Appendix U

Evaluation of stochastic & statistic methods for spacecraft thermal analysis

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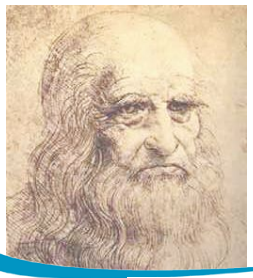
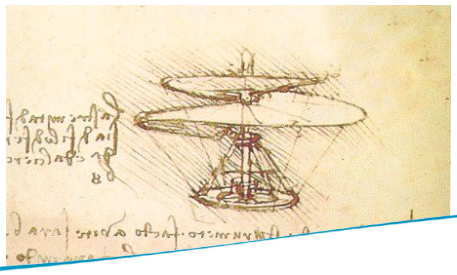
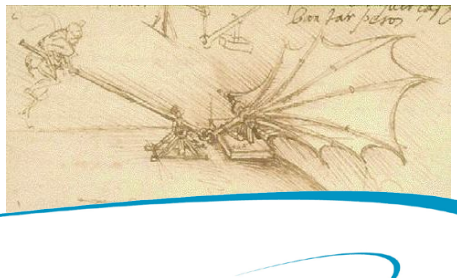
Abstract

The design and analysis of thermal control system are particularly important during the development of a space project. These projects are characterized by a small number of specialists in thermal processes and consolidation of the concept often imposed by customers.
Anyway for years this context has been challenged by the need to continuously improve the overall thermal analysis and design process. There is in particular a growing trend to avoid over-design. In this sense, the duration and costs are reduced and the concept, in general, is more flexible with regard to changes that it may undergo throughout a project.
In this new area, the evaluation of new methodologies is seen as useful and necessary for the development of thermal control in space projects. The management problem of inaccuracies of the parameters, which is largely presented and considered in several other domains, arises with increasing insistence.
Therefore, it is interesting to evaluate the feasibility of advanced approaches such as stochastic, heuristic or metamodeling to improve development process in terms of consolidation of thermal control.
This study aims to evaluate the feasibility and methodology of various of above mentioned approaches for sensitivity/uncertainty analysis and for correlation of thermal models with regard to the thermal balance test on the "real satellite."
OPTIMUS tool has been chosen since it proposes a large panel of methods for sensitivity and optimisation.
The aim is to compare various of these methods between themselves and with the traditional method currently used by Thales Alenia Space thermal engineers. The comparison is based on efficiency on results, such as reduced gap between measurement and calculation for correlation exercise or impact on margin for sensitivity analysis. Impact on the duration of analyses and compatibility with industrial process in place are also considered as output of this project.

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Evaluation of stochastic & statistical methods for spacecraft thermal analysis

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Summary

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Context & objectives

Context

- For few years it has been shown that stochastic approach can improve spacecraft thermal analysis activity (FSASTA study in 2004 ,…)
- R&T TAS–CNES for the present study on new stochastic & statistical approach

Objective of this study

- Confirm profit and applicability of stochastics for internal use
- Evaluating new methods to reduce cost of the approach on two test cases : correlation and sensitivity/uncertainty analysis for which SM was revealed as promising but heavy time consuming
- To reduce cost the idea is to evaluate the feasibility of using predictive approaches based on meta-modeling techniques versus direct simulation approach

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SM : Stochastic Methods MCS : Monte Carlo Simulation, DOE : Design of Experiment , RSM : Response Surface Model, EGO : Efficient Global Optimisation

Summary

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Meta-modeling approach

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Definition :

Meta-modeling is a statistical technique to approximate the response of an analysis code. These statistical approximations or metamodels are built and used to replace time-consuming numerical analysis calculation in order to facilitate activities such as optimization/calibration, exploration of design, multi-discipline simulation.

Meta-modeling may use deterministic or stochastic approaches. It includes techniques such as design of experiments (DOE), Response surface models (RSM)

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Meta-modeling approach

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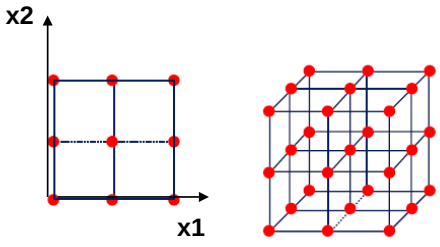
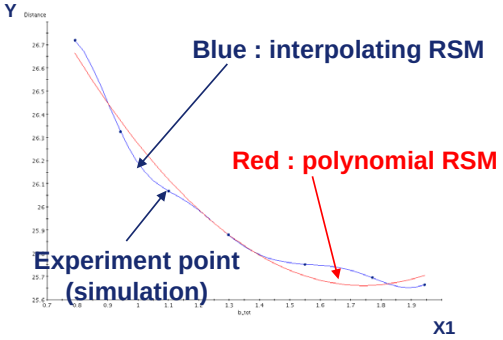
- Design of Experiment (DOE) : DOE is a powerful tool aiming at sampling design space with limited computed experiments
  - Wide panel of recent DOE available in OPTIMUS (orthogonal, random, …)



