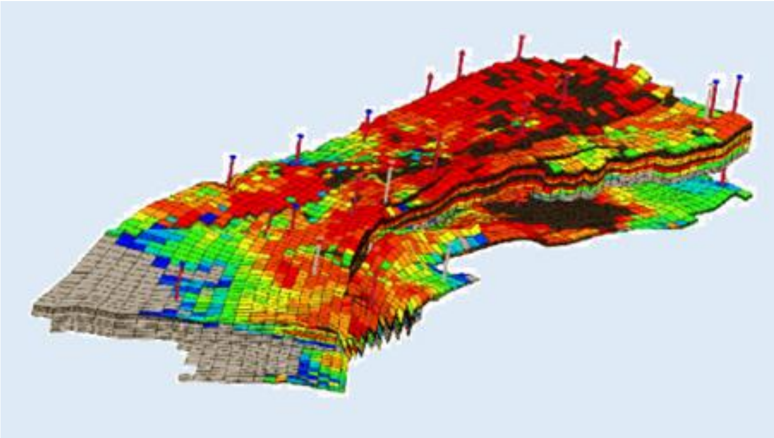
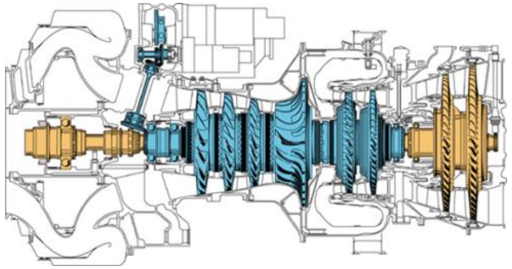
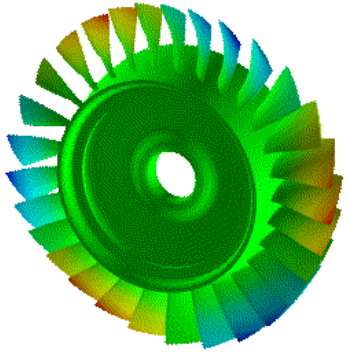
DERIVATIVE FREE OPTIMIZATION AND APPLICATIONS

Delphine Sinoquet (IFPEN)

COURSE 2: VARIOUS APPLICATIONS OF DFO







https://www.ifpenergiesnouvelles.fr/page/delphine-sinoquet

DERIVATIVE FREE OPTIMIZATION AND APPLICATIONS

- Course 1: main DFO methods
- **Course 2: various applications of DFO**
- Course 3: some challenges in DFO

CLASSIFICATION OF OPTIMIZATION APPLICATIONS

- **Parameter estimation for numerical simulations from experimental data = data calibration**
  - Inverse problems (geosciences)
  - Parameter estimation for complex models (combustion simulation for engines, kinetic models)

- **Optimal settings of experimental devices**
  - **From experimental data**: catalysis, engine calibration
  - **From models**: networks of oil pipelines

- **Optimal design**
  - Wind turbine, risers, well placement, engine design

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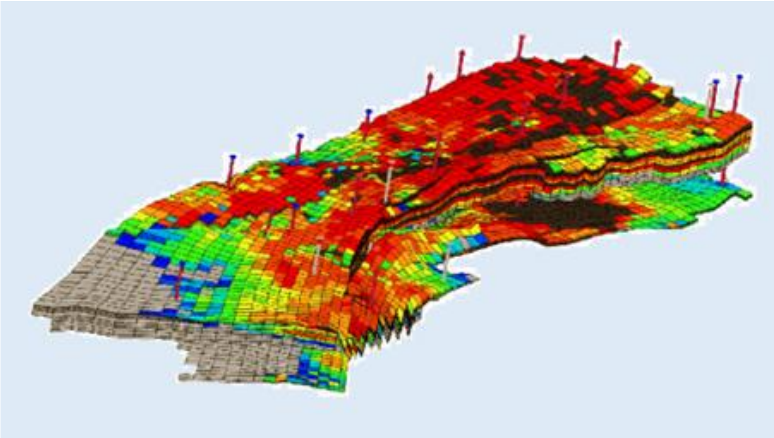
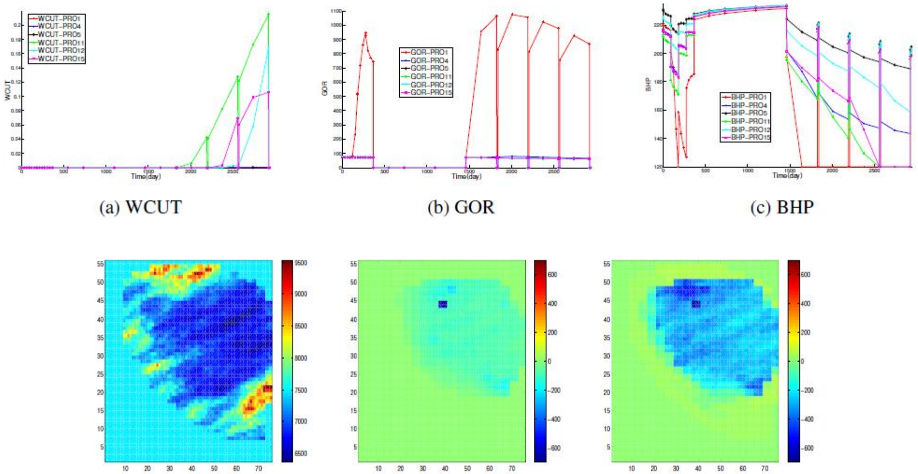
- History matching, uncertainty reduction and propagation in reservoir characterization

Langouët et al., 2010, 12th European Conference on the Mathematics of Oil Recovery

→ **Nonlinear derivative free constrained optimization problem**





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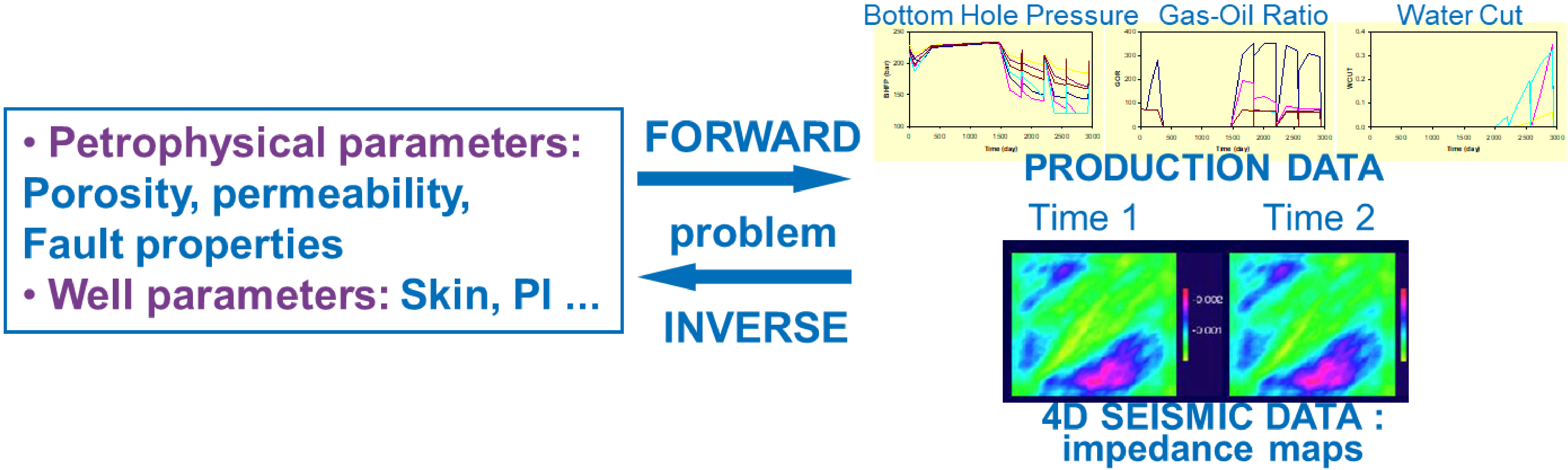
RESERVOIR CHARACTERIZATION

History matching from production data and 4D seismic data

For characterization of dynamic behavior of reservoir during the production of a field



Forward problem:

- Fluid flow simulation in reservoir
- Petro-elastic modelling

Characteristics of the optimization problem

$$\min_{x} f(x) := \left\| d_P(x) - d_P^{obs} \right\|_{C_P}^2 + \left\| d_S(x) - d_S^{obs} \right\|_{C_S}^2$$

- Nonlinear least-square problem
- Data space: up to 1.000.000 measurements
- Parameter space: ~10 up to 100 (various types)
- **Unavailable gradient**
- Simulation expensive in computational time (1mn - hours)

PUNQ TEST CASE: 3D SYNTHETIC RESERVOIR

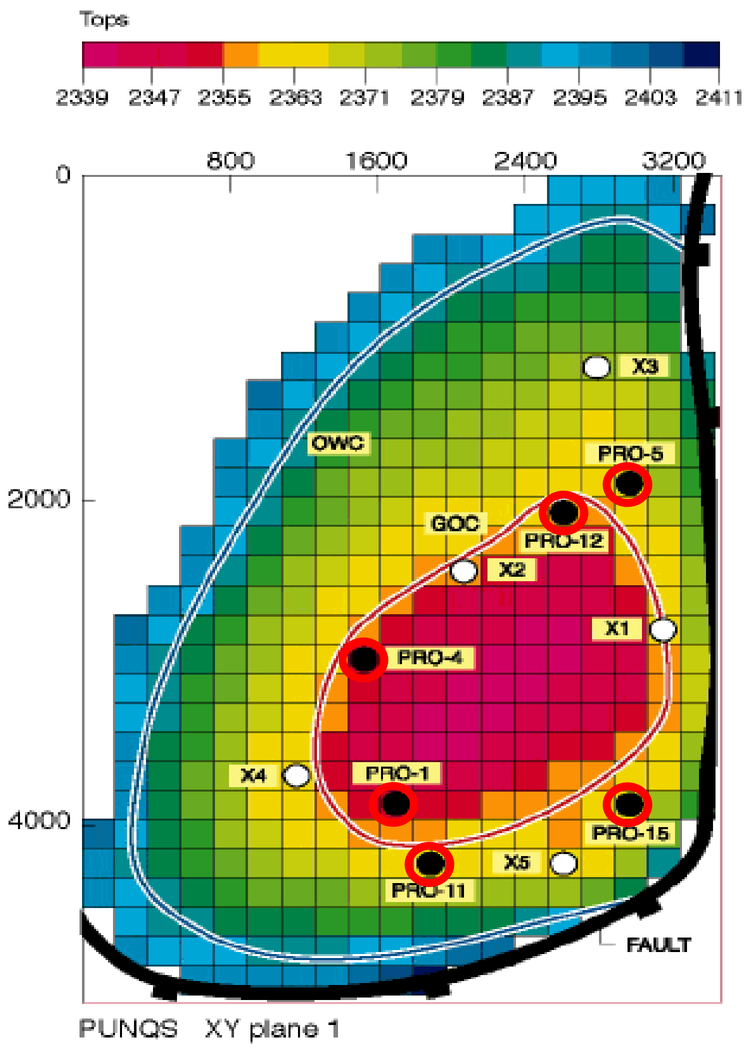
- **Parameters:** 25 geostatiscal parameters (porosity & permeability)

- **Data:** 128436
  - 127680 seismic data
  - 756 production data from 6 wells (3 per well at 41 different days)

- **Nonlinear least-square problem**

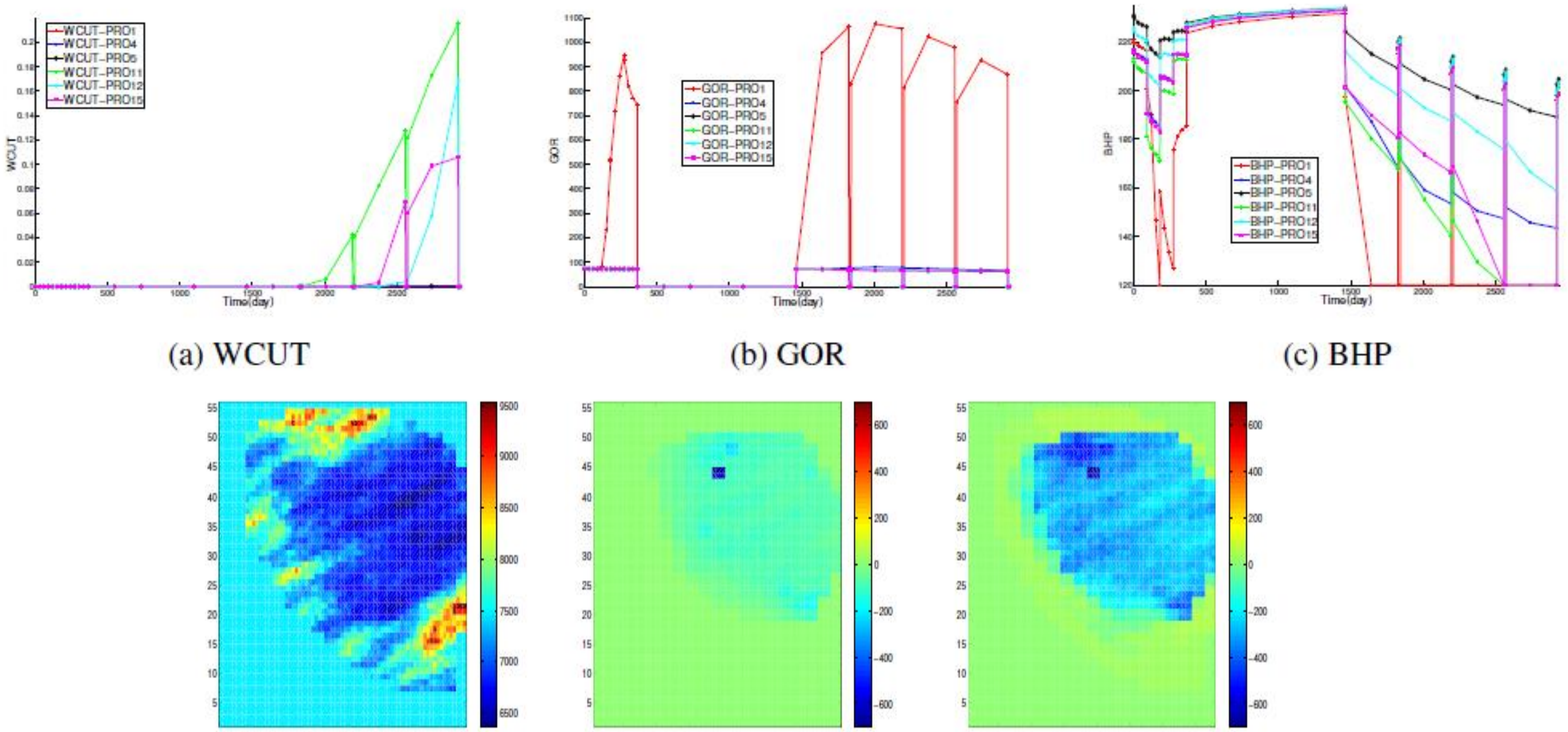
$$\min_x f(x) := \|d_P(x) - d_P^{obs}\|_{C_P}^2 + \|d_S(x) - d_S^{obs}\|_{C_S}^2$$

