Software for Uncertainty Quantification (MS91)

- 8:35-9:00 OpenTURNS for Uncertainty Quantification

 <u>Michael Baudin</u>, Anne Dutfoy, <u>Anne-Laure Popelin</u>, *EDF, France*
- 9:05-9:30 Promethee Environment for Computer Code Inversion Yann Richet, Gregory Caplin, *IRSN, France*
- 9:35-10:00 'Mystic': Highly constrained Non-convex Optimization and Uncertainty Quantification

Michael McKerns, California Institute of Technology, USA

10:05-10:30 - Uranie: the Uncertainty and Optimization Platform Fabrice Gaudier, Jean-Marc Martinez, Gilles Arnaud, *CEA*, *France*



OpenTURNS for Uncertainty Quantification

Thursday, April 7

MS91: Software for Uncertainty Quantification

SIAM Conference on Uncertainty Quantification

Michael Baudin, Anne Dutfoy, Anne-Laure Popelin

Industrial Risk Management, EDF R&D, Chatou, France











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Some EDF applications

Safety and reliability of structures :

- Margins assessment
- Safety compliance

Calibration/validation

- quality of our studies
- validity domain of numerical codes (« VVUQ »)

Robust Optimization

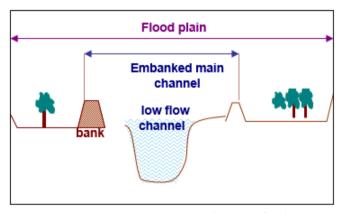
- Performance of new systems
- Optimization of maintenance policy



Optimization of buildings' energy performance



Cooling tower,
Civaux (Vienne)



Inverse calibration of Strickler coefficient in a flood model



Outline

- Global framework of uncertainty treatment
- OpenTURNS overview
 - A simple exercise
 - External modules

- New features and perspectives
 - Optimized LHS
 - EGO
 - GUI
 - Visualization in uncertainty study



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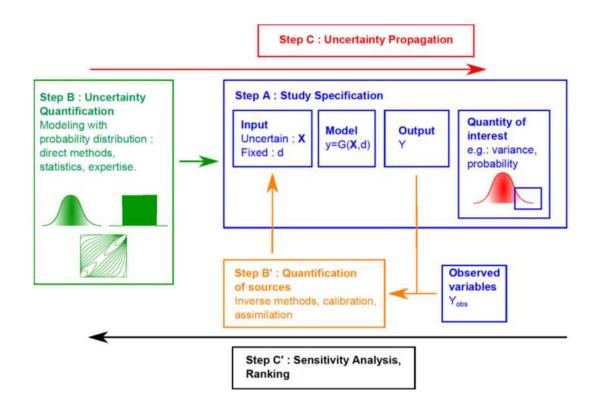
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Uncertainty methodology

OpenTURNS uses the « Global Methodology of Treatment of Uncertainties »:

- Step A: Study specification: uncertain input variables, model, variable of interest, quantity of interest (e.g. central dispersion)
- Step B : Uncertainty quantification : defines the joint distribution of the input (e.g. μ in the Normal distr.)
- Step C : Uncertainty propagation : estimates the quantity of interest (e.g. the mean)
- Step C': Sensitivity analysis: ranks the input variables from the variable with highest impact to the lowest





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OpenTURNS: www.openturns.org

Features

- Steps : A, B, C, C'
- Stochastic processes
- Meta-models : polynomial chaos, kriging, support vector machine
- Sensitivity analysis : Morris, Sobol'
- Threshold probability: FORM/SORM, Subset Sampling, Adaptive Directional Sampling

Computer code G :

- Multi-thread evaluation of an analytical formula (exact derivatives)
- Distributed and multi-thread evaluation of a Python function (with finite differences)
- Evaluation by SALOME

Context :

- Since 2005
- Four partners :







- Documentation : for Python users, for developers
- Programing interface : Python module, C++ library
- Licence: LGPL
- Linux, Windows
- 1 technical committee / month
- 1 board committee / month



OpenTURNS: a simple exercise

Four independent input variables

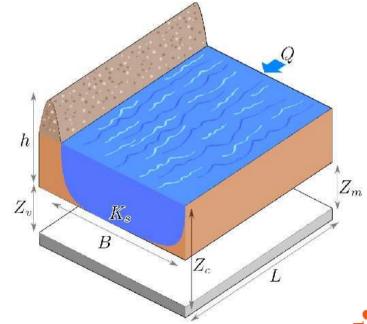
Variable	Distribution
Q : max. annual discharge (m^3/s)	Gumbel (mode=1013, scale=558)
Ks : Manning- Strickler coefficient $(m^{1/3}/s)$	Normal(mean=30, st.dev.=7.5)
Zv : downstream level of the riverbed (m)	Uniform(49,51)
Zm: upstream level of the riverbed (m)	Uniform(54,55)

Output : overflow S

$$H = \left(\frac{Q}{300K_S\sqrt{\frac{Z_m - Z_v}{5000}}}\right)^{0.6}$$

$$S = Z_v + H - 58.5$$

• Quantity of interest : P(S > 0)





OpenTURNS: a simple exercise in Python

Here is a simple exercise in Python, which is used in The next step is to define each input variable and its the OpenTURNS training.

