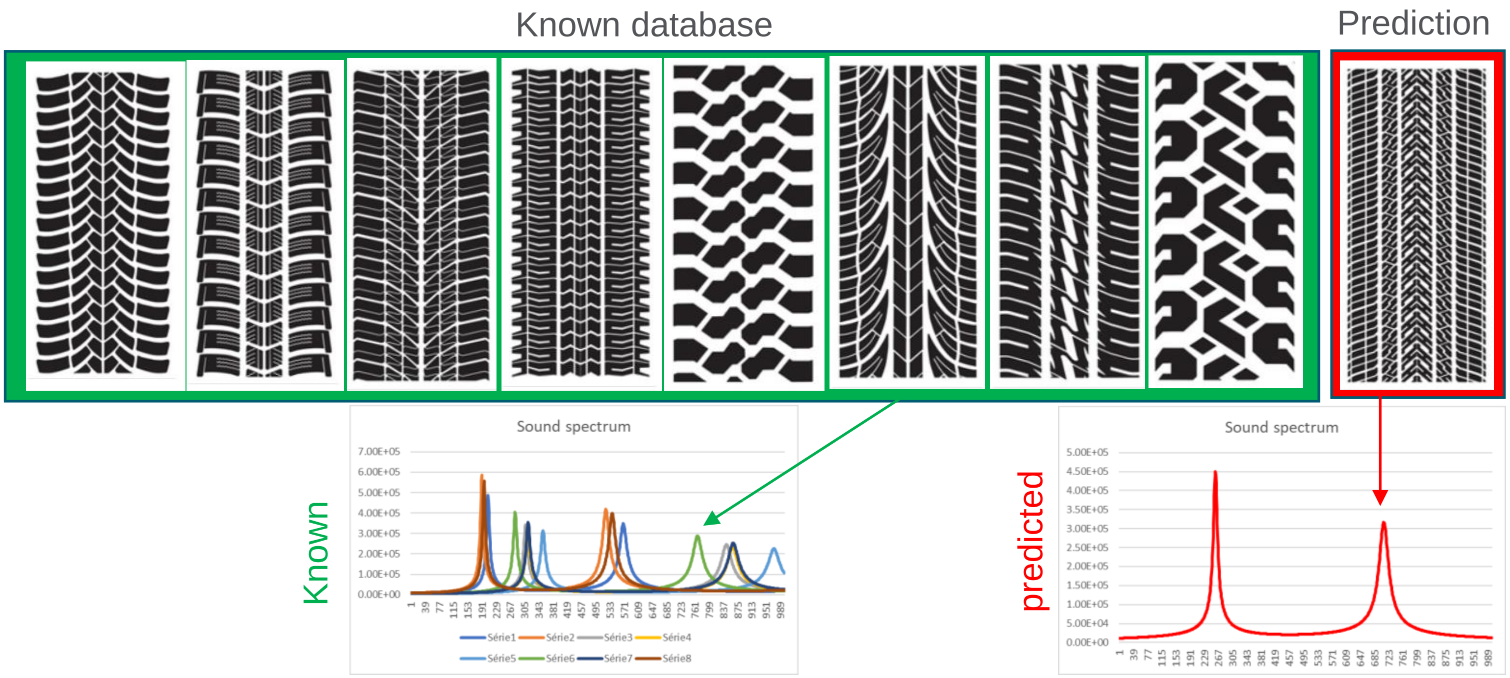


CFD | Neighbour = 1, pow = 1.0 | CFD | Neighbour = 2, pow = 0.0

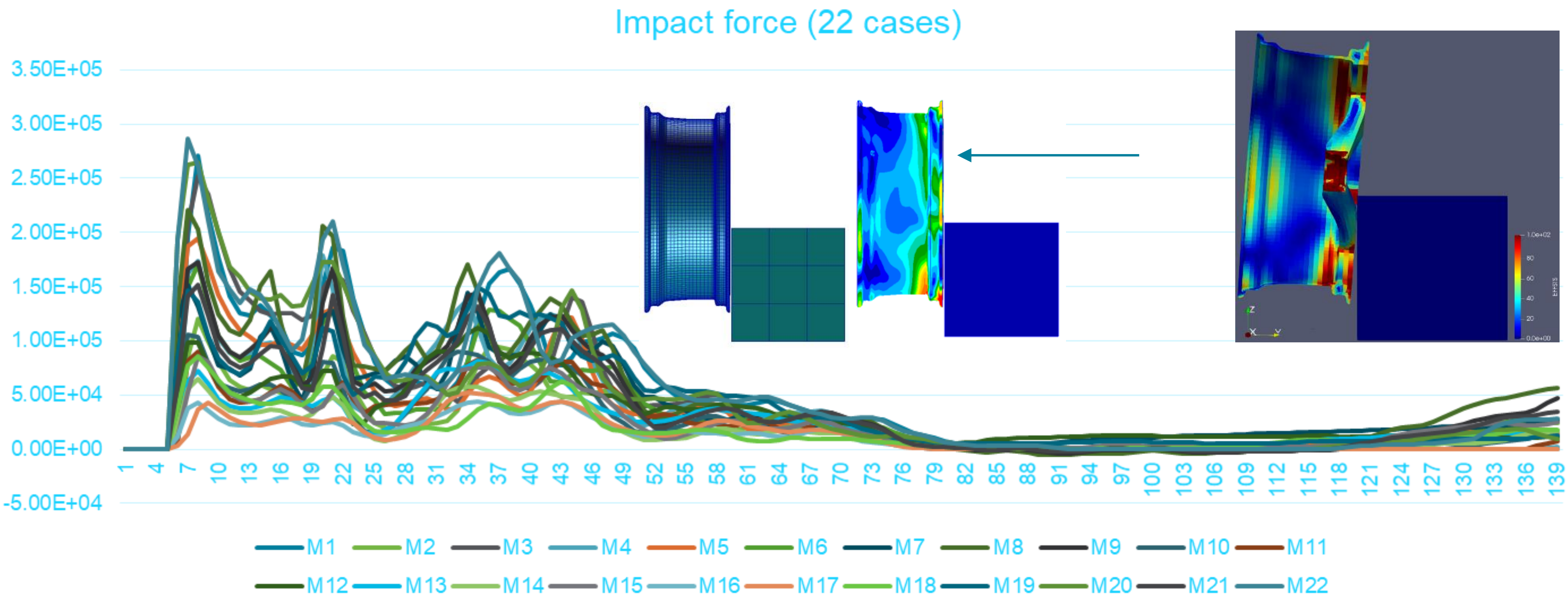


Courtesy of Cradle (scStream)

Sound spectrum prediction form images



Wheel impact on pavement - Learning from images : Y(t)

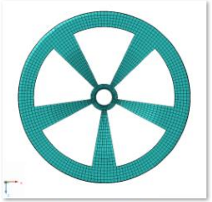


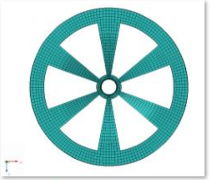
Wheel impact on pavement - Learning from images : Y(t)

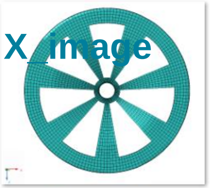
X_parameters

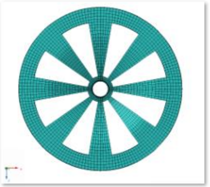
	Initial Velocity	Number of branches
M1	9	9
M2	4	9
M3	9	10
M4	8	8
M5	7	10
M6	6	9
M7	10	6
M8	10	7
M9	8	7
M10	5	8
M11	6	6
M12	7	5
M13	5	5
M14	3	8
M15	4	7
M16	3	6
M17	3	5
M18	3	10
M19	10	5
M20	10	10
M21	7	7
M22	10	9