- **Bound constraints**



PUNQ TEST CASE: 3D SYNTHETIC RESERVOIR

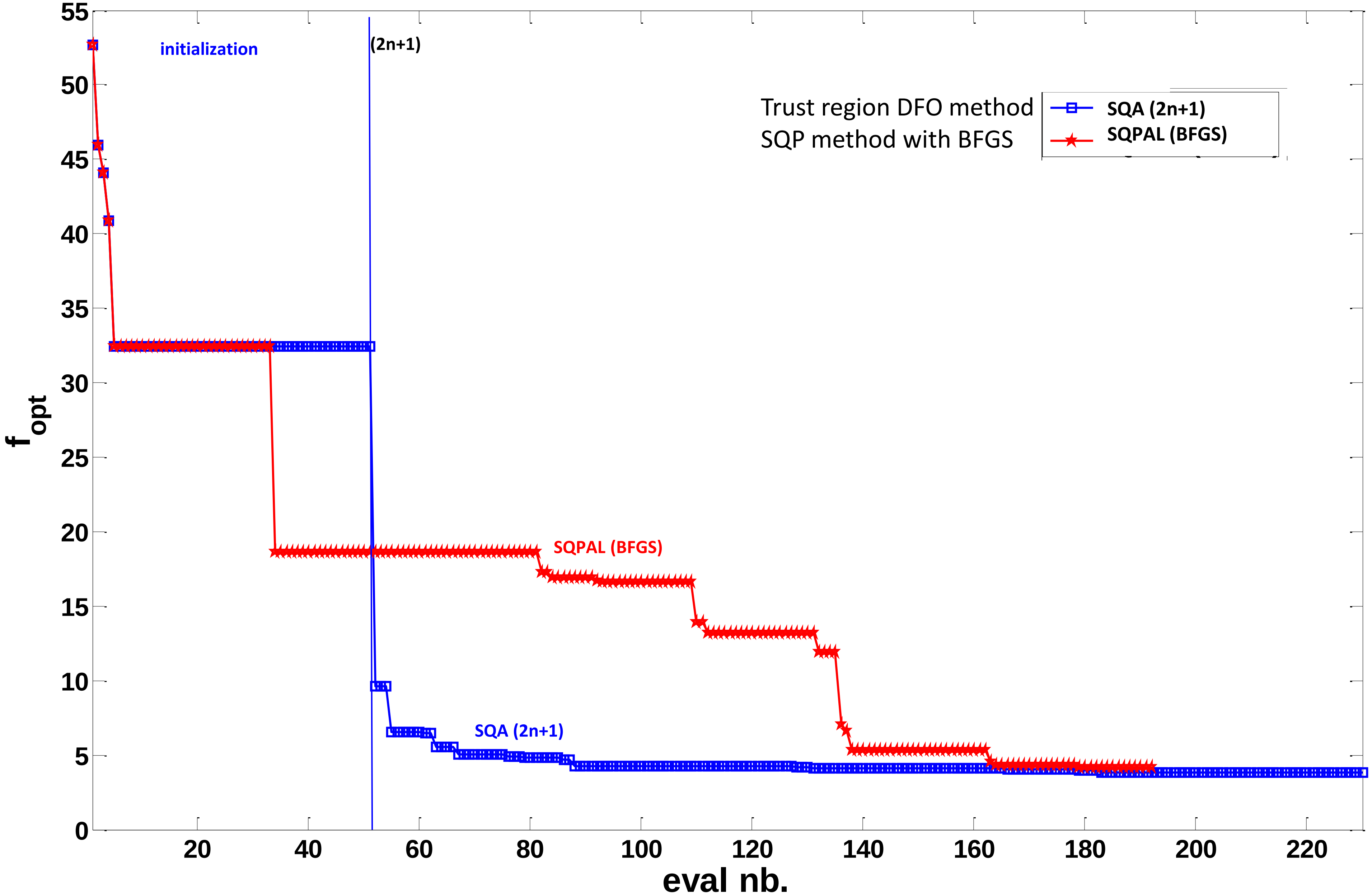
Reference data



(a) WCUT (b) GOR (c) BHP

(d) I_P at time 0 (e) ΔI_P at time 181 (f) ΔI_P at time 2192

HISTORY MATCHING RESULTS



POSTERIOR ANALYSIS OF THE INVERSION PROBLEM

From previous history matching result on $[T_0, T_{present}]$

- **forecast** the oil production in the future $[T_{present}, T_{future}]$

  → SIMULATION

- determine the **extreme production scenarii** $[d^i_{\min}, d^i_{max}]$ maintaining the calibration results on $[T_0, T_{present}]$

  → POSTERIOR UNCERTAINTY ANALYSIS

POSTERIOR ANALYSIS OF THE INVERSION PROBLEM

From previous history matching result, forecast the oil production in the future via **extreme scenarii**

$$\max_x / \min_x \int_{T_{present}}^{T_{future}} d^i(x,t)\,dt$$

Cumulated oil production

Derivative free

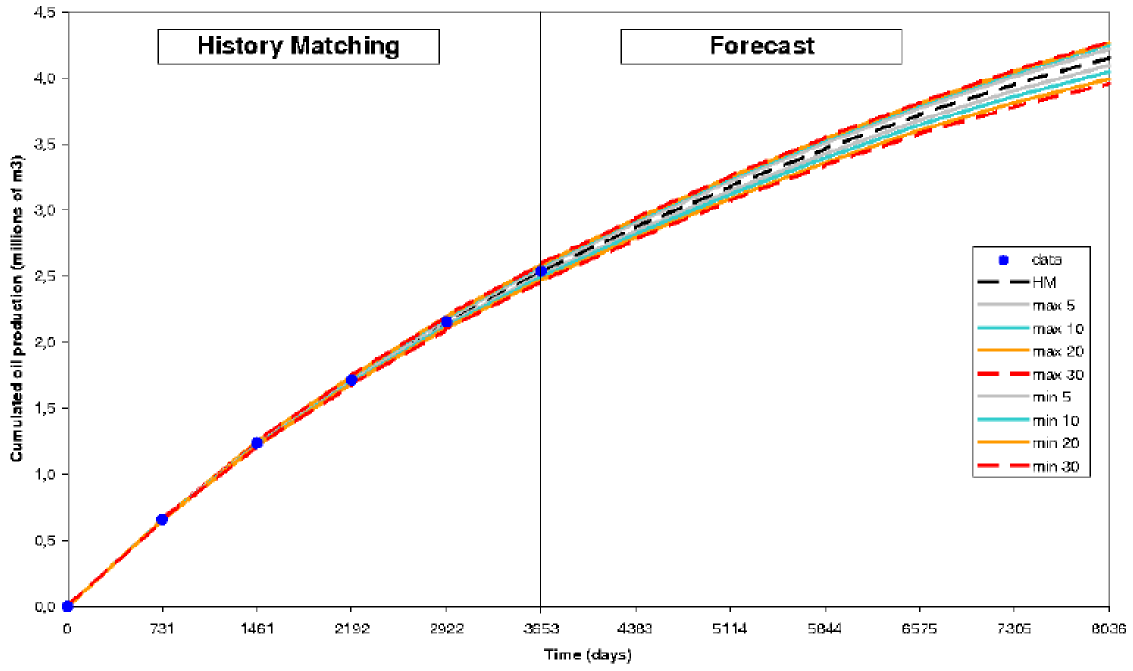
History matching constraint

$$\text{s.t. } \left\| d(x) - d^{obs} \right\|^2_{[T_0, T_{present}]} \leq \boxed{(1+\epsilon_{rel}) \left\| d(x_{HM}) - d^{obs} \right\|^2_{[T_0, T_{present}]}}$$

= constant

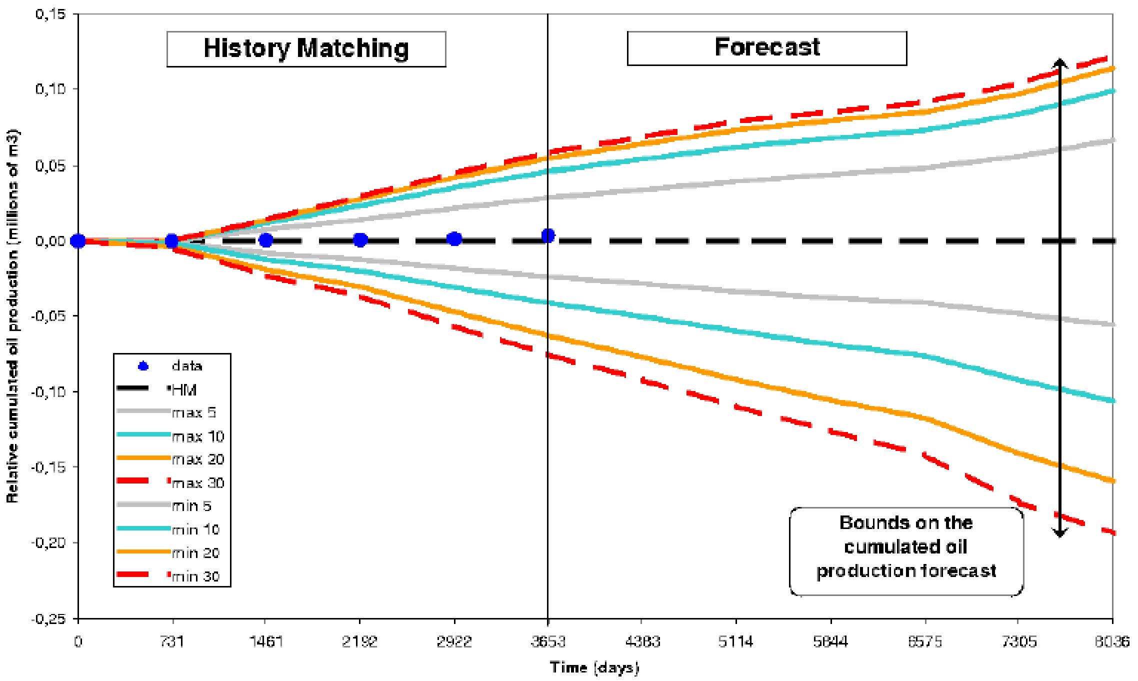
→ **Nonlinear derivative free constrained optimization problem**

POSTERIOR ANALYSIS OF THE INVERSION PROBLEM



Various values of ϵ_{rel}

5, 10, 20, 30



CONCLUSIONS

DFO methods used

- For data calibration
- For posterior uncertainty analysis: define extreme scenarios of oil production

= alternative to statistical Bayesian calibration (estimation of the whole posterior uncertainty distribution)

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- **Optimal settings of experimental devices**
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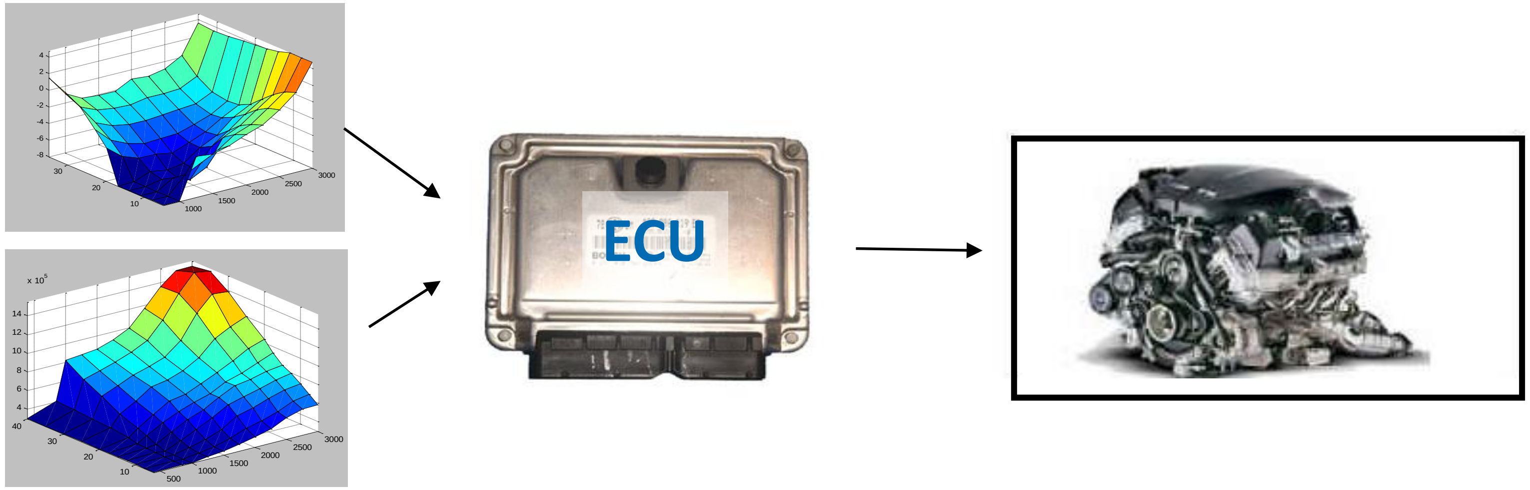
- Engine calibration