We first import the openturns module.

```
from openturns import *
```

We then define the G Python function which takes the input X as argument and returns the output S.

```
# 1. Define G
def functionCrue(X) :
    Q, Ks, Zv, Zm = X
    alpha = (Zm - Zv)/5.0e3
   H = (Q/(300.0*Ks*sqrt(alpha)))**0.6
    S = [H + Zv - 58.5]
   return S
```

We finally use the PythonFunction class which converts the Python function into a function callable by OpenTURNS.

```
myWrapper = PythonFunction(4,1,functionCrue)
```

marginal distribution.

```
# 2. Define input variables
Q = Gumbel(1./558., 1013.)
Q = TruncatedDistribution(Q, 0, inf)
Ks = Normal(30.0, 7.5)
Ks = TruncatedDistribution(Ks, 0, inf)
Zv = Uniform(49.0, 51.0)
Zm = Uniform(54.0, 56.0)
```

We create the input random vector by combining the marginal distributions with an independent copula and create the output random vector.

```
# 3. Create the output Y=G(X)
inputX = ComposedDistribution([Q, Ks, Zv, Zm])
inputvector = RandomVector(inputX)
outputvector = RandomVector(myWrapper, inputvector)
```



OpenTURNS: a simple exercise in Python

We define the event by combining the output random vector with the zero threshold and a comparison operator.

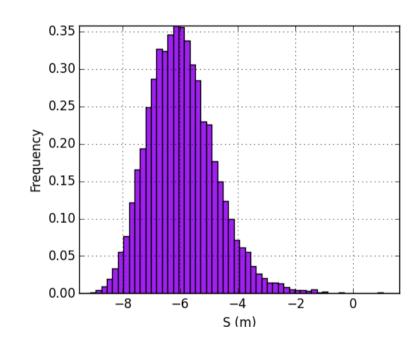
```
# 4. Estimate the probability
eventF = Event(outputvector, GreaterOrEqual(), 0)
```

We use a simple Monte-Carlo estimate.

```
algoProb = MonteCarlo(eventF)
algoProb.setMaximumOuterSampling(1000000)
algoProb.setMaximumCoefficientOfVariation(0.1)
algoProb.run()
resultAlgo = algoProb.getResult()
neval = myWrapper.getEvaluationCallsNumber()
pf = resultAlgo.getProbabilityEstimate()
```

In the Python console:

```
Number of function calls = 153501
Failure Probability = 6.514616e-04
```





OpenTURNS: modularity PMML: xml files for metamodel exchange **Optimized** Mixmod: LHS supervised & unsupervised classification Subset method for rare event estimation FFTW: Fast Fourier **OpenTURNS** Transform Stratified **Directionnal** github Adaptative (rare event) Agrum: Bayesian module **SVM Networks** classification

SIAM-UQ 2016, OpenTURNS

How to contribute to OpenTURNS?

doc.openturns.org/sphinx/contribute

- Report bugs on the bugtracker
- Suggest a new feature on github
- Your developpment can be included in the core or as a module



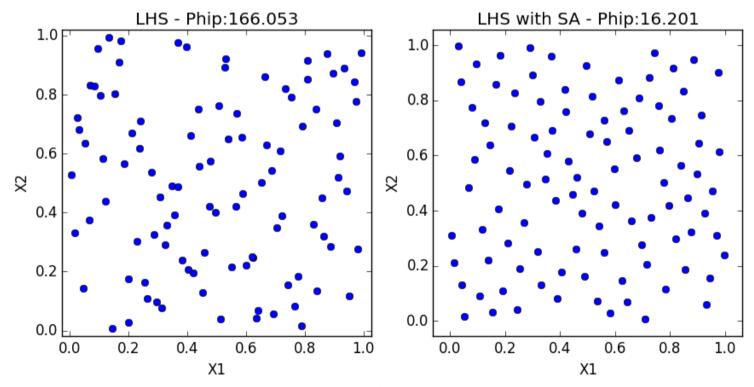
Outline

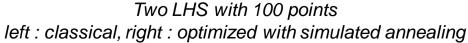
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The Optimized LHS module

