SIAM CSE17

Computational Science and Engineering Achievements in the Designing of Aircraft

B. STOUFFLET

CTO Dassault Aviation

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HIGHER TOGETHER™

DASSAULT AVIATION

The Falcon Family, Rafale and nEUROn

FALCON 8X
6,450 NM - Trijet

RAFALE

FALCON 2000S
3,350 NM – Twin-jet

nEUROn

The Falcon Family, Rafale and nEUROn

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2007 New wing: erodynamic ficiency +30%

FALCON 7X
5,950 NM - Trijet

FALCON 5X
5,200 NM - Twin-jet

FALCON 8X
6,450 NM - Trijet

RAFALE

FALCON 2000S
3,350 NM – Twin-jet

FALCON 2000LXS
4,000 NM - Twin-jet

FALCON 900LX
4,750 NM - Trijet

nEUROn

Introduction

- **Computational Science and Engineering**
  - Mainly Engineering standpoint will be addressed
- **CSE is predominant in Design activities**
- **New fields of CSE applications are however emerging**
  - Stochastic approaches

The Falcon Family, Rafale and nEUROn

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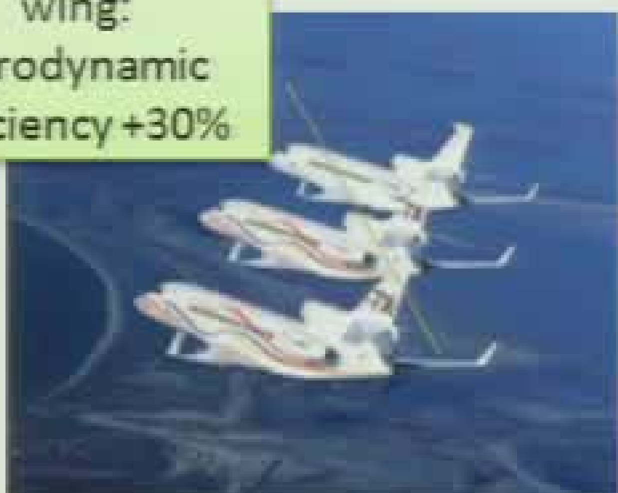
2007 New wing: erodynamic ficiency +30%



FALCON 7X
rijet

New Wing with Flaperon
115V AC
less hydraulic
more electric

FALCON 5X
5,200 NM - Twin-jet

Extended F7X
Mass optimization
New Winglets

FALCON 8X
NM - Trijet

Multi-role airc
Tens of configurations

RAFALE

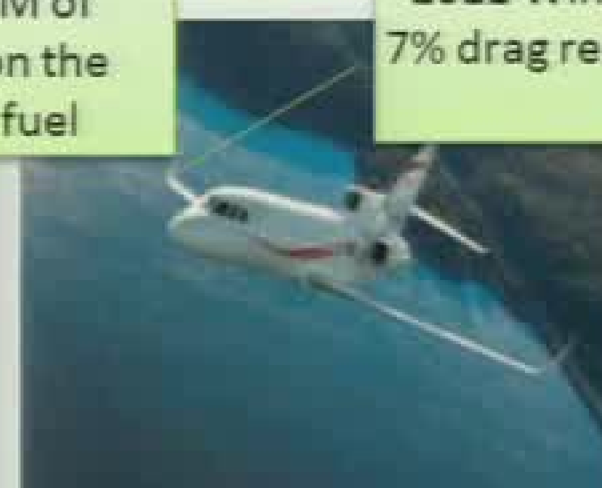
2011 New ngine version reduces missions 20%

FALCON 2000S
3,350 NM – Twin-jet

2009 Winglets: +200NM of range on the same fuel

FALCON 2000LXS
4,000 NM - Twin-jet

2011 Winglets: 7% drag reduction



FALCON 900LX
4,750 NM - Trijet

Technological demonstrator o stealth UCAV

nEUROn

Introduction

- **Computational Science and <u>Engineering</u>**
  - Mainly Engineering standpoint will be addressed
- **CSE is predominant in Design activities**
- **New fields of CSE applications are however emerging**
  - Stochastic approaches

Computational engineering in the product life-cycle

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DESIGN	DEVELOPMENT	SUPPORT
High Fidelity Modeling MDO Multiphysics	System engineering Safety analysis Embedded software	Predictive maintenance Fleet analysis
Numerical Analysis Scientific Computation HPC Optimization Uncertainty quantification Robust Design	Automatics Formal methods Static analysis of codes Rare events probabilities	Data Analytics System Identification

Outline

Design

- Industrial state-of-the art of CFD
- Automatic shape optimization
- Multiphysics: example of Aeroelasticity
- Computational Electromagnetics
- Surrogate models
- Uncertainty quantification – Robust design
- Challenges of next generation HPC (towards Exascale)

Development

- An example of rare-event probability evaluation

Support

- First attempts in Data Analytics

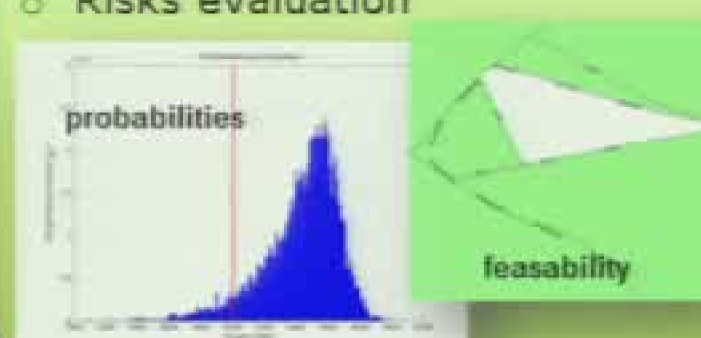
Multidisciplinary Design Loop

Global options
- Architectures
- Technologies

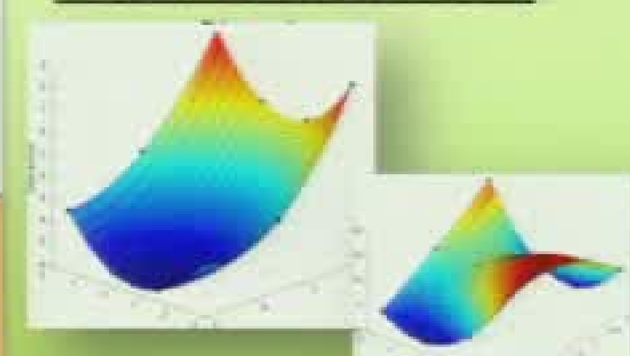
Design per discipline and Optimization
- Aerodynamics
- Structure
- Acoustics
- Propulsive integration
- Vehicle systems

Requirements (market, regulation)
- Range
- Fields length
- Cruise speed
- Comfort
- Environmental objectives
- Costs

Global synthesis
- Exploration of design space
- Global sensitivities
- Risks evaluation



Parametric models



A tremendous evolution of computational fluid dynamics codes (CFD)

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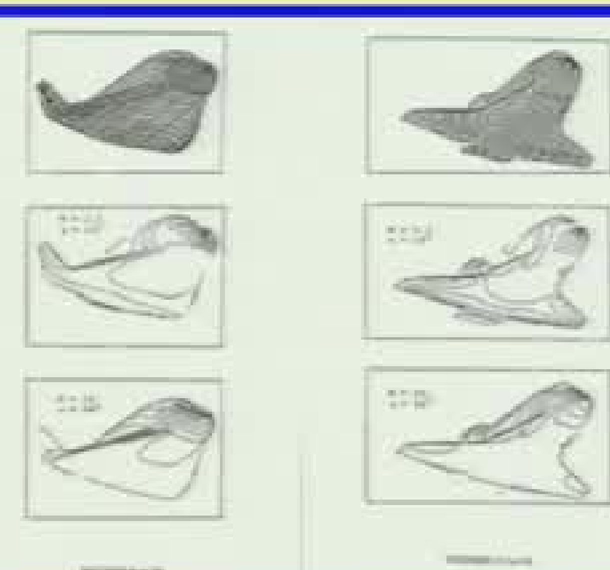
EARLY 80s
A premiere: the first industrial complete aircraft aerodynamics computation

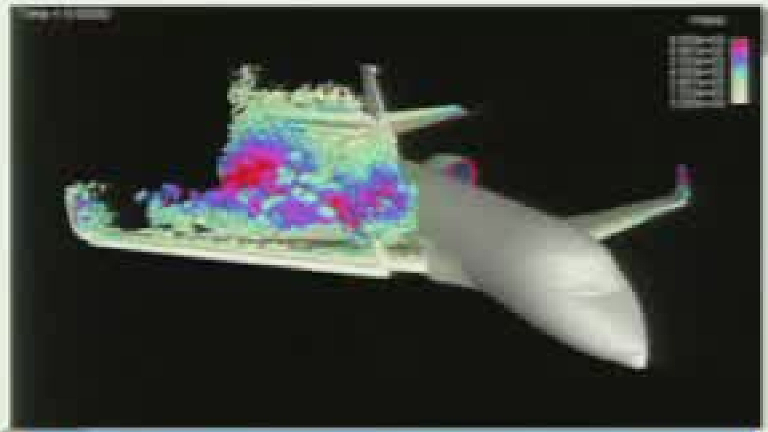
Full potential equations
Finite element discretization
Least-square formulation

MID 80s
Euler solvers
10 000 nodes for a half geometry



Euler equations
Unstructured meshes
Finite Volume / Finite Element
Implicit methods
Geometric Multigrid

MID 2000s
Navier-Stokes solvers
10 Million nodes



Navier-Stokes equations
Unstructured meshes
Petrov-Galerkin formulation
Implicit methods
GMRES

Current operational CFD code

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- Navier-Stokes solver
  - In house development (cooperation with research teams)
  - Stabilized Finite-Element method
  - Implicit methods : GMRES with BSOR preconditioning
  - Turbulence models : two-layer k-ε, k-kL, w/wo EARSM (and S-A, k-ω, DRSM, LES/DES)
  - Efficient parallel code architecture (routine use on 2048-core classes)

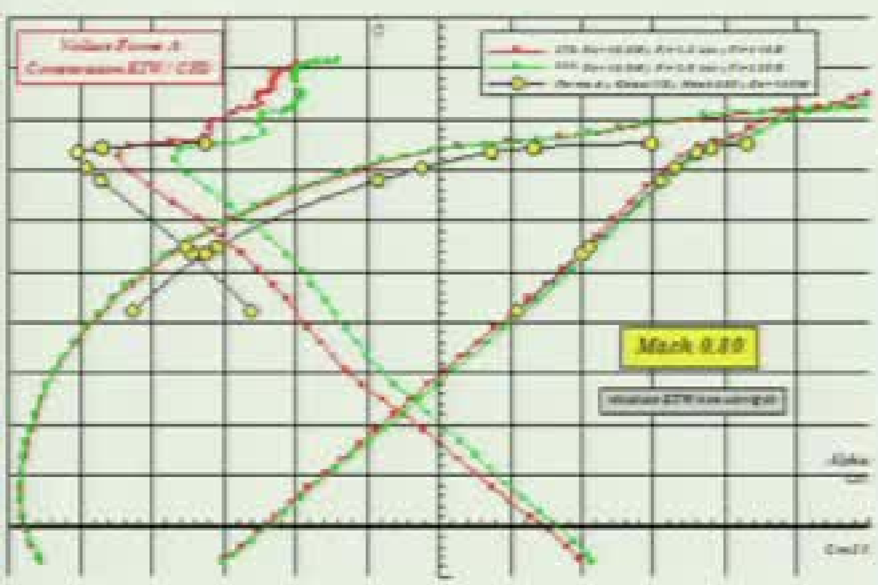
- Two types of computations:
  - Reynolds average Navier-Stokes (RANS) => steady equations
  - Direct Eddy-Simulation (DES) => unsteady equations

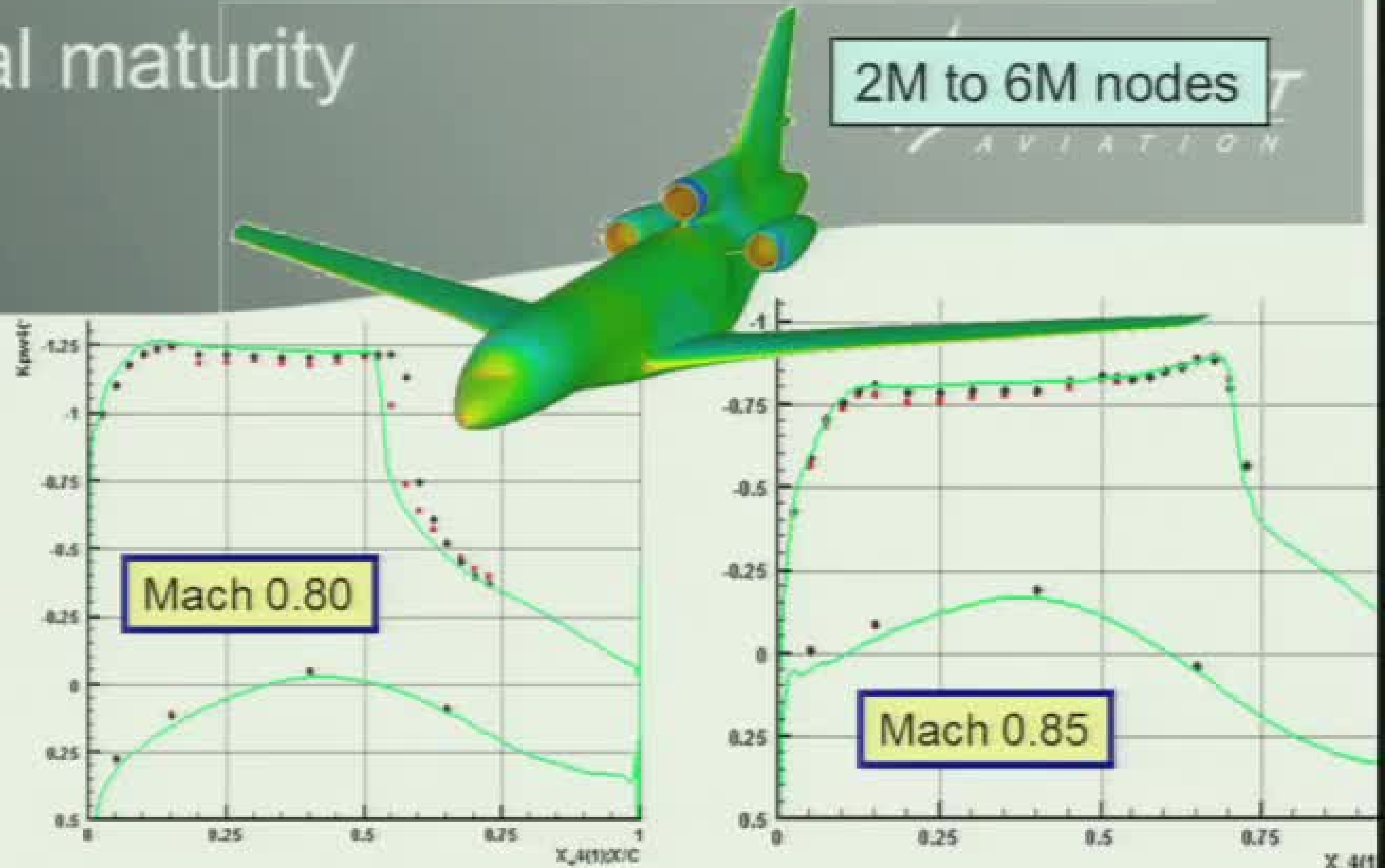
Collaborations with INRIA, Stanford University, ONERA + turbulence experts

Mid 2000's: Industrial maturity of CFD codes

2M to 6M nodes

Cryotechnic test of generic Falcon shape in ETW





- Full aircraft Navier-Stokes simulations are used at all stages of design
  - Very good validation is obtained at cruise conditions
  - Design for cruise conditions is based on CFD
- Wind tunnel tests can be limited to intermediate and final check-out if sufficient validation is obtained at the actual flight Reynolds number

CFD: State of the art of RANS codes
Transonic cruise

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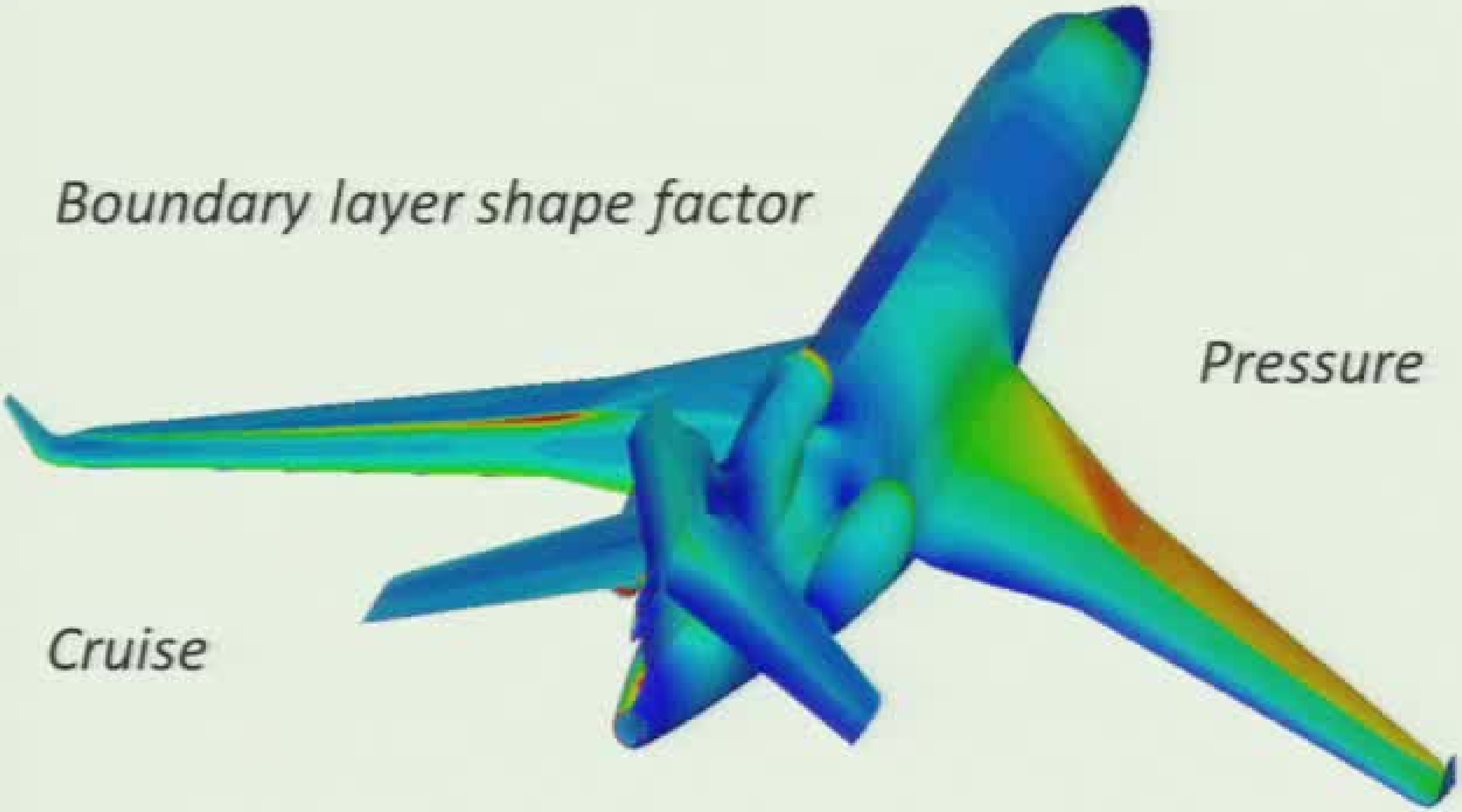
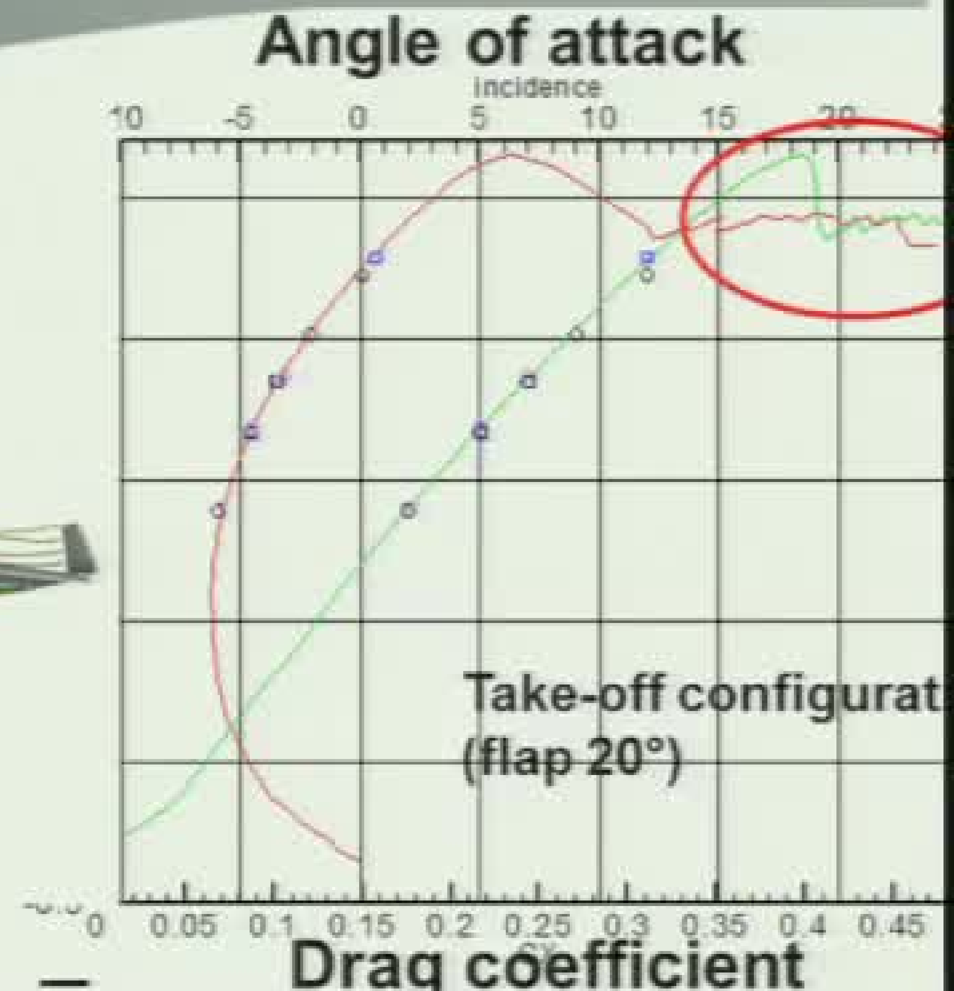


2001 – several hours
1 million grid points

2014 – 15 minutes
~20 million grid points
~500 computations possible per day

Challenges for the future :
- drag accuracy at cruise ~0.5-1% (viscous drag accuracy, corner flows, …) → improved RANS modeling
- 30 secs as typical computing time

CFD: State of the art of RANS codes
Low-speed configurations

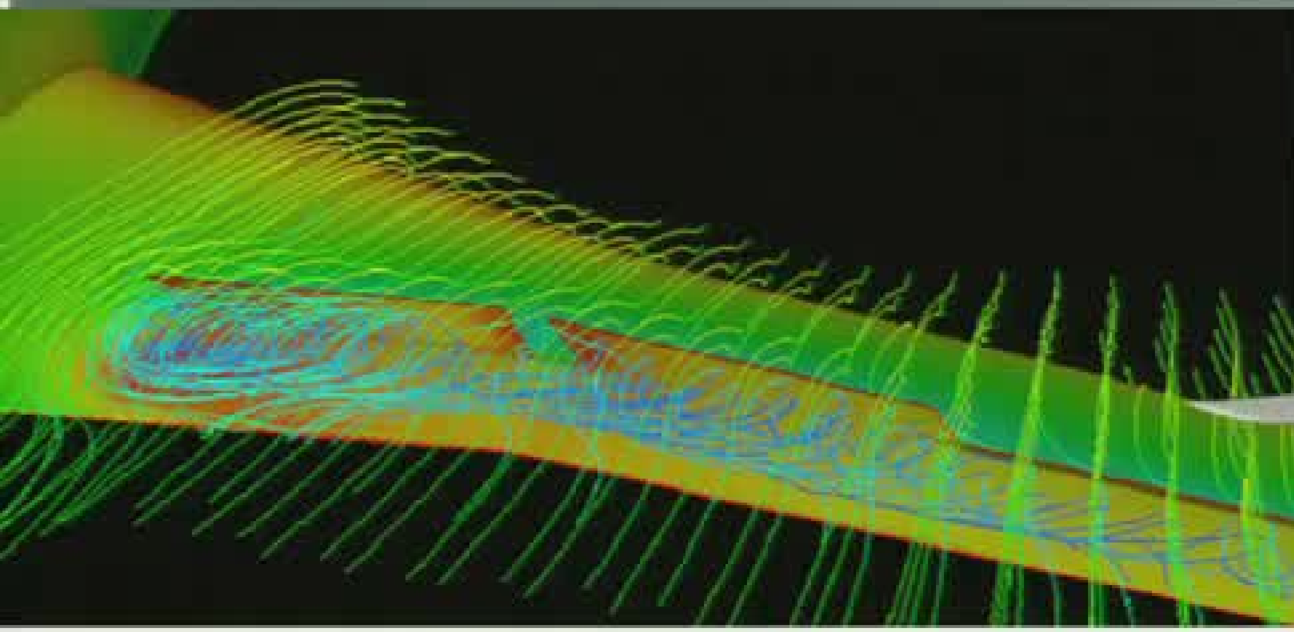


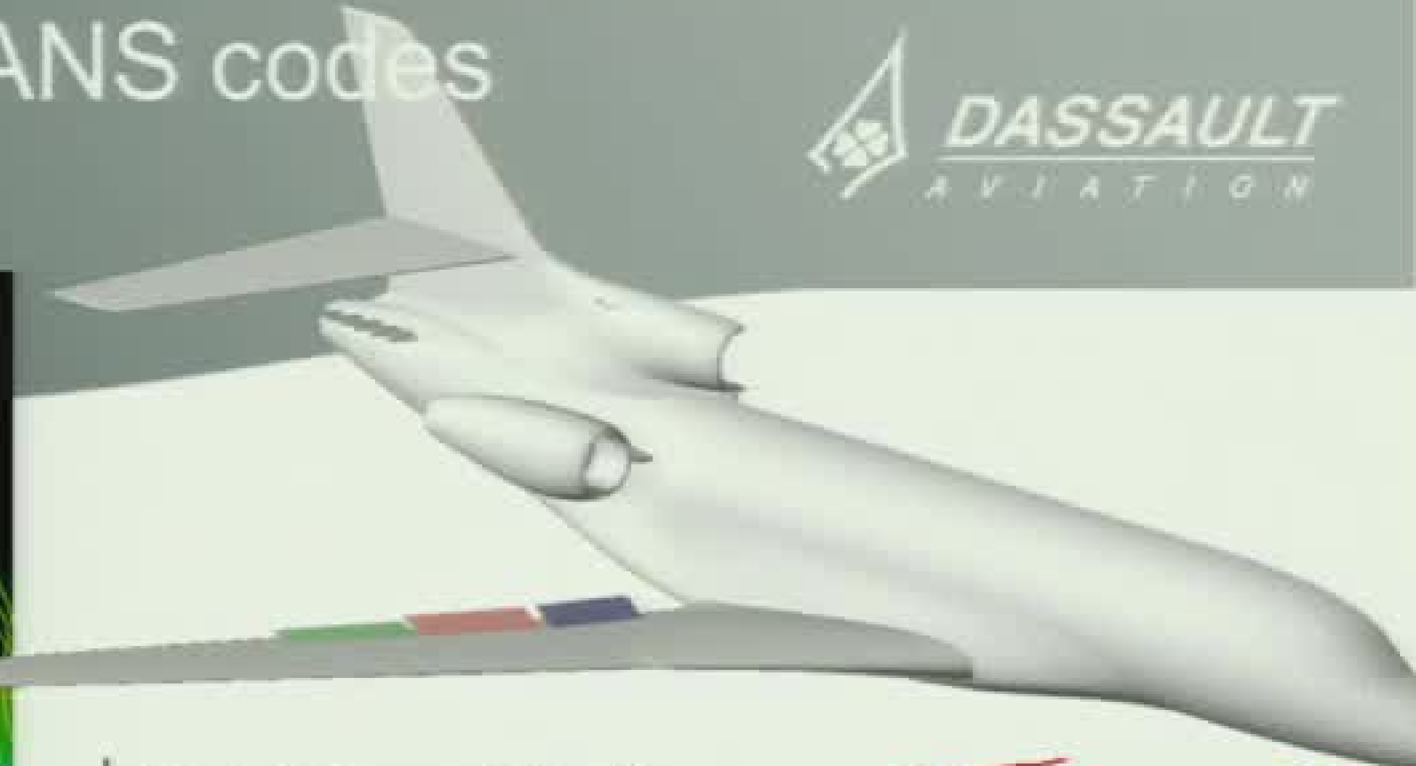
- CFD is not yet reliable enough to predict max lift
- CFD is a key tool for analysis and understanding of the local flow physics
- Challenge for the future : accurate max lift (illustrate trend towards use of CFD for limits of flight domain)