D. Sinoquet, H. Langouët, G. Font, S. Magand, F. Chaudoye and M. Castagné, ICCOPT, 2010

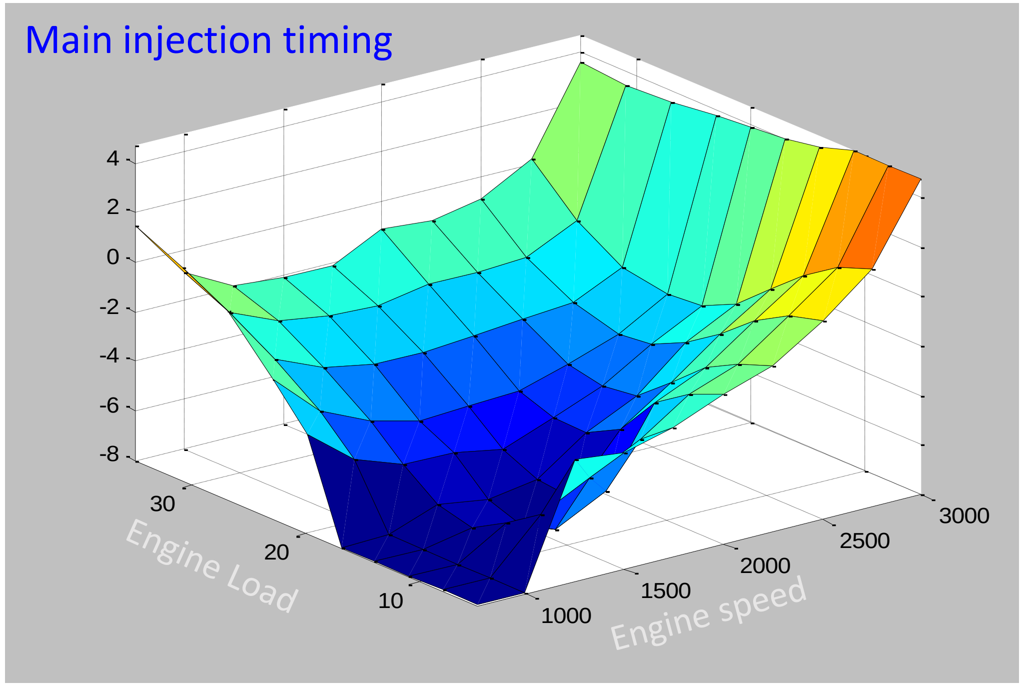
→ ***a constrained derivative free optimization problem with an adapted parametrization***



ENGINE CALIBRATON: PRINCIPLE

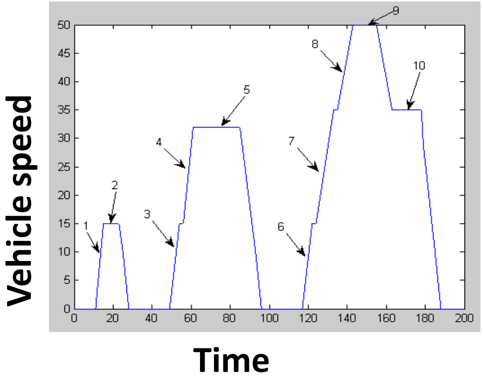
- Optimization of the engine parameters with respect to several criteria as **fuel consumption, pollutant emissions, noise, drivability** along a given driving cycle

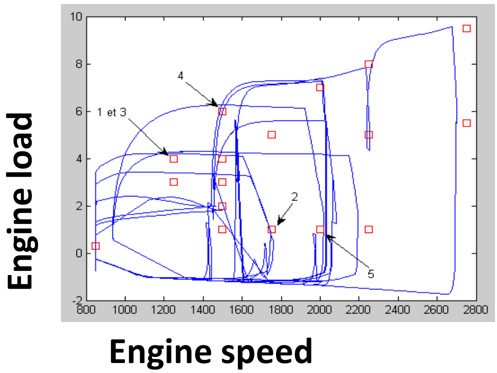
- Deliverables : **calibration maps** (one for each parameter) to be implemented in the Engine Control Unit (ECU) in the vehicle



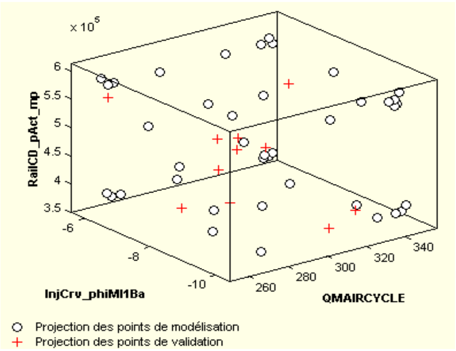
ENGINE CALIBRATON: PRINCIPLE

Driving cycle

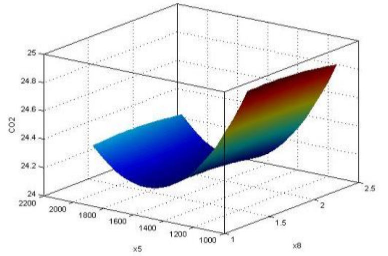


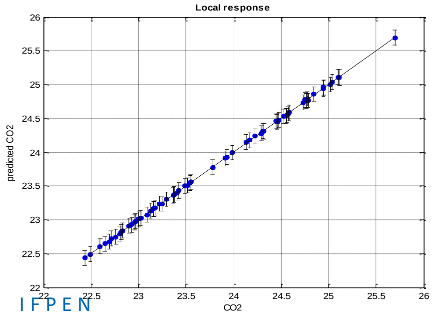


D.O.E / measurements at test bench

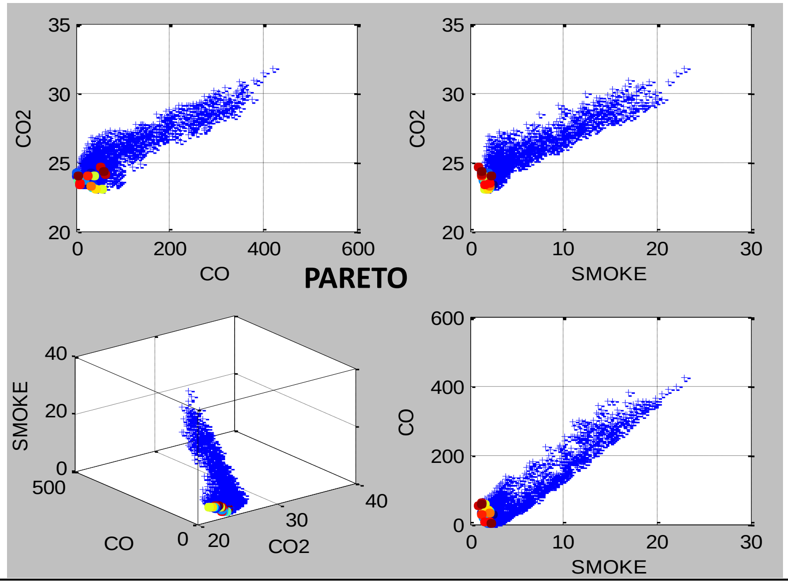


Modelling

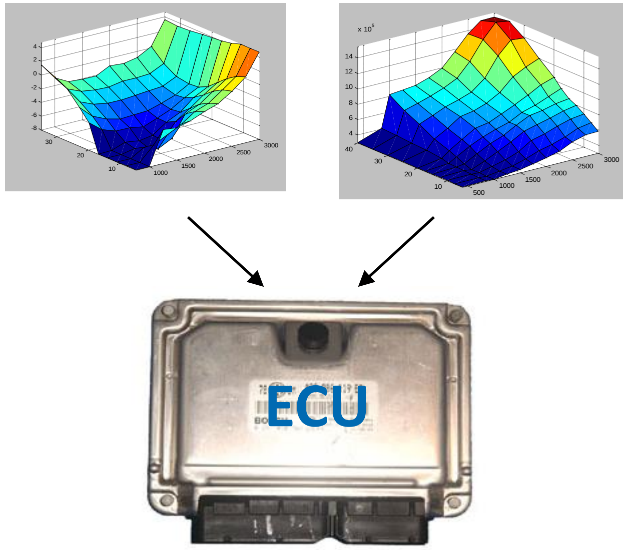




Optimization

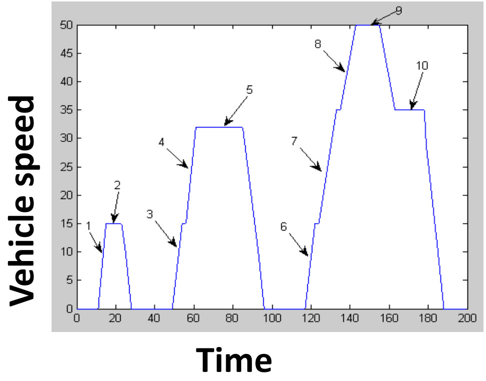


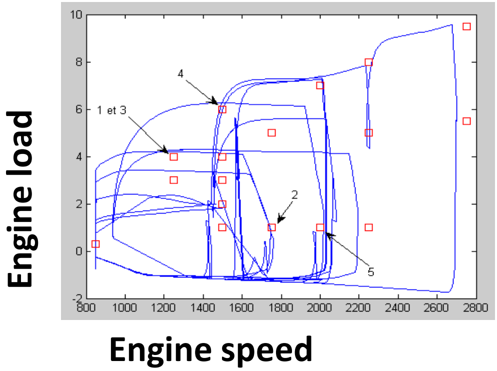
Engine maps



ENGINE CALIBRATON: PRINCIPLE

Driving cycle





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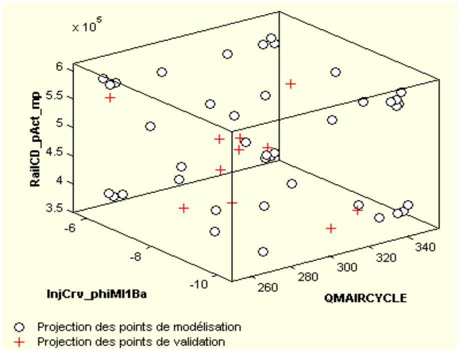
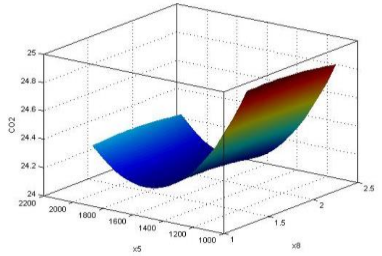
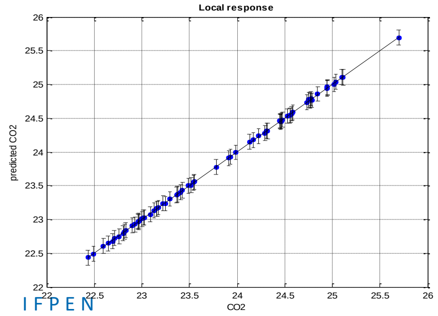


Modelling





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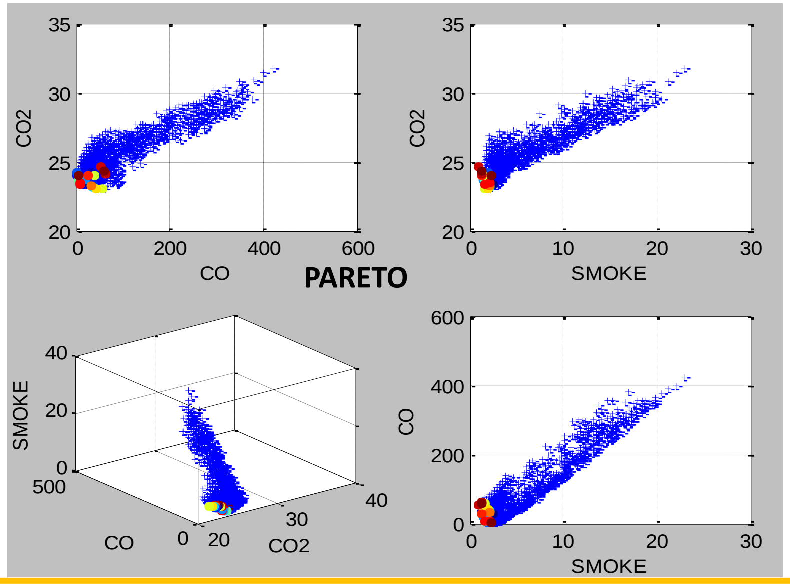

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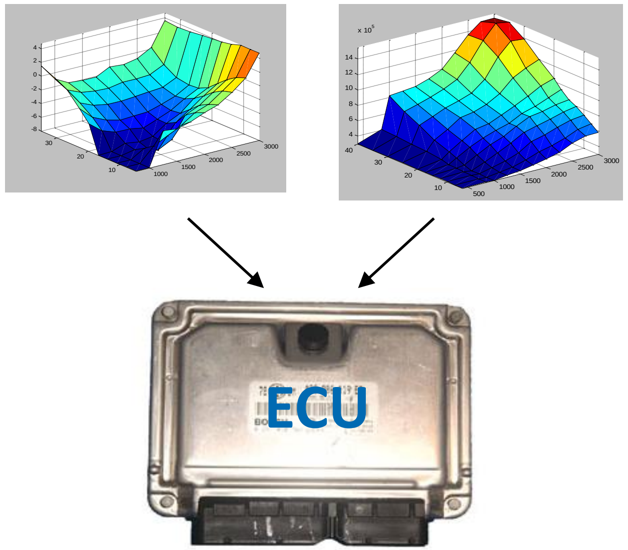