- Goal
- Create space-filling, optimized Latin Hypercube Sampling designs
- Algorithm :
 - Several space-filling criteria: mindist or phi-p
 - Optimization by simulated annealing (or Monte-Carlo)







Ongoing work: Efficient Global Optimization (EGO)

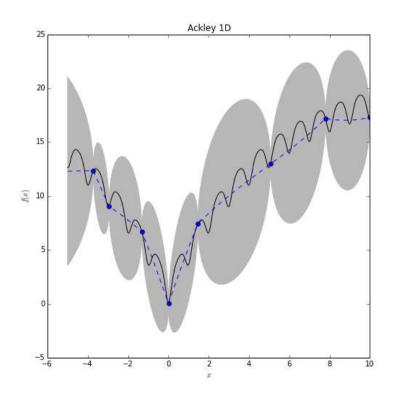
Objectives

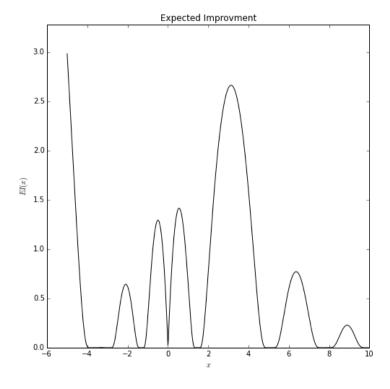
- Optimize a nonlinear, blackbox, costly objective function.
- Get a global optimum by exploring the whole input space.
- Use a kriging meta-model.

Algorithm

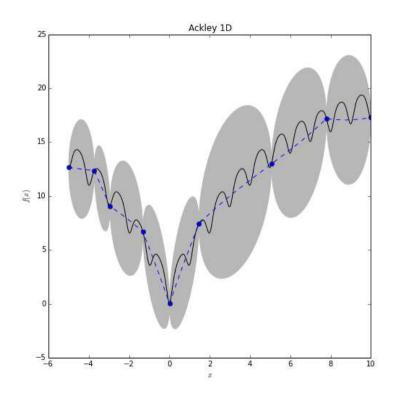
- Create an initial design of experiment D (e.g. optimized LHS)
- Evaluate the G function on the design
- Create the kriging meta-model
- Loop over the iterations :
 - Find a new point X minimizing the expected improvement
 - Add this point to the design D, evaluate Y=G(X)
 - Update the kriging meta-model
- Output : the best point X so far

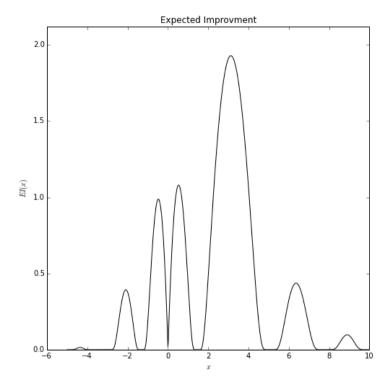




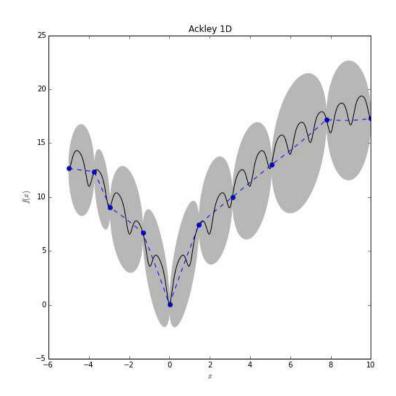


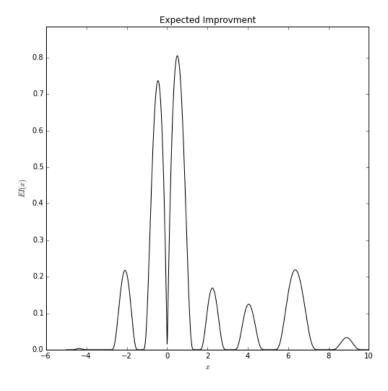




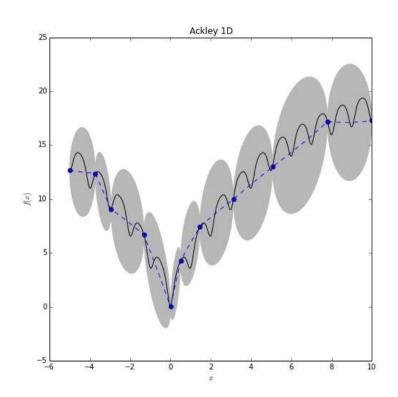


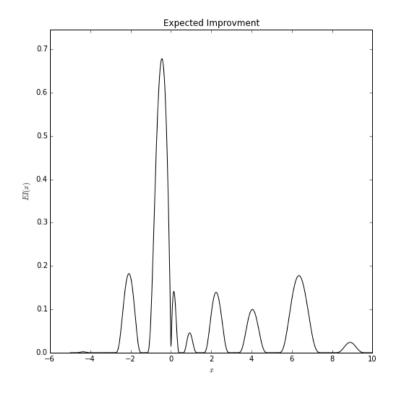












▶ In OpenTURNS v1.8 (summer 2016)