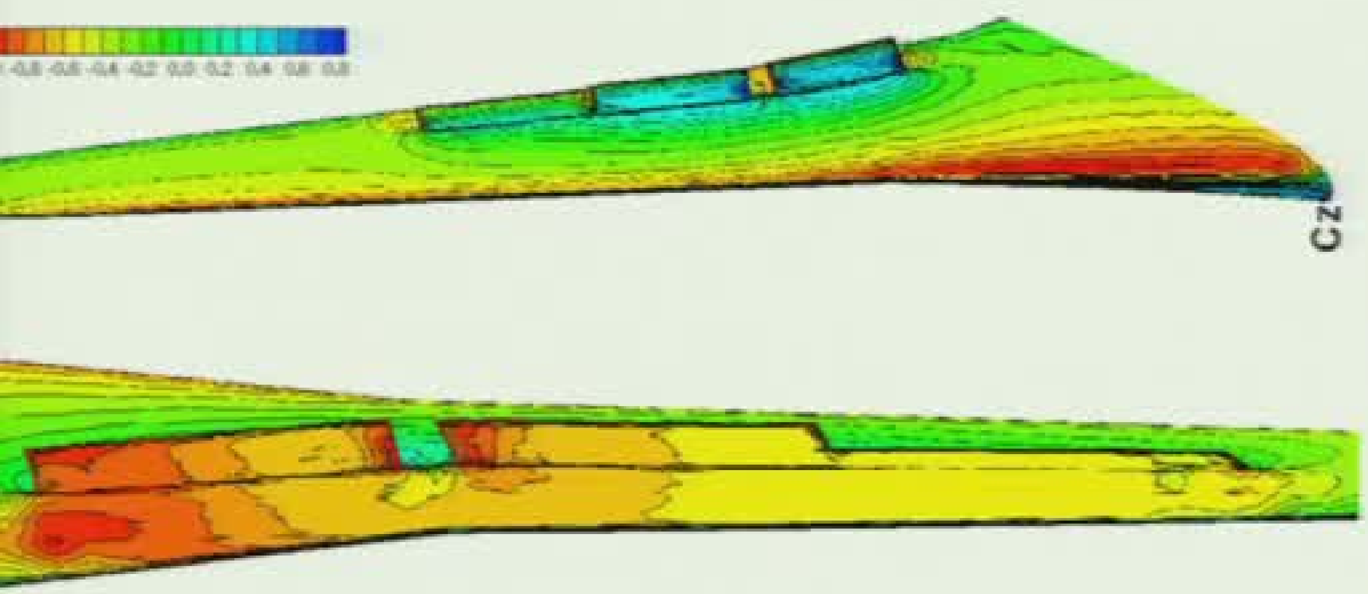
→ Improved RANS modeling

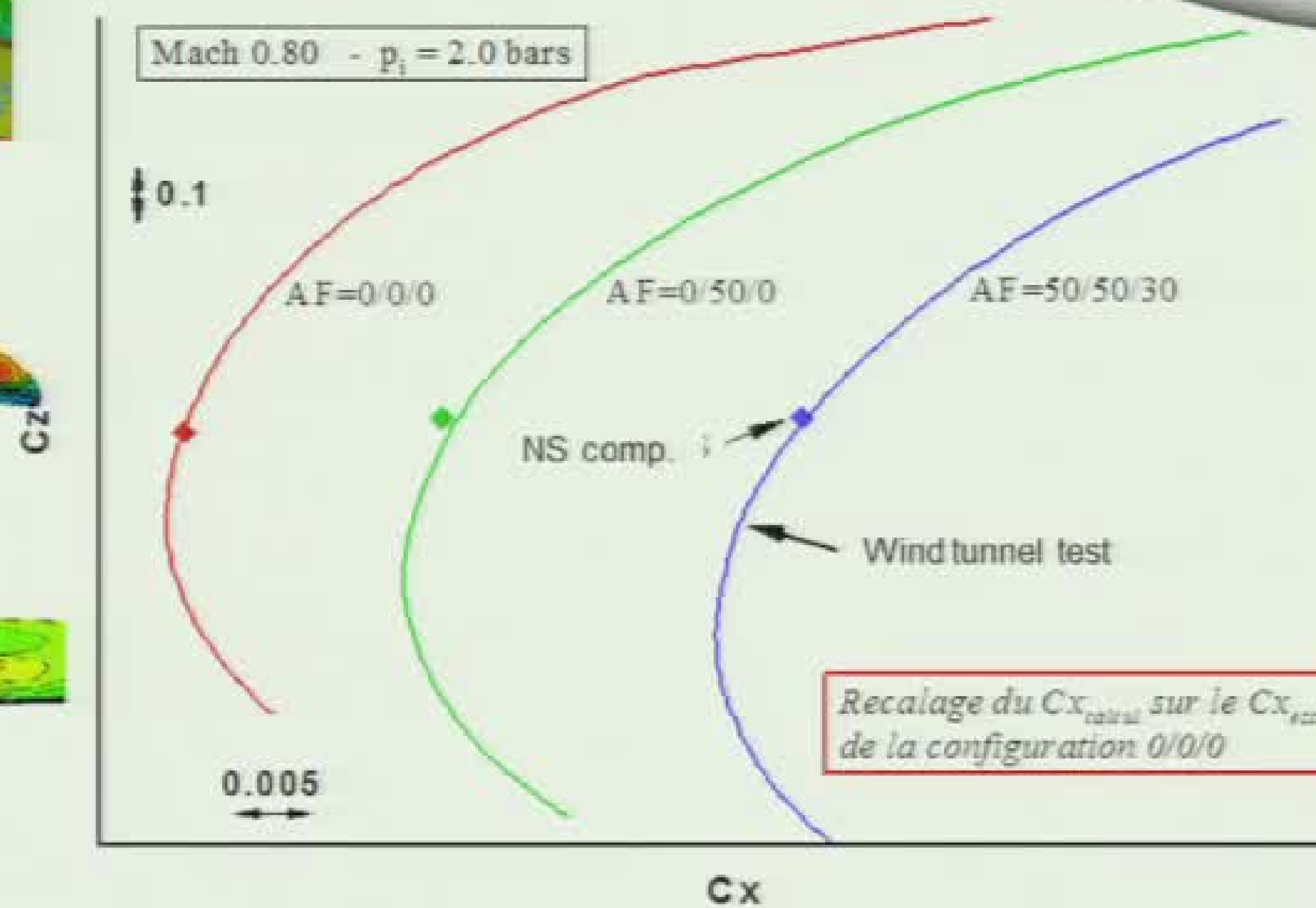
CFD: State of the art of RANS codes

Airbrake design

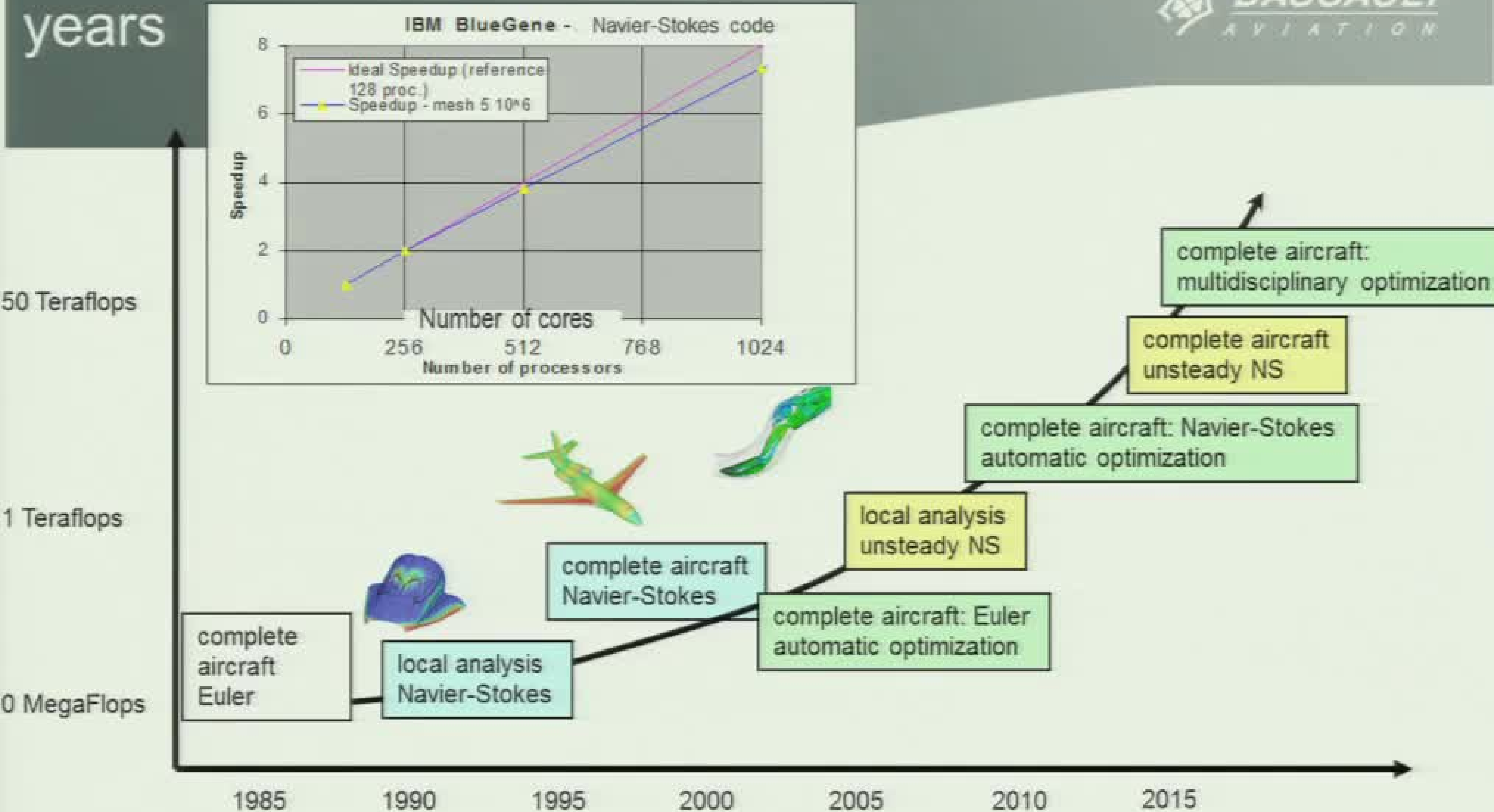








CFD: Computational capabilities over 30 years



CFD: DES application to airframe aeroacoustics

Landing gear noise

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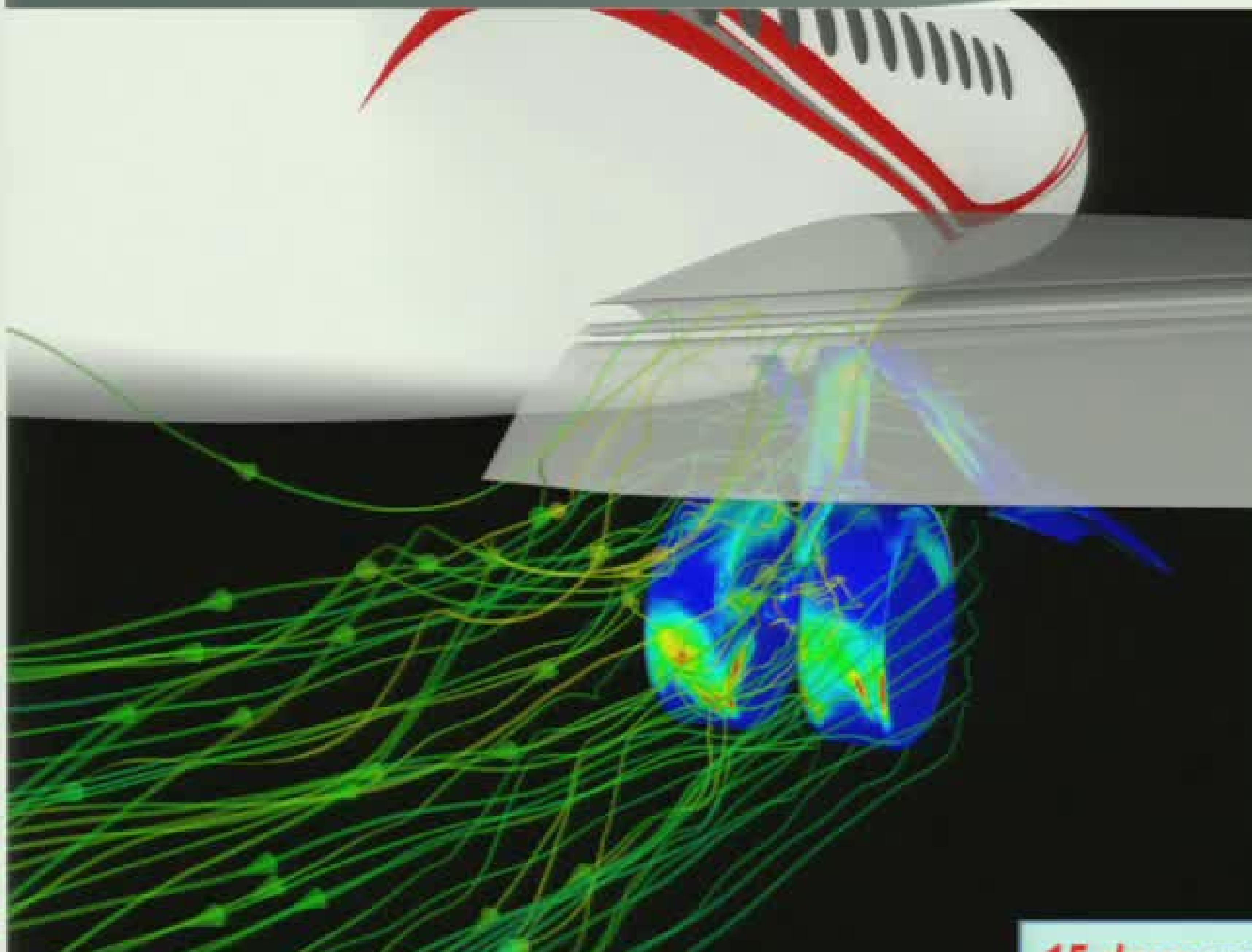

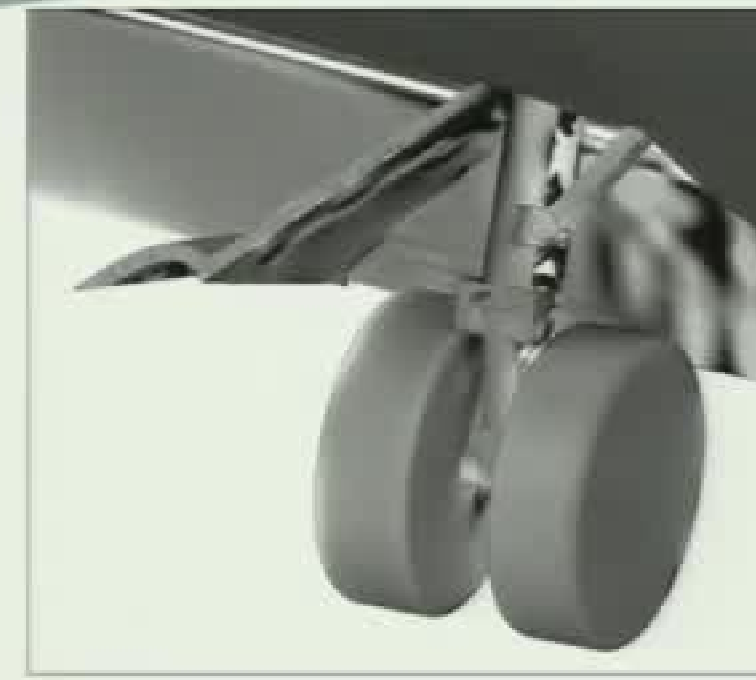

15 days on 2048 BG/P cores

CFD: DES application to airframe aeroacoustics
Landing gear noise
Influence of landing gear bay

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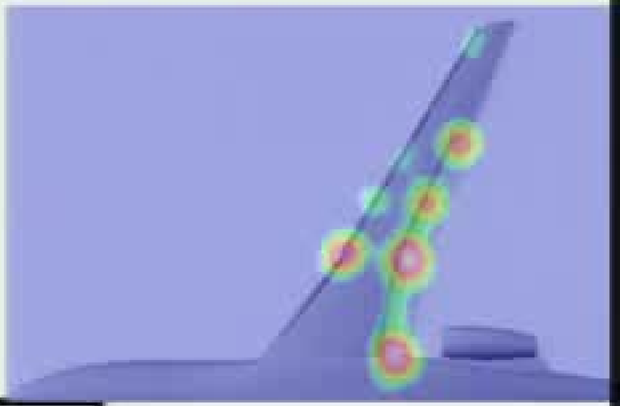
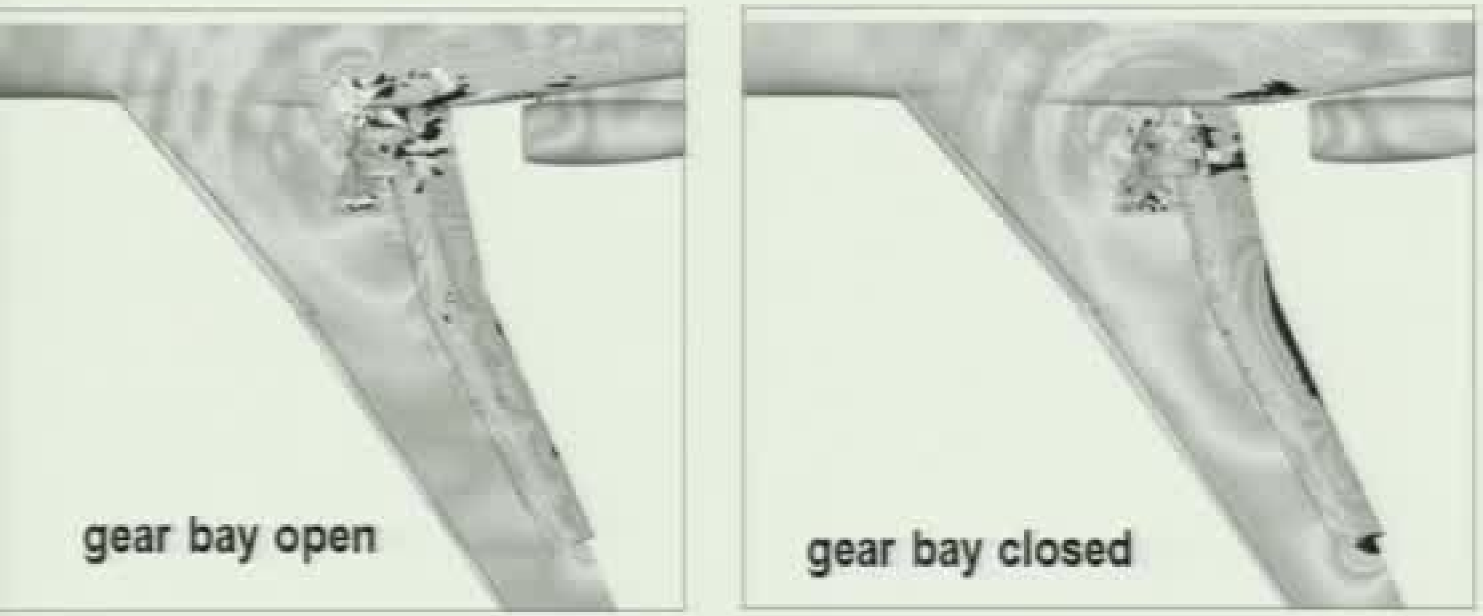
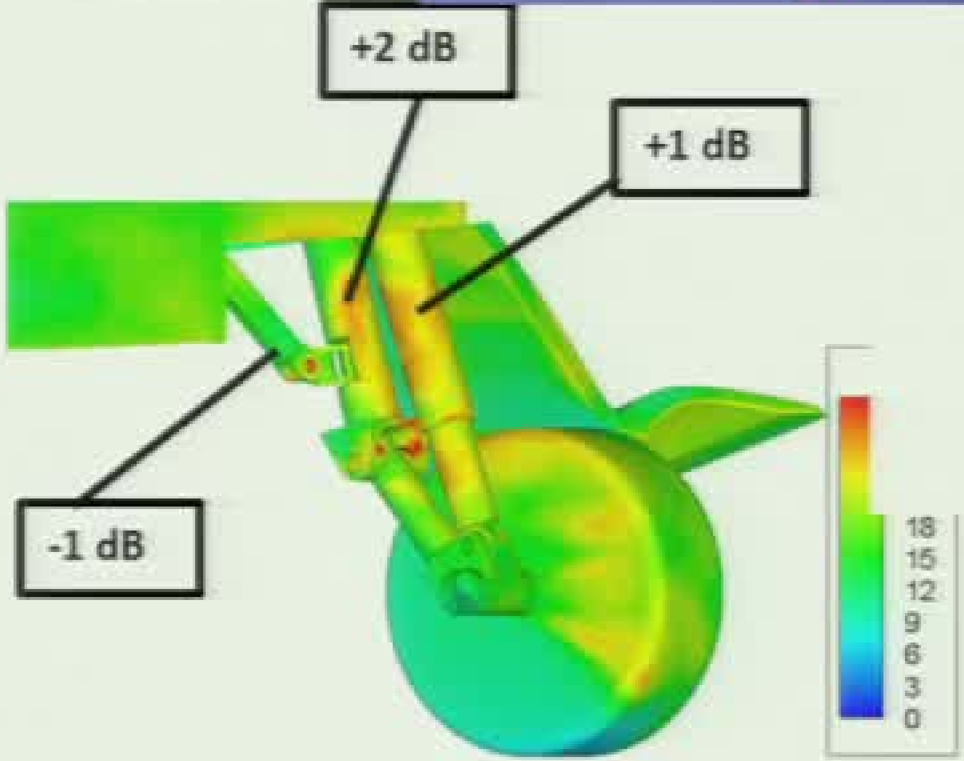
Example of detailed study: gear bay integration

- Gear bay as a noise source
- Disturbance of mean flow field due to gear bay
- Mixing layer over the bay interacting with gear components





Acoustic pressure (bottom view of the aircraft)



Modification of noise sources intensity due to gear bay opening

CFD: DES application to airframe aeroacoustics

Landing gear noise

Influence of geometrical details

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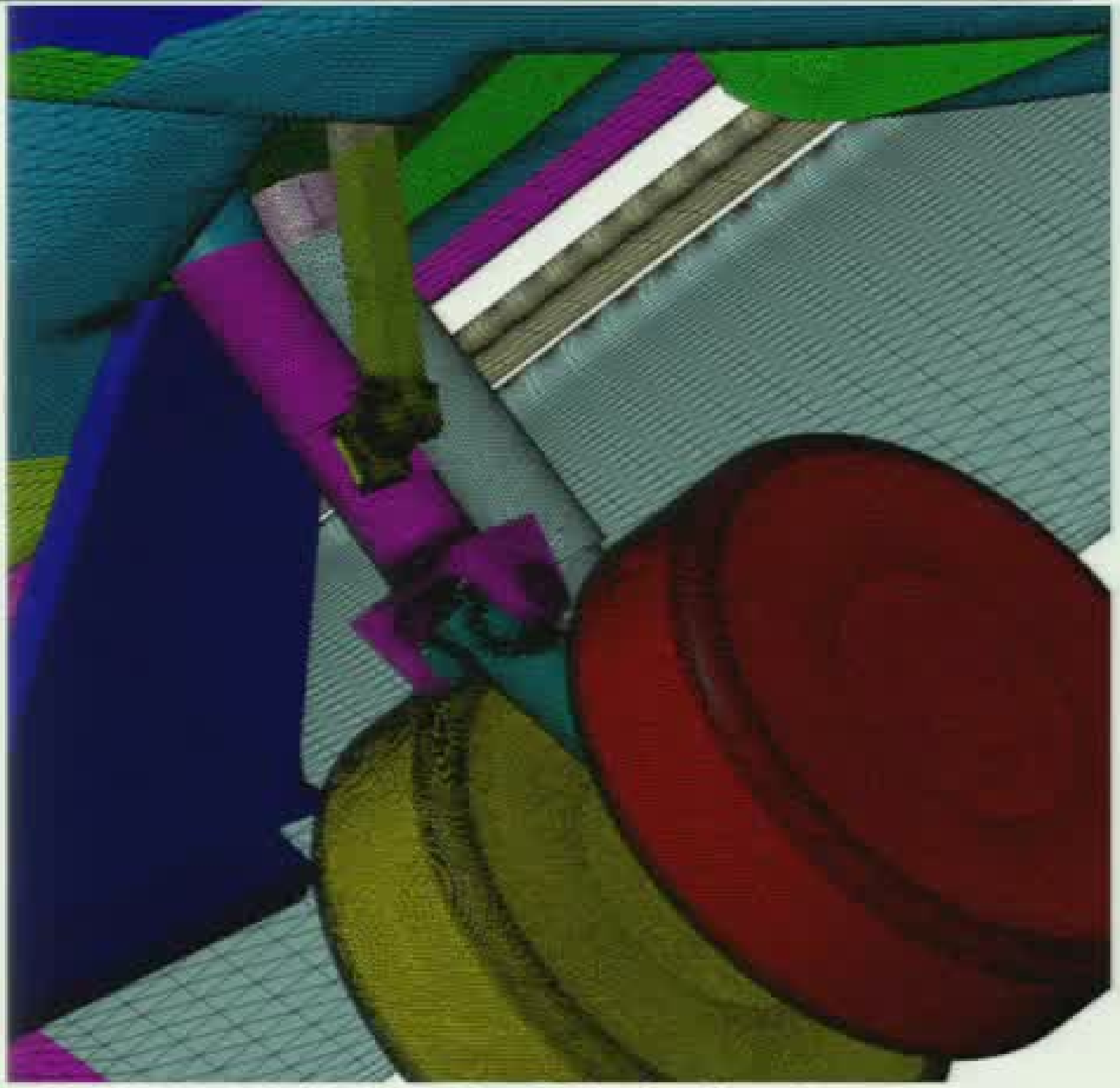
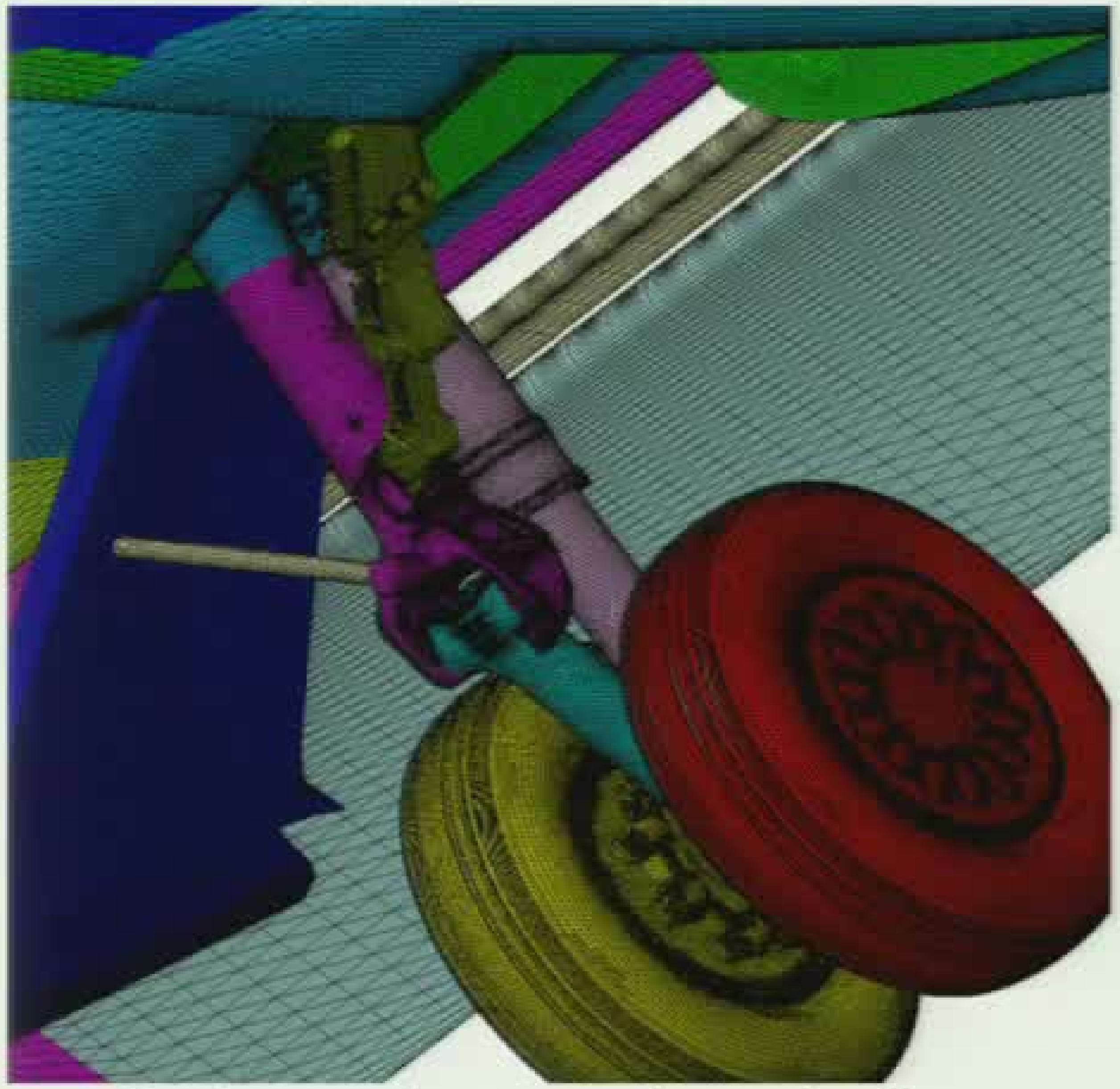