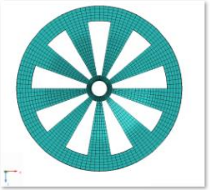
X_image


5_Branches_APEX.PNG

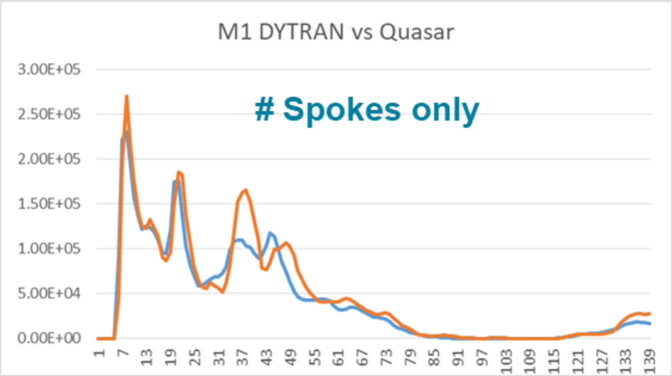

6_Branches_APEX.PNG

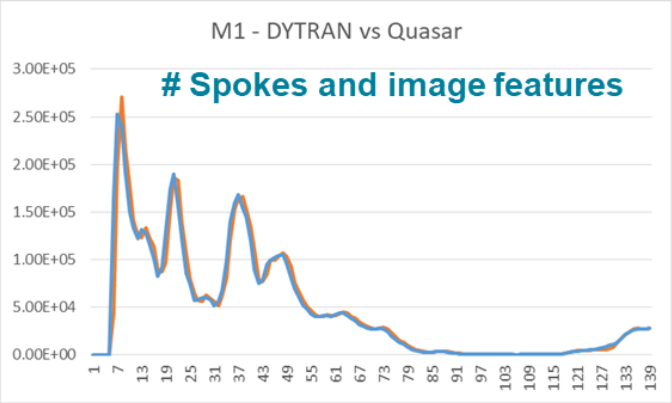

7_Branches_APEX.PNG


8_Branches_APEX.PNG


9_Branches_APEX.PNG


10_Branches_APEX.PNG





Full vehicle Passenger safety

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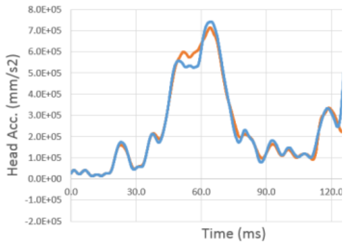
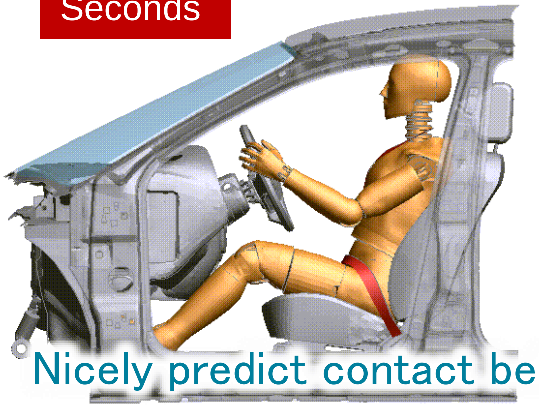
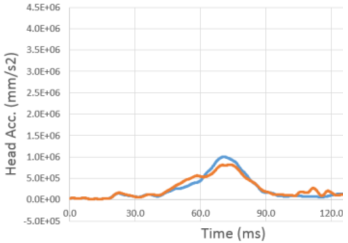


Odyssee | Seconds

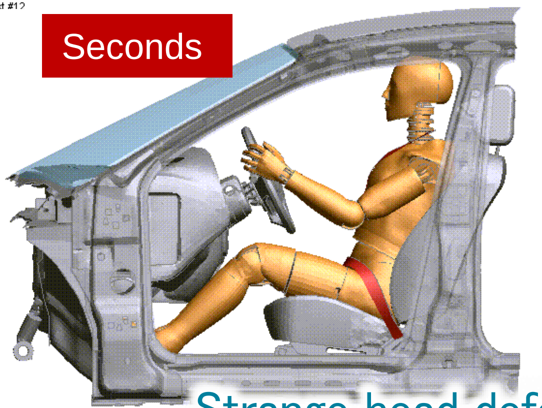


LS-DYNA | Hours x

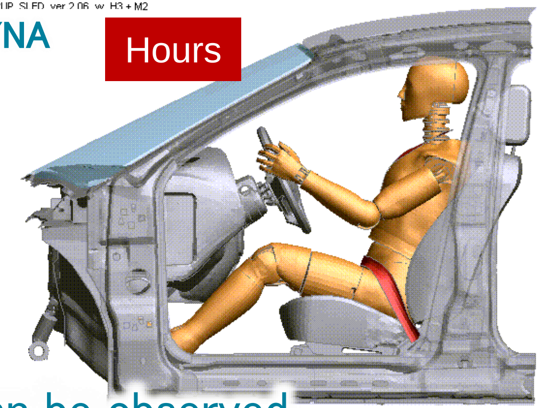
Nicely predict contact behavior between airbag and dummy



Odyssee | Seconds



LS-DYNA | Hours



Strange head deformation can be observed

Courtesy of JSOL

Human biomechanics

ODYSSEE
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	Training data		Computation time		
	DoF	# of data	Learning	Prediction(25steps)	Dyna (16 cores)
Arm	3	13	2m 6s	**1m 15s**	**9 h 40 m 56 s**
Leg	4	20	2m 54s	**2m 27s**	**11 h 7 m 42 s**

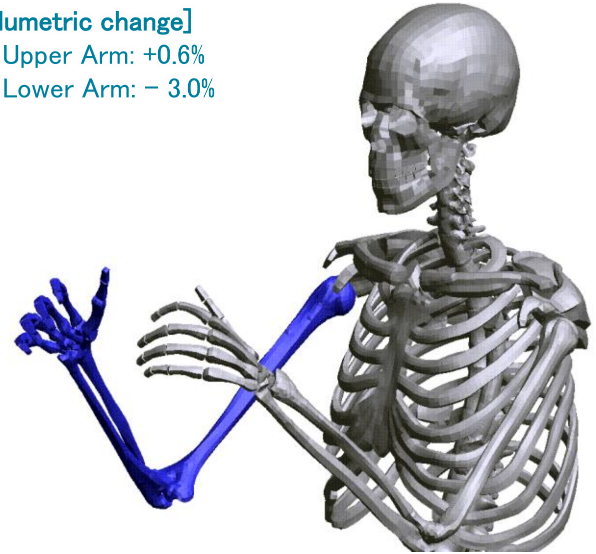
[Discrepancy at fingertips]