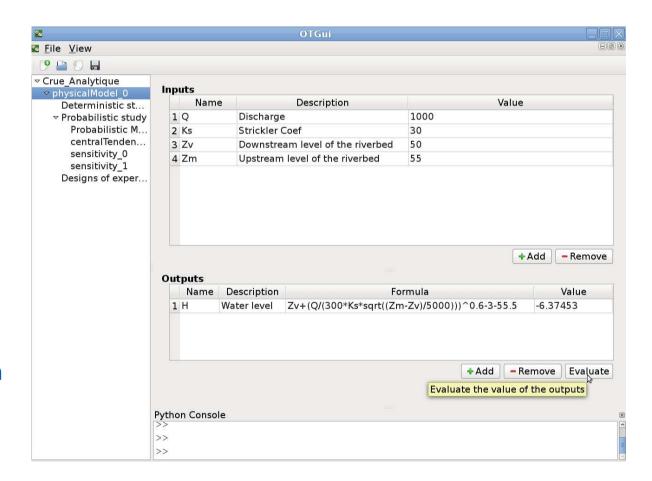


- GUI features
 - Generic (not dedicated to a specific application)
 - Access to the main functions of A, B, C, C' steps
- Schedule :
 - Release : Summer 2016
 - Then: one release each year
- Development : with our partner Phimeca (50% / 50%)
- Licence : LGPL



Definition of the physical model

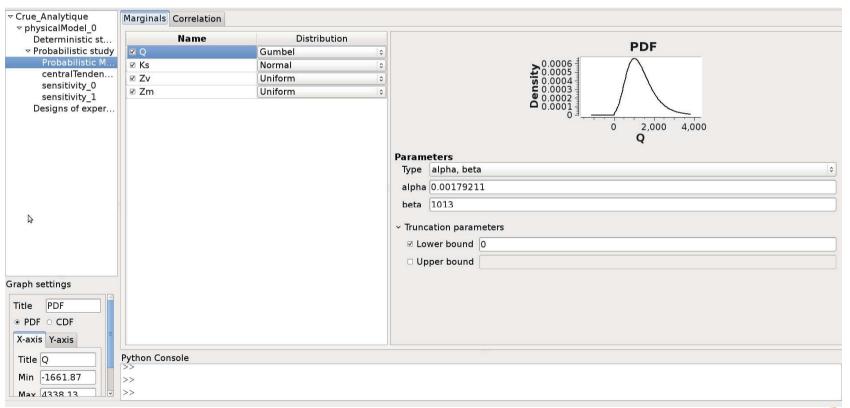
- > Can be:
 - An analytical formula
 - A Python Function
 - An external model given in a dedicated xml file





Uncertainty Quantification step: Define the joint distribution:

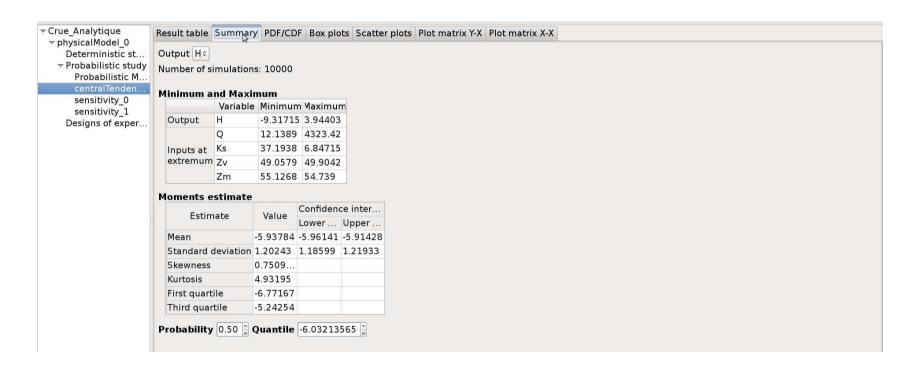
- marginals and their parameters
- correlation (Gaussian copula in the GUI)