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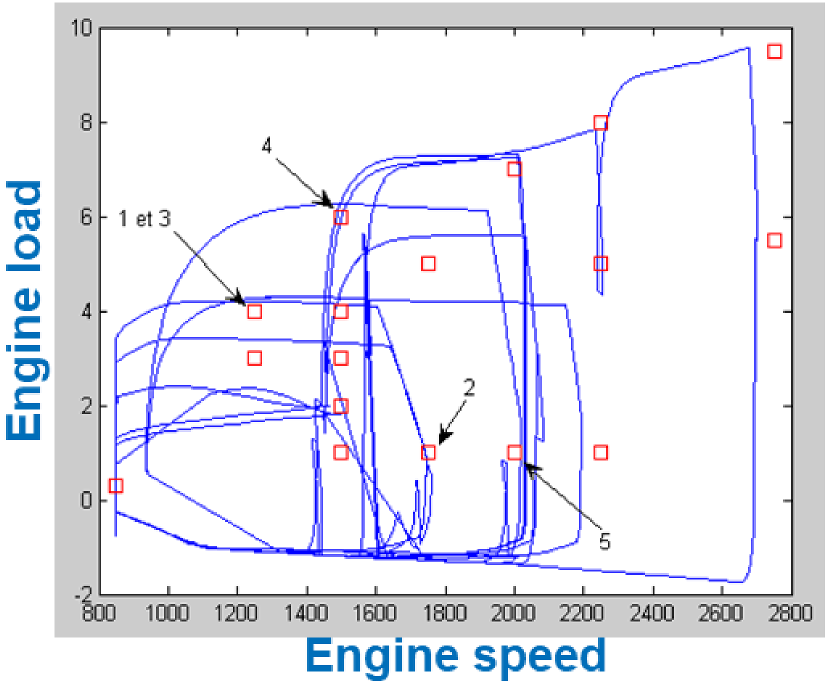
TWO MAIN FORMULATIONS

- **OP formulation**

  at given reference engine Operating Points, optimize the engine tunings with respect to the pollutant emissions of the engine at this OP

  + a posteriori smoothing step (drivability, feasibility) → **engine maps**



- **Map formulation**

  optimize the maps of the engine tunings w.r.t. the pollutant emissions of the engine cumulated along the given driving cycle

  regularity constraints on maps (drivability, feasibility) are introduced in optimization problem

TWO MAIN FORMULATIONS

- **OP formulation**
  - \+ simple modeling phase (polynomial models), small size optimization problems
  - − but a posteriori smoothing step may destroy optimization work
  - − OP optimization problem is valid for only one vehicle configuration

- **Map formulation**
  - − complex DOE and modeling steps : models valid on the whole operating domain (kriging / RBF)
  - \+ provides directly the engine maps
  - \+ optimization for different vehicle applications may be processed wo. any additional experimental tests

FORMULATION OF THE MAP OPTIMIZATION

Optimize the maps of the engine tunings with respect to the pollutant emissions of the engine cumulated along the given driving cycle

$$F = (F_1, F_2, \ldots, F_m)^T$$
$$m^p \in \mathcal{M} : \mathbb{R}^2 \to \mathbb{R}^{N_p}$$

Global engine responses modeled on the operating domain (depending on engine speed r and engine torque c)

$$\begin{cases} \min\limits_{m^p \in \mathcal{M}} \int_0^T F\left(r(t), c(t), m^p(r(t), c(t))\right) dt \\ \text{subject to} \\ l(r,c) \leq A m^p(r,c) \leq u(r,c) \\ \int_0^T F\left(r(t), c(t), m^p(r(t), c(t))\right) dt \leq S \end{cases}$$

+ regularity constraints on maps for drivability / feasibility (2nd derivatives of maps)

MODELING THE ENGINE RESPONSES

- **Statistical models:** kriging
  response surfaces built from experimental data on the engine test bench (stabilized measurements)

- **Physical models:** (AMESim) modeling the behavior of the vehicle (control) and the transient behavior of the engine during combustion

➢ **Combine the 2 models to obtain more accurate predictions of the pollutant emissions and the engine noise**

FORMULATION OF THE MAP OPTIMIZATION

Optimize the maps of the engine tunings with respect to the pollutant emissions of the engine cumulated along the given driving cycle

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Constraints of parameter variation domain on the operating domain (depending on r and c)

FORMULATION OF THE MAP OPTIMIZATION

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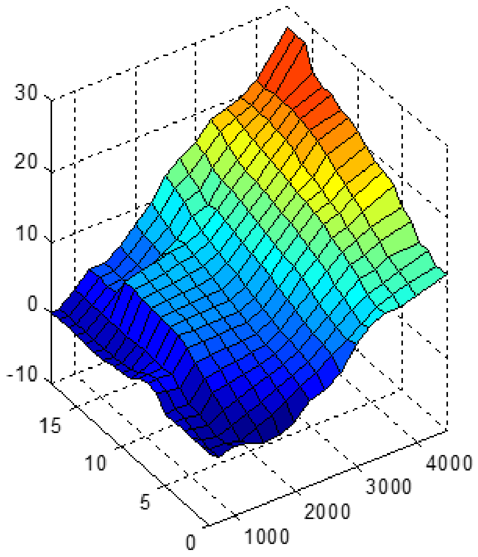
+ regularity constraints on maps
for drivability / feasibility
(2nd derivatives of maps)

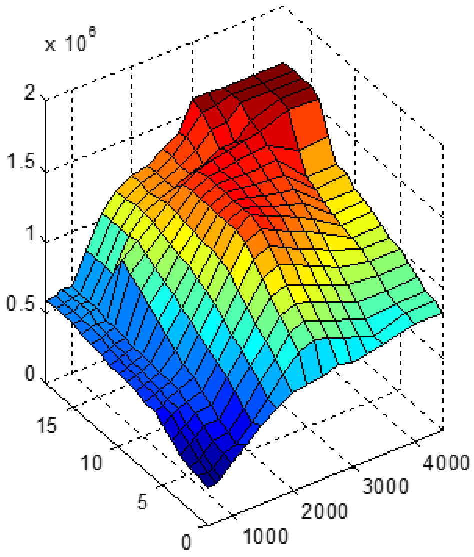
ADAPTED MAP PARAMETERIZATION

A flexible parameterization to represent shapes of the different engine maps

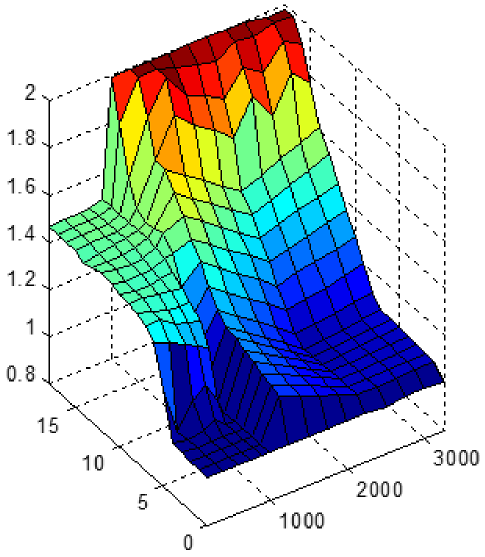
Main injection timing



Fuel injection pressure



Pilot fuel injection quantity



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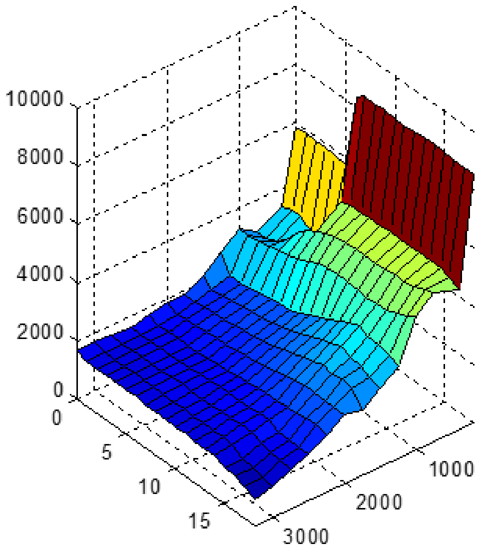


ADAPTED MAP PARAMETERIZATION

A flexible parameterization to represent shapes of the different engine maps

- Limit the number of parameters for optimization
  Number of parameters = ∑ number of map parameters

- Ability to control the map regularity
  feasibility, drivability

➢ LoLiMoT functions: Local Linear Model Tree

ADAPTED MAP PARAMETERIZATION

LoLiMoT functions

$$y = \sum_{i=1}^{N} \hat{y_i}(r,c)\Phi_i(r,c)$$

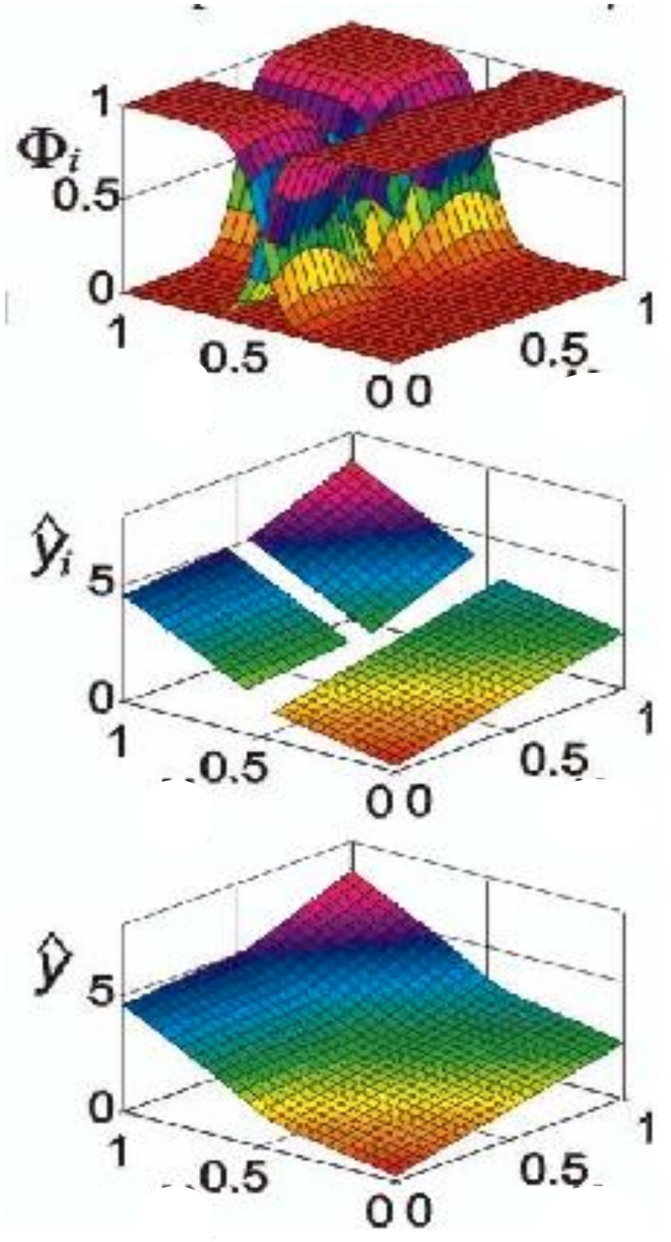
$$\hat{y_i}(r,c) = \omega_{0i} + \omega_{ri} r + \omega_{ci} c$$

$$\Phi_i(r,c) = \frac{\mu_i(r,c)}{\sum_{j=1}^{N} \mu_j(r,c)}$$

normalized Gaussian validity functions of local models

$$\mu_i(r,c) = exp\left(-\frac{1}{2\alpha}\left(\frac{(r-{r_i}^0)^2}{\sigma_i^{r2}} + \frac{(c-{c_i}^0)^2}{\sigma_i^{c2}}\right)\right)$$

➢ **α controls the global regularity of the map**



A constrained derivative free optimization problem

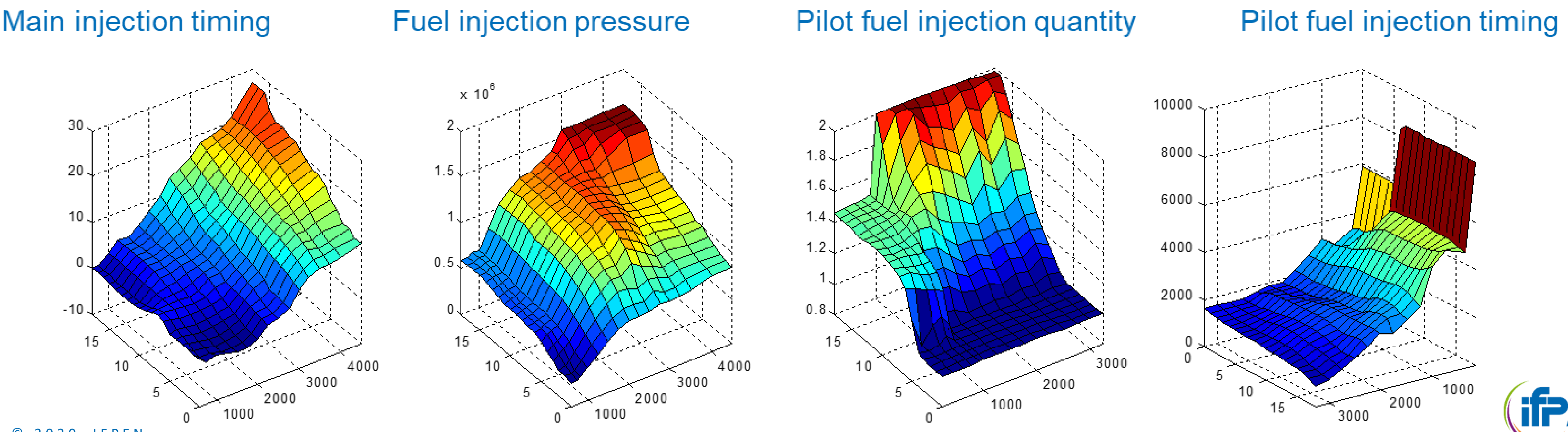
- Derivative free objective function
- Derivative free constraints: constraints on the responses of the simulator
- 20-1000 LoLiMoT parameters to represent engine maps