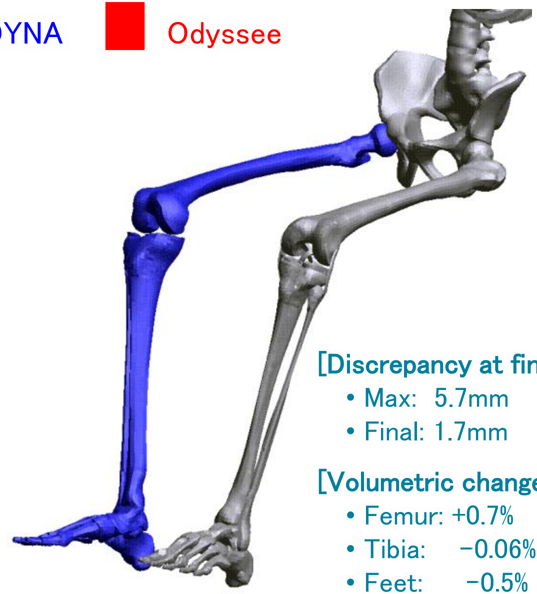
- Max: 4.3mm
- Final:3.0mm

[Volumetric change]

- Upper Arm: +0.6%
- Lower Arm: − 3.0%

LS-DYNA Odyssee





[Discrepancy at fingertips]

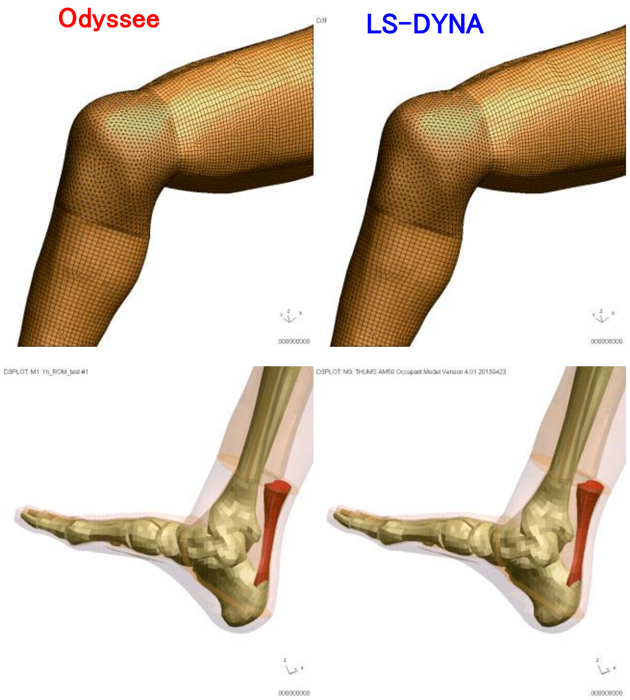
- Max: 5.7mm
- Final: 1.7mm

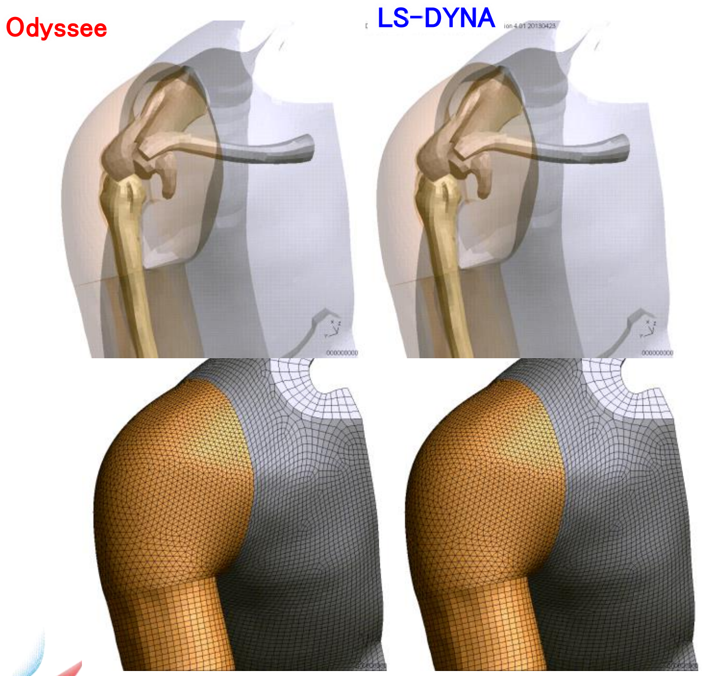
[Volumetric change]