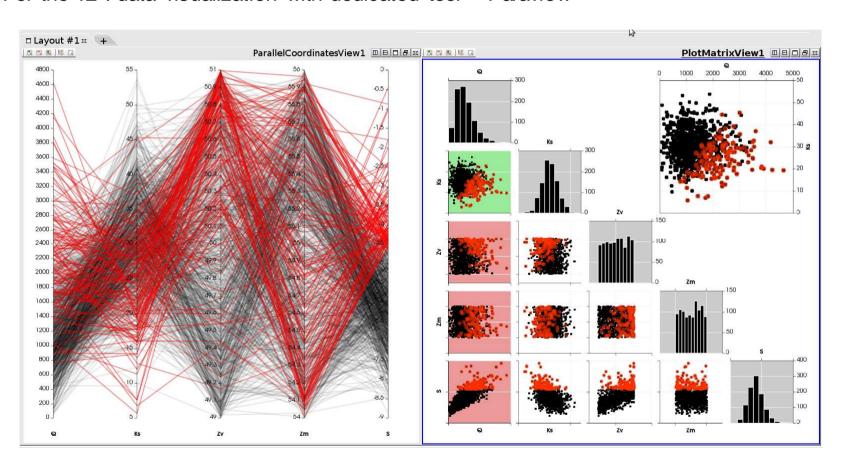
Uncertainty propagation results : central dispersion (by Monte Carlo Sampling here)

- analysis of the summary statistics
- other tabs : graphical results





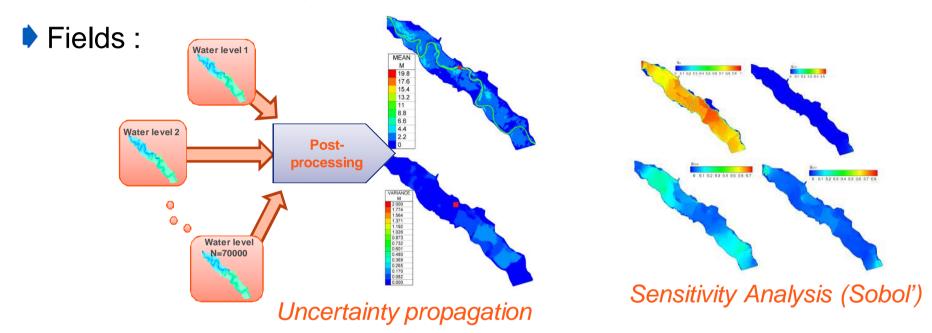
For the v2: data visualization with dedicated tool « Paraview »



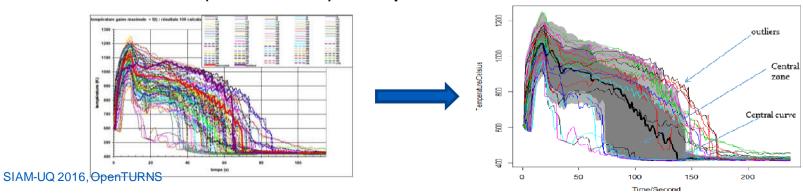


Visualization: next steps

See also: Wednesday, April 6 - MS61: Visualization in Computer Experiments



Functionnal (2D or 3D) boxplot:





OpenTURNS

Thanks!