➢ **Trust region derivative free method**

APPLICATION OF MAP OPTIMIZATION

on a turbo-charged direct injection diesel engine

- **1 single objective:** CO_2 emissions cumulated on an acceleration extracted from a legislative driving cycle
- **4 engine control parameters** (controlling the injection)
  = 28 LoLiMoT parameters
  LoLiMoT parameterization defined from reference maps



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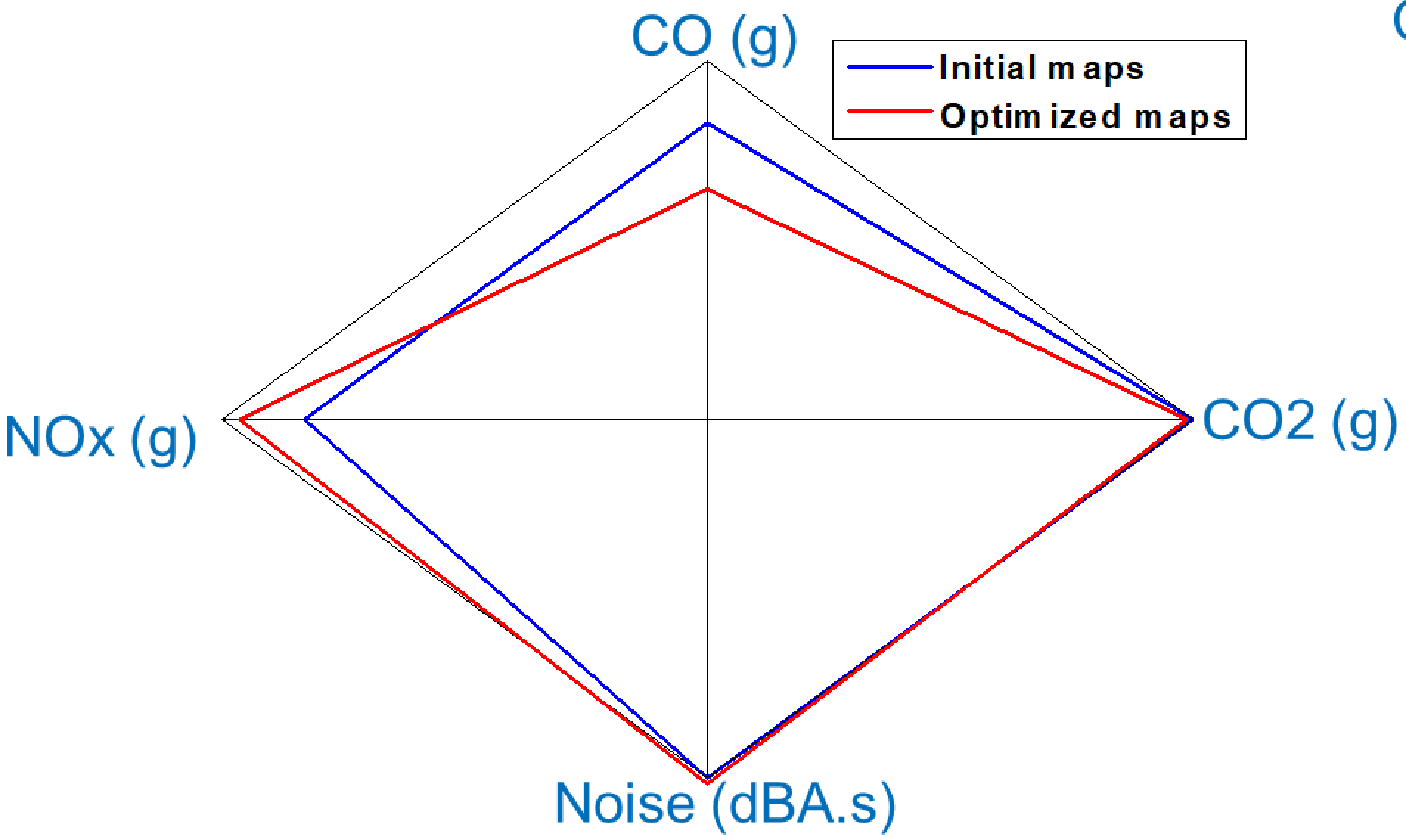
- **Robustness constraints that** take into account parameter dispersions in the optimization process (avoid boundaries of the parameter variation domain)
- **Engine responses**
  AmeSim models coupled with kriging models = 12mn/simulation

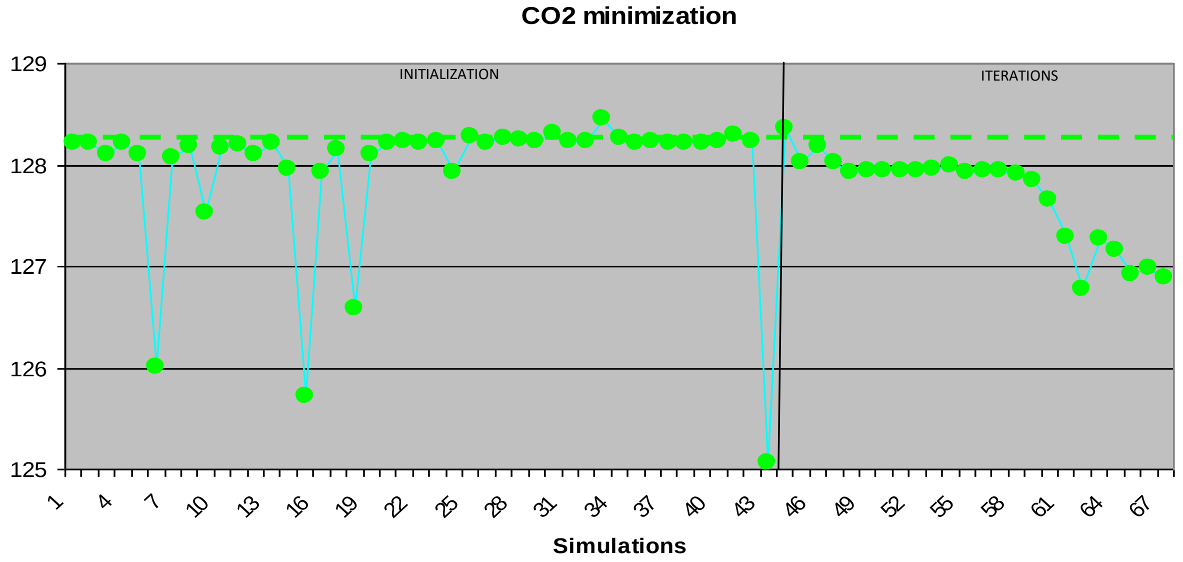
APPLICATION OF MAP OPTIMIZATION

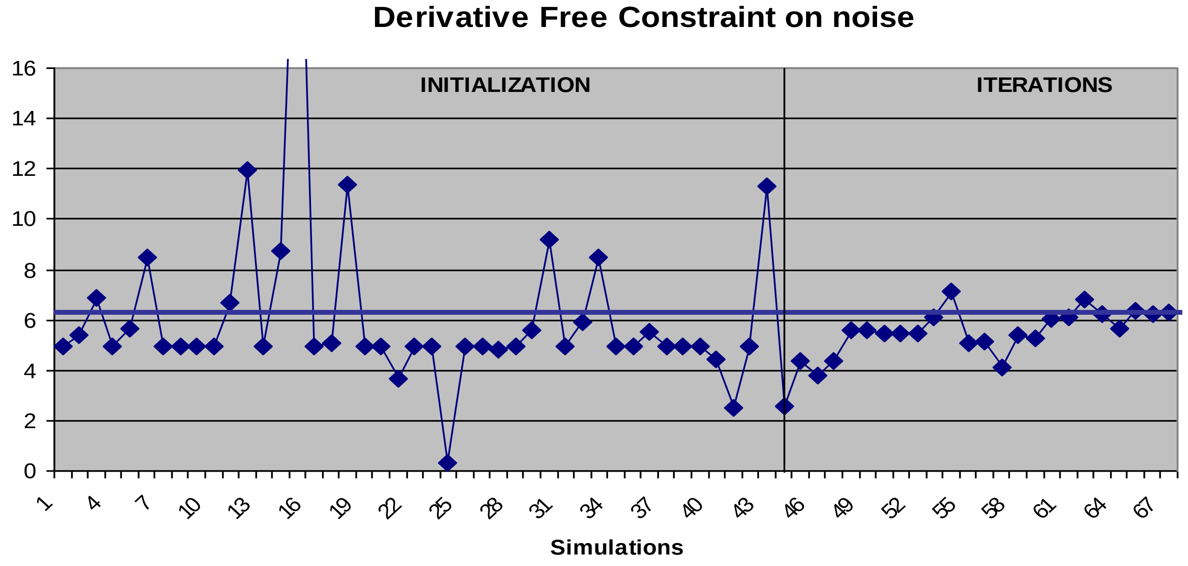
	INITIAL	OPTIMIZED	CONSTRAINT
CO2 (g)	128,26	126,88	minimized
CO (g)	262,86	205,46	315,44
NOx (g)	626,29	733,02	751,54
Noise (dBA.s)	6,42	6,29	6,42