- Femur: +0.7%
- Tibia: −0.06%
- Feet: −0.5%

Courtesy of TOYOTA/JSOL

Human biomechanics





Courtesy of TOYOTA/JSOL

Odyssee: 1 min (1 core) – ls-dyna: 10 hours (16 cores) to

Pre-crash avoidance manoeuvre and crash

ODYSSEE
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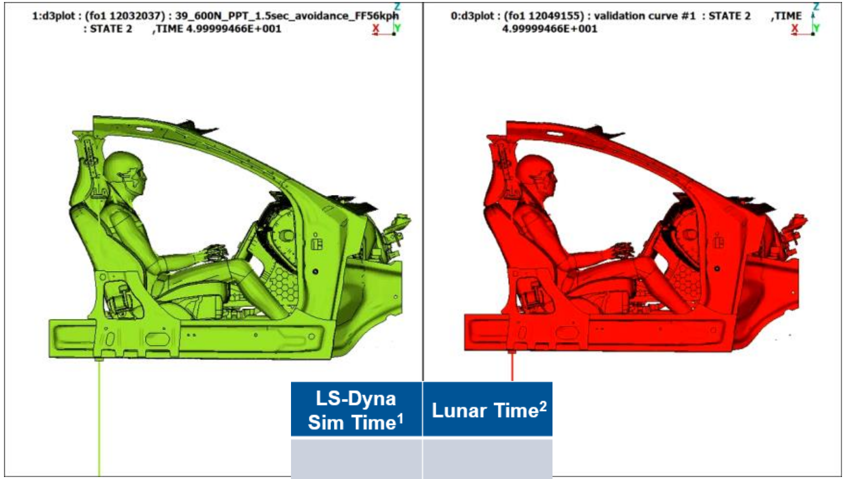

LS-Dyna Sim Time[1]	Lunar Time[2]
47h 35min	1h 32min

"At AUTOLIV we are concerned with safety of real humans (and not only dummies). This requires a yet challenging computing effort for evaluation of our safety solutions. CADLM's ODYSSEE.Lunar software is a real breakthrough and provides a very promising perspectives in order to reduce drastically computing time and optimize our designs" Bengt Pipkorn (Director Simulation and Active Structures, Autoliv Research)

6 Runs only

1. Simulation carried out in Autoliv Research Cluster – PBS Nodes – Intel Xeon E5 (32 cores)
2. Calculations on company HP Zbook laptop (Intel Core i7 – 4910MQ – 4 cores)

Restraint system robustness
Coupling CADLM / DynaS+ software

ODYSSEE
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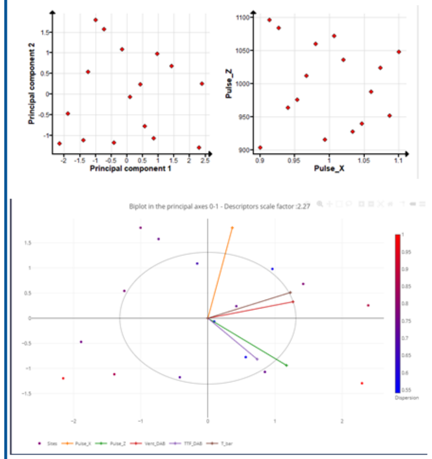
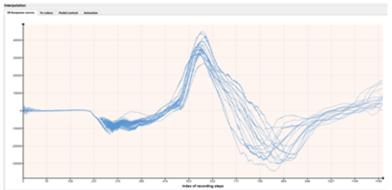
D.O.E

Lunar: Latin Hypercube



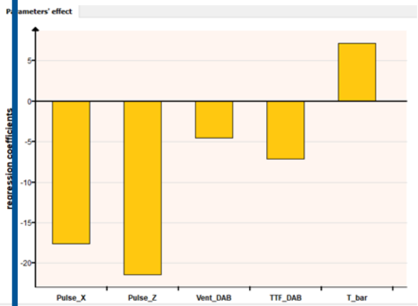
LSDYNA Simulations

Lunar : LSDYNA Model parsing for input/output



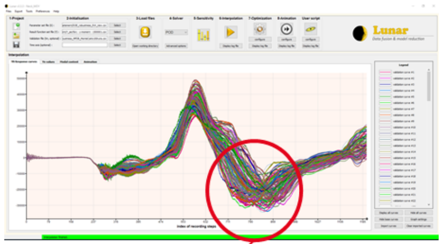
ROM

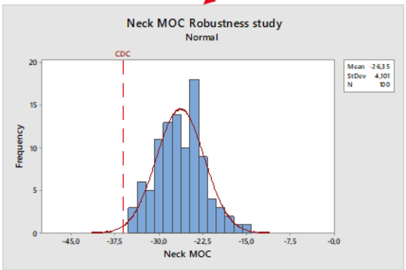
Lunar :Reduction Of Model



100 Monte Carlo runs

Lunar : Interpolation





Courtesy of Autilv France

CPU times reduced by 86%
Time of study : 5 days instead of 1 month

Autoliv

PSA - Automotive Sector: crash automobile

ODYSSEE
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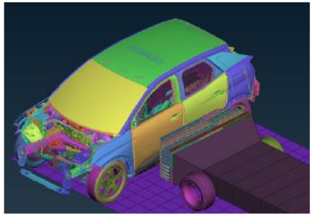
Side crashworthiness