- [1] www.openturns.org
- [2] Handbook for UQ, Springer, 2016

users@openturns.org

Next users day: 21st June 2016, Chatou, France

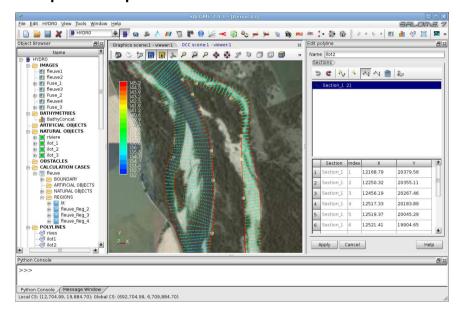


OpenTURNS and SALOME

SALOME

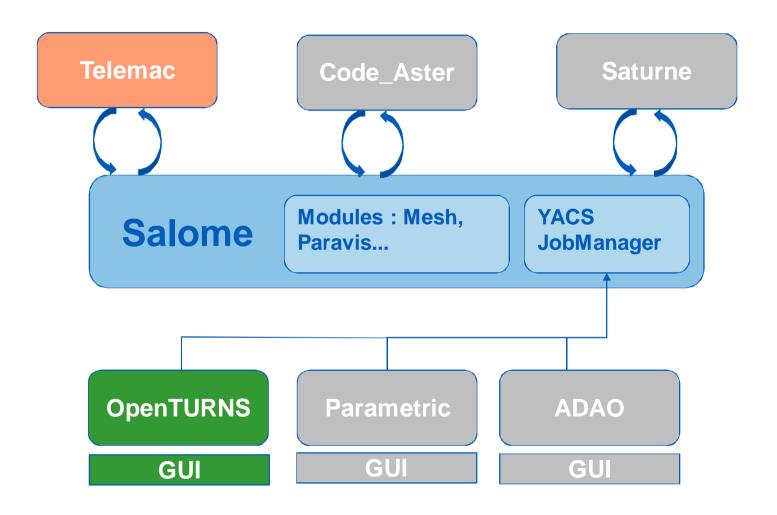
- 3 partners : EDF, CEA, Open Cascade
- Integration platform for pre and post processing, and 2D/3D numerical simulation
- Features: geometry, mesh, distributed computing
- Visualization, data assimilation, uncertainty treatment
- Licence: LGPL
- Linux, Windows
- www.salome-platform.org

A specific platform : SALOME-HYDRO



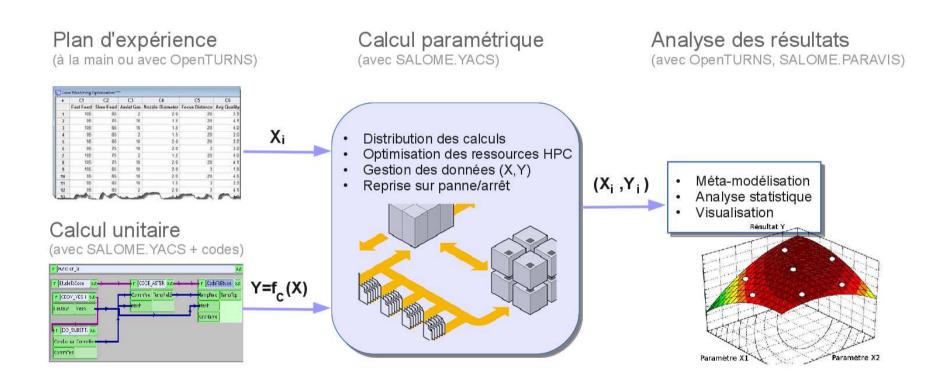


OpenTURNS and Salome





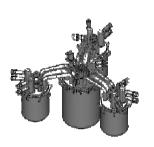
OPENTURNS: UTILISATION DE YACS







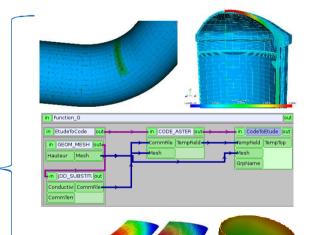
Simulation numérique des systèmes physiques d'intérêt EDF

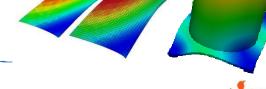






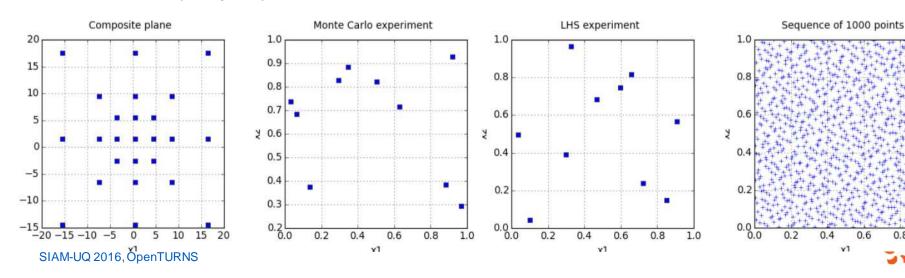
- Mécanique (Code_Aster)
- Thermohydraulique (Code_Saturne, Neptune_CFD)
- Electromagnétisme (Code_CARMEL3D)
- Neutronique (ANDROMEDE)
- Hydraulique à surface libre (Telemac, Mascaret)
- ...
- Besoins génériques de la simulation dans ce domaine
 - Modélisation 3D (CAO, maillages, visualisation)
 - Orchestration des calculs (composition, distribution)
 - Traitement de données complexes (champs, matrices)