Surface mesh – « simplified » landing gear
430 809 nodes

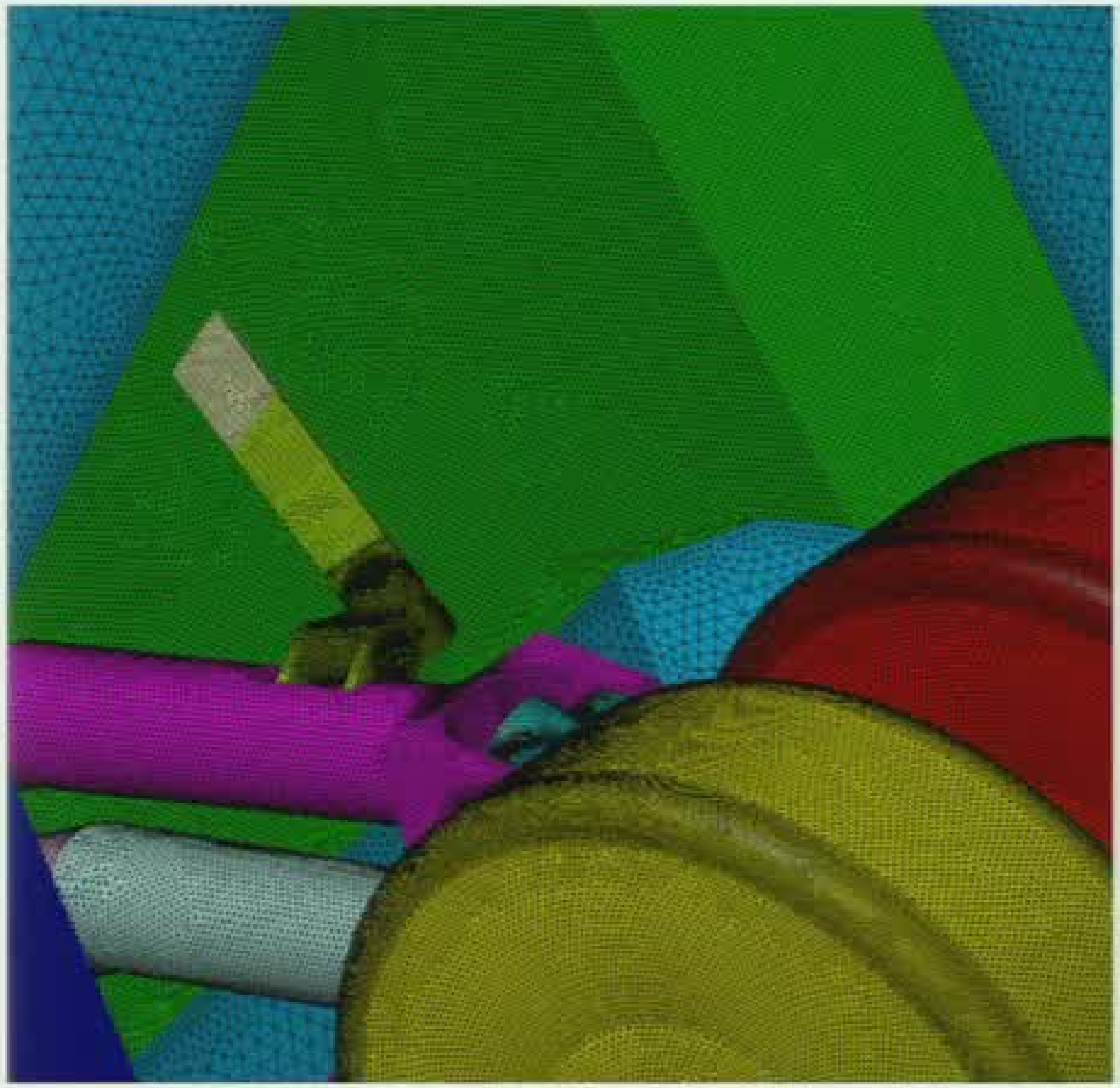


Surface mesh – « complexe » landing gear
493 445 nodes

CFD: Application to airframe aeroacoustics

Landing gear noise

Influence of geometrical details



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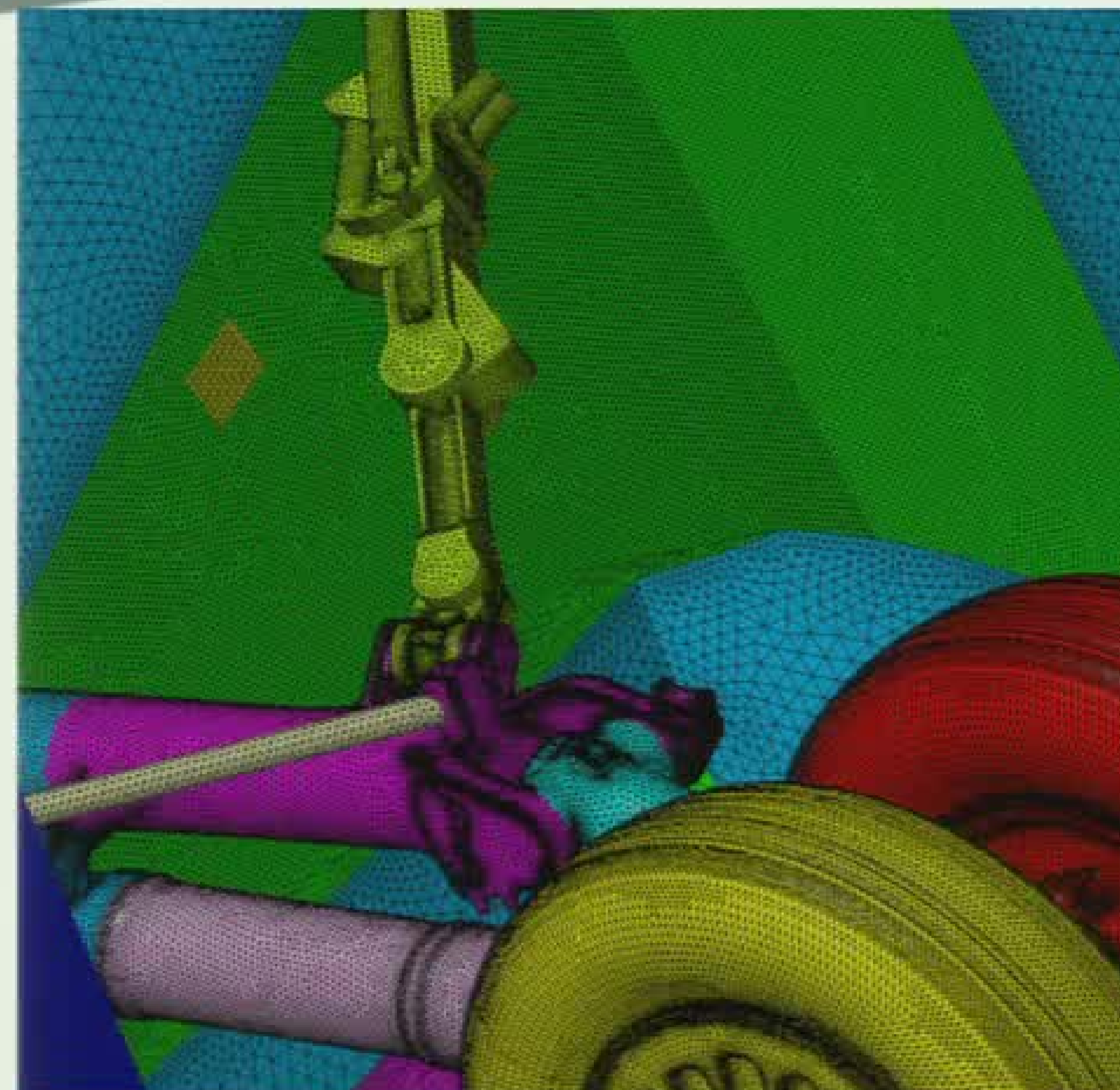

Surface mesh – « complex » landing gear
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CFD: Application to airframe aeroacoustics

Landing gear noise

Influence of geometrical details

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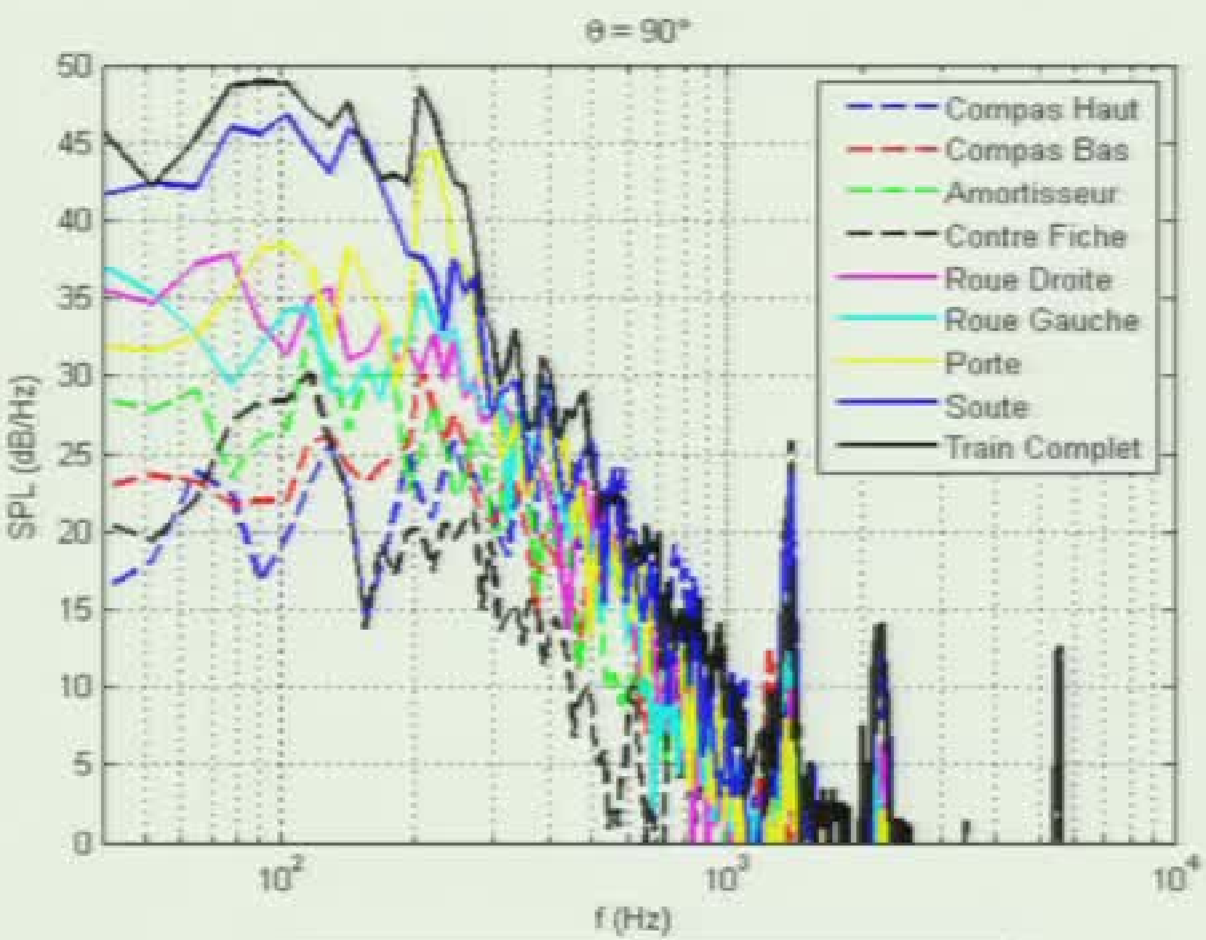
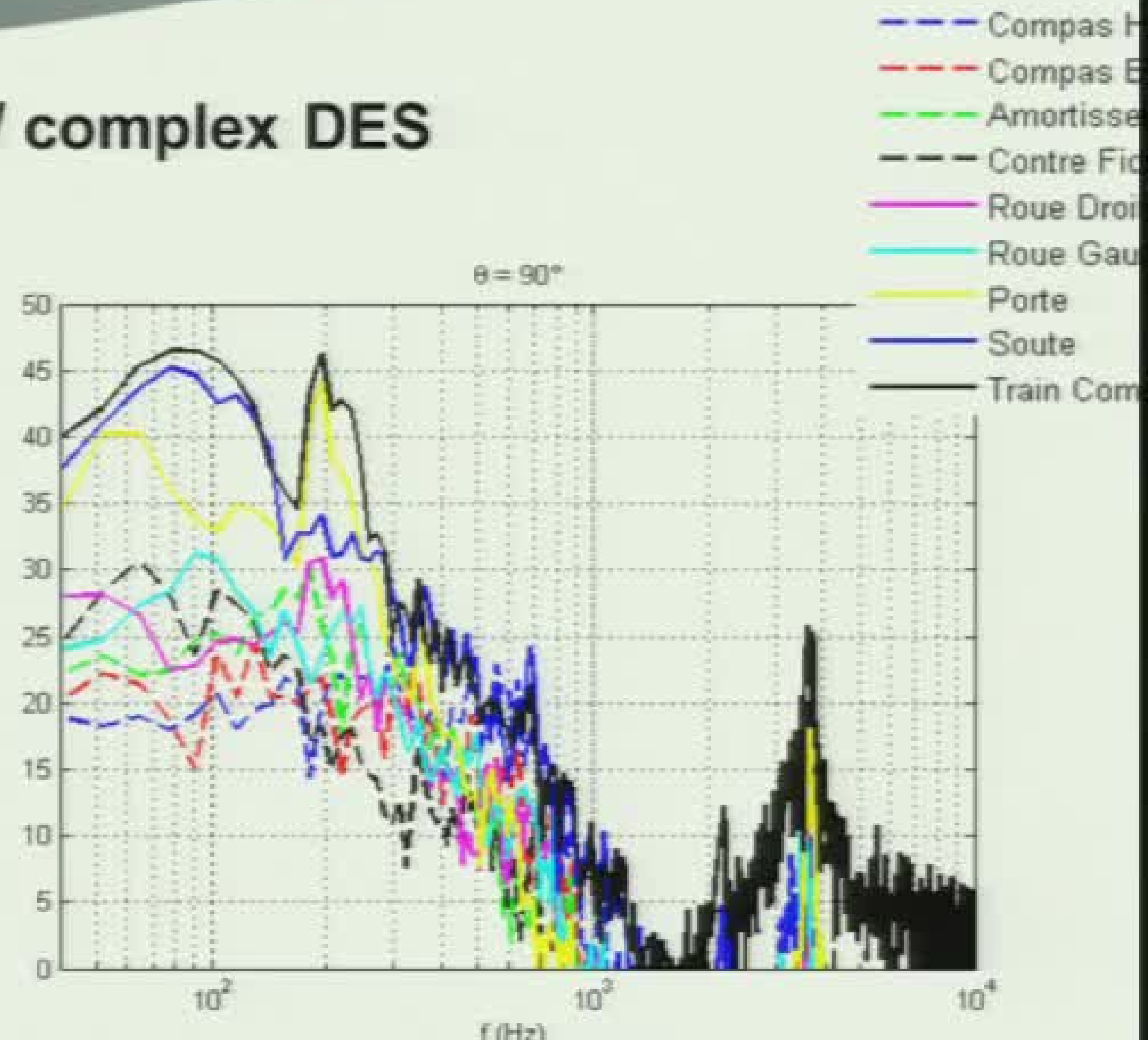
Far field spectra – simple / complex DES



SPL (dB/Hz)
Simple landing gear / Experiment



SPL (dB/Hz)
Complex landing gear / Experiment

Automatic shape optimization
Introduction

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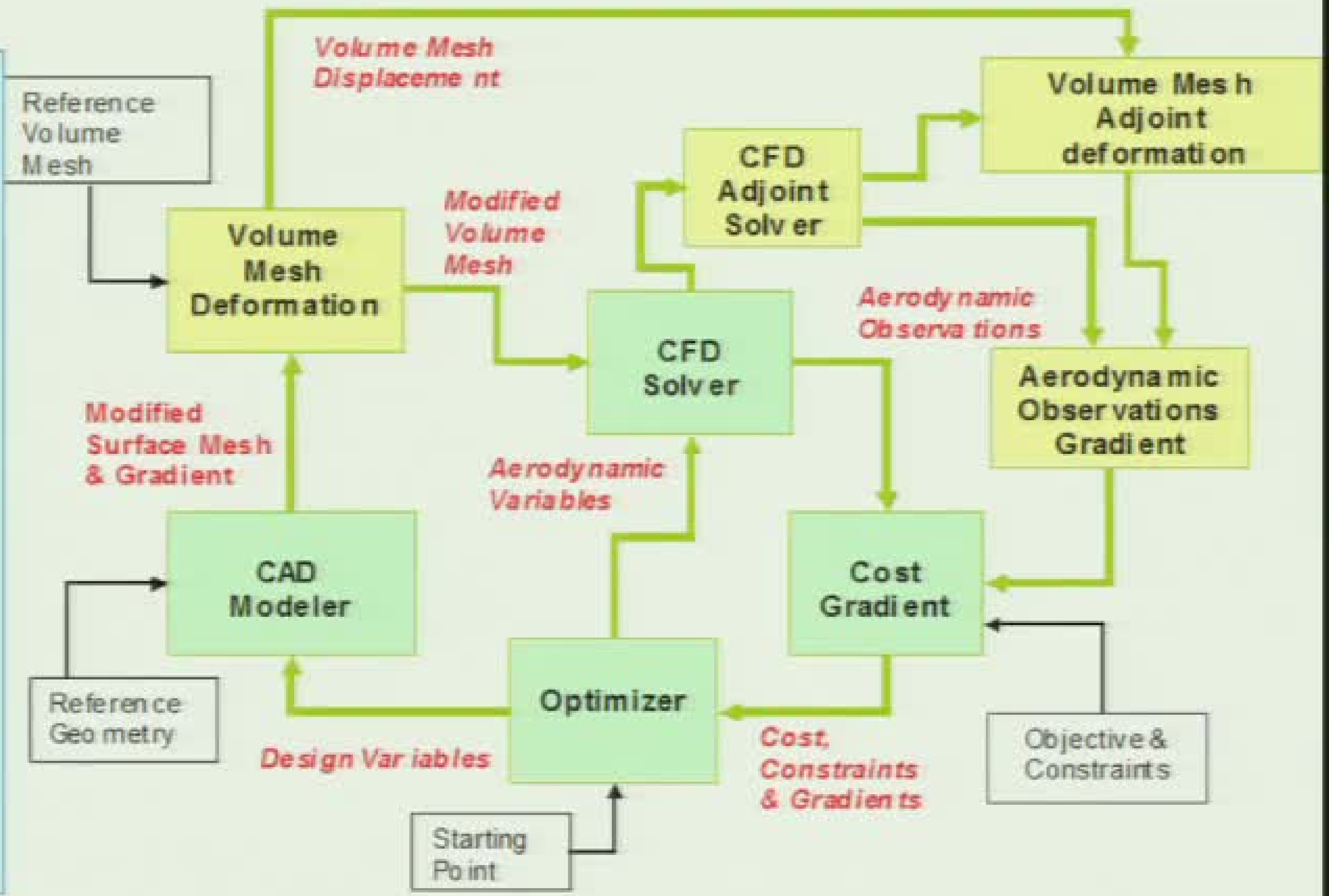
- Complex process : large effort to develop and mature
- Key ingredients:
  - Adjoint approach including mesh motion
  - Parameterization (CAD + features)
  - Extensive library of cost functions
- Process progressively applied to many real life design problems
  - Strong interaction with design team to define relevant formulation of the problem



Automatic shape optimization
Gradient computation

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- State equation $E(\mu, W(\mu)) = 0$
- Cost function $j(\mu) = J(\mu, W(\mu))$
- Constraints functions $g(\mu) = G(\mu, W(\mu))$
- Minimizing $j(\mu)$ while respecting constraints $g_i(\mu) \leq 0$
- Observation

$$f(\mu) = F(\mu, W(\mu)) = \left(J(\mu, W(\mu)), G(\mu, W(\mu))\right)$$

$\mu = (l, v)$ with l = aerodynamic parameters and v = geometric parameters

- CAD modeler $v \rightarrow d(v)$
- Mesh deformation equation $L(d(v), D(v)) = 0$

PDE control theory
J-L Lions
Dunod, 1968

Automatic shape optimization
Gradient computation

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- To estimate

$$\delta f = \frac{df(\mu)}{d\mu} \cdot \delta\mu = \frac{dF(\mu, W(\mu))}{d\mu} \cdot \delta\mu$$

$$\mu = (l, v)$$

$$\delta f = \frac{\partial F}{\partial W}\frac{\partial W}{\partial l} \cdot \delta l + \frac{\partial F}{\partial W}\frac{\partial W}{\partial v} \cdot \delta v + \frac{\partial F}{\partial l} \cdot \delta l + \frac{\partial F}{\partial v} \cdot \delta v$$

- Thanks to the state equation $E(\mu, W(\mu)) = 0$
- and then

$$\delta E(\mu, W(\mu)) = \frac{\partial E}{\partial W} \cdot \delta W + \frac{\partial E}{\partial \mu} \cdot \delta\mu = 0$$

- Thanks to the mesh deformation equation $L(d(v), D(v)) = 0$
- and then

$$\delta L(d(v), D(v)) = \frac{\partial L}{\partial d} \cdot \delta d + \frac{\partial L}{\partial D} \cdot \delta D = 0$$

Automatic shape optimization
Gradient computation

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- *Evaluate variations of the Lagrangian* $\delta f^{*} = \delta f - \Psi(\mu)^{T}\,\delta E - \Phi(\nu)^{T}\,\delta L$
- *with*

$$\left(\frac{\partial E}{\partial W}(l, D(\nu), W(\mu))\right)^{T}\Psi(\mu) = \left[\frac{\partial F}{\partial W}(\mu, W(\mu))\right]^{T}$$

$$\frac{\partial F}{\partial D}(l, D(\nu), W(\mu)) - \Psi^{T}\frac{\partial E}{\partial D}(l, D(\nu), W(\mu)) = \Phi^{T}\frac{\partial L}{\partial D}(d(\nu), D(\nu))$$

- *to obtain*

$$\begin{cases} \dfrac{dF}{dl} = \dfrac{\partial F}{\partial l} - \Psi^{T}\left[\dfrac{\partial E}{\partial l}\right] \\ \dfrac{dF}{d\nu} = -\Phi^{T}\left[\dfrac{\partial L}{\partial d}\dfrac{\partial d}{\partial \nu}\right] \end{cases}$$

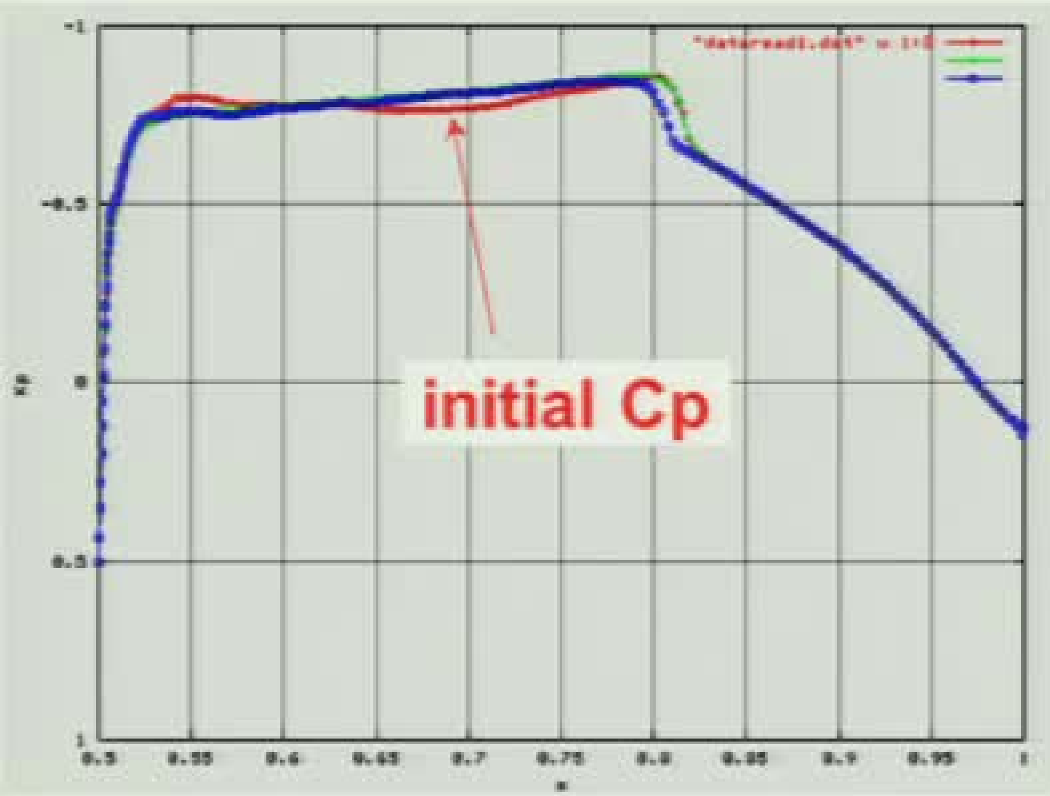
Automatic shape optimization
Optimization ingredients

Automatic Differentiation software Tapenade (INRIA-Sophia-Antipolis)

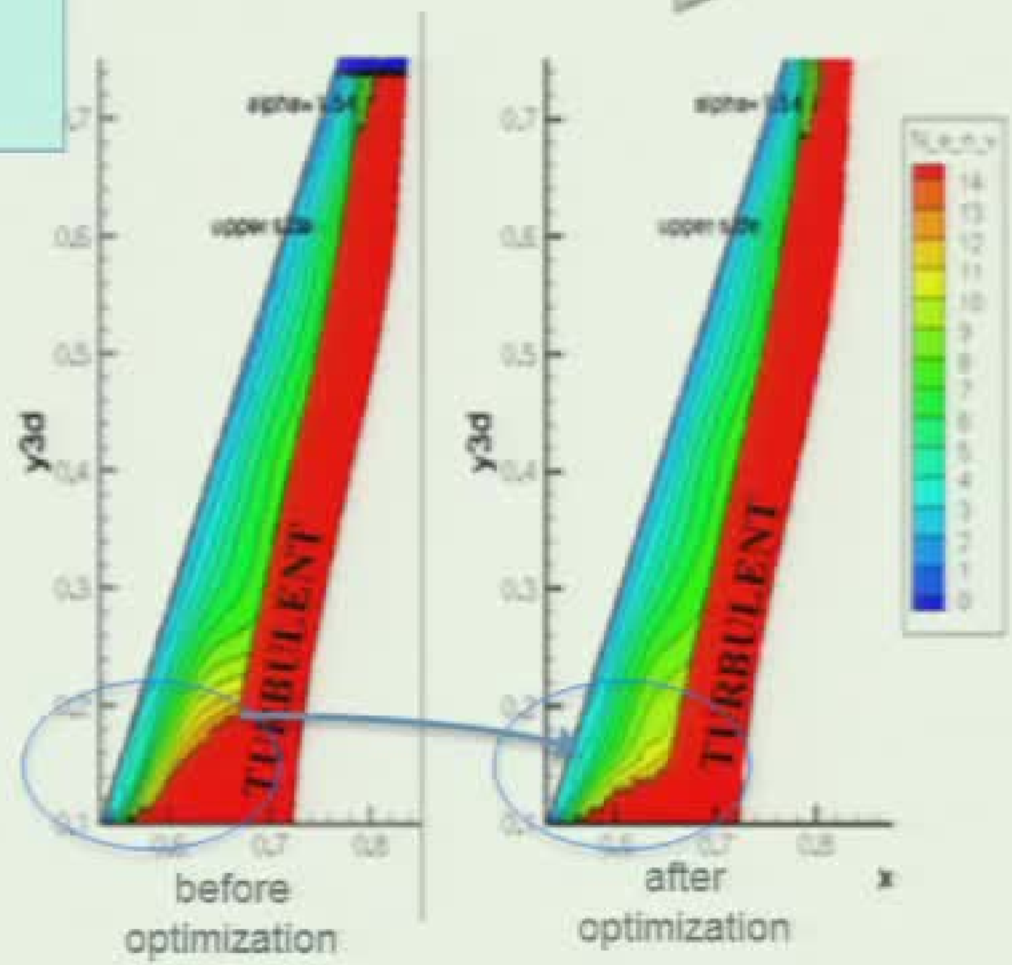
Gradient-based optimization
Feasible (direction) Sequential Quadratic Programming
Feasible Arc Interior Point Algorithm (FAIPA) developed by Prof. J.N. Herskovits & co-workers

Automatic shape optimization
Laminar wing optimization to increase laminar area on wing next to the fuselage

- Laminar wing, $\Phi = 20°$
- Mach = 0.75, angle of attack= 3°
- Objective : increase laminar area on wing next to the fuselage → Cp & δCp/δx target locally
- Variables: Leeward wing section profile
- Navier-Stokes with discrete adjoint



Cp(x/c) – Laminar wing



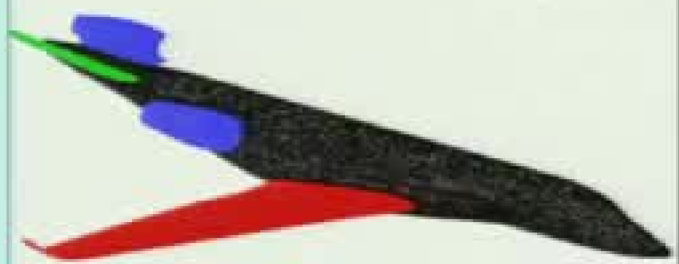
Transition line on leeward side of ECO2 wing