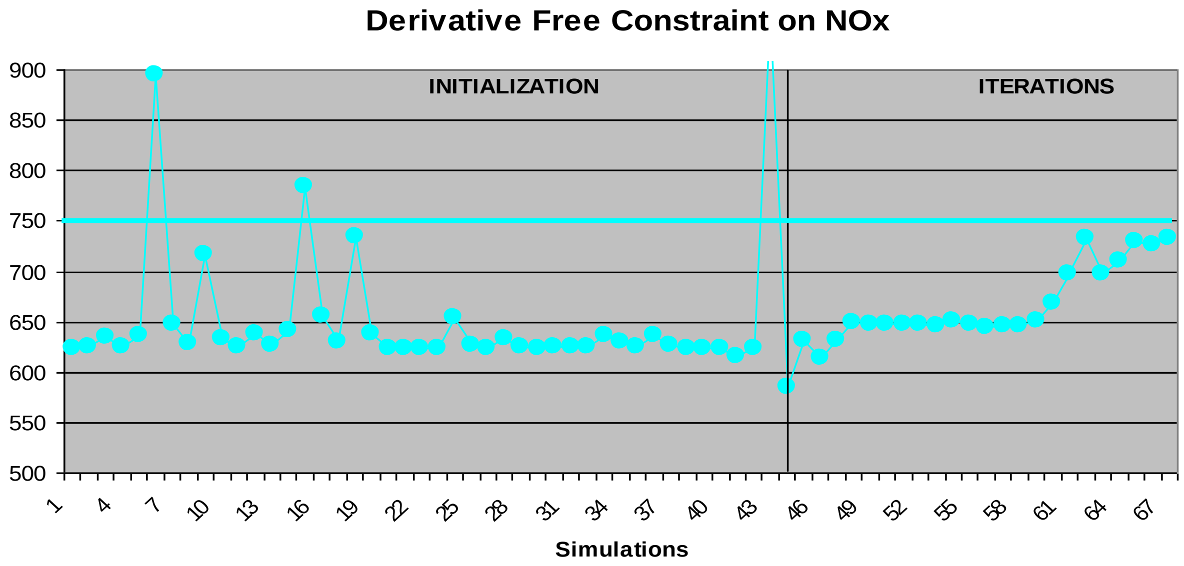
CPU time : ~14h

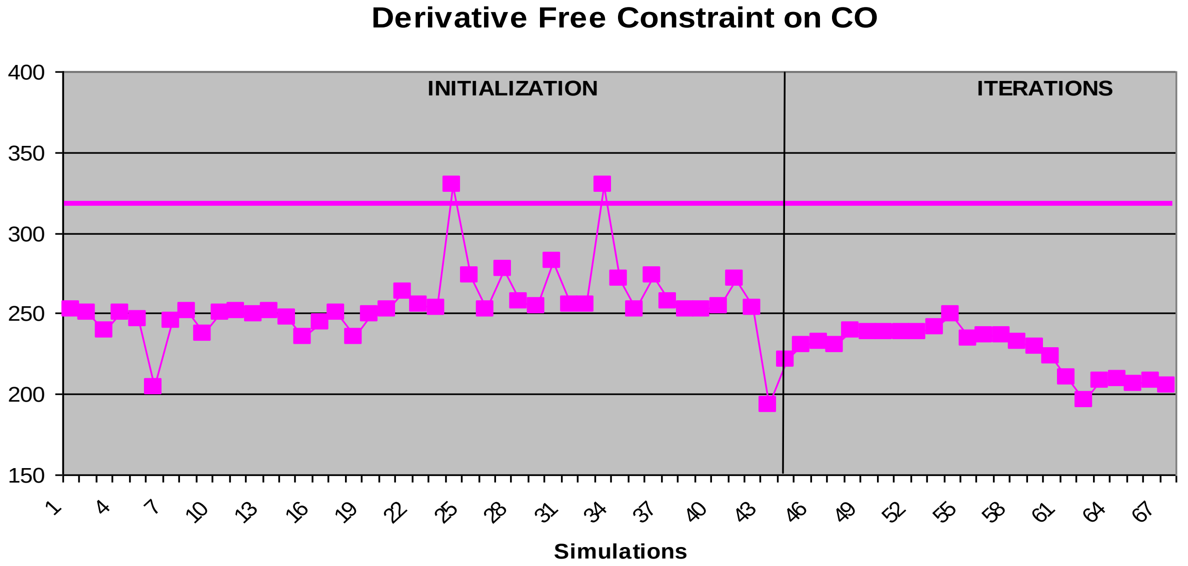


APPLICATION OF MAP OPTIMIZATION

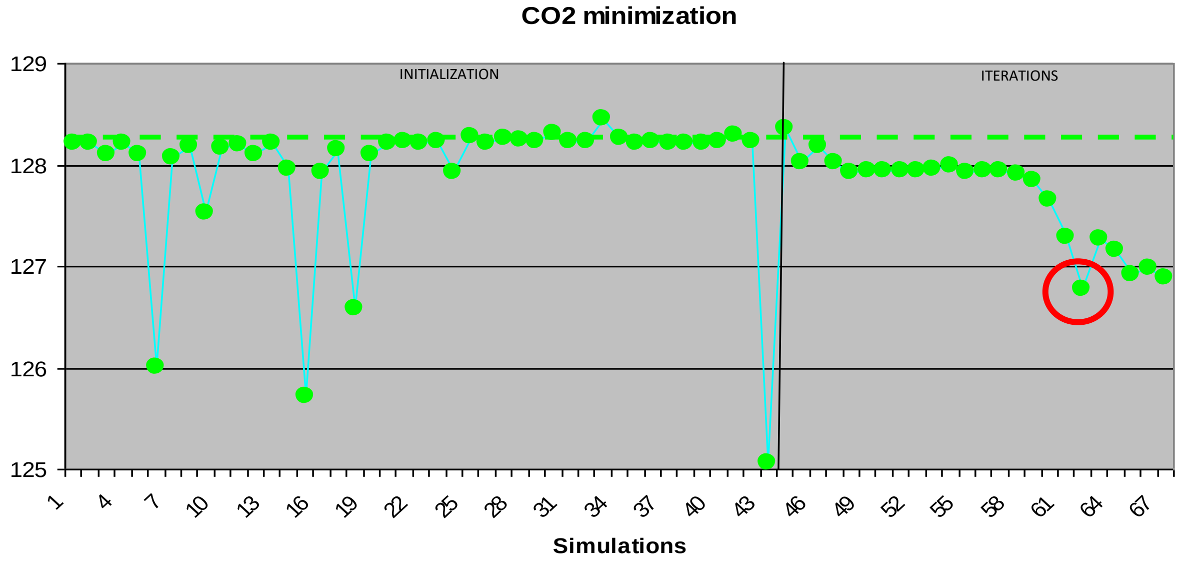


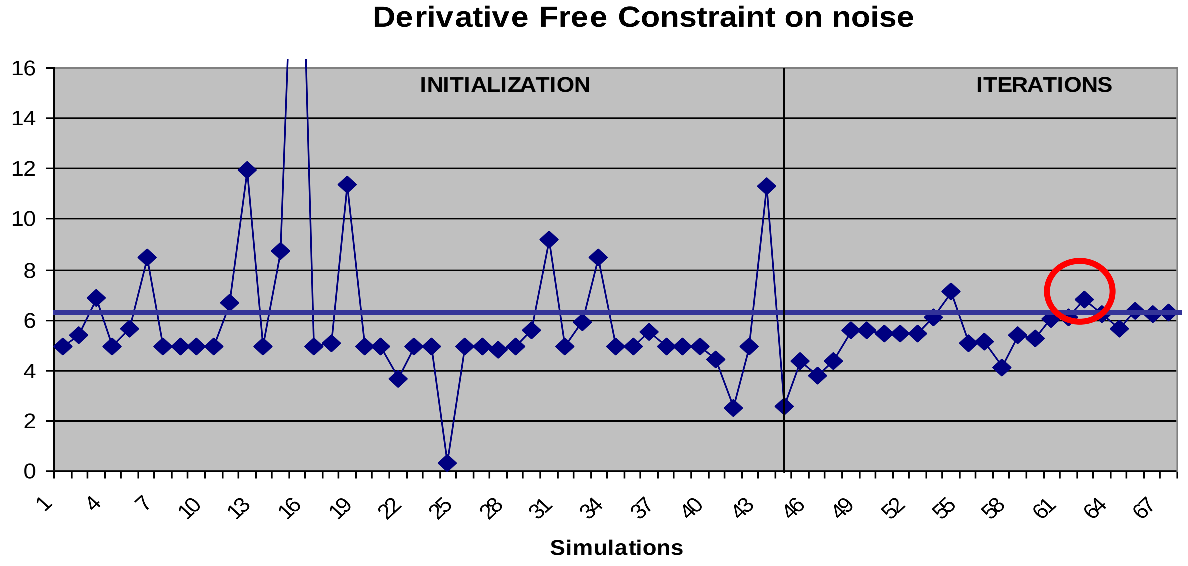


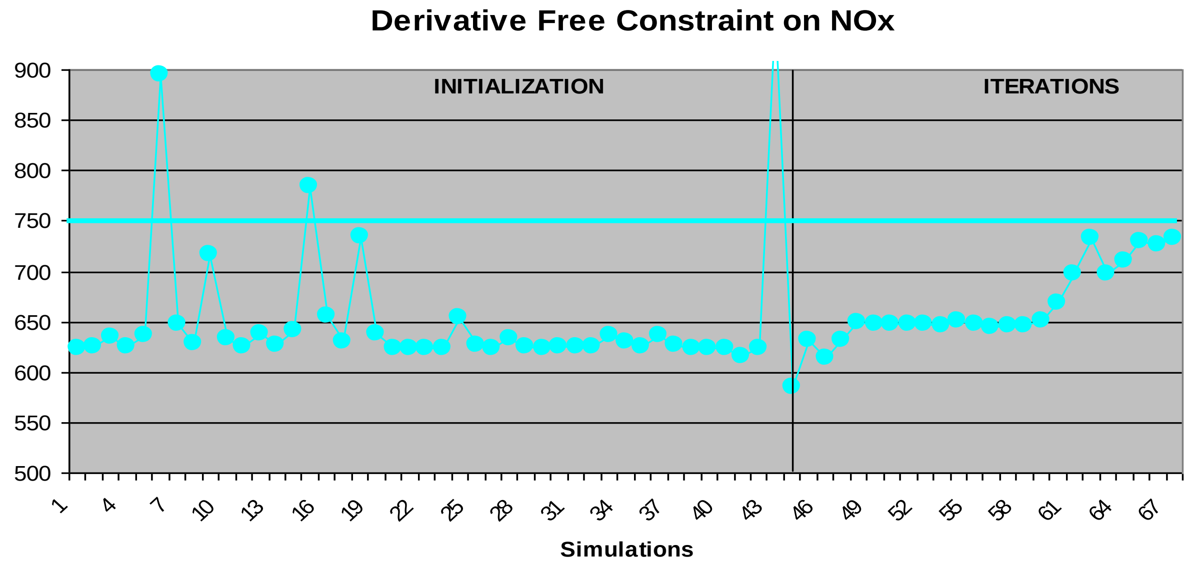


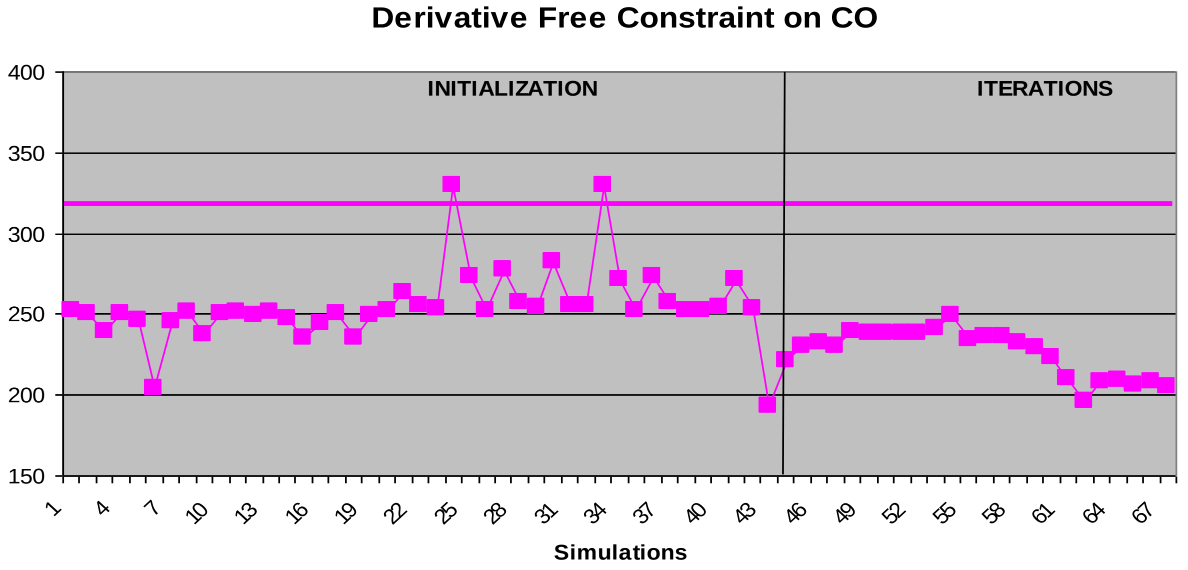


APPLICATION OF MAP OPTIMIZATION





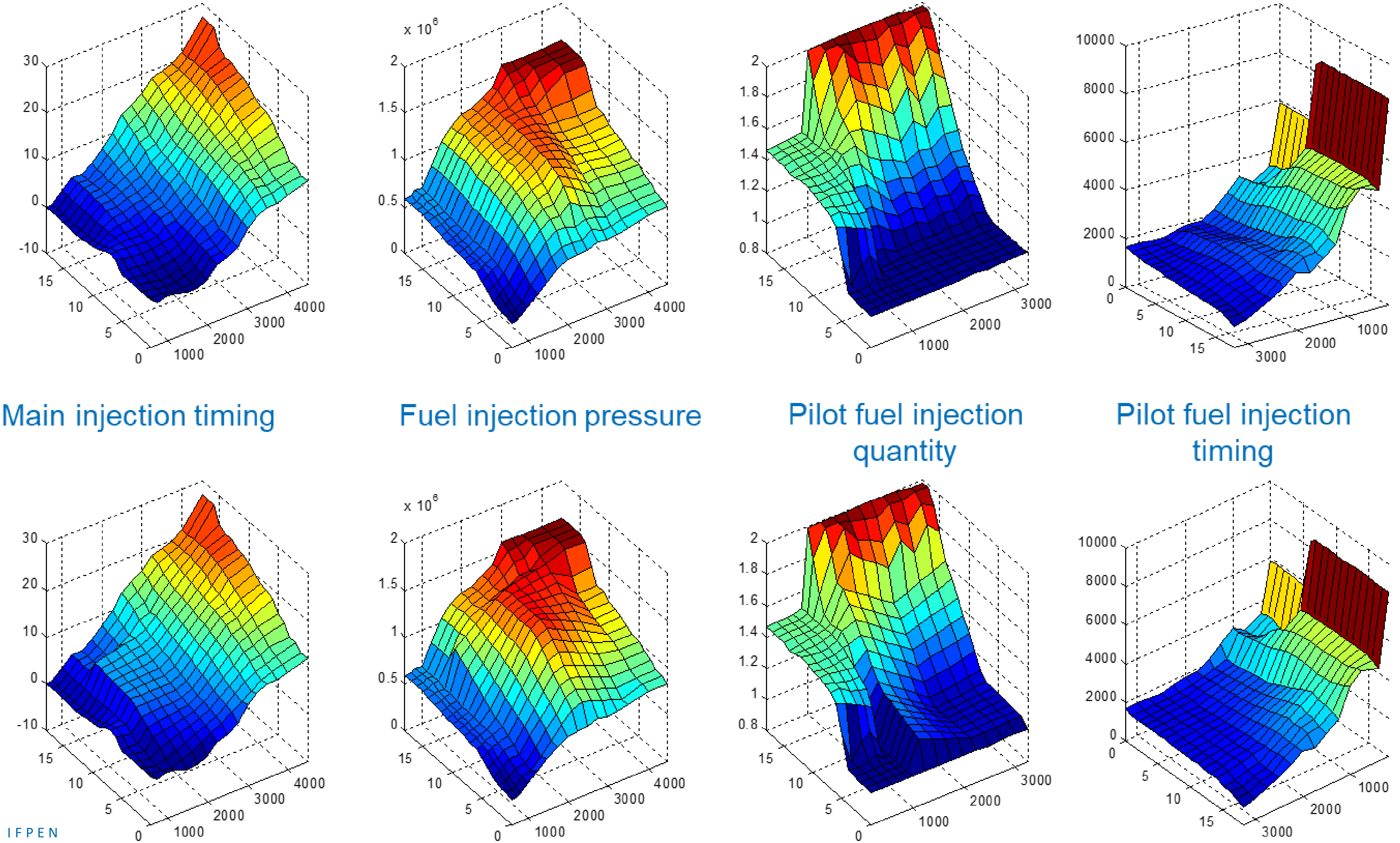




APPLICATION OF MAP OPTIMIZATION

INITIAL

OPTIMIZED



CONCLUSIONS

- Engine map optimization based on physical models coupled with response surfaces built from experimental data
- Adapted parameterization of the maps
- A constrained derivative free optimization problem
- Trust region DFO method gives encouraging results on this real calibration problem

CLASSIFICATION OF OPTIMIZATION APPLICATIONS

- **Parameter estimation for numerical simulations from experimental data = data calibration**
  - Inverse problems (geosciences)
  - Parameter estimation for complex models (combustion simulation for engines, kinetic models)

- **Optimal settings of experimental devices**
  - **From experimental data**: catalysis, engine calibration
  - **From models**: networks of oil pipelines