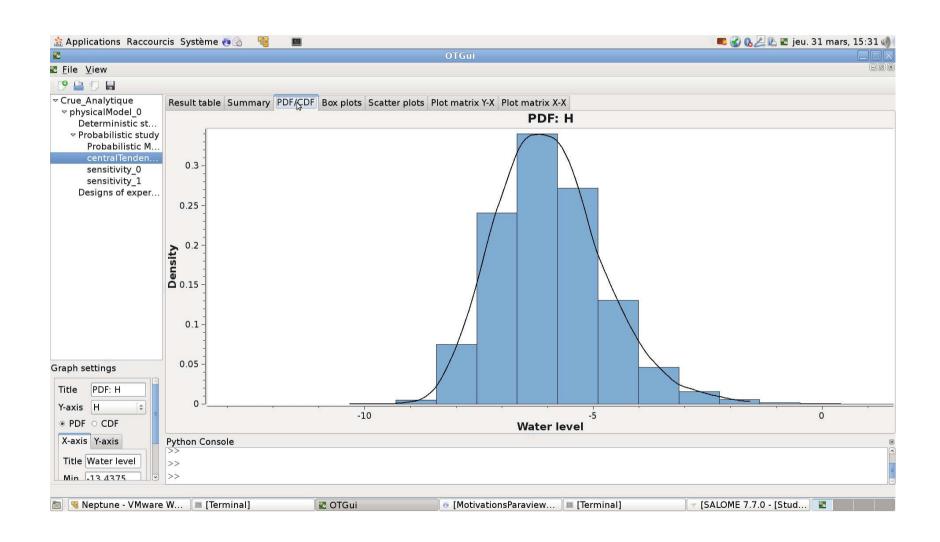


Design of experiments

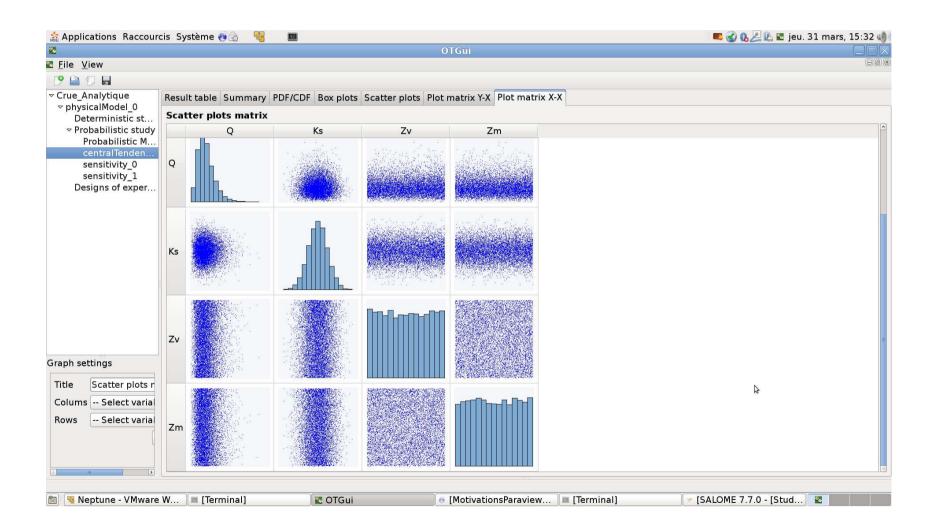
- What for ?
 - Model exploration
 - Central tendency : estimate mean, standard variation
 - Create meta-models, e.g. Polynomial chaos, Kriging, etc...
- Deterministic DOEs :
 - o central composite, factorial: axial, composite, box
- Probabilistic DOEs :
 - Monte Carlo with given distribution
 - Bootstrap resampling
 - Importance sampling
 - Latin Hypercuve Sampling (LHS) and optimized LHS
- Low discrepancy sequences : Sobol, Faure, Halton



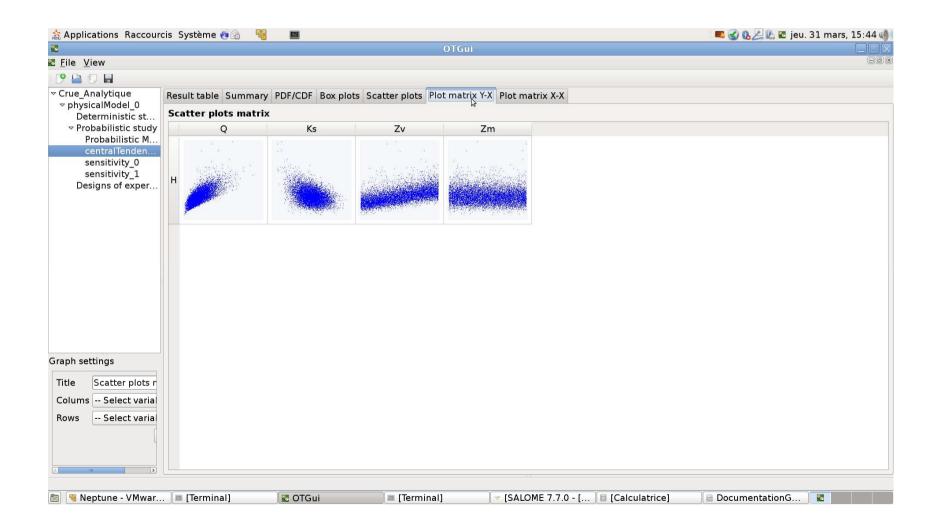
OpenTURNS GUI













OpenTURNS Trainings

EDF

- « Uncertainty Management : Open TURNS » : 3 days
 - o next session : 5-7/09/2016, ITECH ref : 4889
- « Uncertainty Management : Methodology » : 3 days
 - o next session: 14-16/09/2016, ITECH ref: 4888
- contact : Corine Tripet : 01 47 65 58 41