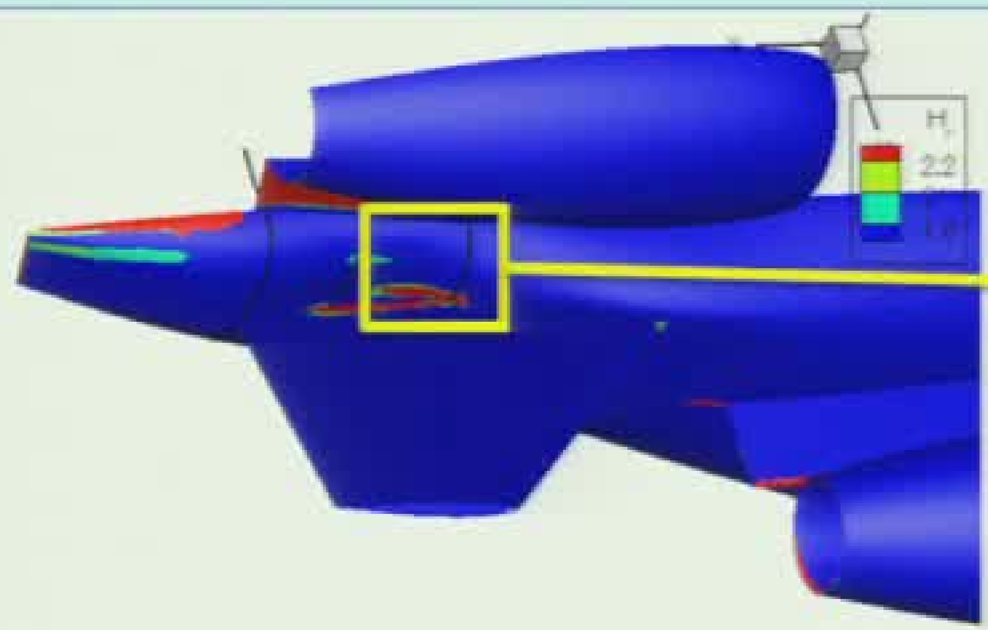
Automatic shape optimization

Afterbody optimization of innovative configuration

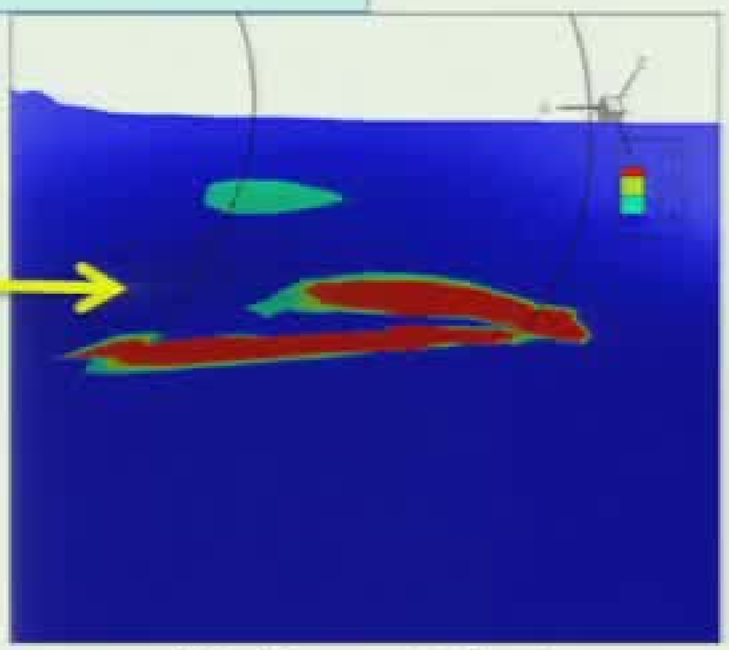
Example of complex objective functions

- Mach = 0.85, angle of attack = 1.5°
- **Cost function is based on the boundary layer shape parameter H_i (ratio of displacement and momentum thickness)**
- Fuselage shape: 10 variables
- Adjoint approach - Convergence requires about 20 NS computations

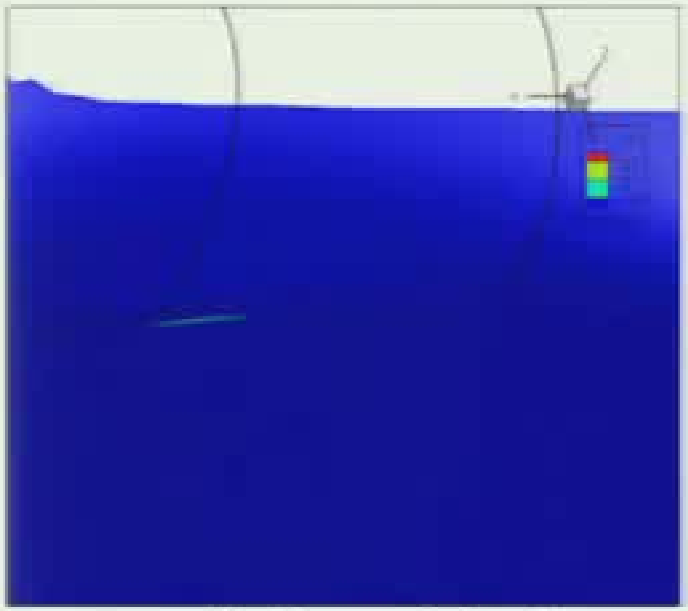




Recirculation zone (Hi>2.2) red

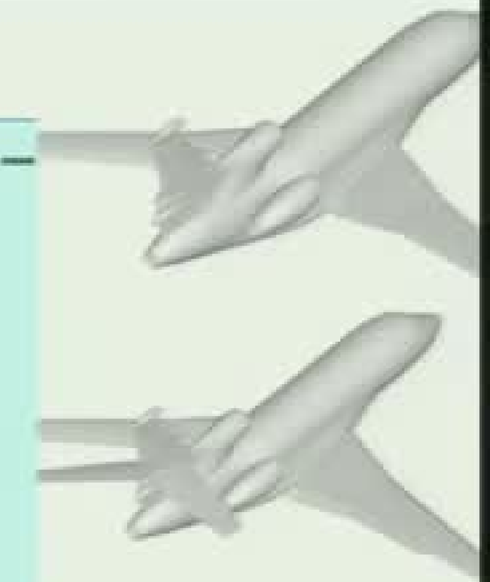


Hi before optimization

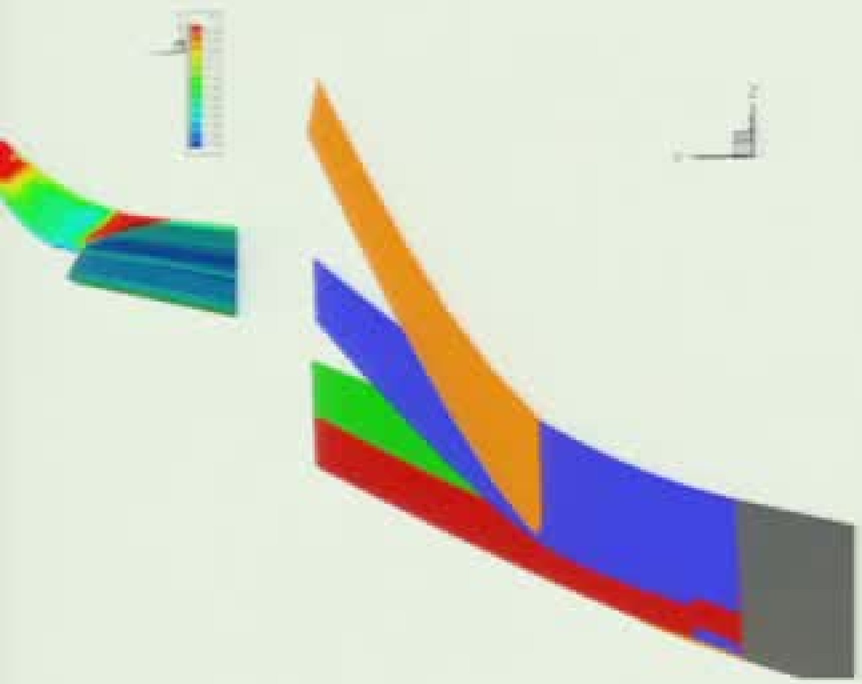


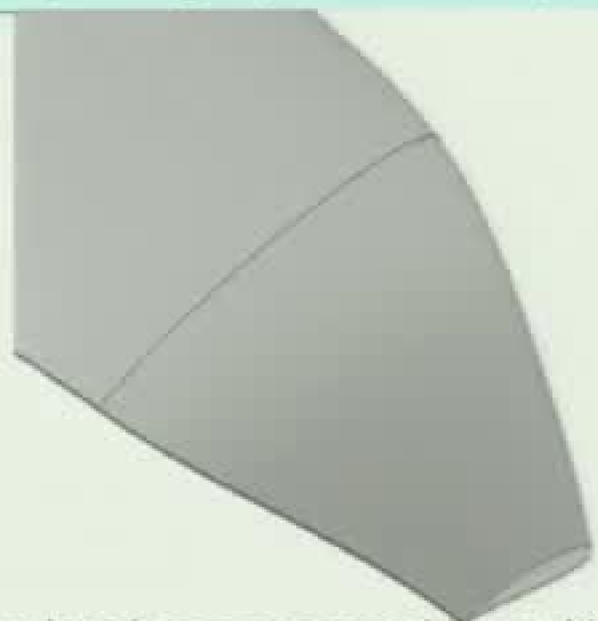
Hi after optimization

Automatic shape optimization
Low speed – high speed wing tip optimization



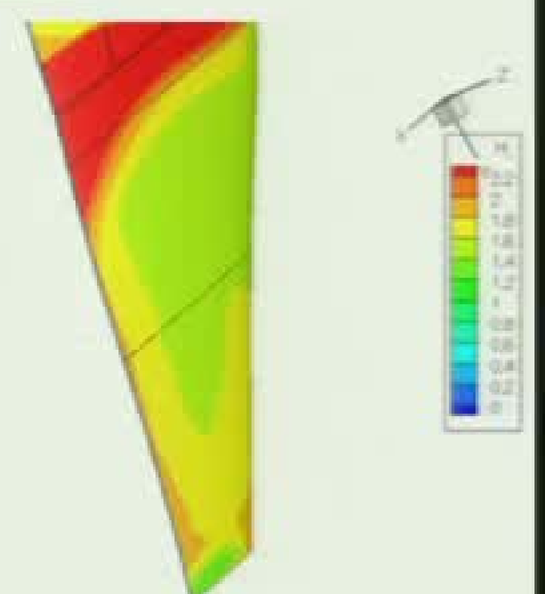
- ultipoint optimization : low speed (Mach = 0.18, high lift configuration) – igh speed (Mach = 0.8, cruise configuration)
- inimize
  - drag at high speed (constraints on lift + bending moment at y = 8 m)
  - surface $H_i > 2$ at low speed
- arameters: aoa (at High speed), twist, sweep angle, dihedral, thickness, span





winglet shape proposed by multipoint optimization

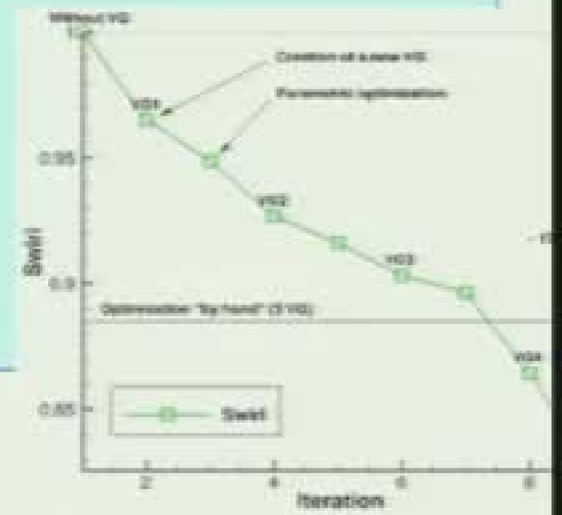
1 % reduction of drag

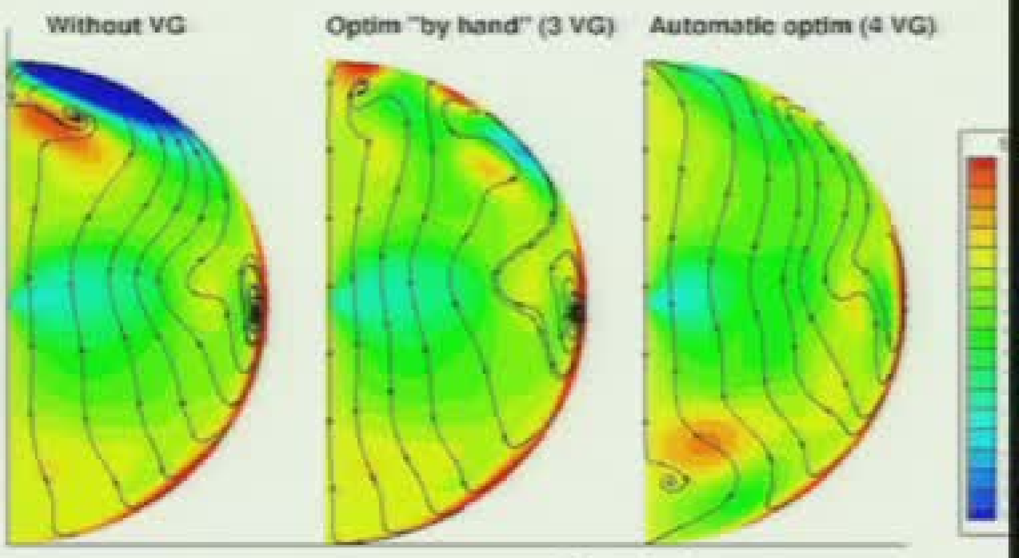


Boundary layer shape factor on the optimized winglet – high lif configuration

Automatic shape optimization
Combination with topological optimization

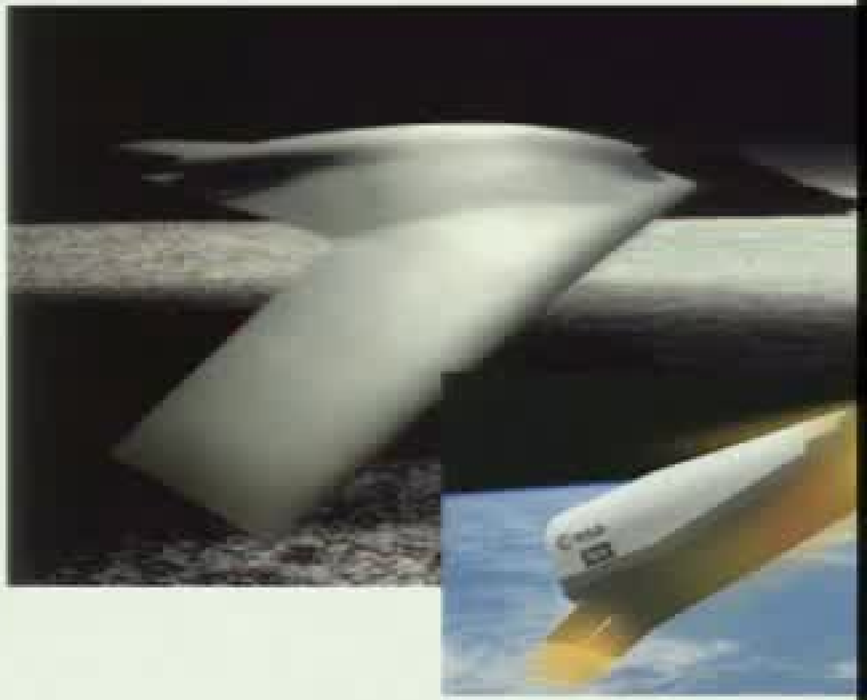
- Automated methods for the control and the optimization of separated flows
- Application to curved air ducts for UCAV
- Use of mechanical or fluidic vortex generators (VG)
- Optimization: topological + shape





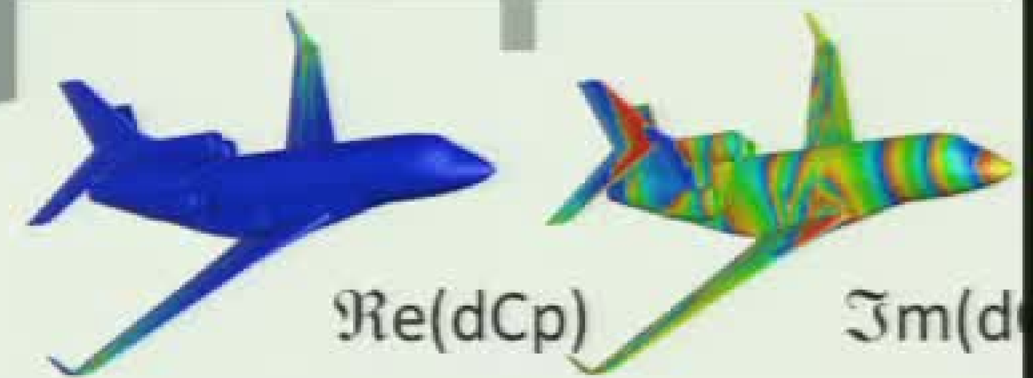
PhD thesis J. Chetboun : Dassault Aviation / Ecole Polytechnique / DGA.

Automatic shape optimization
Achievements



- The total in-house control of the tooled process enables us to develop an optimization chain for aerodynamic design at the industrial level
- Automatic shape optimization accelerates the elementary design cycle and gives access to an enlargement of exploration of potential solutions
- The analysis by engineers remains an essential element of the design cycle
- This optimization chain is currently daily used for industrial design

Multiphysics: CFD for Aeroelasticity
Linearized Euler and Navier-Stokes equations



Aerodynamics : Euler or Navier Stokes equations $E(\boldsymbol{V}_0, \boldsymbol{x}_0) = 0$

Linearization:

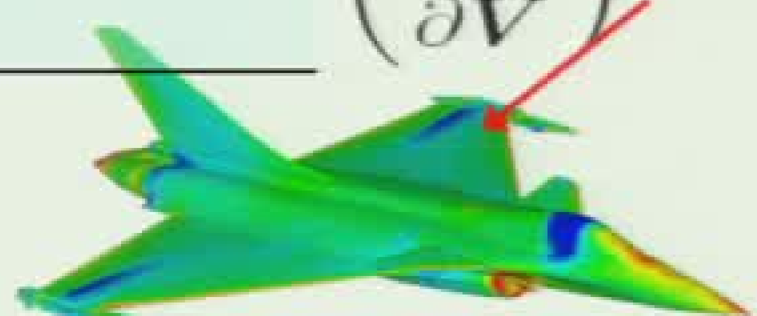
$$\boldsymbol{V} = \boldsymbol{V}_0 + d\boldsymbol{V}$$

$$\boldsymbol{x} = \boldsymbol{x}_0 + d\boldsymbol{x}$$

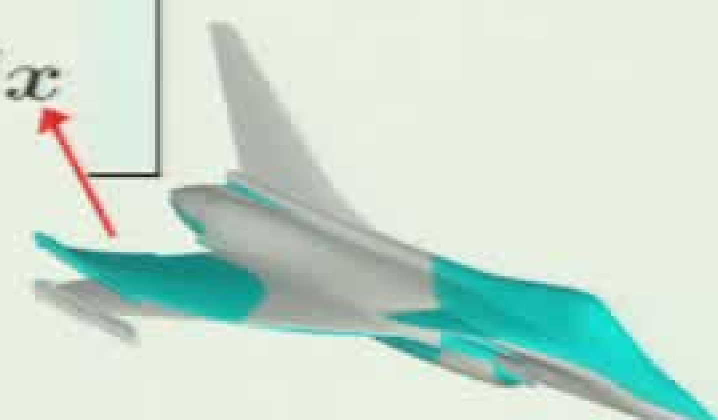
$$dE = \frac{\partial E}{\partial \boldsymbol{V}} d\boldsymbol{V} + \frac{\partial E}{\partial \boldsymbol{x}} d\boldsymbol{x} = 0$$

Linear problem

$$\left(\frac{\partial E}{\partial \boldsymbol{V}}\right) d\boldsymbol{V} = -\left(\frac{\partial E}{\partial \boldsymbol{x}}\right) d\boldsymbol{x}$$



Output = dV (complex aerodynamic pressure force)



Input = dx (complex nodal displacement)

Multiphysics: CFD for Aeroelasticity

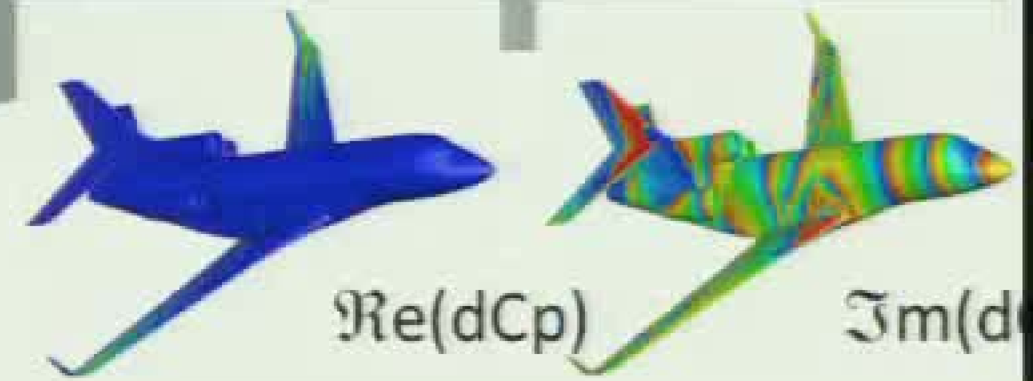
Linearized CFD - Validation

Transonic wing in ONERA S2MA wind tunnel

- Linearized CFD can predict “transonic dip”
- Linearized NS leads to improved results compared to linearized Euler

Multiphysics: CFD for Aeroelasticity
Linearized Euler and Navier-Stokes equations

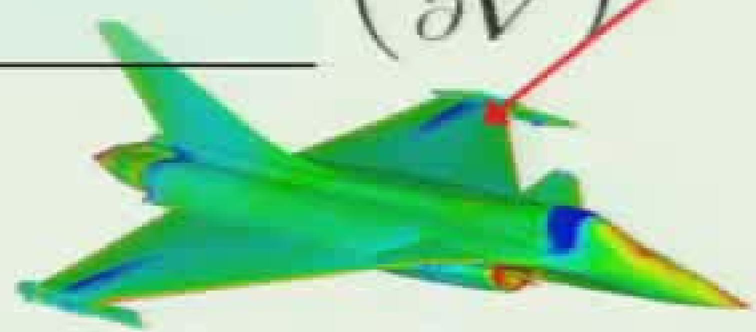
DASSAULT AVIATION



Aerodynamics : Euler or Navier Stokes equations $E(\boldsymbol{V}_0, \boldsymbol{x}_0) = 0$

Linearization:
$$\boldsymbol{V} = \boldsymbol{V}_0 + d\boldsymbol{V}$$
$$\boldsymbol{x} = \boldsymbol{x}_0 + d\boldsymbol{x}$$
$$dE = \frac{\partial E}{\partial \boldsymbol{V}} d\boldsymbol{V} + \frac{\partial E}{\partial \boldsymbol{x}} d\boldsymbol{x} = 0$$

Linear problem
$$\left(\frac{\partial E}{\partial \boldsymbol{V}}\right) d\boldsymbol{V} = -\left(\frac{\partial E}{\partial \boldsymbol{x}}\right) d\boldsymbol{x}$$



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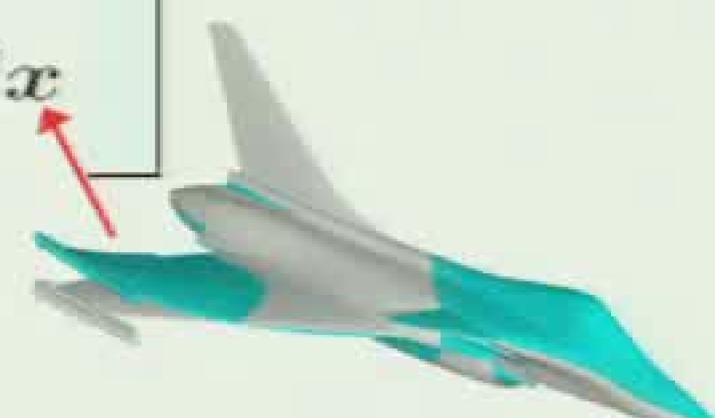

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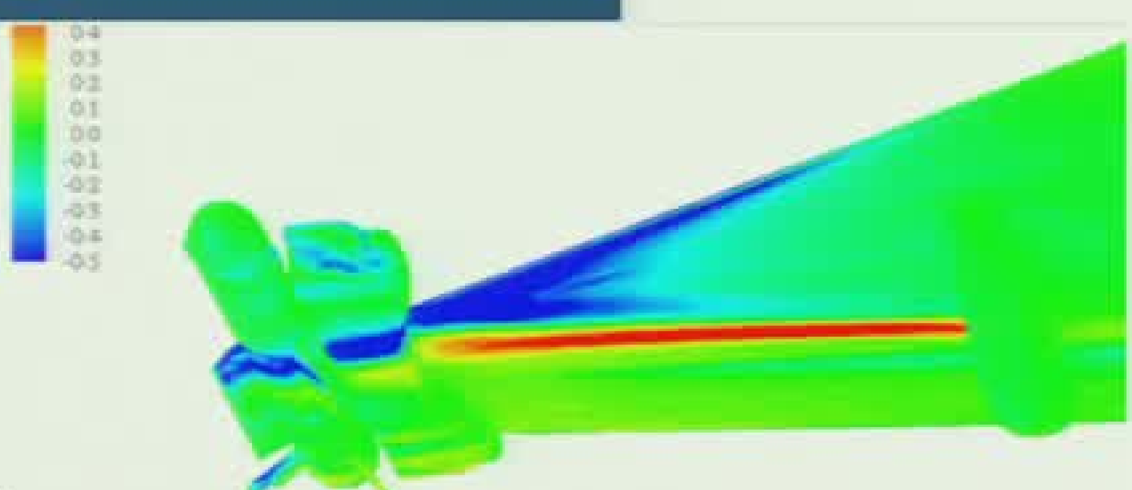
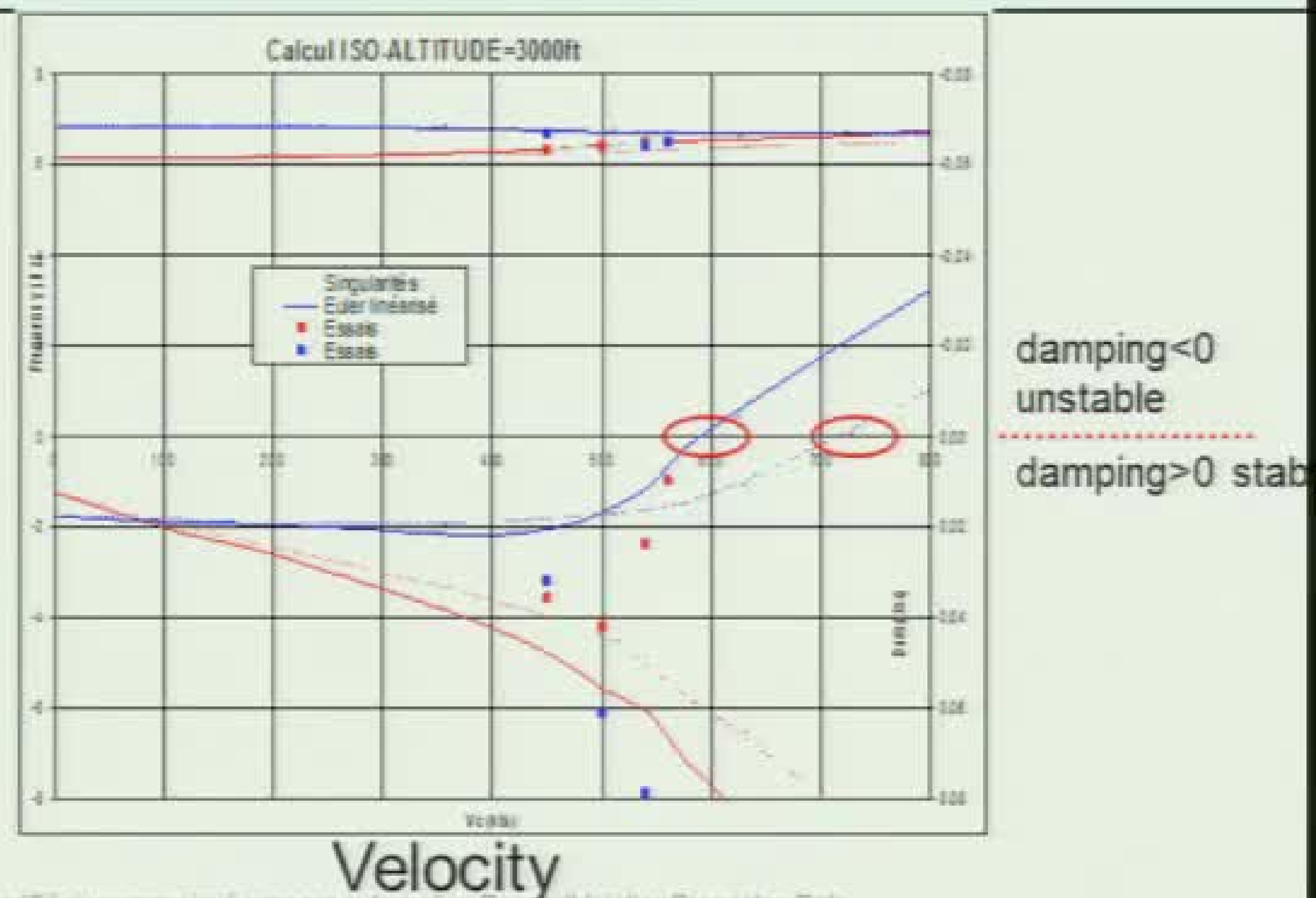
Multiphysics: CFD for Aeroelasticity
Application to military aircraft

- Linearized Euler approach applied to various weapon configurations f[cut off] a combat aircraft (more than 10 000 computations)
- Example : influence of the missile correctly predicted (agreement with flight test)