- **Optimal design**
  - Wind turbine, risers, well placement, engine design

OPTIMAL DESIGN

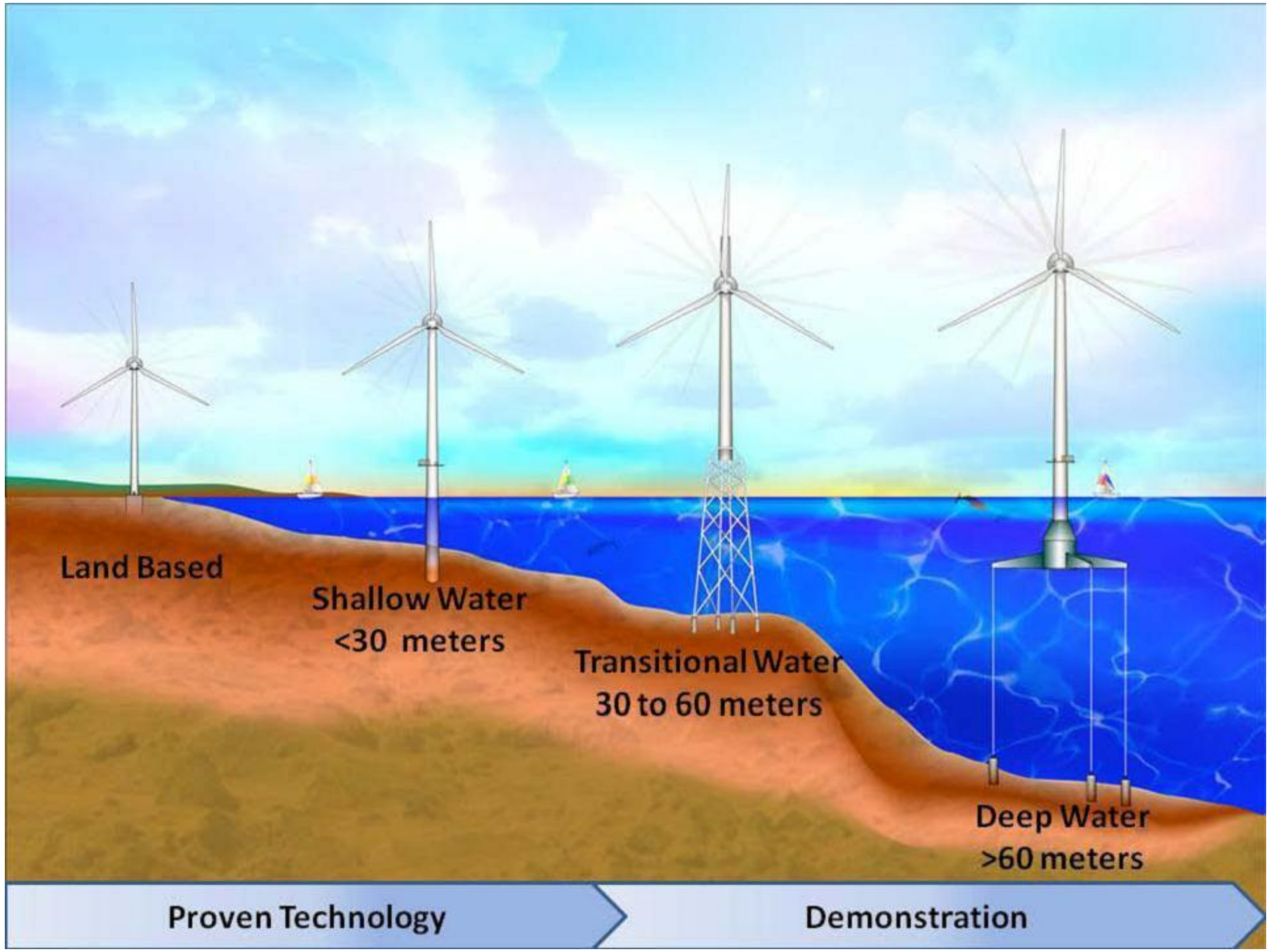
- Design of of mooring lines of floating offshore wind turbines

D. Sinoquet, Martin Guiton, Yann Poirette, workshop DFO, 2016

→ ***a derivative free optimization problem with multiple constraints***

OFFSHORE WIND MARKET : GENERAL CONTEXT

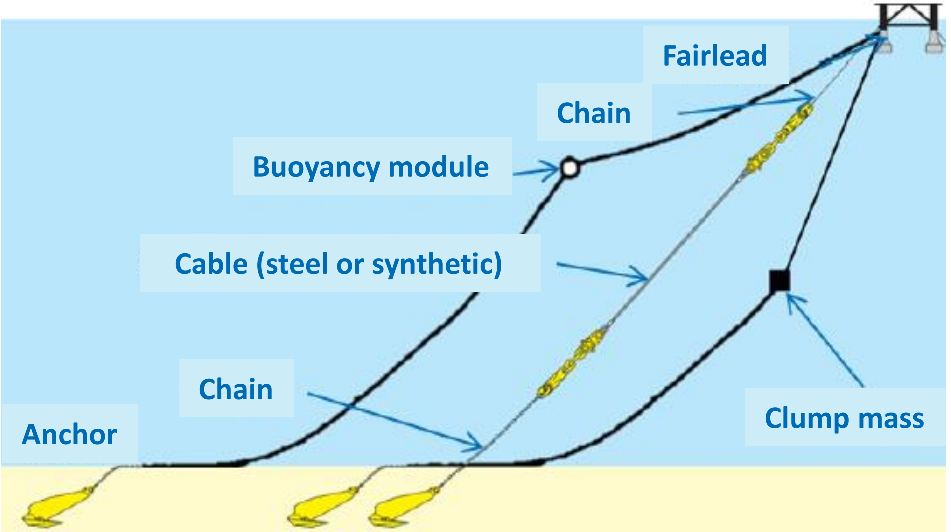
- The offshore **wind market is growing** rapidly thanks to several drivers :
  - important wind resources
  - lower turbulence offshore
  - reduced visual impact
- The offshore wind market is moving into deeper waters with bigger turbines for which **floating foundations** become economically attractive.



source : NREL

IFPEN'S OBJECTIVE AND APPROACH

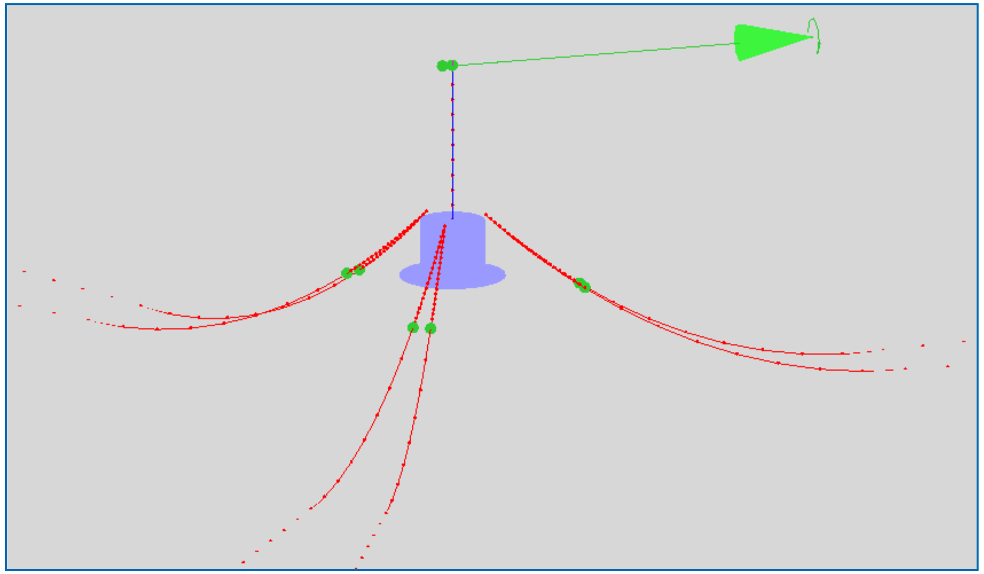
- The objective of IFPEN is to participate in the development of floating offshore wind turbines
  - by proposing reliable solutions with adapted technologies to **lower the cost**
  - by offering a set of solutions for floaters and **mooring technologies adapted** to solve technical and economic challenges of offshore environment



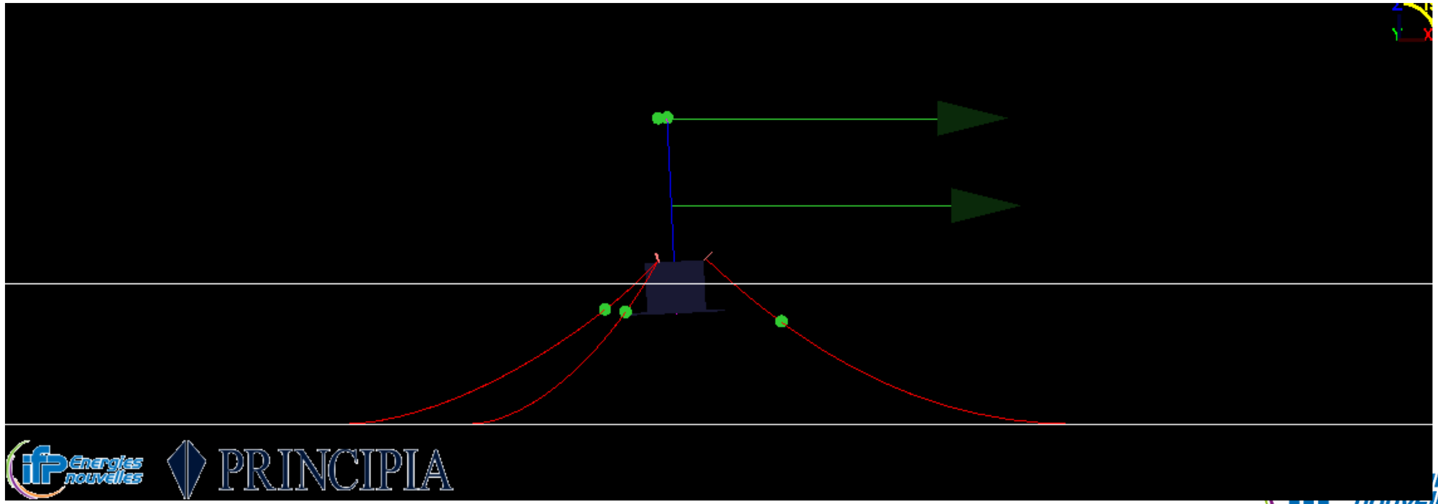
APPLICATION TEST CASE

Design the **mooring system** for a cylindrical platform

- 6 **catenary** lines grouped by pairs
  a part of each line lies on the sea floor
- **Buoyancies** to reduce cable tension
  or **additional mass**
- Elastic element at the head of each line
- Line material : **chain**, steel cable, polyester,
  high density polyethylene



- For a wind turbine
  - $3.6MW$
  - Total weight : $210t$
  - $127m$ high



APPLICATION TEST CASE

- Simulation with Deeplines^{TM} : FE solver
  - Computes the **dynamic response** of the mooring lines given the hydrodynamic behavior of the floater

- Design with respect to **extreme load conditions**
  - 2 cases : producing or **parked wind turbine**

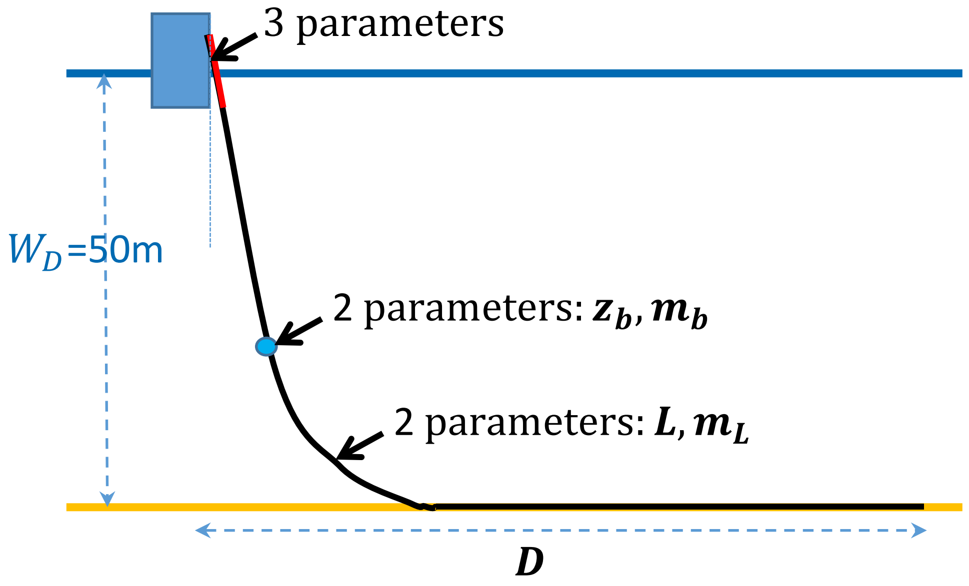
  - with co-directional wind and waves
    - **Wind load** modelled by thrust loads on the gravity center of the rotor and on the tower
      reference wind speed : 42.5m/s – for parked turbine –

    - **Wave load** modelled by an energy spectral density
      (JONSWAP spectra from real measures in North sea)
      H_s, reference wave amplitude and T_p, associated period – ($H_s = 10\text{m}$, $T_p = 14\text{s}$) for parked turbine –

APPLICATION TEST CASE

9 design parameters

- Length of the lines (m) : $\boldsymbol{L}$
- Line weight (kg/m) : $\boldsymbol{m_L}$
- Projected distance between anchor and floater (m) : $\boldsymbol{D}$
- Angle between the 2 lines of the pairs (°) : $\boldsymbol{\alpha}$
- Weight of the buoy or additional mass (< 0 if buoy) (t) : $\boldsymbol{m_b}$
- Buoy/mass location along the line (m) : $\boldsymbol{z_b}$
- Elastic element described by 3 parameters



+ Bound constraints

+ 3 inequality constraints coupling some design parameters

APPLICATION TEST CASE

- **Objective to be minimized** : cost of the mooring system

$$f(x) = n_{lines} \underbrace{C_C L_{C_i}}_{\text{line cost}} + n_{lines} \underbrace{C_b |m_b|}_{\text{mass/buoy cost}}$$

- **Inequality constraints** on Deeplines^{TM} simulator outputs
  - vertical angle of the lines — $|\beta_i| \geq 10°$
  - line tension — $0 \leq T_i(s) \leq 60\% B_C$
  - vertical location of the buoys/mass — $-W_D \leq Z_i \leq 0$
  - vertical location of the end point of the line (sea floor) — $|Z_{\max_i} + W_D| \leq 0.2m$