3^2 and 3^3 Ful Factorial DOE

- Response Surface Model (RSM) : RSM is built from a reduced sampling (DOE typically) to simulate analytically the model response
  - Wide panel of RSM available in OPTIMUS : least square (deterministic), Interpolating (Kriging, stochastic),

$$f(x_1, x_2, ...x_n) = \mu + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n} \sum_{j=i}^{n} b_{i,j} x_i x_j$$



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f = response of the meta-model to variations of xi variables

Meta-modeling approach

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Meta-modeling approach has been tested for both exercices :

- For sensitivity/uncertainty analysis
  - DOE allow to reduce number of factors within a limited number of simulation
  - RSM lead to a « low cost » sampling for uncertainty propagation
- For correlation
  - Correlation is optimisation ➔ Minimisation of observation / model distance
  - 1- DOEs are used to build the highest fidelity RSM as possible
  - 2- RSM is then used to simulate analytically the model response
  - 3- Optimisation methods are run on RSM in order to save CPU
  - WARNING : RSM has to be validated before optimisation in order to get efficient AND reliable results

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Direct simulation approach

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More commonly used approaches using direct simulation have been also assessed for comparison:

- Direct MCS for sensitivity/uncertainty analysis
  - Reference method but costly sampling (1 experiment = 1 simulation)
  - More efficient with Latin Hypercube (LH) DOE for sampling
- Random Search and Evolutionary algorithm for correlation
  - Random Search with LH : Equivalent method in PANAMA (Blue), STORM, ..
    - Global optimum search but can be unreasonably time consuming
  - Self-Adaptive Evolution method (SAE) : Evolutionary algorithm quite close to genetic algorithm
    - Convergence usually more rapid when a two step optimisation process : 1- Global SAE for 5-6 iterations and 2- gradient like local optimisation

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Hybrid optimisation method : EGO

EGO : Hybrid method between RSM and simulation for optimisation

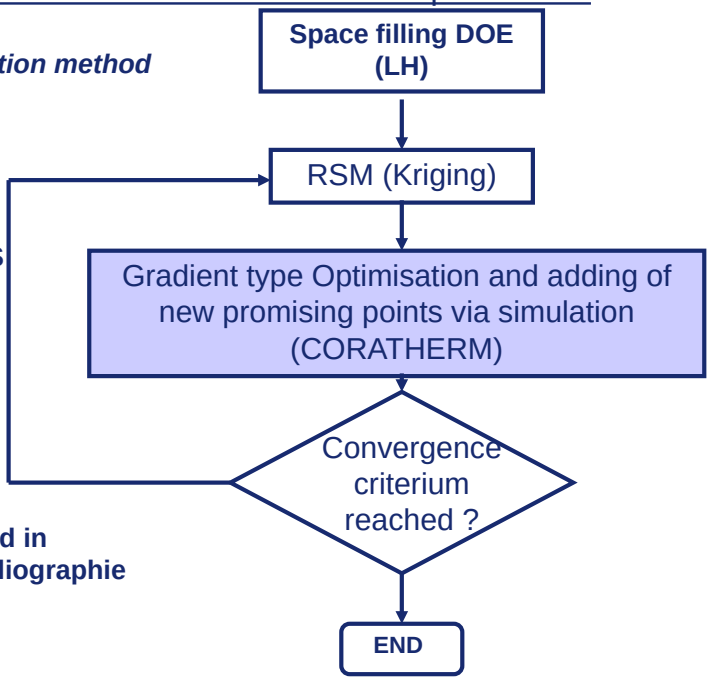
EGO : *Efficient Global Optimization method*

Major interests :

-*Low cost*

-Self validation of RSM

-Fully implemented in OPTIMUS



EGO widely plebiscited in specialized recent bibliographie (1997-2010)