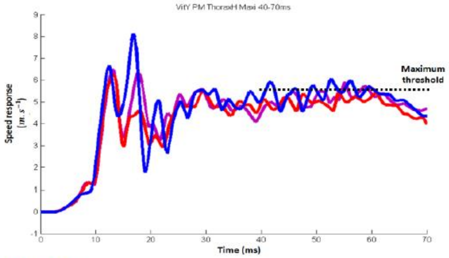
Collaboration PSA/CADLM

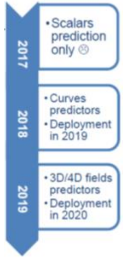
PSA GROUPE

Side crashworthiness performance sizing



New Peugeot 3008 side crash
Euro NCAP test and FE model



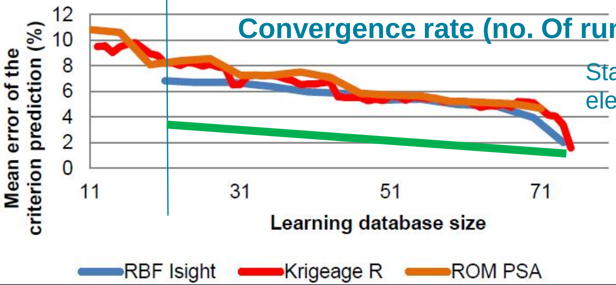


Criteria:

- Nodal displacements, velocities, stresses…

Application of the NI-POD approach

- Test-case: Peugeot 3008 FE model
- Implementation: SVD done in Matlab and surrogate models calculated with the 'DiceKriging' R package.
- Tests done:
  - Prediction of various responses: displacements, velocities, forces…
  - Test of various surrogate models (GP, RBF…)
  - Various databases
  - Calculation of the prediction error



Starting with ~20 runs for 1M element Full car crash (side)

TOYOTA – Side rail buckling

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Development of Prediction Method by Reduced Model for Structural Deformations in Frontal Impact

Hota Hashimoto, Hiroaki Onodera, Yasuo Yamane, Tsuyoshi Yasuli, Development of Prediction Method by Reduced Model for Structural Deformations in Frontal Impact, JSAE Paper Number: 20186154, Oct, 2018 Issued No.135-18

TOYOTA

hota Hashimoto Hiroaki Onodera Yasuo Yamamae Tsuyoshi Yasuki

Fig. 2 Car crash FE model

Fig. 3 Design parameters

Table 1 Maximum and minimum values of thickness and length of difference thickness for design parameters

Part	Design parameter	Min.	Max.
1	Thickness	1.1 mm	2.5 mm
2	Thickness	1.4 mm	2.8 mm
3	Thickness	1.9 mm	3.3 mm
4	Thickness	1.3 mm	2.7 mm
5	Thickness	0.7 mm	2.1 mm
6	Thickness	0.9 mm	2.3 mm
7	Length of difference thickness	100 mm	300 mm
8	Length of difference thickness	400 mm	640 mm

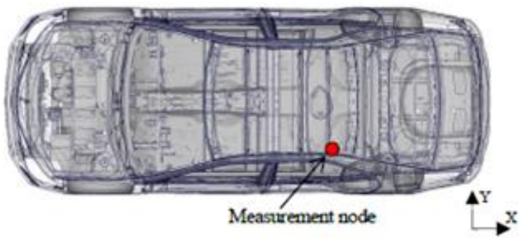

Fig. 4 Measurement node for vehicle acceleration and displacement

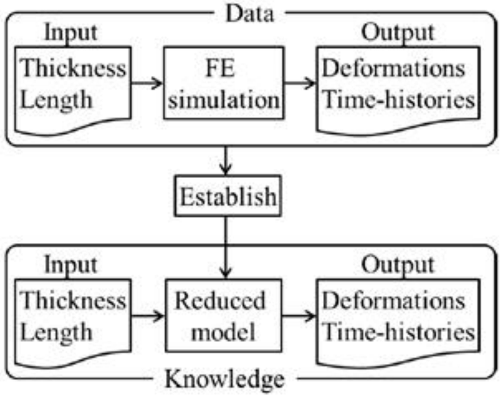

Fig. 1 Prediction method for deformations and time-histories

TOYOTA – Side rail buckling

Correlation

Prediction

Clustering

Hota Hashimoto, Hiroaki Onodera, Yasuo Yamane, Tsuyoshi Yasuli, Development of Prediction Method by Reduced Model for Structural Deformations in Frontal Impact, JSAE Paper Number: 20186154, Oct, 2018 Issued No.135-18

Reduced model による最大車両加速度と最大移動量の予測精度を図 10、11 に示す。最大加速度の平均誤差は 6%、最大移動量の平均誤差は 1%だった。