Multiphysics: CFD for Aeroelasticity

Linearized Euler and Navier-Stokes equations

Challenge for the future :

- **further increase efficiency and robustness of linear solvers**

- very large scale linear problem :100-200 million unknowns
- very sparse ill-conditioned non symmetric matrix
- massively parallel computers and novel architectures

→ Research need: innovative iterative solvers in HPC environment

Computational Electromagnetics

DASSAULT AVIATION

Formulations by multidomain equations: for each domain *j* write

$$\frac{jZ_j}{4\pi}\int_{\Sigma_j}(k_jG_j-\frac{1}{k_j}\nabla\nabla' G_j)J'ds'-\frac{1}{2}(jM\times n)-\frac{j}{4\pi}\int_{\Sigma_j}(\nabla' G_j)\times jM'ds'=E_i$$

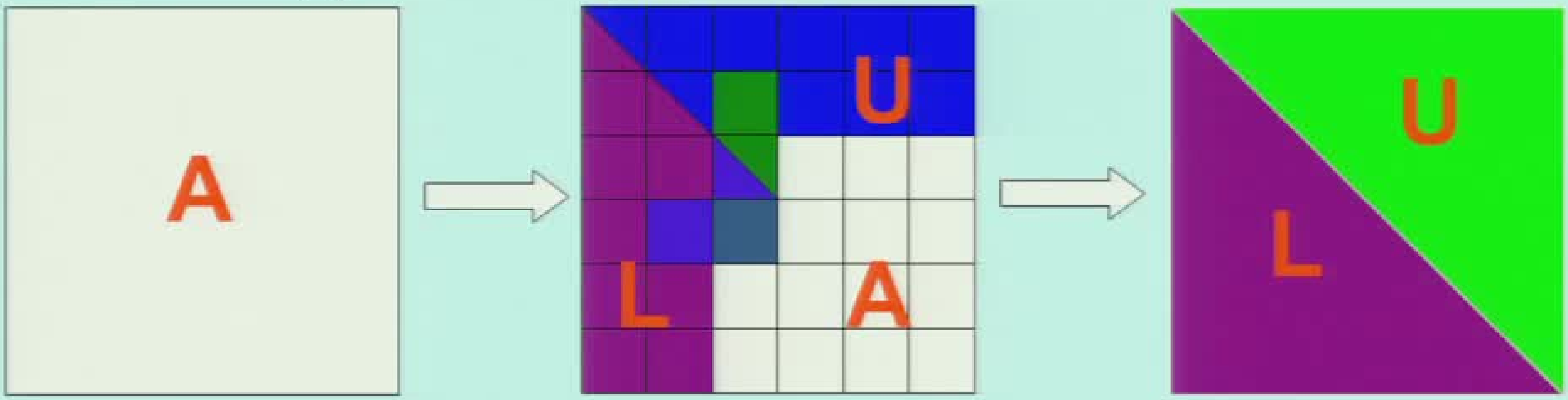
$$-\frac{1}{2}(J\times n)-\frac{j}{4\pi}\int_{\Sigma_j}(\nabla' G_j)\times J'ds'+\frac{j}{4\pi Z_j}\int_{\Sigma_j}(k_jG_j-\frac{1}{k_j}\nabla\nabla' G_j)jM'ds'=jH_i$$

Frequency domain
Variational formulation
Finite elements discretization

Homogeneous materials, thin materials (impedance conditions)

Computational Electromagnetics
Out-of-core linear solvers

Solution of linear systems ($AX = B$) with A complex full matrix, p right hand-sides
A stored on disk (up to over 7 To)

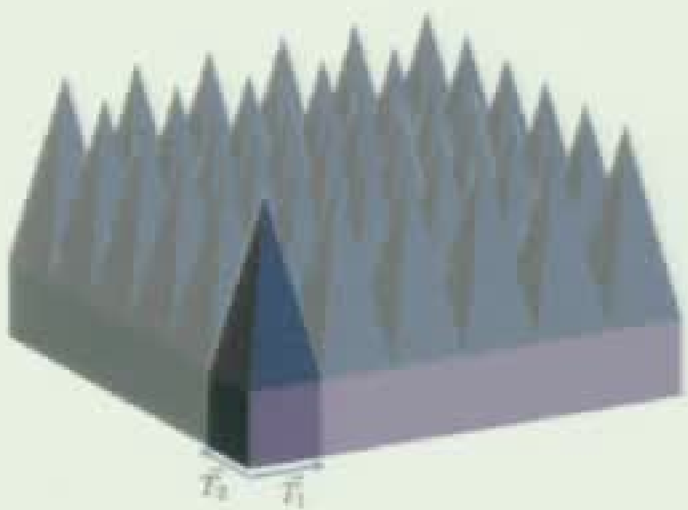


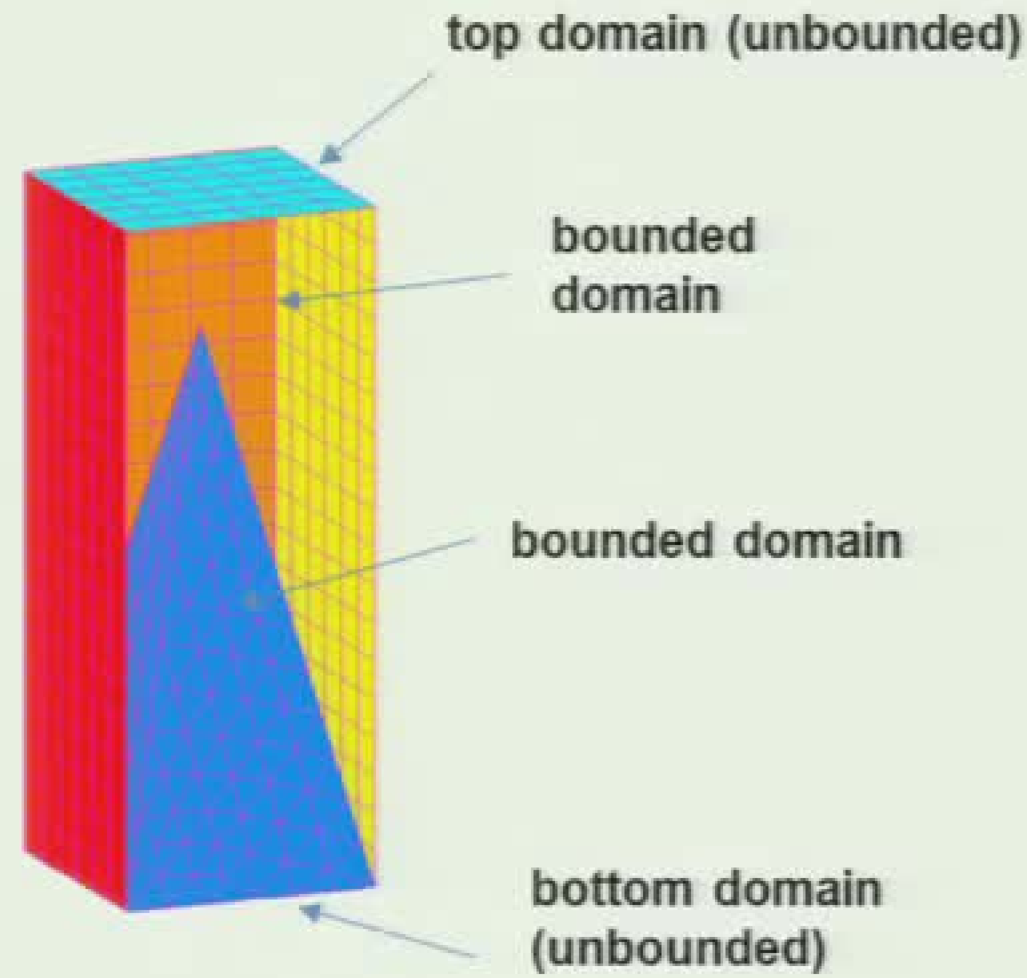
FMSlib :

- commercial product
- portable (Bull, IBM, PC…), efficient, reliable

Computational Electromagnetics
Complex materials

- **Metamaterials : bi-periodic networks of complex cells**
- **Fictitious surface to use limited domains**
- **Pseudo-periodic conditions at the interfaces**
- **Pseudo-periodic Green function**



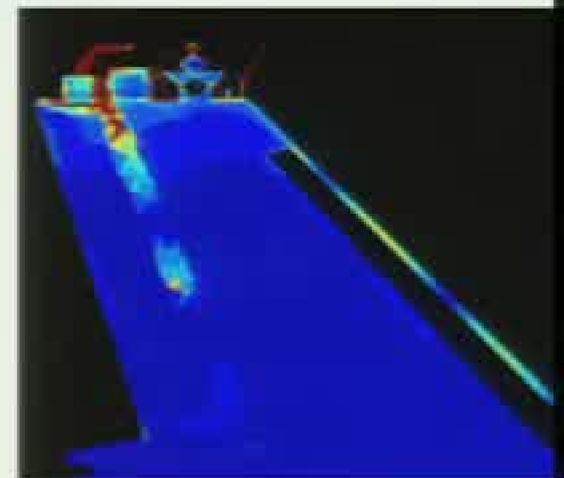


Example of a multi-domain unit cell

Cooperation with CNRS laboratories, CEA

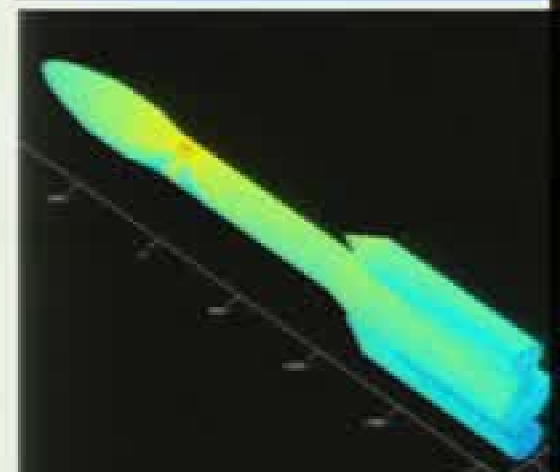
Computational Electromagnetics
Multi-level Fast Multi-Pole Method (MLFMM) to sustain the frequency increase

When the direct solution becomes too heavy (~ some days to . years) or simply impossible (disk size)



Limited robustness of iterative solver:

- sensitive to local mesh refinements: geometrical details (antennas, …), materials with high index
- very much dependent upon the complexity of physical phenomena



Limitation in size of iterative solver:

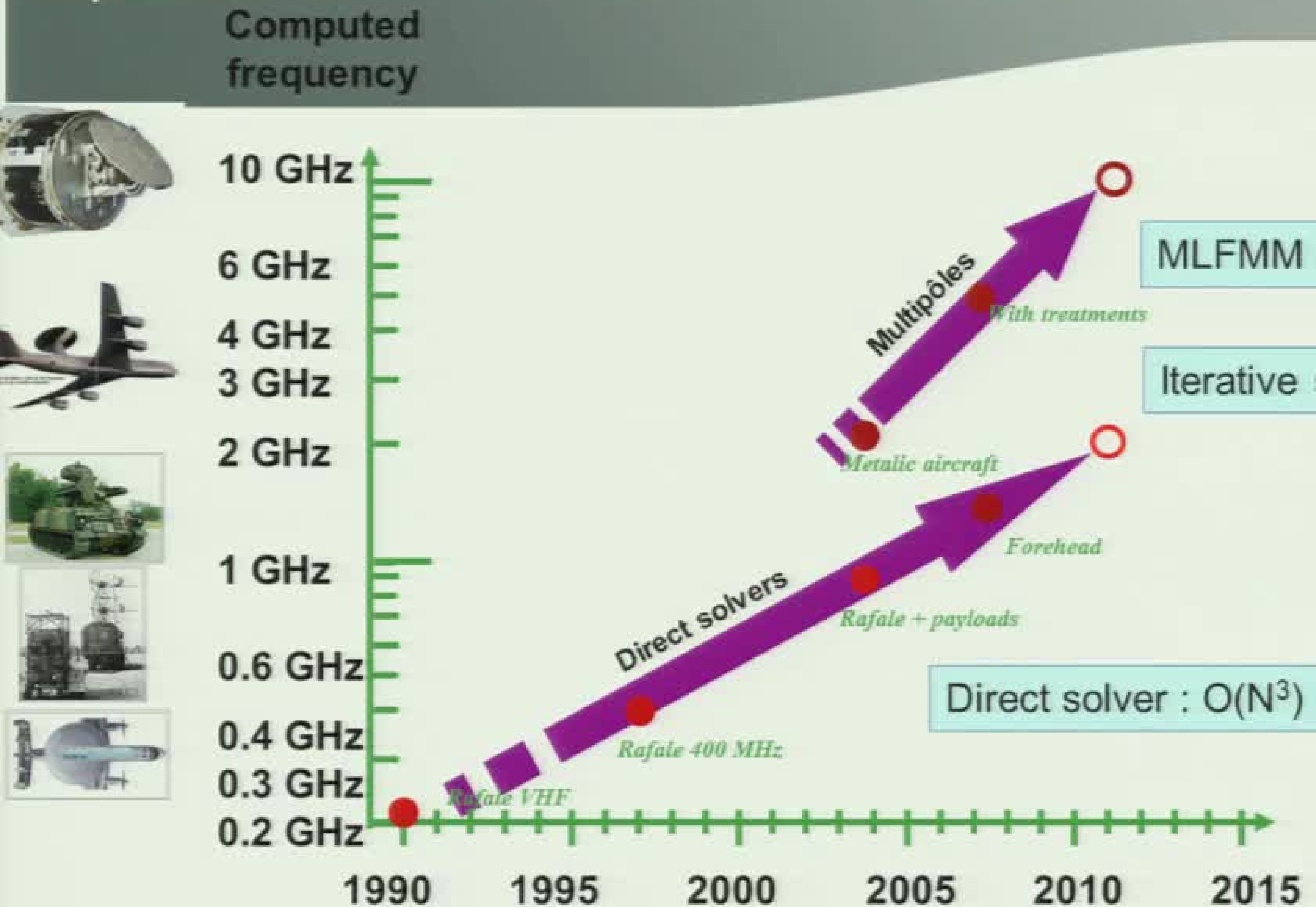
- Computational time directly proportional to the number of incident fields to be evaluated

he full characterization of a complete aircraft in X band would require years of omputation

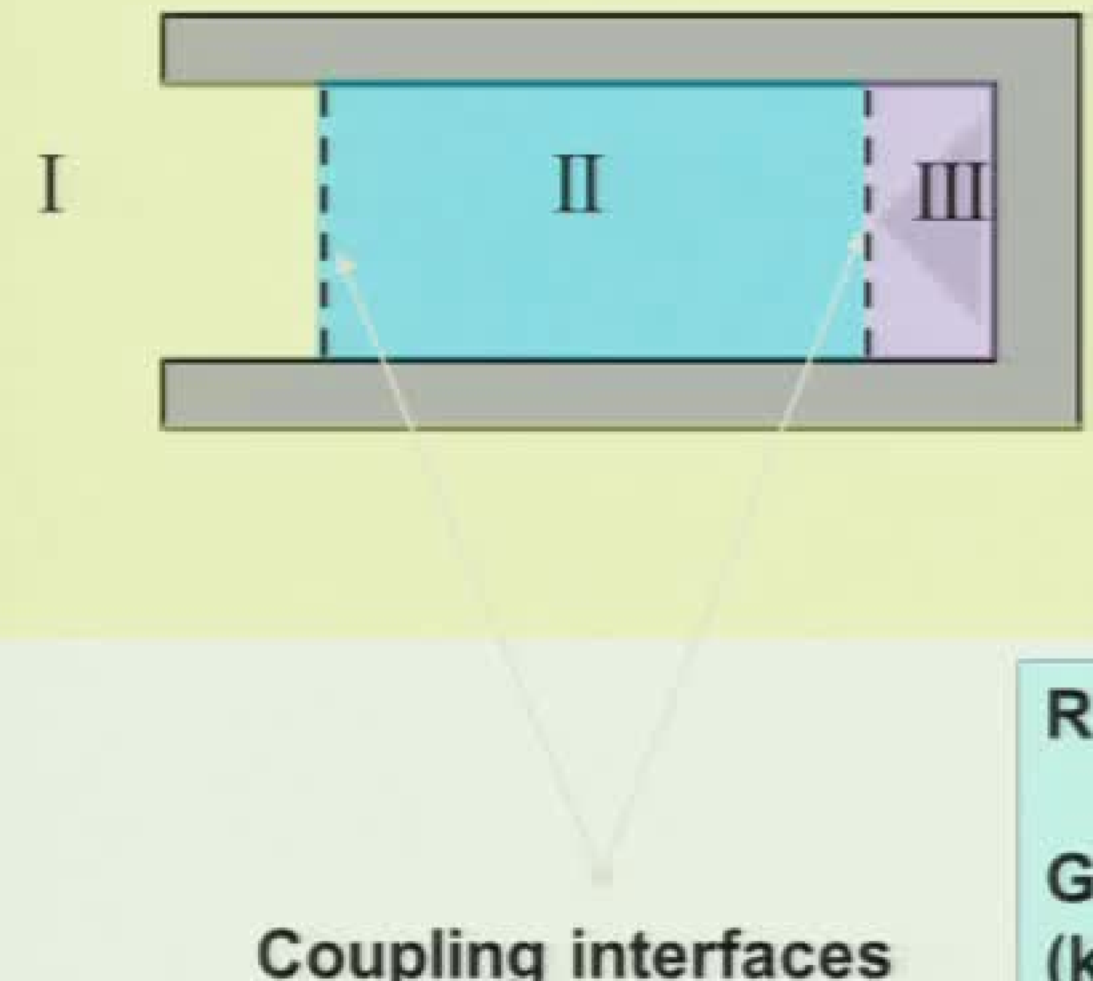
> MLFMM based on mathematical developments of the Green function (truncature o e series) as an accelerator of an iterative method

Computational Electromagnetics

Capacities



Computational Electromagnetics
Collaborative computations by the multi-domain technique



Decomposition of the computational domain

- I : external domain
- II : conduct
- III : engine

Reduction of problem sizes

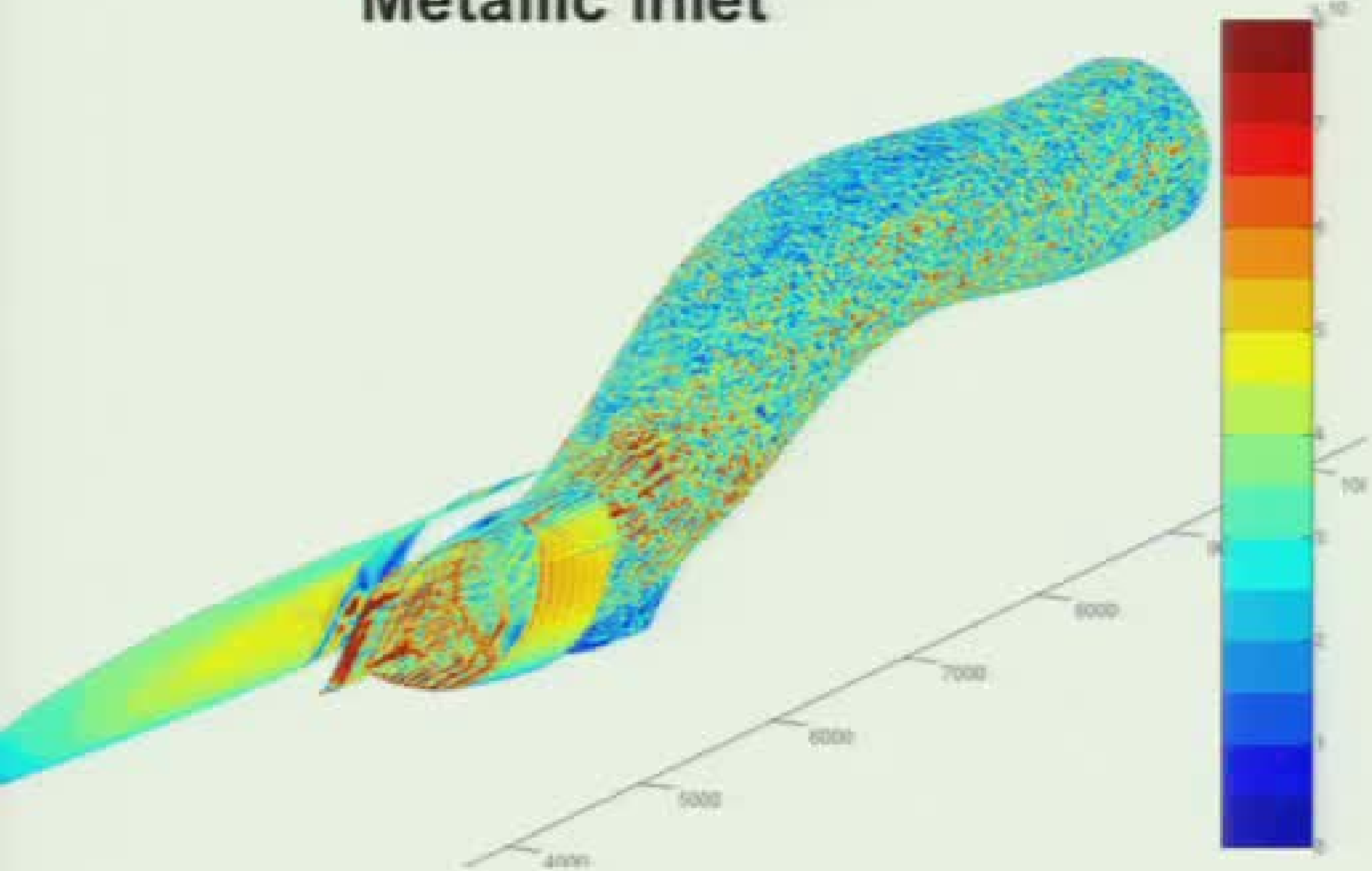
Gain between k and k^2
(k number of sub-domains)

Respect of the industrial sharing of responsibility

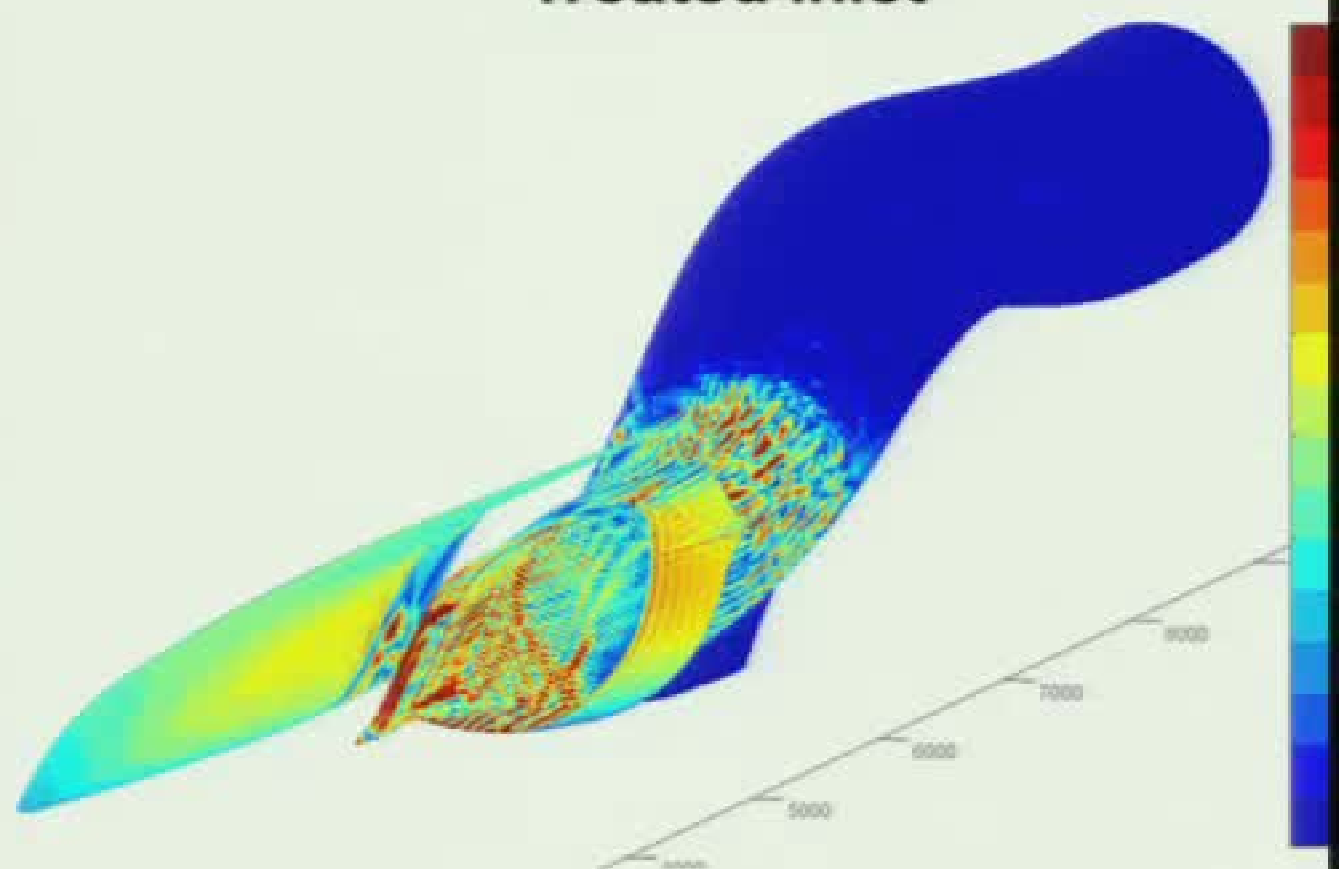
Computational Electromagnetics
Collaborative computations by the multi-domain technique

10 GHz

Metallic inlet

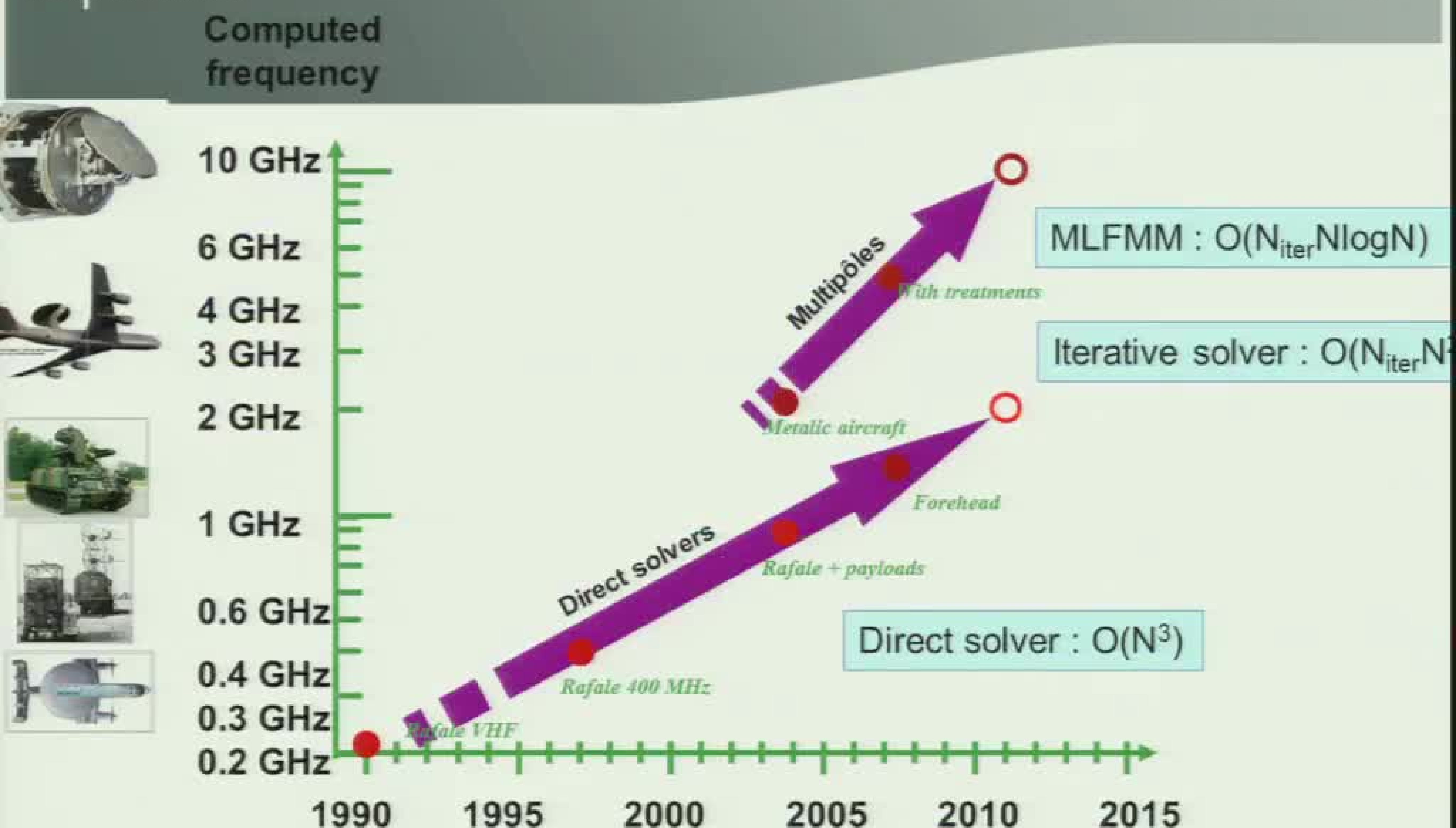


Treated inlet



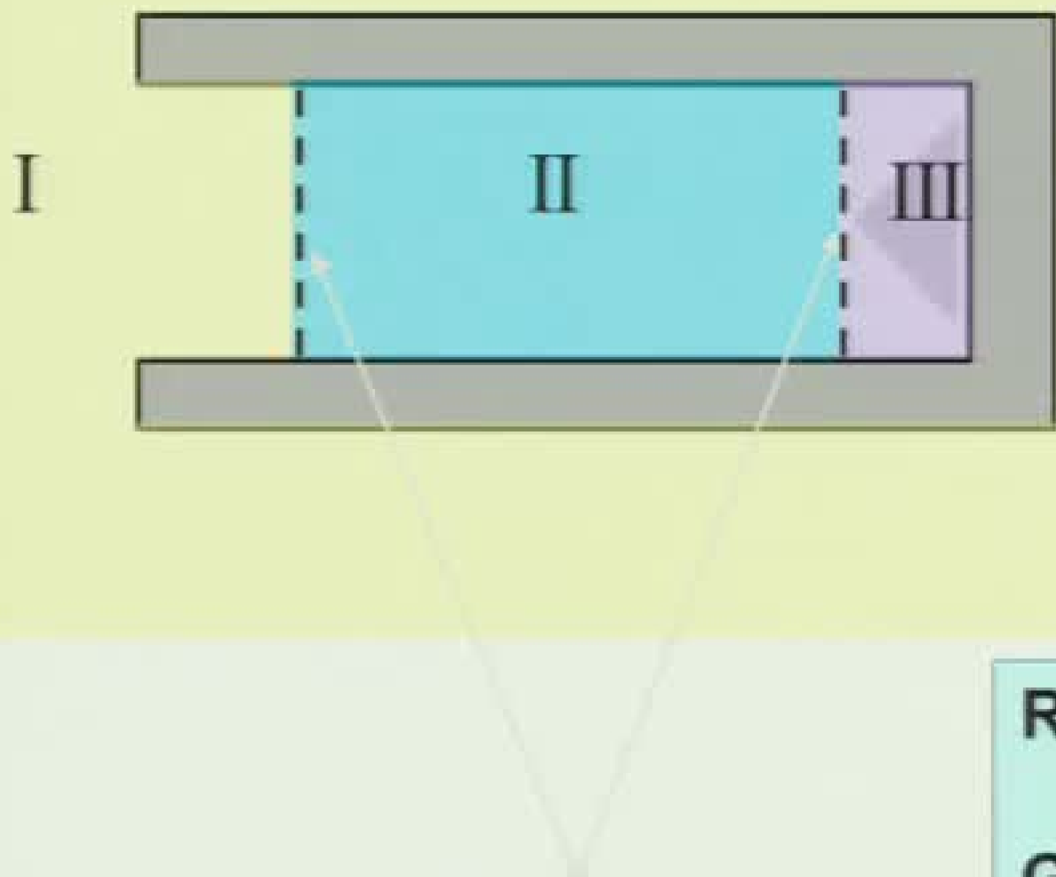
4 500 000 unknowns (FMM)