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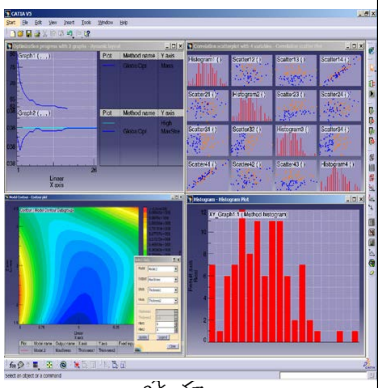
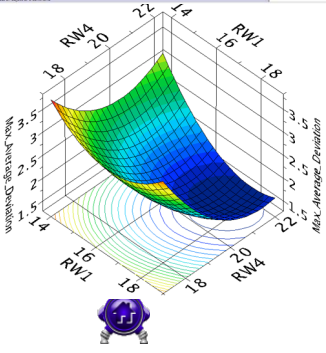
About selected tool : OPTIMUS

OPTIMUS (LMS Noesis) assessment

- Large panel of stochastic and statistical methods (DOE, RSM, MCS, …)
- Powerful and user friendly dedicated **pre and post processing**
- **Highly automated process for computation integration**
  Easy with CORATHERM and ESATAN codes
- Strong interest of **parallel run capability**
  - Significant saving of computation time
  - Higher added value with free license code (Coratherm in TAS for example)





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Summary

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- Introduction / context
- Stochastic and meta-modeling methods assessed
- Application # 1 : Model correlation
- Application # 2 : Sensitivity/uncertainty analysis
- Conclusion

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Correlation exercice

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Selected approach

- **No interest for “all stochastic” :**
  - Too much factors and not enough information on input distribution
  - Too much impact on industrial process (step by step),
- **Decision to use a step by step process and gathering most or all of them in a unique workflow**
  - By using OPTIMUS for steps for which its methods are the best adapted and keep other steps for traditional process (modeling error, material change,…)
  - For a limited number of parameters per optimisation (< 20 for the moment)

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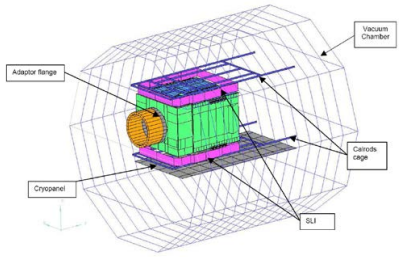
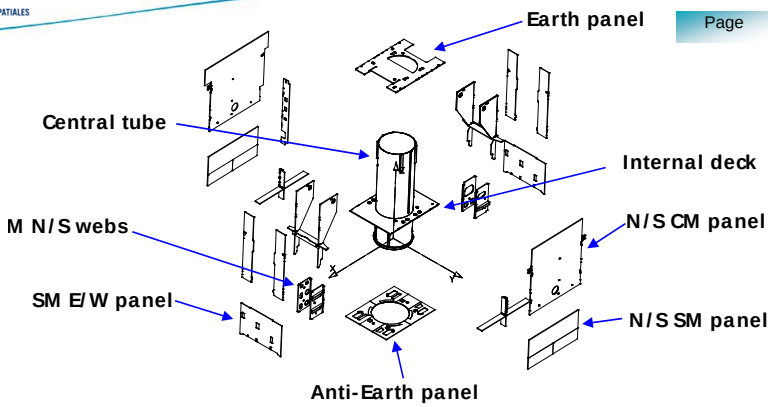
Correlation exercice





Application #1 : Correlation exercise on a *SATCOM*

4 steps selected for model test correlation from traditional approach :

- Step 1 : Reaction wheels dissipation evolution in E2 (SM)
- Step 4 : Update of unit payload dissipations (crossing CM)
- Step 7: Update of Ka TWT- Heat Pipe coupling (CM)
- Step 8 (added) : Update of conductivity of CM North & South panels

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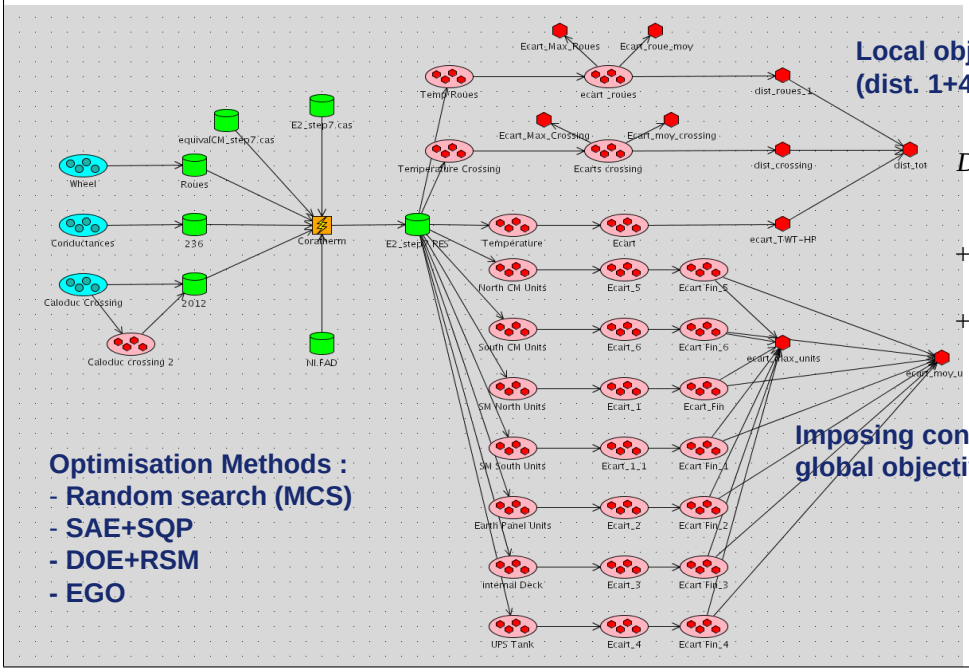
Correlation exercice