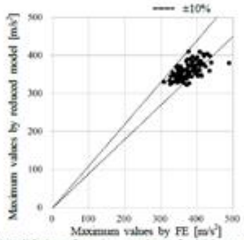

Fig. 10 Validation of maximum values of vehicle acceleration

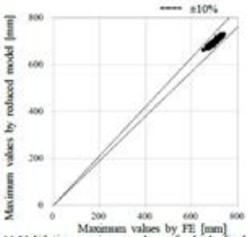

Fig. 11 Validation maximum values of vehicle displacement

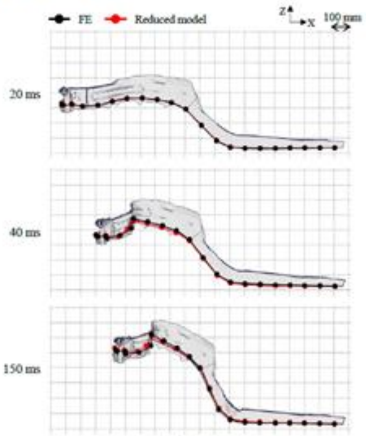

Fig. 13 Deformation of front side rail in Case 15

(1) 猪口純一ほか：Reduced Model による SUV 側突時のセンターピラー変形モードの予測, 自動車技術会論文集, Vol.49, No.2, p359-364(2018)

(2) 小野寺啓祥ほか：前突乗員傷害値予測のためのReduced Modelの開発, 自動車技術会 2017年秋季大会 学術講演会 講演予稿集, No. 159, p1277-1282, 20176235(2017)

(3) Kambiz kayvantash, et al. : Model Reduction Techniques for LS-DYNA ALE and Crash Applications, Proceedings of 10th European LS-DYNA Conference(2015)

(4) NCAC, Toyota Camry Finite Element Model Version 1. Technical Report, The George Washington University, 2014

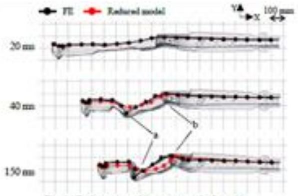

Fig. 14 Deformation of front side rail in Case 61

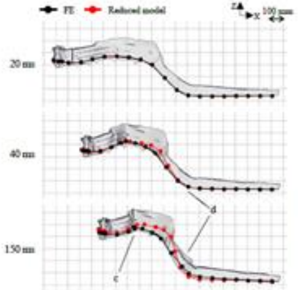

Fig. 15 Deformation of front side rail in Case 61

3.3. 変形モードのクラスタリング

Reduced model による変形モードが FE 結果と異なるケースがあった（図 14、15）。変形モードが複数存在するため予測

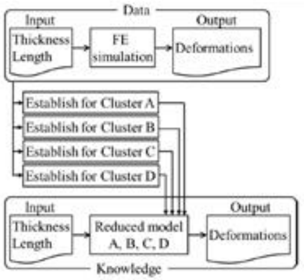

Fig. 16 Prediction method by clustering deformations

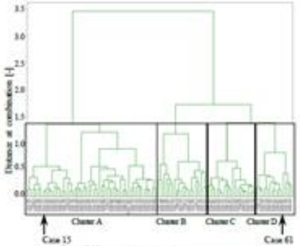

Fig. 17 Hierarchical clustering dendrogram

Hota Hashimoto, Hiroaki Onodera, Yasuo Yamane, Tsuyoshi Yasuli, Development of Prediction Method by Reduced Model for Structural Deformations in Frontal Impact, JSAE Paper Number: 20186154, Oct, 2018 Issued No.135-18

TOYOTA

TOYOTA – Vehicle Aerodynamics

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Development of Reduced Model for Aerodynamic Drag and Lift

Mashio Taniguchi;Junichi Inokuchi;Yasuo, Development of Reduced Model for Aerodynamic Drag and Lift, JSAE Paper Number: 20186092, Oct, 2018 Issued No.121-18

Mashio Taniguchi Junichi Inokuchi Yasuo Yamamae Hiroshi Tanaka Tsuyoshi Yasuki

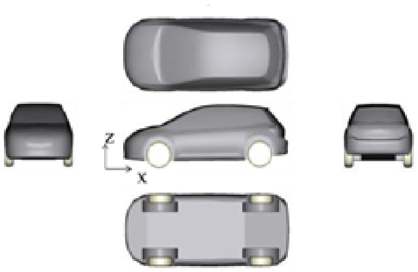

Fig. 2 Vehicle model (Base)

Table 2 Design variables and range

Design Variable	Base	Minimum	Maximum
A1 [deg]	14.0	14.0	24.0
H1 [mm]	144.7	144.1	194.0
H2 [mm]	2.6	2.6	129.7
H3 [mm]	0.0	-16.5	278.9
L1 [mm]	819.6	821.7	1336.7
L2 [mm]	997.4	997.4	1196.8
R1 [mm]	0.0	-771.8	777.7
W1 [mm]	45.5	45.5	199.5
W2 [mm]	29.5	25.3	109.8