Computational Electromagnetics
Capacities



Computational Electromagnetics
Collaborative computations by the multi-domain technique

DASSAULT AVIATION



Coupling interfaces

Decomposition of the computational domain

- I : external domain
- II : conduct
- III : engine

Reduction of problem sizes

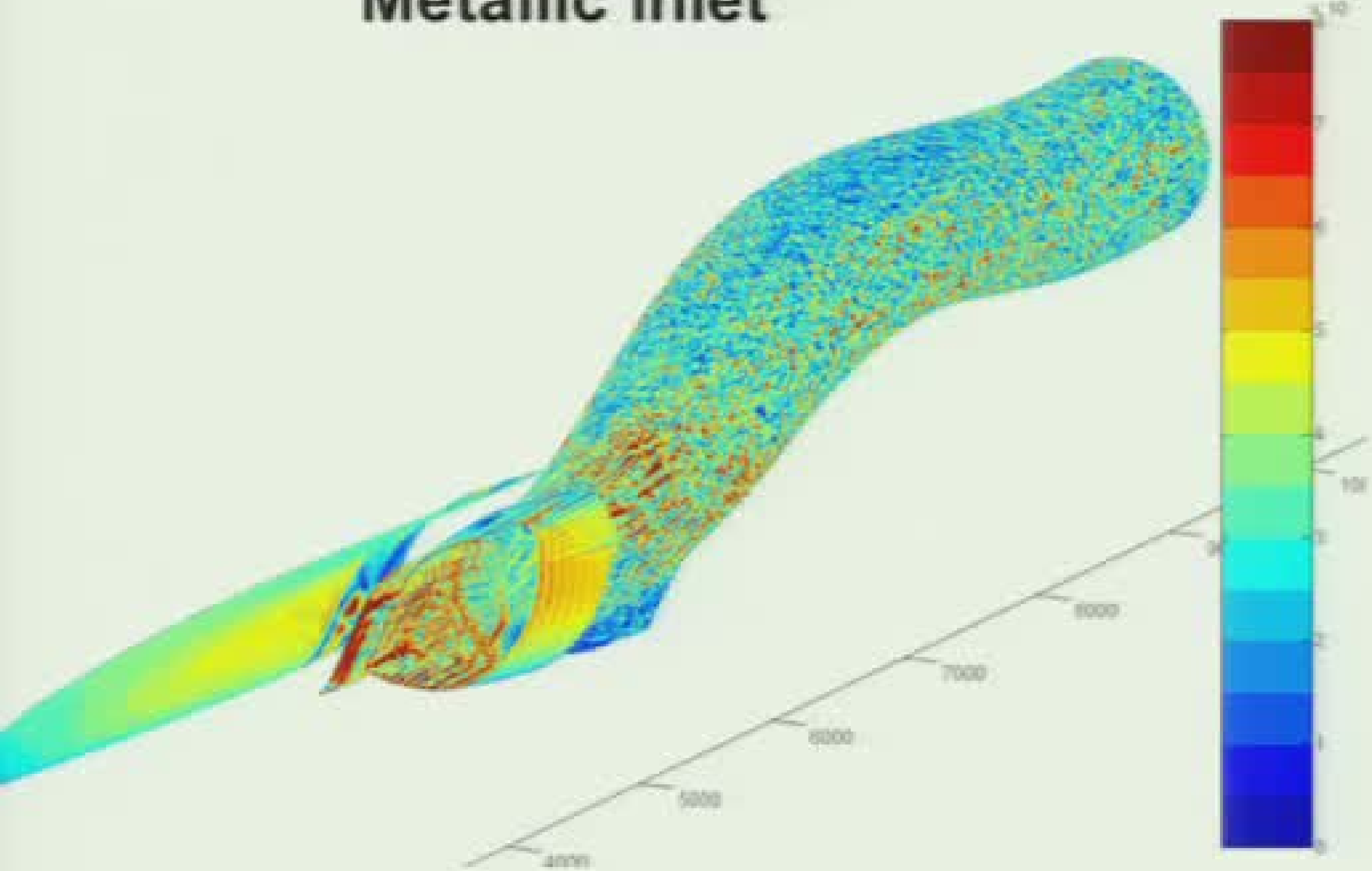
Gain between k and k^2
(k number of sub-domains)

Respect of the industrial sharing of responsibility

Computational Electromagnetics
Collaborative computations by the multi-domain technique

10 GHz

Metallic inlet



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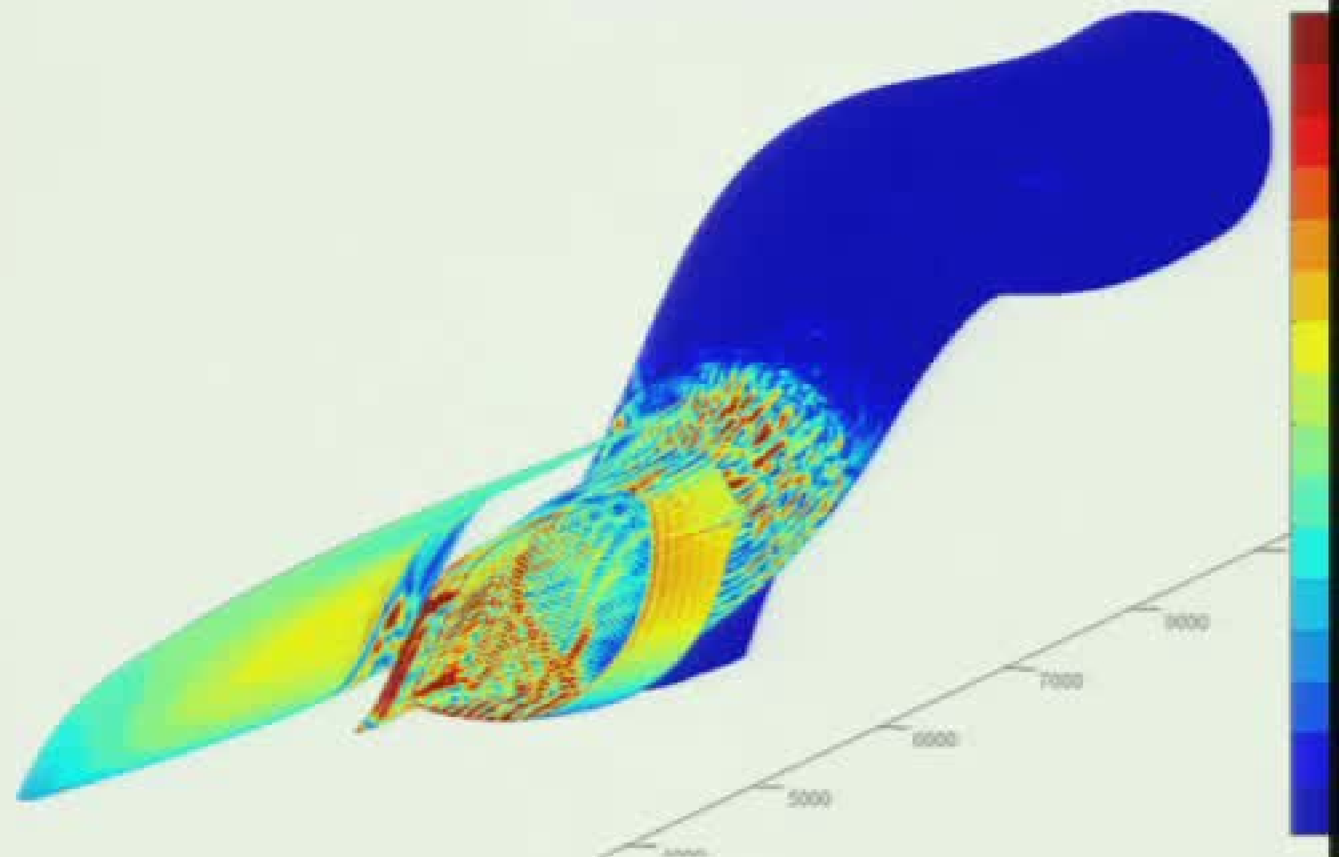


4 500 000 unknowns (FMM)

Multidisciplinary Design Loop

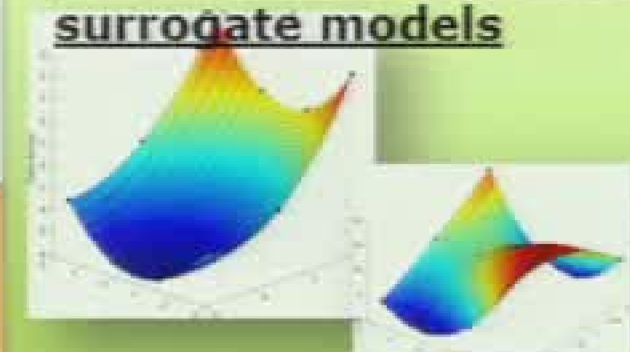
Global options
- Architectures
- Technologies

Design per discipline and Optimization
- Aerodynamics
- Structure
- Acoustics
- Propulsive integration
- Vehicle systems

Requirements (market, regulation)
- Range
- Fields length
- Cruise speed
- Comfort
- Environmental objectives
- Costs

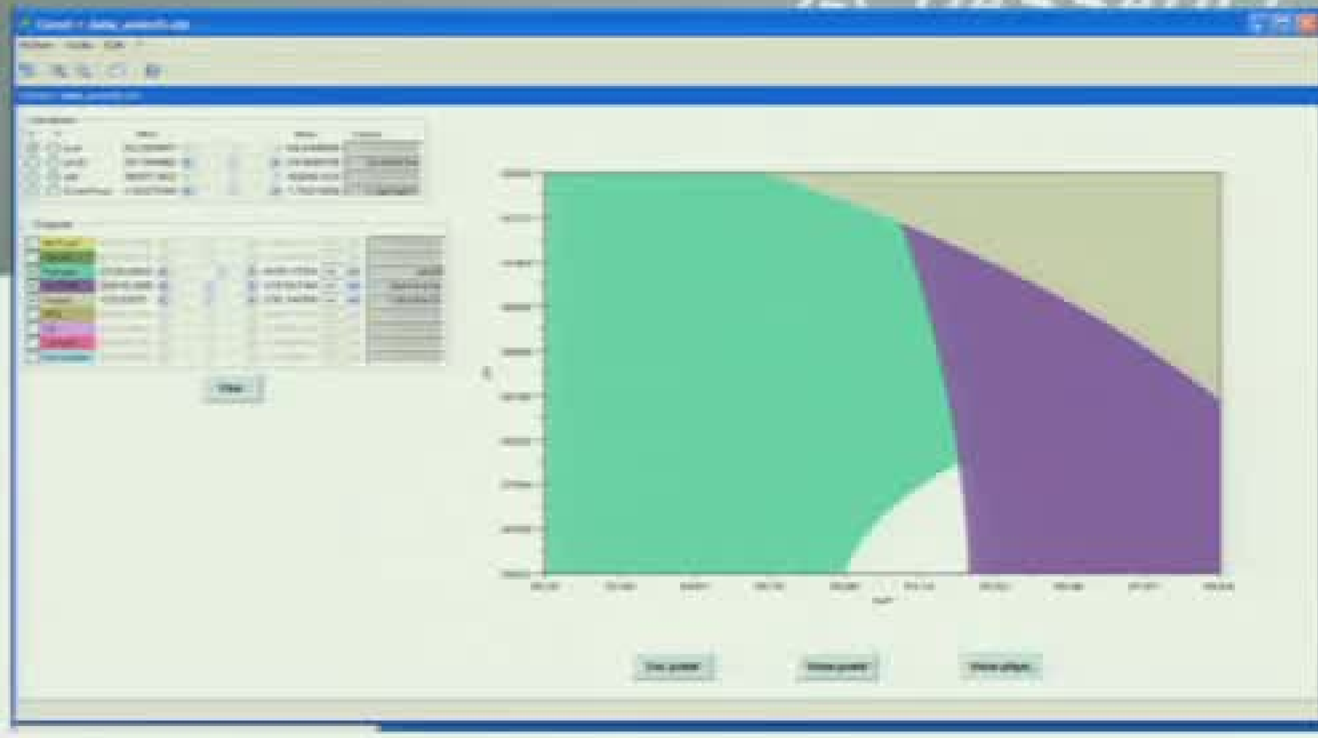
Global synthesis
- Exploration of design space
- Global sensitivities
- Risks evaluation

Parametric models with surrogate models

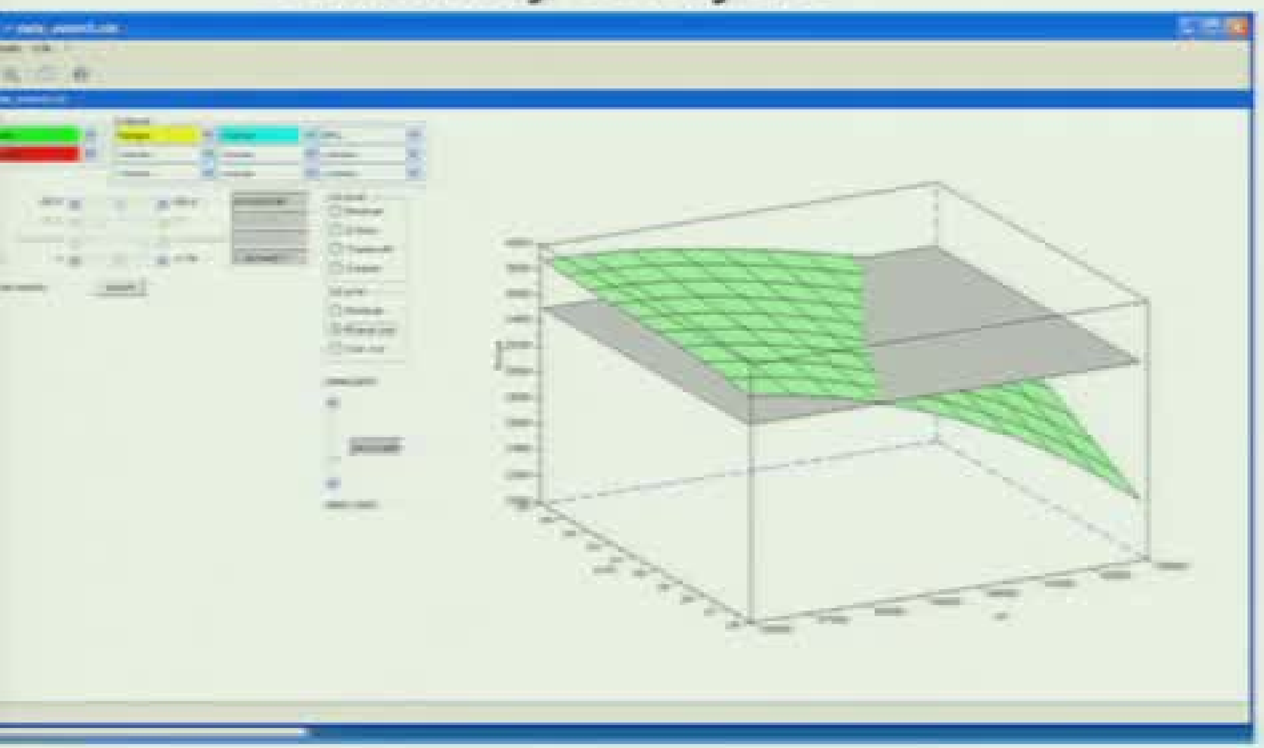


Surrogate models for interactive exploration

Sensitivity Analysis



Feasible domain evalutaion

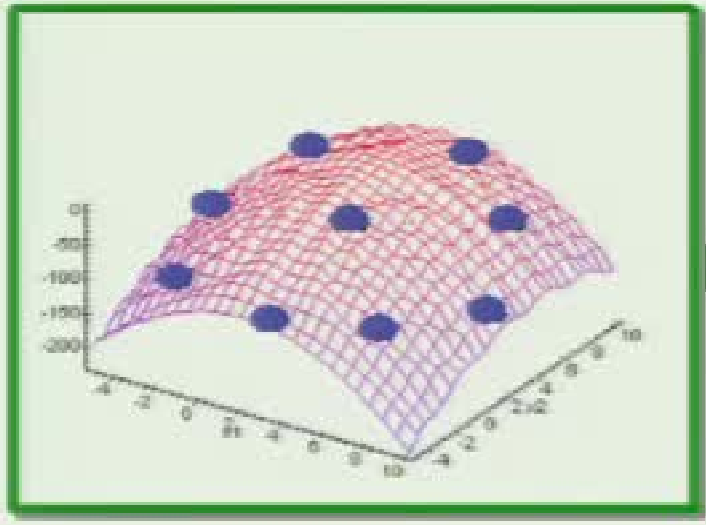


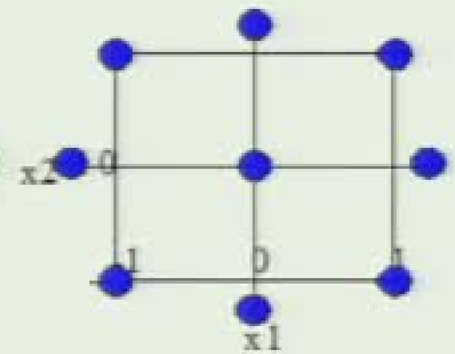
Data Exploration

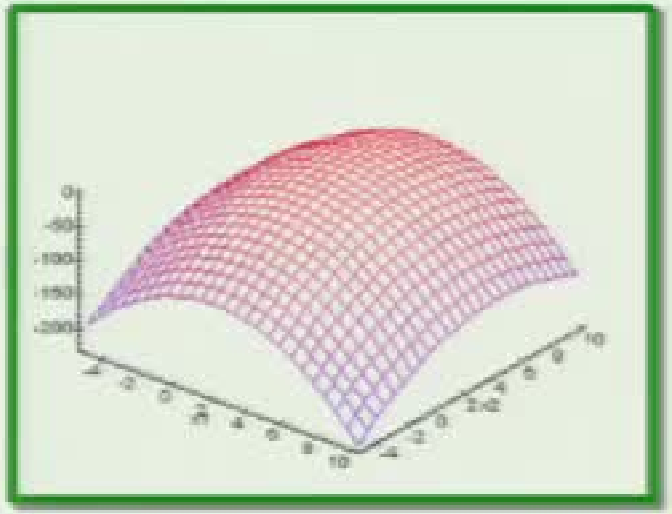
Generation of new configurations and filtering

Surrogate models: ingredients

System to model → **D.O.E** → **Surrogate**

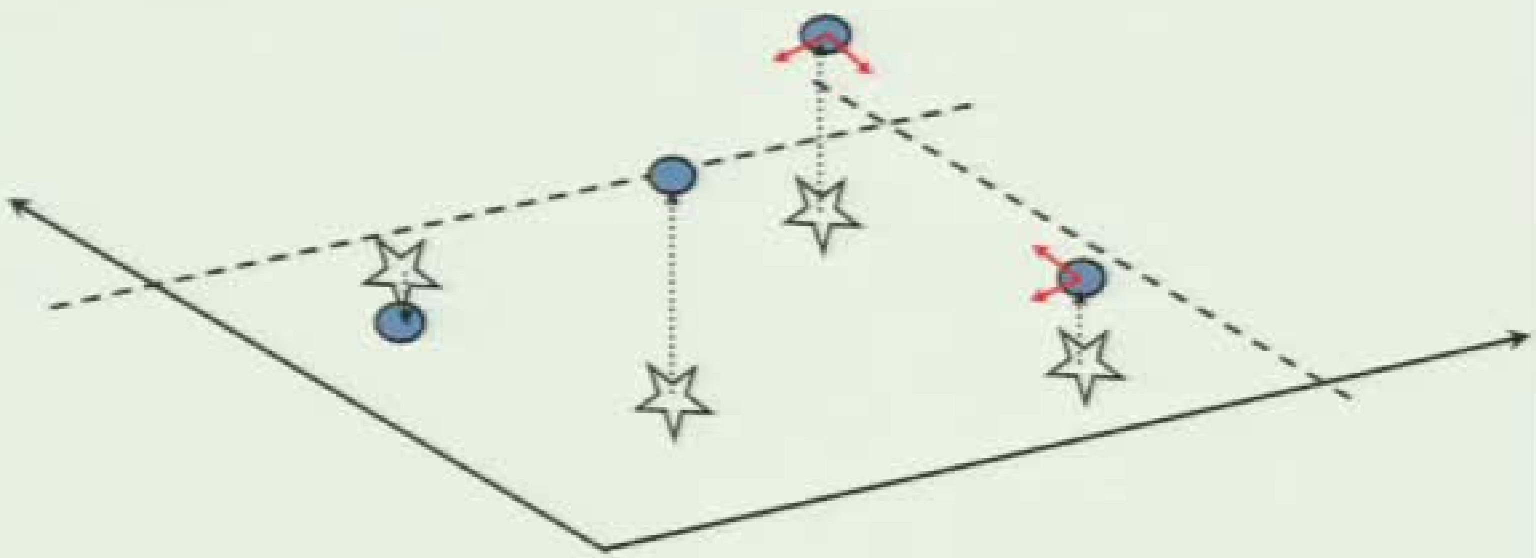






D.O.E

- Latin Hypercube Sampling
- max(min)
- pseudo MC
- Adapted



Design under uncertainty

Robust design : Find a shape which is as less as possible insensib to small variations of uncertain parameters

Reliability-based design : Find a shape associated to a probability not realize a target less than a given acceptable value i.e. P (X > given value)

Uncertainty quantification in aerodynamics

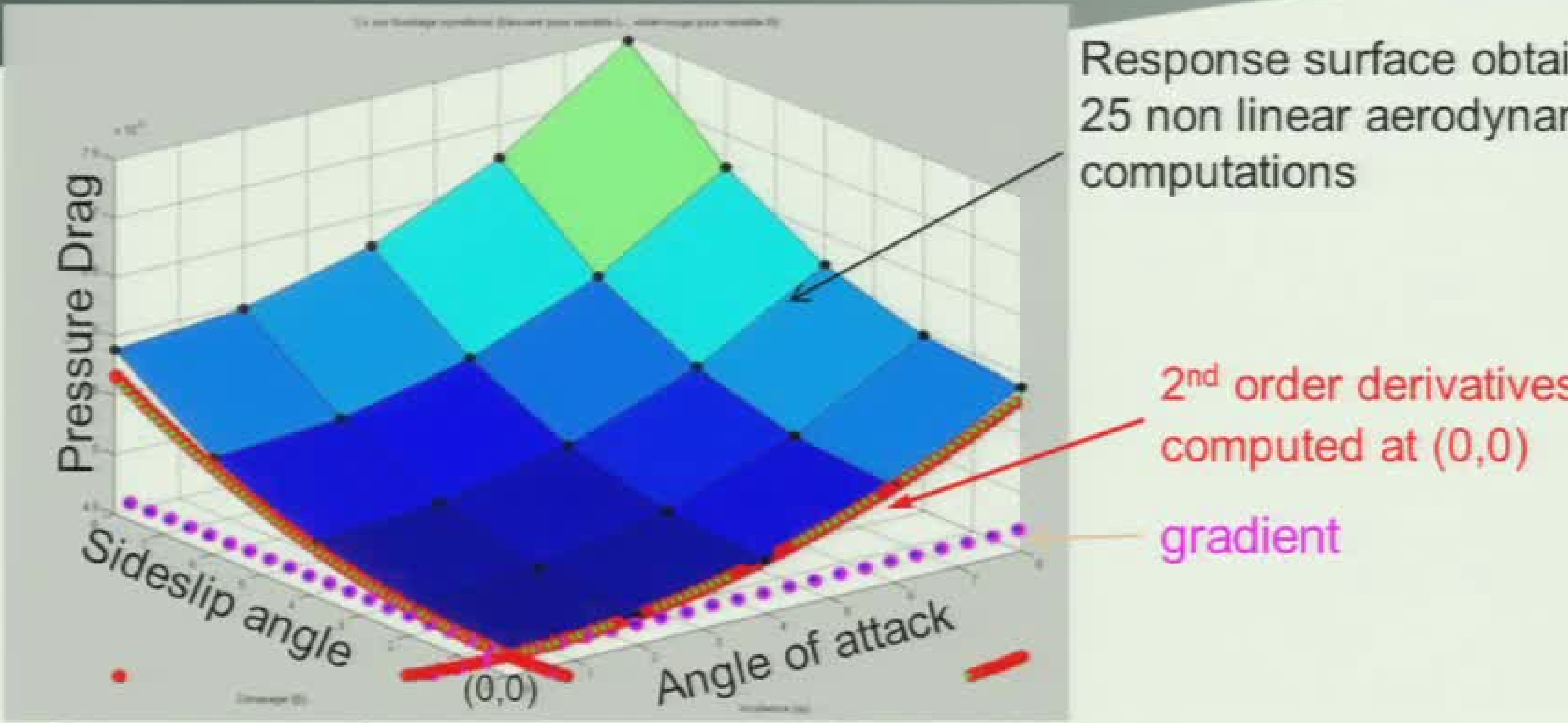
DASSAULT AVIATION

- Objective : "manage uncertainties" instead of adding "margins"
- Need to propagate uncertainties :

Probability density function of uncertain input data *I* (geometry, inflow ..)	→	Method to propagate uncertainty: - Monte Carlo - Polynomial Chaos (~3 input) - Perturbation method	→	Probability density function of output drag, lift, …

- Second-order derivatives ($\delta^2 O / \delta^2 I$) are needed both for the Monte Carlo method (response surface) and the Perturbation Method
- Computation of second-order derivatives is feasible using CFD solvers
  - new formulations
  - automatic differentiation tools (ex Tapenade)

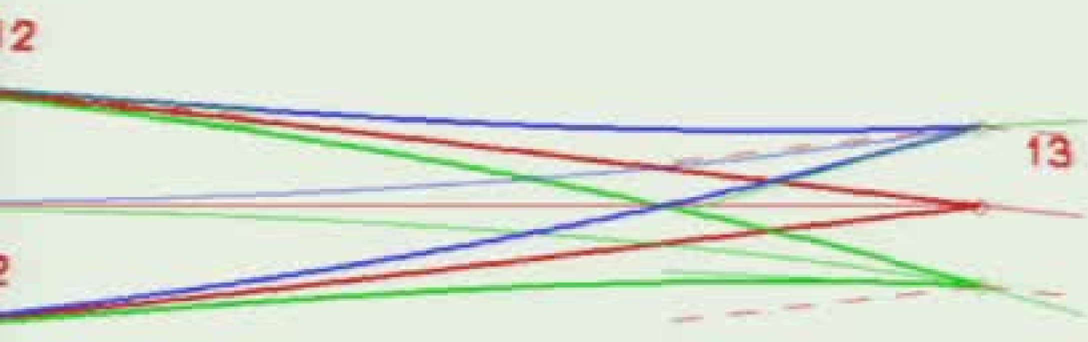
Uncertainty quantification in aerodynamics
Computation of 2nd order derivatives