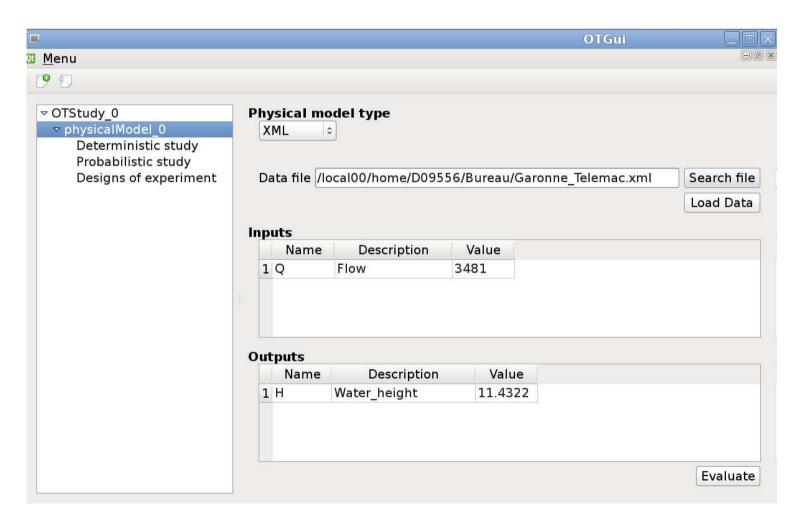
PRACE

- 1 annual session at « Maison de la Simulation (Saclay) », 3 days
- Methodology + TP with OpenTURNS or Uranie

Phimeca

- 2 sessions each year
- www.phimeca.com

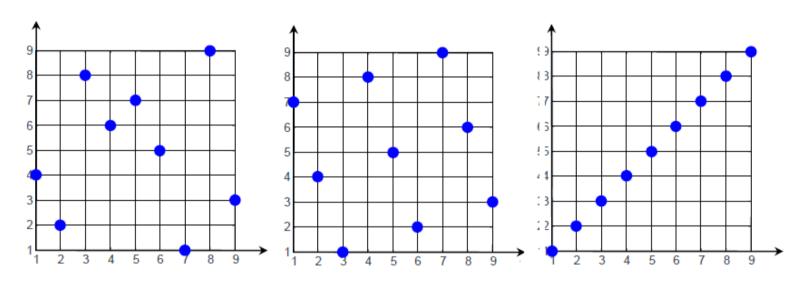






The LHS module

▶ Goal : create Latin Hypercube Sampling (LHS) designs with good space filling properties

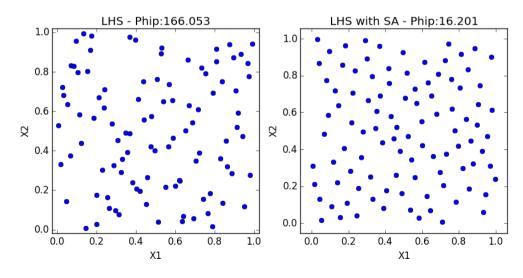


- What for ?
 - Model exploration
 - Central tendency : estimate mean, standard variation
 - o Create meta-models, e.g. Polynomial chaos, Kriging, etc...
- In this module :
 - Types of designs : centered or randomized
 - Criteria : C2, mindist, φp
 - Algorithms: simulated annealing (or Monte-Carlo)
 - Limitation : independent copula



The LHS module

```
>>> import openturns as ot
>>> import otlhs
# Fix the uniform bounds (0 ,1)^2, size = 100
>>> Bounds = ot.Interval(2)
>>> lhs = otlhs.LHSDesign (bounds, 100)
# Fix criterion
>>> crit_sf = otlhs.SpaceFillingPhiP ()
# Defining a temperature profile (10,0.95,2000)
>>> temp_prof = otlhs.GeometricProfile ()
>>> algo = otlhs.SimulatedAnnealingLHS (lhs , temp_prof , crit_sf )
>>> result = algo.generate ()
# Retrieve optimal design
>>> design = result.getOptimalDesign()
```



HO