  For each line

  - horizontal displacement of the floater — $H_{\text{offset}} \leq 15m$
  - floater incline — $|\psi| \leq 15°$

  For the floater

OPTIMIZATION PROBLEM

Black-Box constrained optimization problem

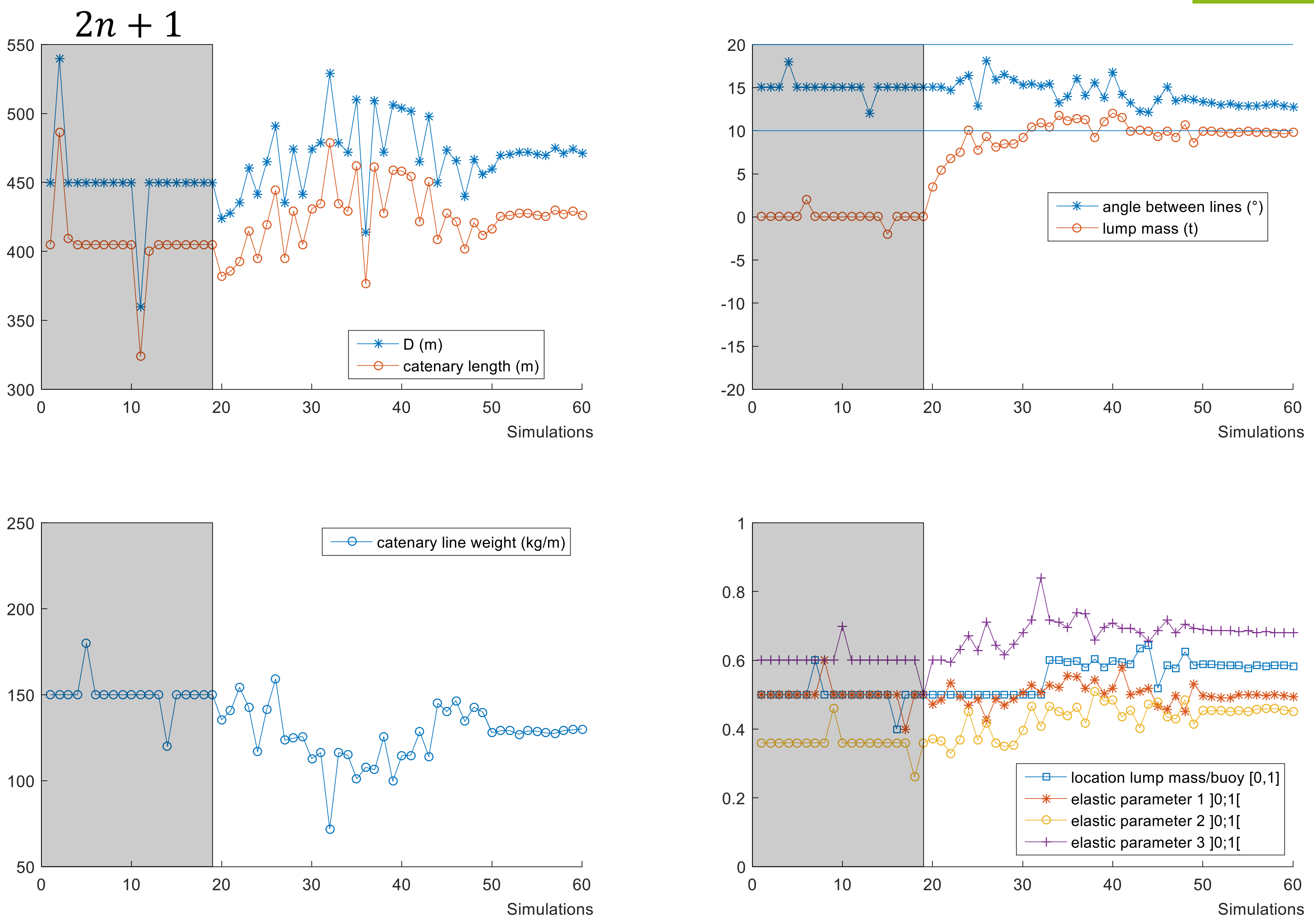
$$\min_x f(x)$$

$$\text{s.t.} \begin{cases} l \le x \le u & \\ C_{DB}(x) \le 0 & \text{derivative based constraints} \\ C_{DF}(x) \le 0 & \text{derivative free constraints} \end{cases}$$

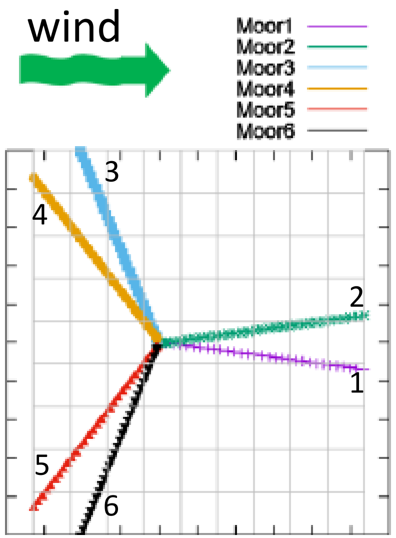
- 1 simulation ~ 45mn
- 9 design parameters
- 3 nonlinear “derivative based” constraints
- 32 “derivative free” constraints

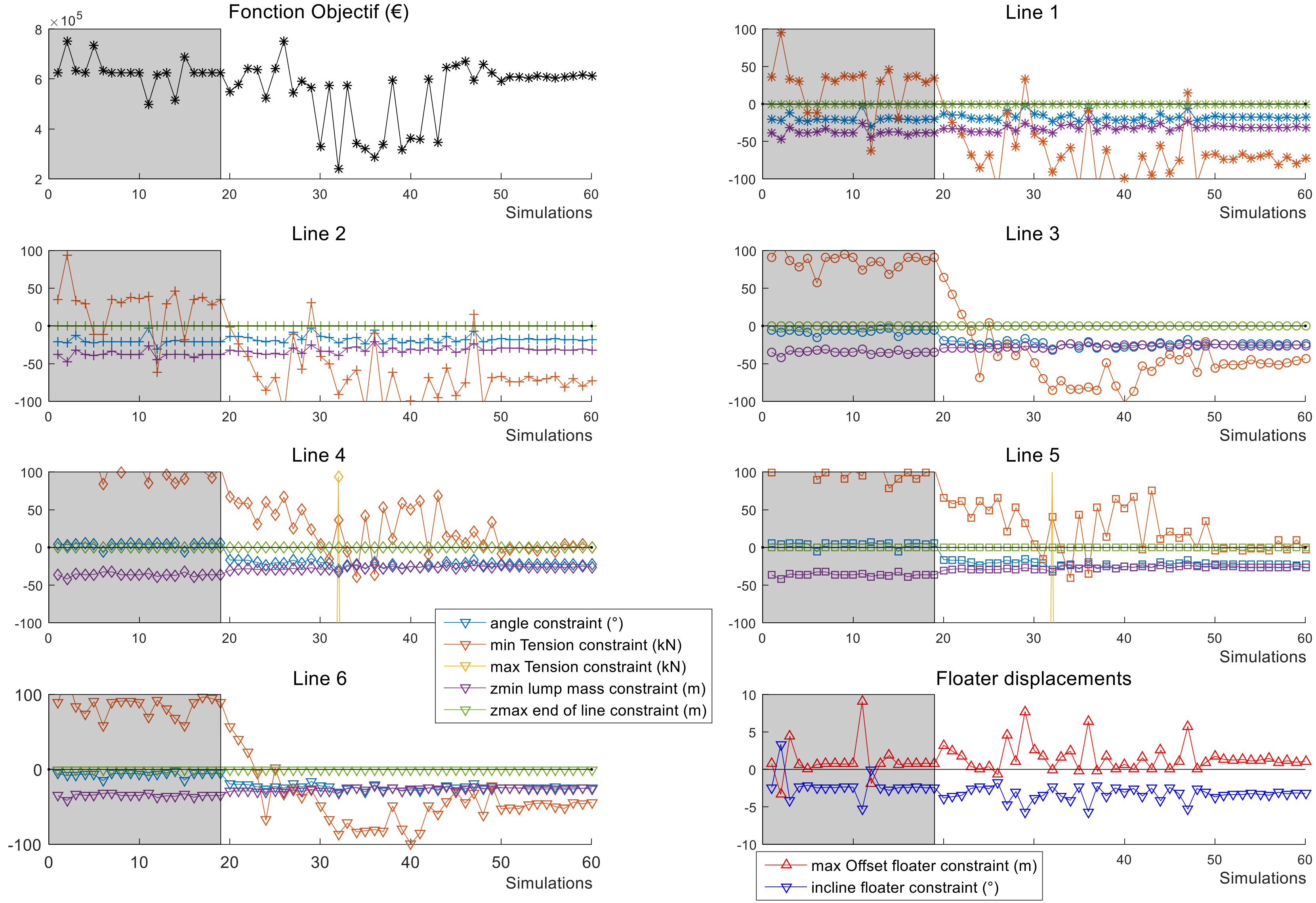
➢ **requires an adapted derivative free optimization method**

Design parameters along iterations

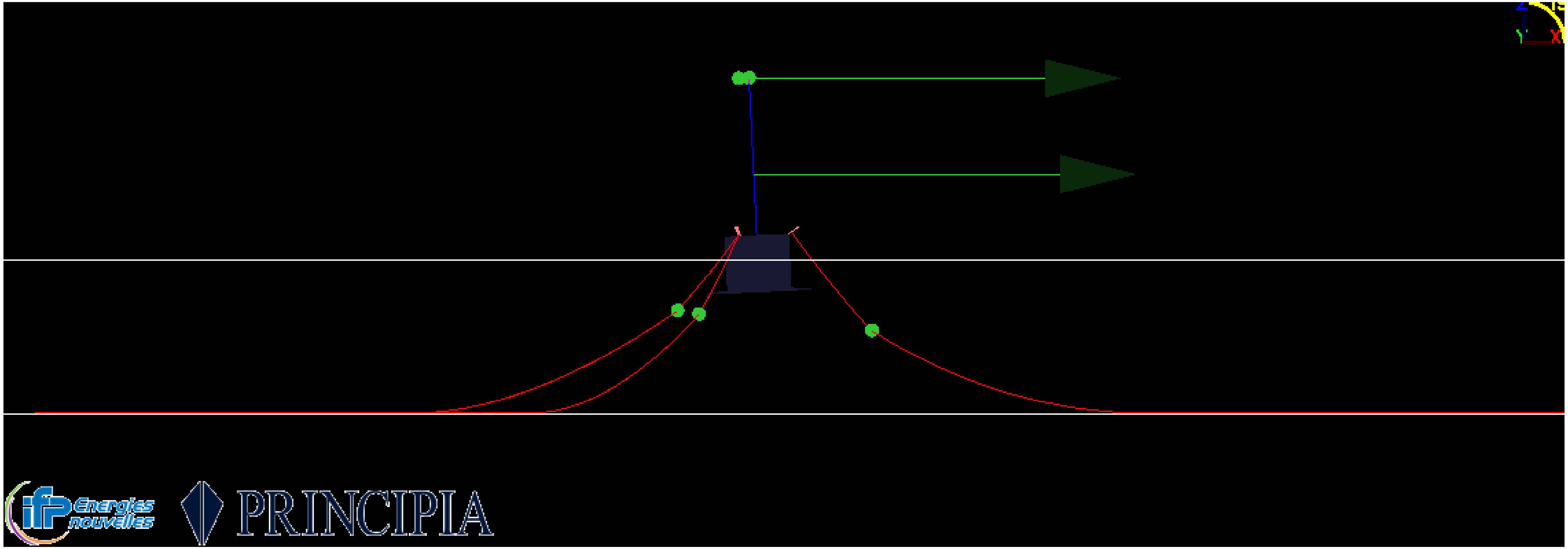


Objective function and constraints $C_{DF}(x) \leq 0$ along iterations





Dynamic simulations of the solution design



CONCLUSIONS

- First optimization results :
  design of mooring lines reliable to extreme conditions for parked turbine
- Two constraints are active at the solution
  - Minimal tension constraint for the 2 upwind lines
  - Maximal displacement constraint : 1m over the threshold
  - Limited cost reduction (3%) compared to the (unfeasible) initial point because of the active constraints

To go further

- add some additional parameters to distinguish the upwind lines from the downwind lines (different lengths and lump mass)
- run optimization from different initial points (Latin hypercube design)
- Evaluate other optimization methods (EGO, Nomad …)

OUTLOOK

NEW ENERGIES

- Additional design parameters : **integer or categorical variables**
  - number of buoyancies or mass
  - type of material : chain / steel / cable polyester / high density polyethylene
  - extension of trust region DFO method for mixed integer variables (course 3)

- Design of the mooring system according to **its resistance against the fatigue**
  - avoid the ruin caused by accumulated damages during the lifespan of the system
  - **reliability to fatigue chance constraint**

$$\mathbb{P}_{\xi}(g(x,\xi,X_{LT}) > s) \leq p$$

ξ random variables modelling the fatigue behaviour of the structure
X_{LT} a given long term behaviour of the environmental conditions (sea state)
$g(x,\xi,X_{LT})$ damage caused by X_{LT}

REAL APPLICATIONS OF DFO

- Relevant choice of parameterization
- Cost of simulations
  - Practitionners are interested in the best solution in a given simulation budget
  - Stopping criteria based on an objective target and a maximal number of simulations
- Often multiple derivative free constraints
  - For optimal design, one looks for feasible solutions
- Uncertainties
  - For data calibration: deal with data uncertainties and estimation of posterior uncertainties
  - Optimal design: notion of robustness, fiability regarding uncertainties (c.f. Didier Lucor's talk)

DERIVATIVE FREE OPTIMIZATION AND APPLICATIONS

- Course 1: main DFO methods
- Course 2: various applications of DFO
- Course 3: some challenges in DFO