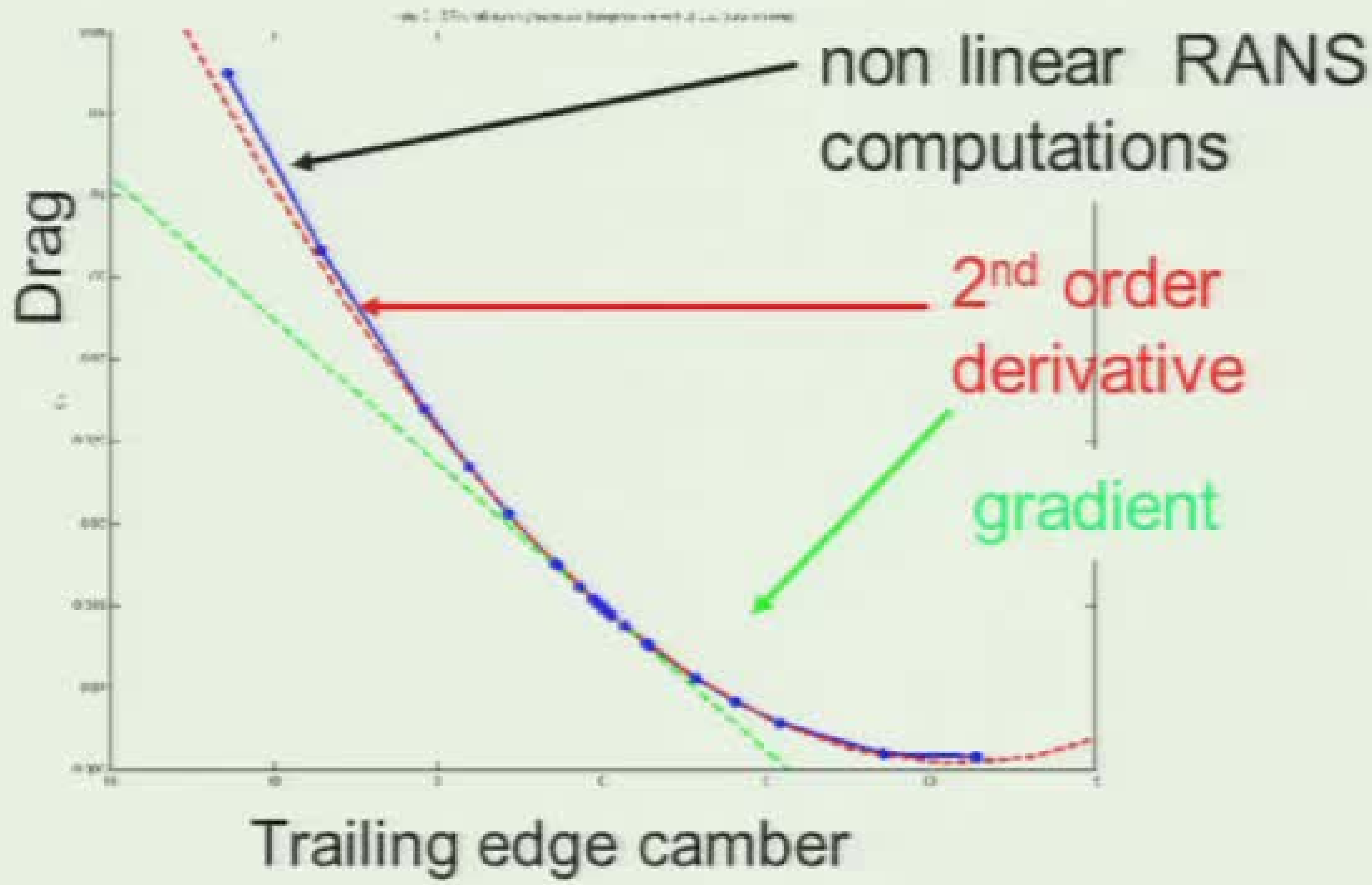
Pressure Drag(angle of attack, side slip angle)
generic fuselage

→ Computed second-order derivatives give a good approximation of the response surface

Uncertainty quantification in aerodynamics
Computation of 2nd order derivatives



Trailing edge camber



→ Computed second-order derivatives give a good approximation of the response surface

Uncertainty quantification in aerodynamics

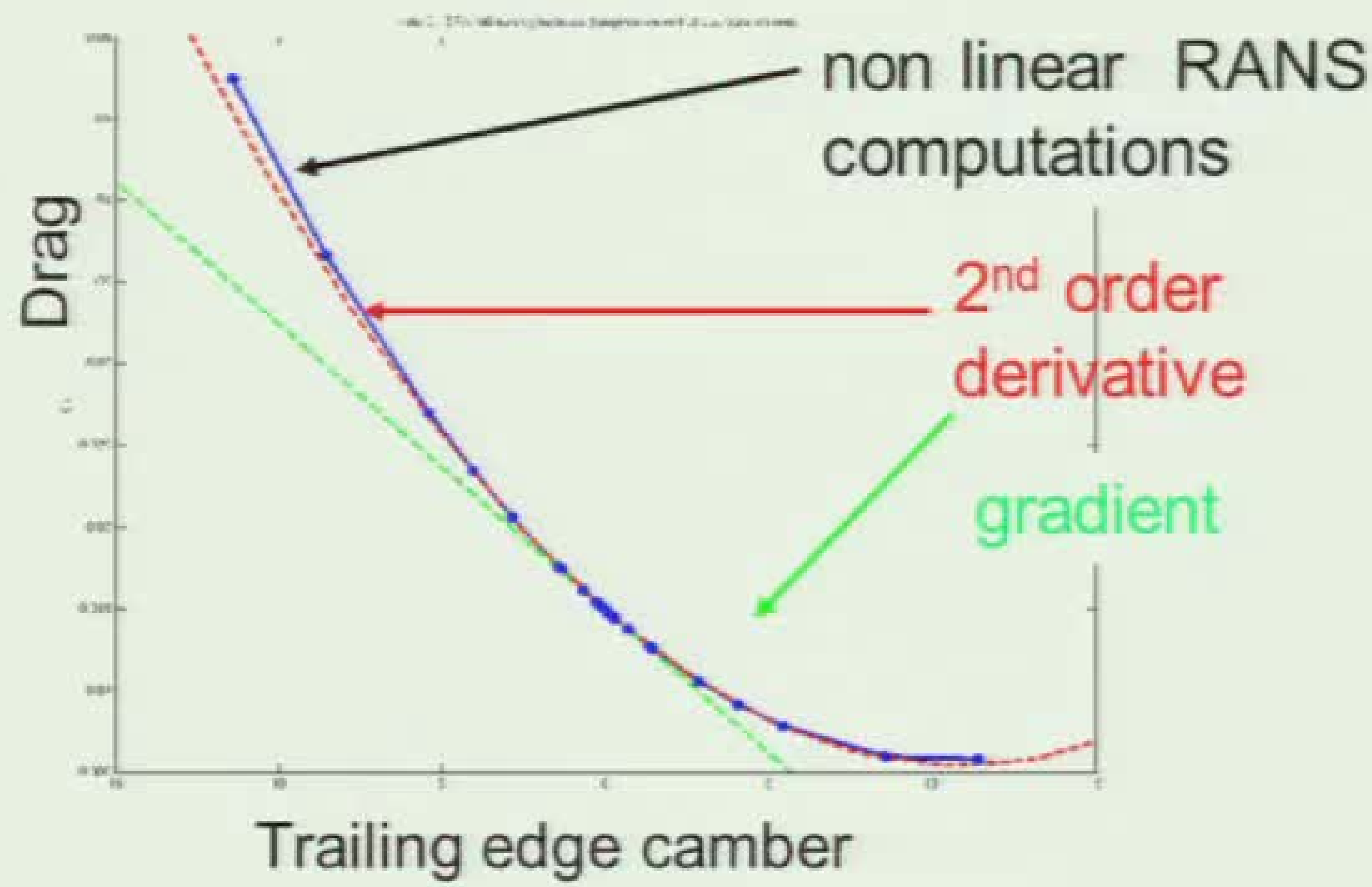
DASSAULT AVIATION

- **Key ingredients for numerical assessment of robust design**
  - Ability to compute second-order derivatives with CFD tools
  - Perturbation method : (second-order derivatives) → (moments of the probability distribution function (pdf))
  - Pearson's method : (moments of the pdf) → (pdf)

- **Uncertainties can be combined in MDO framework**
  - Assess uncertainty in global performance given uncertainty in aero, structure, engine …

Uncertainty quantification in aerodynamics
Computation of 2nd order derivatives

DASSAULT AVIATION



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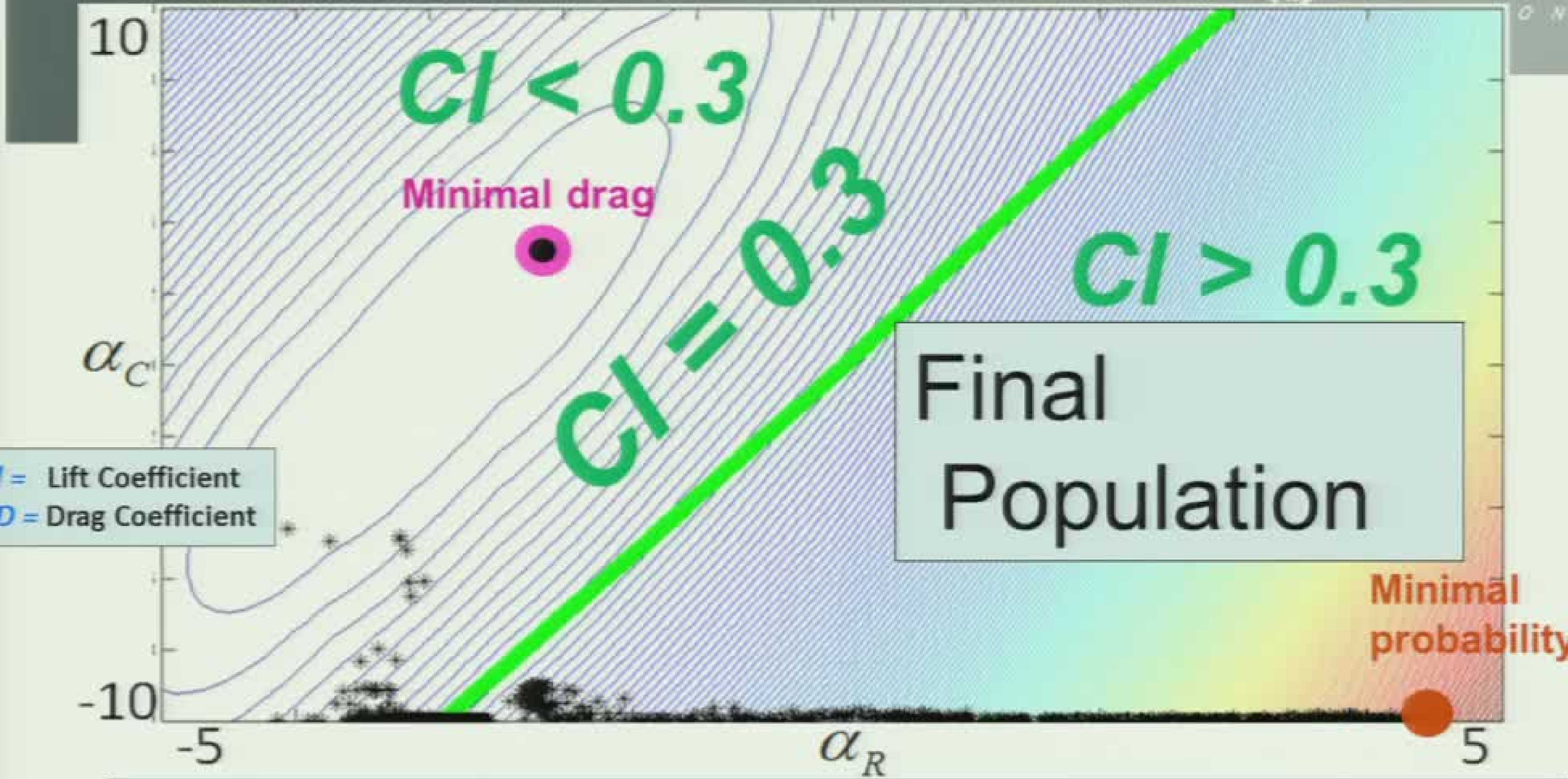
Reliability-Based Design
An example

- Test case: ONERA M6 wing
- CFD solver: 3D Euler solver
- Construction of the surrogate model by Radial Basis Functions by using first and second-order derivatives
- Two design parameters: Twist and Trailing Edge camber angles
- Objectives: Minimize Drag (mean Drag Coefficient ***E(CD)***) and probability ***P(Cl<0.3)***
- Optimization is performed by Genetic Algorithm (MOGA)

Reliability-Based Design: Exploration space



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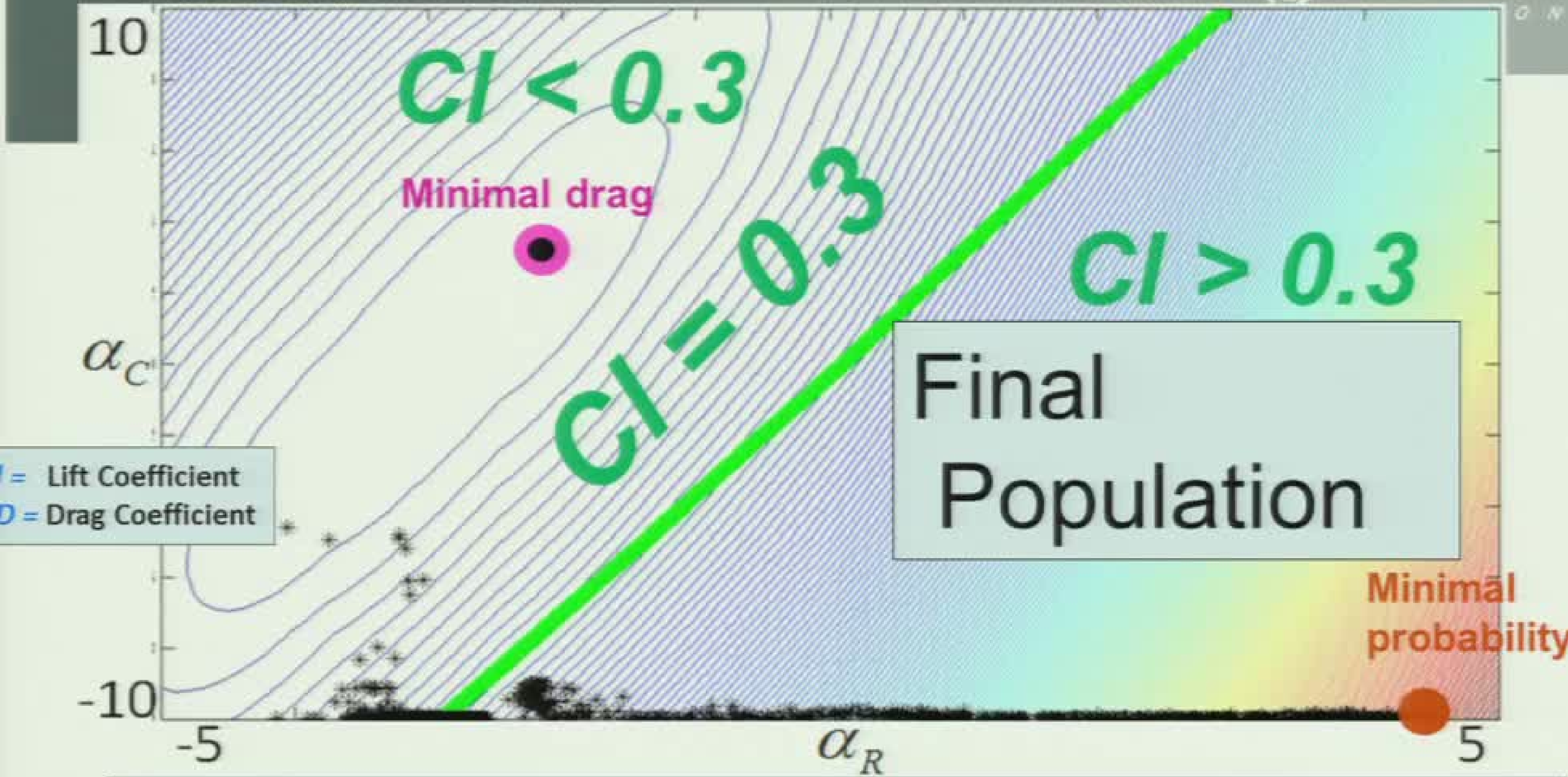
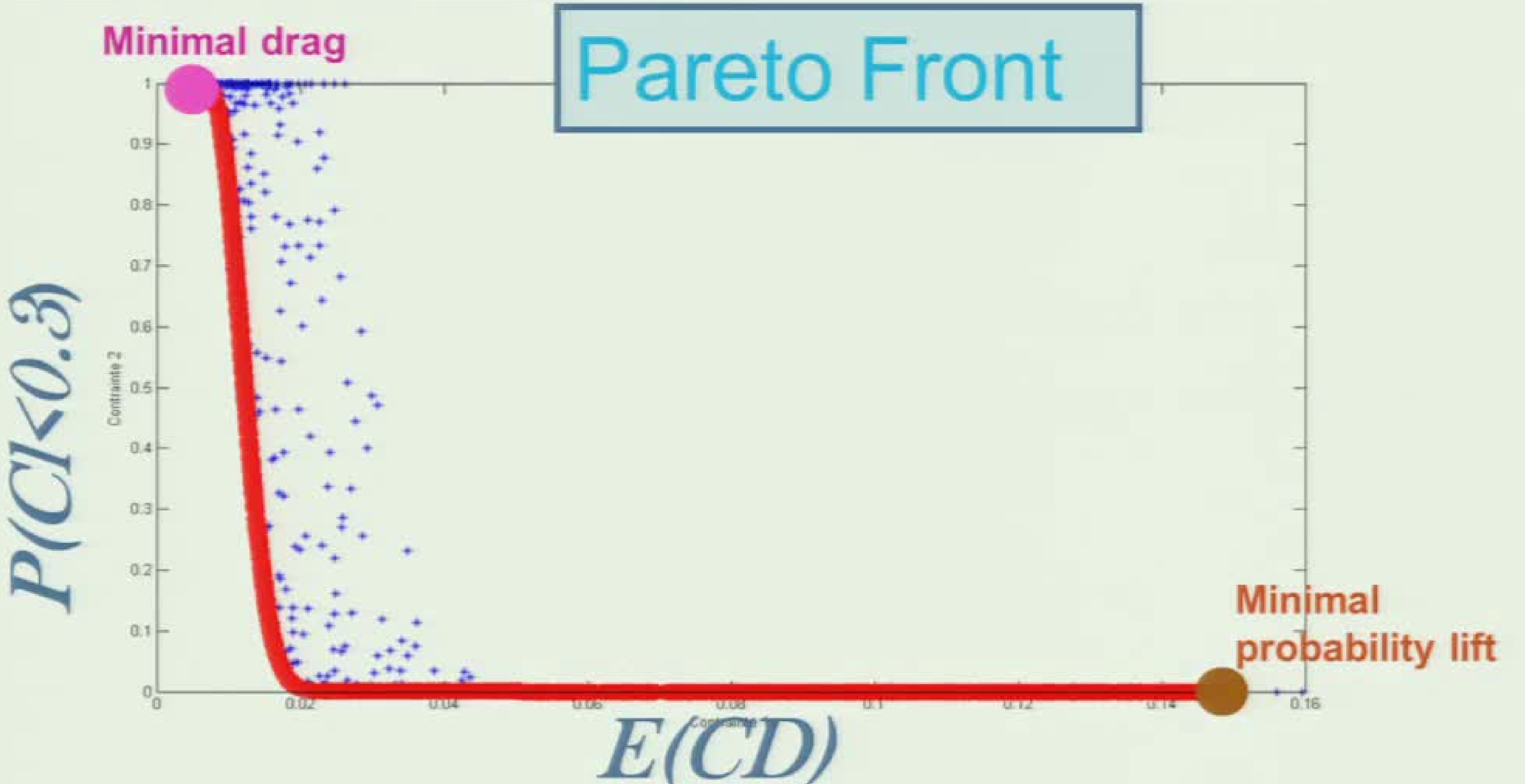


Objectives: Minimize Drag (mean Drag Coefficient *E(CD)*) and probability *P(Cl<0.3)*

Reliability-Based Design: Pareto front



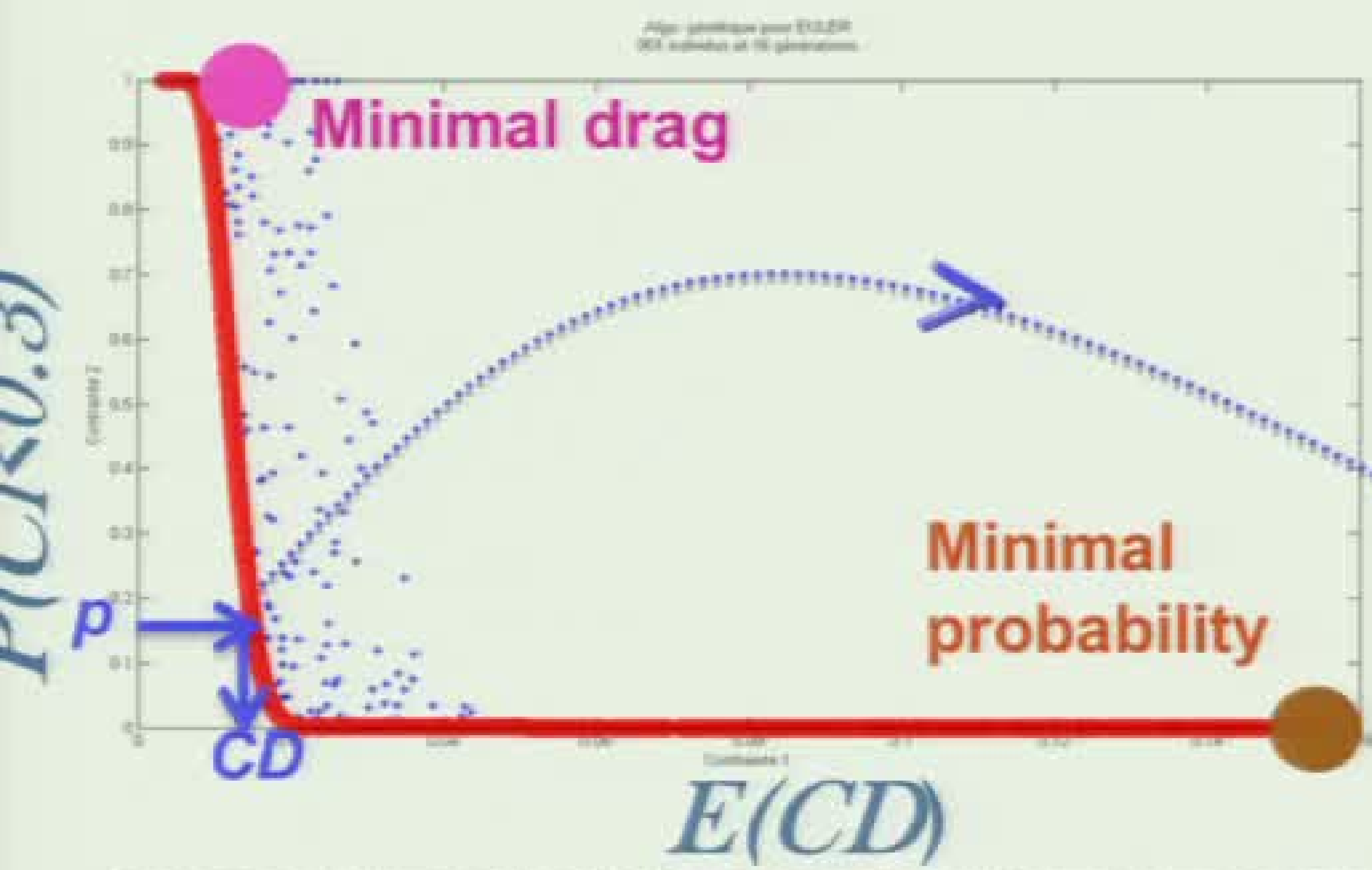
Reliability-Based Design

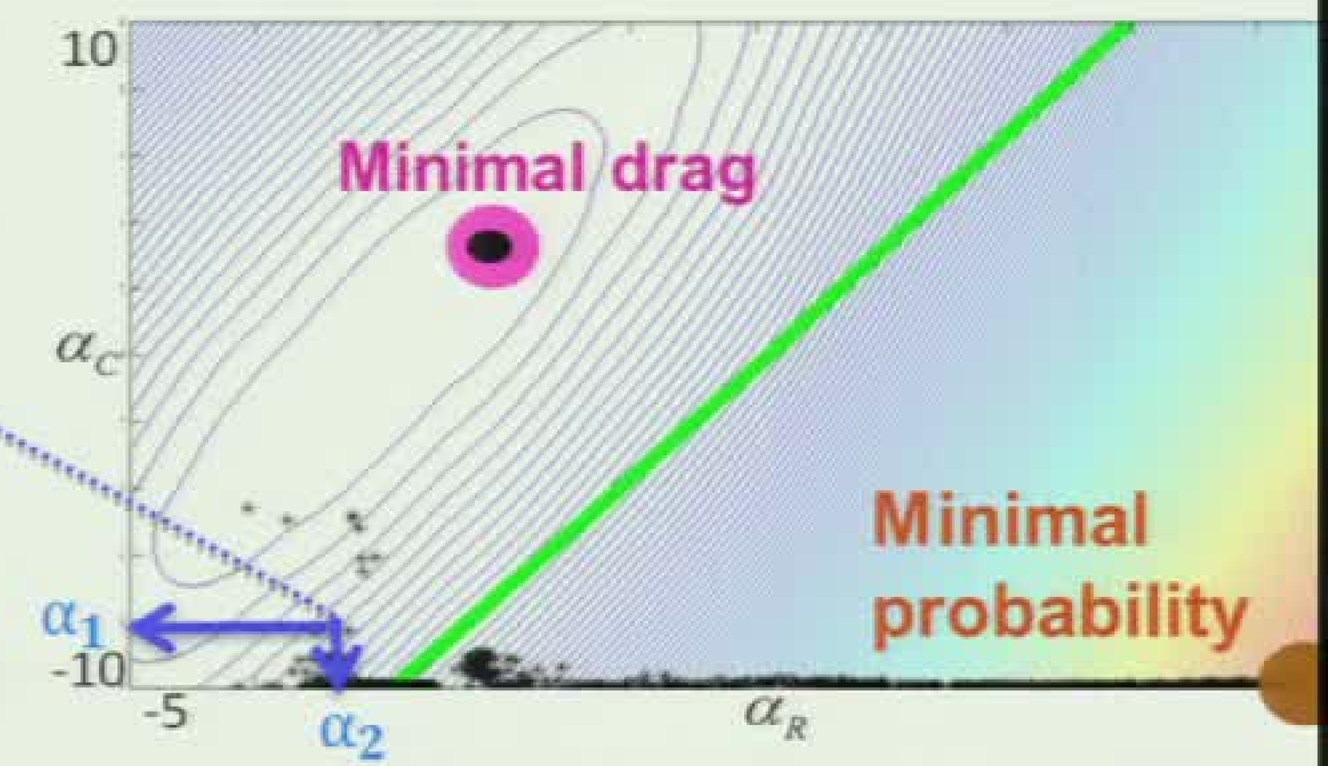
DASSAULT AVIATION

Decision: Accept a probability for the lift to be less than a value with minimal drag

→ Determination of drag mean ***CD*** (Pareto front)

→ Determination of nominal values of geomerical parameters α_1 and α_2 (camber and twist angles)





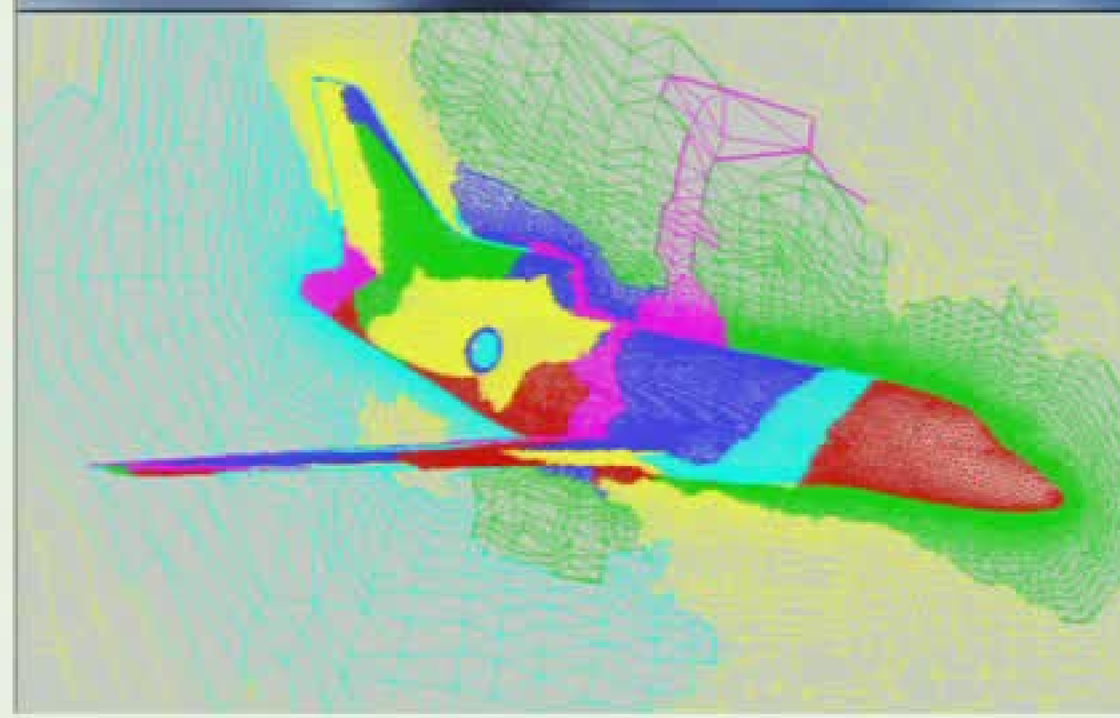
Computational trends

omputers power will increase by a factor ~500 thin the next 10 years:

- week-long computation will be available in 1/2 hour
- day-long computation will be available for automatic timization
- hour-long computation will be available interactively
- Open the way for short cycle Multidisciplinary Design op

omputers architecture evolves to an almost ponentially increasing number of processors

- e architecture of the codes must fit to the computers' one



Next generation HPC (towards Exascale)

DASSAULT AVIATION

- Status : Demonstrated efficiency of domain partitioning using MPI up to 20000 cores

- Challenge :

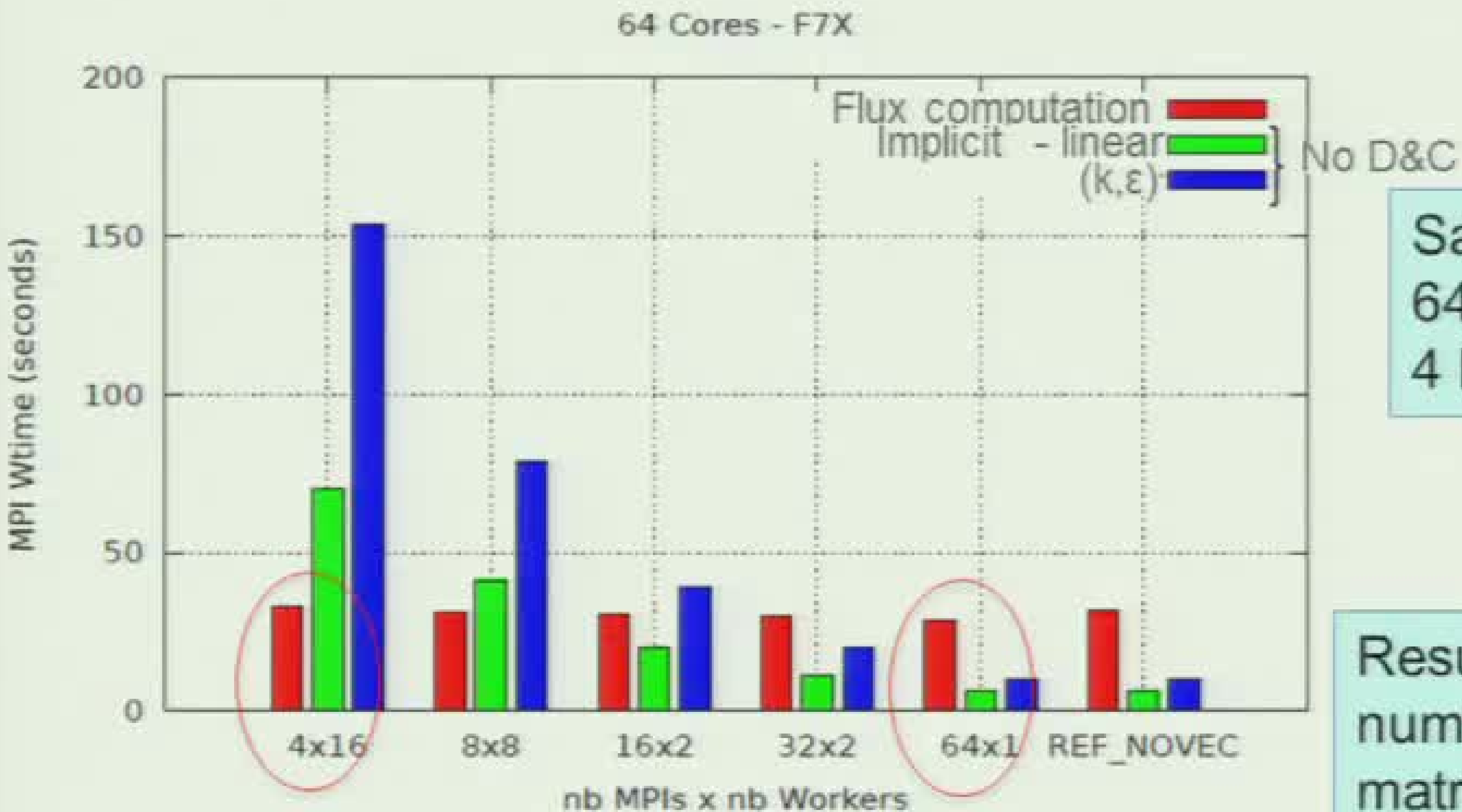
  "classical" multiprocessor architecture → 2 levels: multiprocessor / many cores architecture

- Code modernization effort:
  - From a Bulk Synchroneous Model to a Multi-Level Asynchroneous Model

- On going R&T effort : combine "classical domain partitioning + MPI" and "local sub-partitionning using a Divide & Conquer algorithm + multithreading "

Next generation HPC
Result using the Divide & Conquer approach

Test case of Navier-Stokes solver with a mesh of $5\ 10^6$ grid points on 4 processors with 16 cores each



Same turn around time with
64 MPI
4 MPI + multithreads with D&C

Result must be confirmed on large number of cores and extended to matrix vector product

Outline

Design

- Industrial state-of-the art of CFD
- Automatic shape optimization
- Multiphysics: example of Aeroelasticity
- Computational Electromagnetics
- Surrogate models
- Uncertainty quantification – Robust design
- Challenges of next generation HPC (towards Exascale)

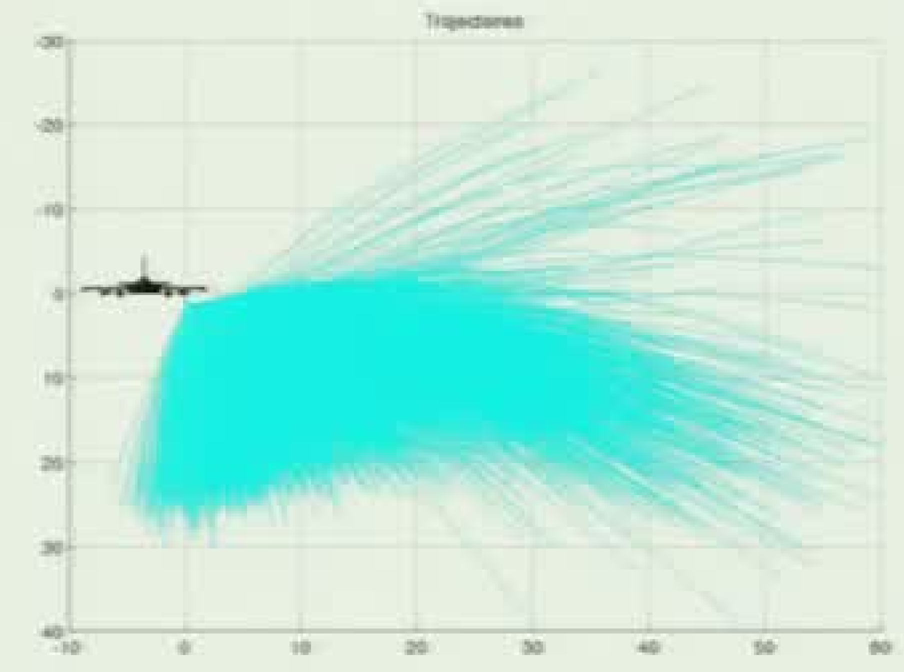
Development

- An example of rare-event probability evaluation

Support

- First attempts in Data Analytics

Rare event probability evaluation:
risk of collision during a store release



Store trajectories depend on 2 types of variables

- $x_C \in C$ variables under pilot control like speed, altitude, load factor
- $x_E \in E$ uncontrolled parameters: load dispatch, turbulence, …

Envelope clearance problem: find the subset of C where load release is safe

Means

- **Simulator: computes the trajectory when variables values are given**
- **Budget: maximum simulator runs**

Dangerousness score (« algebraic distance »)

- $f : C \times E \to R$: collision iff $f(x_C, x_E) < 0$

Rare event probability evaluation: application context

DASSAULT AVIATION

Formalization

- Uncontrolled parameters values are realizations of a random vector X_E whose law can b[e] easily simulated
- Risk at $x_C \in C$ is $\pi(x_C) = \mathbb{P}(f(x_C, X_E) < 0)$

Qualification of the release safety at every point $x_C \in C$

- Safe if $\pi(x_C) < p_S$ (typically $p_S = 10^{-5}$)
- Dangerous if $\pi(x_C) \geq p_D$
- Relatively safe if $p_D < \pi(x_C) < p_S$

Strategy

- Estimate at a sufficient number of $x_C \in C$

Budget matters (number of affordable runs)

Rare event probability evaluation:
brute force Monte Carlo is unfeasible

DASSAULT AVIATION

- Let $X_{1:L} = (X_1, \dots, X_L)$ be a L−sample of X, the following statistic is a binomial $\mathcal{B}(L, \pi)$

$$\Gamma(R,\ X_{1:L}) =_{def} \sum_{k=1}^{L} \mathbb{1}_{]-\infty,0]}\left(f(X_k)\right) = \sum_{k=1}^{L} \mathbb{1}_{R}(X_k)$$

- And so: $a(\Gamma(R, X_{1:L}), L, \alpha) \leq \pi \leq b(\Gamma(R, X_{1:L}), L, \alpha)$ with confidence level $1-\alpha$
- But in most cases, $\pi \sim 0$
  - Which leads to $\Gamma(R, X_{1:L}) = 0$ with high probability
  - Meaning L over 200000 simulator runs (typically one full day of computations) would be necessary to get $\pi \leq 10^{-5} = b(0, L, 0.1)$ with confidence level of 95%

Rare event probability evaluation:
principles of the importance sampling approach

DASSAULT AVIATION

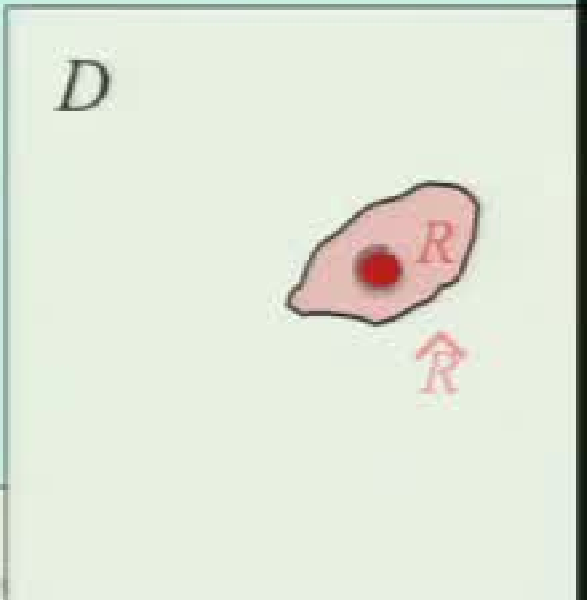
- **Substitute importance random variable Z for X whose law is:**

$$\mathbb{P}_Z : A \subset E \mapsto \mathbb{P}(X \in A | X \in \hat{R})$$

Where $\hat{R} \subset E$ is such that $R \subset \hat{R}$, $\hat{R}$ close to R and $\mathbb{1}_{\hat{R}}$ evaluated at (very) low cost (based on an approximate function $\hat{f}$ of f)

Compute a Monte-Carlo estimation of $\mathbb{P}(Z \in R) = \frac{\mathbb{P}(X \in R)}{\mathbb{P}(X \in \hat{R})}$ from which is taken an estimation of $\mathbb{P}(X \in R)$

Targeted benefit: Z is hitting (far) more frequently R so Monte-Carlo estimate of $\mathbb{P}(Z \in R)$ expected to be (far) more precise



Rare event probability evaluation:
brute force Monte Carlo is unfeasible

DASSAULT AVIATION

- Let $X_{1:L} = (X_1, \dots, X_L)$ be a L−sample of X, the following statistic is a binomial $\mathcal{B}(L, \pi)$

$$\Gamma(R,\ X_{1:L}) =_{def} \sum_{k=1}^{L} \mathbb{1}_{]-\infty,0]}(f(X_k)) = \sum_{k=1}^{L} \mathbb{1}_R(X_k)$$

- **And so:** $a(\Gamma(R, X_{1:L}), L, \alpha) \leq \pi \leq b(\Gamma(R, X_{1:L}), L, \alpha)$ **with confidence level** $1 - \alpha$

- **But in most cases,** $\pi \sim 0$

  - **Which leads to** $\Gamma(R, X_{1:L}) = 0$ with high probability
  - **Meaning** L over *200000* simulator runs (typically one full day of computations) would be necessary to get $\pi \leq 10^{-5} = b(0, L, 0.1)$ with confidence level of 95%

Rare event probability evaluation: principles of the importance sampling approach

DASSAULT AVIATION

- **Substitute importance random variable Z for X whose law is:**

$$\mathbb{P}_Z : A \subset E \mapsto \mathbb{P}(X \in A | X \in \hat{R})$$

Where $\hat{R} \subset E$ is such that $R \subset \hat{R}$, $\hat{R}$ close to R and $\mathbb{1}_{\hat{R}}$ evaluated at (very) low cost (based on an approximate function $\hat{f}$ of f)

Compute a Monte-Carlo estimation of $\mathbb{P}(Z \in R) = \frac{\mathbb{P}(X \in R)}{\mathbb{P}(X \in \hat{R})}$ from which is taken an estimation of $\mathbb{P}(X \in R)$

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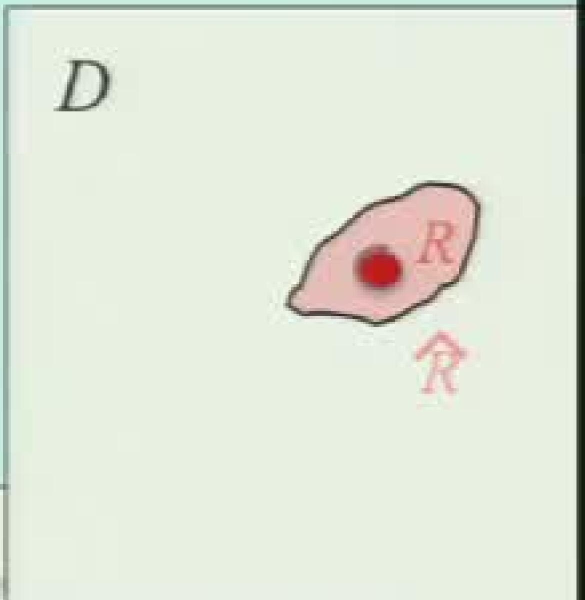


Rare event probability evaluation:
implementation of the importance sampling approach

DASSAULT AVIATION

- A budget of N runs is given
- Define $\hat{R} = \{\hat{f}(x) \leq M\}$ and $\breve{R} = \{\hat{f}(x) \leq -M\}$ on the basis of data $(x_1, f(x_1)), \ldots, (x_{\frac{N}{2}}, f(x_{\frac{N}{2}}))$ with M sufficiently large to ensure that $\breve{R} \subset R \subset \hat{R}$

Step 1 : Sample importance variable $Z : (Z_1, \ldots, Z_L)$

- By sampling original variable $X : (X_1, \ldots, X_K)$ and extract those X_i that hit $\hat{R}$ with K may be $\gg L$
- Computing confidence bounds $\breve{a}_K(\alpha)$ and $\hat{b}_K(\alpha)$ so that $\breve{a}_K(\alpha) \leq \mathbb{P}(X \in \breve{R}) \leq \mathbb{P}(X \in \hat{R}) \leq \hat{b}_K(\alpha)$ with confidence level $1\text{-}\alpha$
- Going on sampling X until one of these conditions is satisfied
  - $\hat{b}_K(\alpha) < p_S$: point x_C is safe
  - $p_d \leq \breve{a}_K(\alpha)$: point x_C is dangerous
  - The number of Z samples reaches $\frac{N}{2}$ => go to Step 2

Rare event probability evaluation:
implementation of the importance sampling approach

DASSAULT AVIATION

Step 2: Compute the binomial $\mathcal{B}\left(\frac{N}{2}, \frac{\pi}{\mathbb{P}(X \in \hat{R})}\right)$ statistic $\Gamma\left(R, Z_{1:\frac{N}{2}}\right)$ consuming the remaining budget to get the confidence bounds

$$a(\alpha) =_{def} a\left(\Gamma\left(R, Z_{1:\frac{N}{2}}\right), \frac{N}{2}, \alpha\right) \le \frac{\pi}{\mathbb{P}(X \in \hat{R})} \le b(\alpha) =_{def} b\left(\Gamma\left(R, Z_{1:\frac{N}{2}}\right), \frac{N}{2}, \alpha\right)$$

with confidence level $1 - \alpha$

CONTROLLED VARIABLES					IMPORTANCE SAMPLING		MONTE CARLO	
M	Z	Carburant	Nz	Pression bouteille	Borne Inf	Borne Sup	Borne Inf	Borne Sup
0.9	5.0	0.2	1.2	270	$3.53\ 10^{-5}$	$7.5\ 10^{-5}$	$1.79\ 10^{-5}$	$14.5\ 10^{-5}$
0.9	5.0	0.2	1.0	350	$0.045\ 10^{-5}$	$0.146\ 10^{-5}$	0.0	$4.6\ 10^{-5}$
0.9	11.0	0.0	1.0	210	$32.06\ 10^{-5}$	$54.67\ 10^{-5}$	$28.4\ 10^{-5}$	$59.7\ 10^{-5}$
0.9	5.0	0.8	1.0	270	$0.94\ 10^{-5}$	$2.19\ 10^{-5}$	$0.44\ 10^{-5}$	$10.04\ 10^{-5}$

2000 runs
Confidence level 99%

10^5 runs

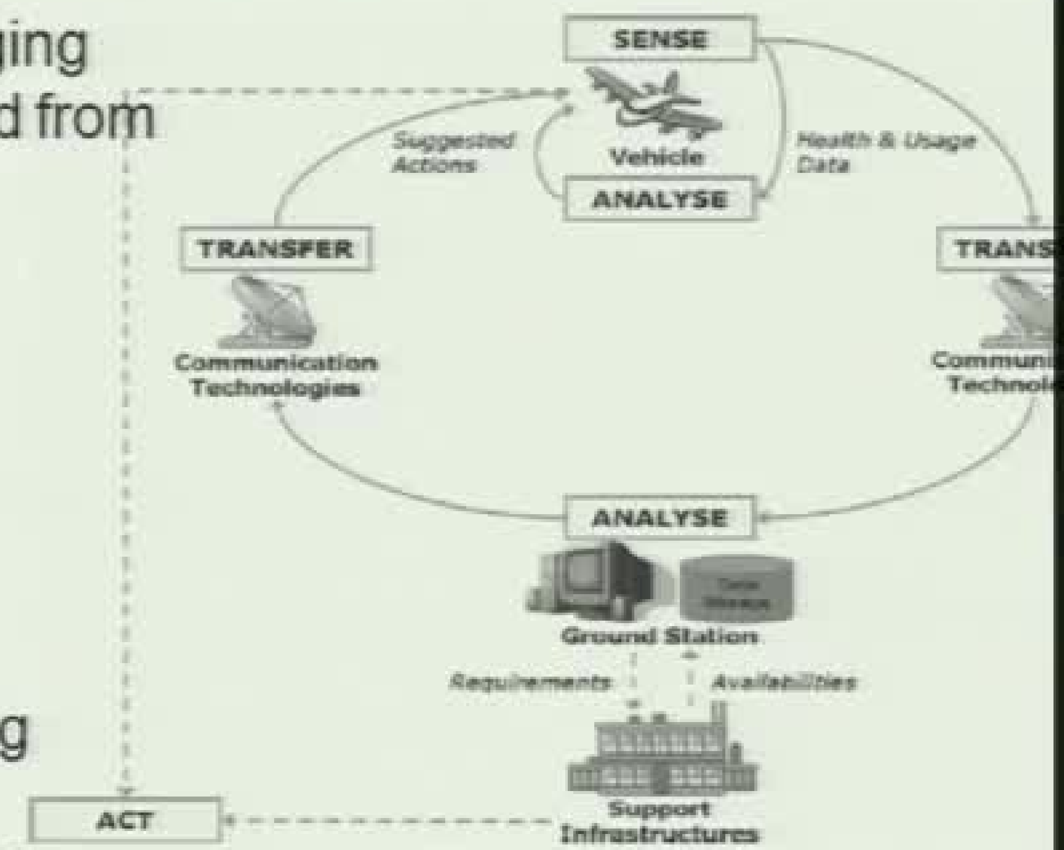
Massive Data Analysis: Practical Motivation

DASSAULT AVIATION

Dramatic increase in our ability to collect data from various connected sources

- « Standard » large scale Web-based applications
- Connected devices – mobile phones, cars, ... – Within the Internet of Things (IoT)
- Cyber-Physical Systems, equipped with large sensor networks
- Complex systems and data intensive applications that raise the data scale to an unprecedented level

Aerospace is highly concerned! Many applications are emerging that relies on the systematic analysis of sensor data collected from aircraft systems



Source: Benedettini et al 2009

Health Monitoring and Predictive Maintenance

- Early anomaly detection/prognostics
- Detection of activity peaks, e.g. significant increases of unscheduled maintenance

Flight Safety Analysis

- Routine recording and analysis of flight parameters during entire flights
- To support a proactive data-driven approach to flight safety

Massive Data Analysis: Practical Motivation

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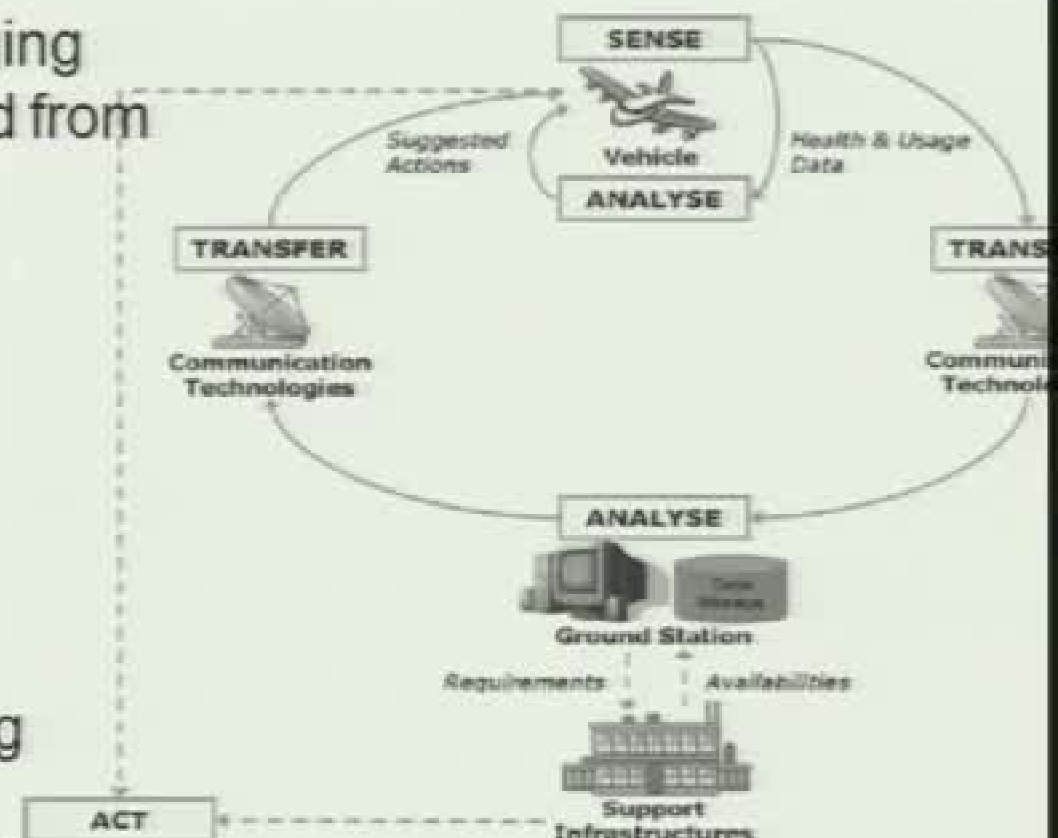

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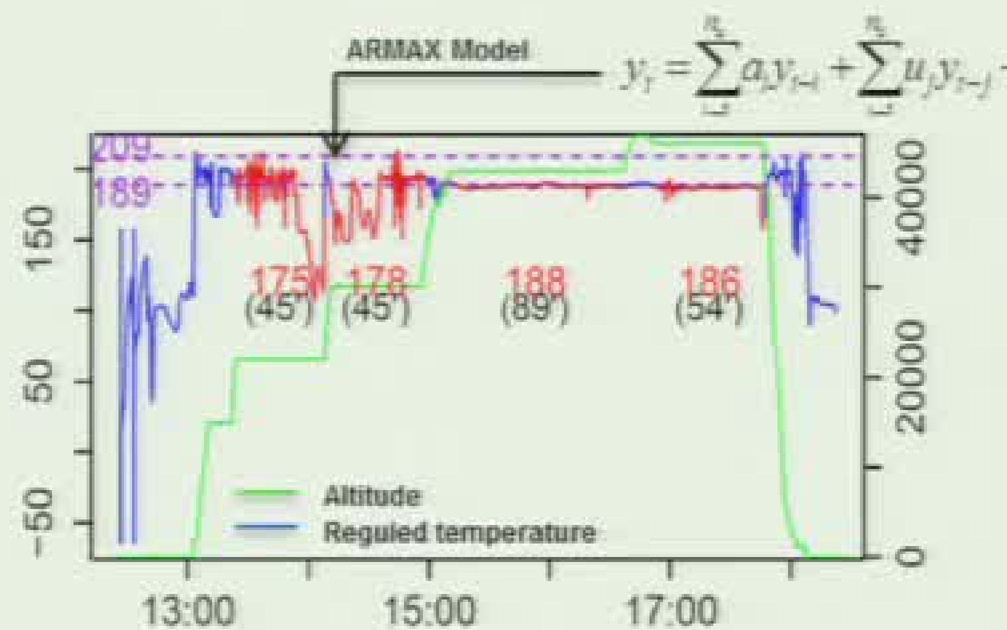
Data-Driven Statistical-based Methods for Data Analysis

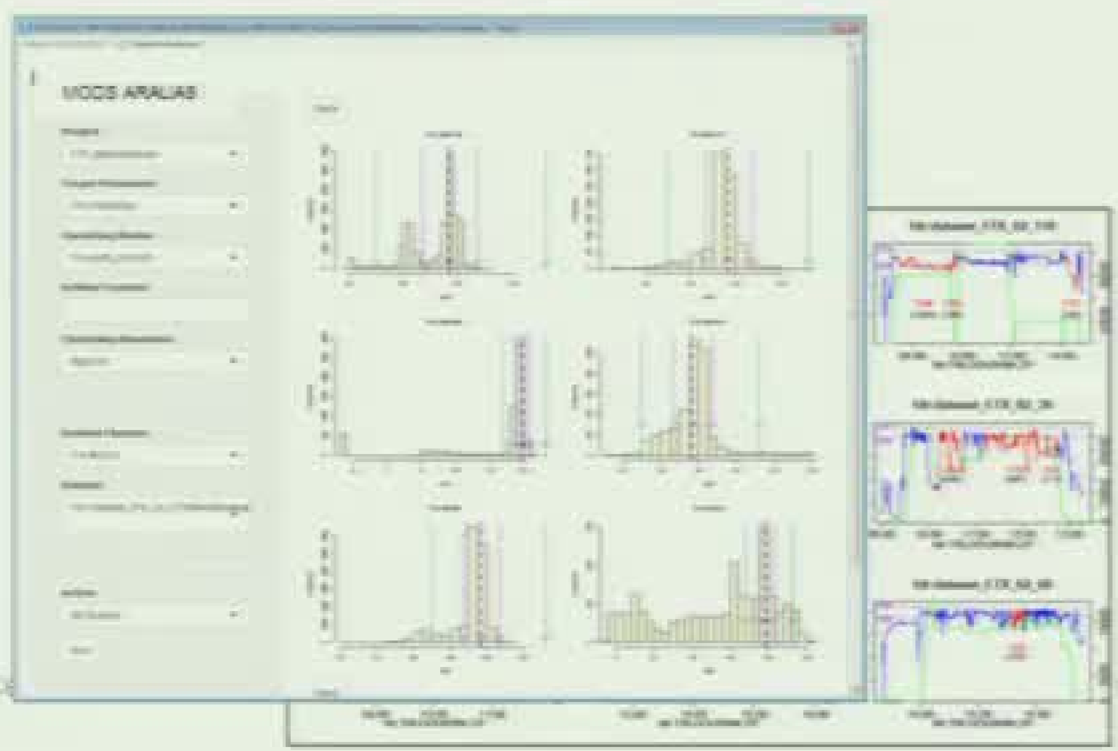
→ Advanced data analysis is required to take advantage of the streams of historical data collected from heterogeneous sources (sensors, ops. databases, ...)

System Identification and Time Series Analysis

- « Time-aware » parametric models to capture aircraft system underlying dynamics
- Suitable statistics and estimation methods to assess the performance of monitored systems
- Trend analysis and forecasting



Novel Data analytics and Visualization techniques



- **A Key Challenge**

  Evolving from « surgical » analysis of isolated datasets t[o] large-scale model estimation and exploitation

Perspectives

Maintain an unceasing effort to increase the efficiency of the design process (engineering time – elementary cycle)

- Algorithmic evolutions identified to reduce the return time
- Taking the maximum advantage from future computer architectures

Exploit the benefits to be provided by UQ

- Robustness regarding a shape degradation (manufacturing tolerance, aging)
- Robustness regarding the jig shape of the aircraft considering the flight point

Increase the confidence of engineers in stochastic approaches

Explore the applications of Data Analytics that bring added-value

- Formulation in scientific language of problems expressed by engineers
- Justification of the correctness and reliability of « Machine Learning »-type algorithms