ベース形状での車両中央断面（y=0m）における圧力分布を図 5 に示す．ルーフ後端からせん断渦が放出され，時間経過とともに車両後方へ移流しており，忠津らの研究における流れ場と同様であった．

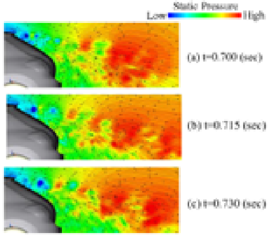

Fig. 5 Pressure Distribution at y=0 Plane (Base)

Reduced Model に新たな変数を入力して，C_D, C_L を算出する．

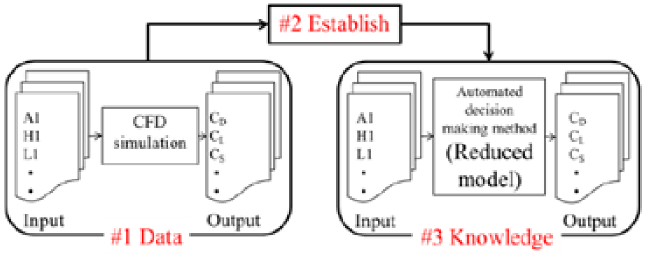

Fig. 1 Automated decision making method

TOYOTA

TOYOTA – Vehicle Aerodynamics

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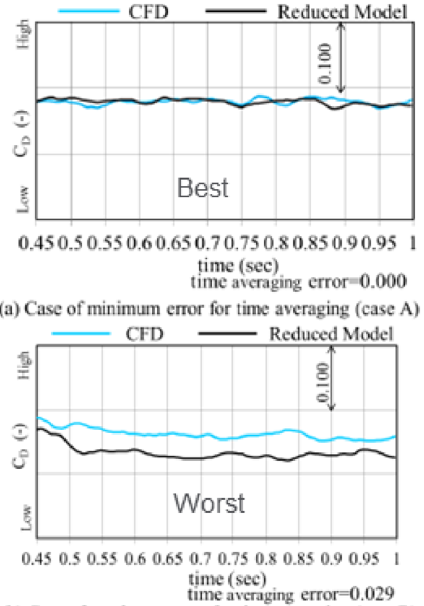
TOYOTA

Mashio Taniguchi;Junichi Inokuchi;Yasuo, Development of Reduced Model for Aerodynamic Drag and Lift, JSAE Paper Number: 20186092, Oct, 2018 Issued No.121-18



(a) Case of minimum error for time averaging (case A)

(b) Case of maximum error for time averaging (case B)

Fig. 8 Time histories of C_D predicted by CFD and Reduced Model

Correlation

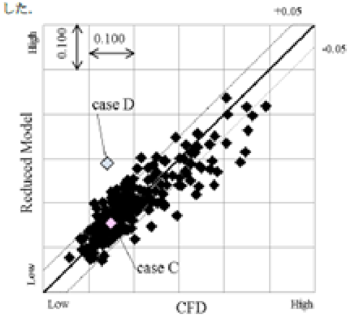


Fig. 9 Cross-validation of C_L

Clustering

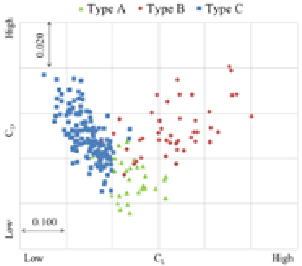


Fig. 12 Relationship between C_L and C_D

Prediction

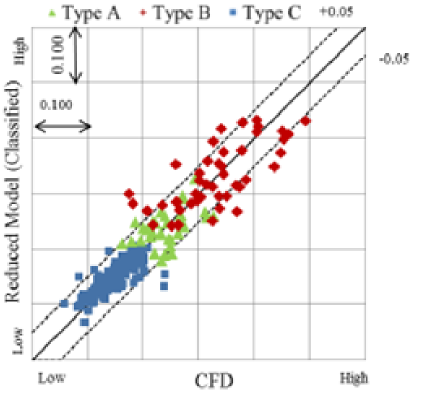


Fig. 14 Cross-validation of C_L using Reduced Model (Classified)

(5) 忠津雅也, 山村淳, 田中博, 安木剛, 高山務, 山田吉伸, 鈴木康方, 加藤千幸：2Box 車の空気抵抗低減に関する研究, 自動車技術会論文集, Vol.44, No.5, p.1287-1294 (2013)

(6) Optimal Decision Support System for Engineering and Expertise (http://odyssee.cadlm.com)

(7) R. Kotapati, A. Keating, S. Kandasamy, B. Duncan, R. Shock and H. Chen : The Lattice-Boltzmann-VLES Method for Automotive Fluid Dynamics Simulation, a Review, SAE Paper No.2009-29-057, p.2-3 (2009)

Try it …

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