OPTIMUS Workflow for updating steps 1, 4 & 7 at a time (cas E2)



Local objective function (dist. 1+4+7)

$$Dist = \sqrt{\sum_{i=1,Crossing}^{13} (\Delta T_i)^2} + \sqrt{\sum_{i=1,Wheels}^{4} (\Delta T_i)^2} + \left|\Delta T_{3376}\right|$$

Optimisation Methods :
- **Random search (MCS)**
- **SAE+SQP**
- **DOE+RSM**
- **EGO**

Imposing constraints on global objectives

Correlation exercice

OPTIMUS correlation approach : Exemple of relevant results

Best tested solution : EGO with constraint imposed on outputs
➔Lowest local distance model/observation
➔Global criteria totally respected
➔Lowest time

steps 1,4 & 7 (full drive conf)	temperature deviations > 5°C	mean deviation on all obs units (110 nodes)	local deviation on critical nodes	total time
Traditional	8	0.1	13.3	2 days
OPTIMUS (EGO)	0	0.05	3.02	5 hours

Key results of SATCOM correlation with OPTIMUS (EGO) and comparison with traditional method on steps 1, 4 & 7

➔ OPTIMUS use was proven to improve the correlation results and the analysis run time using stochastic & meta modeling methods

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Correlation exercice : Conclusions

- About Global Process
  - The stochastic methodology revealed as very interesting when locally applied within a “step by step” process,
  - Interest to group several steps in one, by imposing specific constraints besides the local objective was demonstrated
  - Use of OPTIMUS tool is flexible and allow to choose different calculation methods
  - Theoretical competences needed are minimised (compared with the possible advantages)
- About Methodology
  - EGO > SAE+SQP > SAE only > Random Search
  - EGO is the best compromise duration / efficiency / reliability and it is easy to use
  - DOE and Polynomial RSM can save lot of time on case by case basis,
    - but since they are not fully implemented in OPTIMUS the validation phase of the RSM is iterative and can limit the gain
    - Number of required simulation for polynomial RSM building increase rapidly with number of parameters

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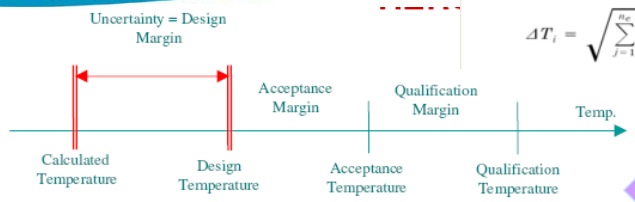
Stochastic approach for uncertainty analysis

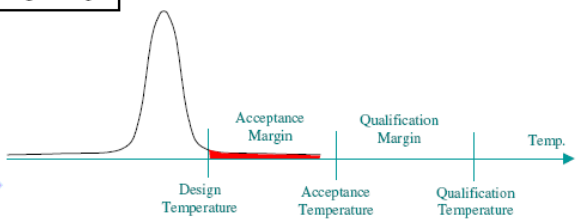
$$\Delta T_i = \sqrt{\sum_{j=1}^{n_e}(\Delta T_{e,j})_i^2 + \sum_{k=1}^{n_p}(\Delta T_{p,k})_i^2 + \sum_{l=1}^{n_t}(\Delta T_{t,l})_i^2 + \sum_{r=1}^{n_m}(\Delta T_{m,r})_i^2} + (\Delta T_s)_i$$



Traditional Approach:
T Calculated < Design Temperature - Design Margin

Design margins with traditional method

Design margins with stochastic method: design to fit with specific probability to remain within limits



Stochastic Approach:
T Calculated < Design Temperature with a determined confidence level

Source : Etude ESA, TAS-I, Blue : Feasibility of Stochastic Approach For Space Thermal Analysis, 2004

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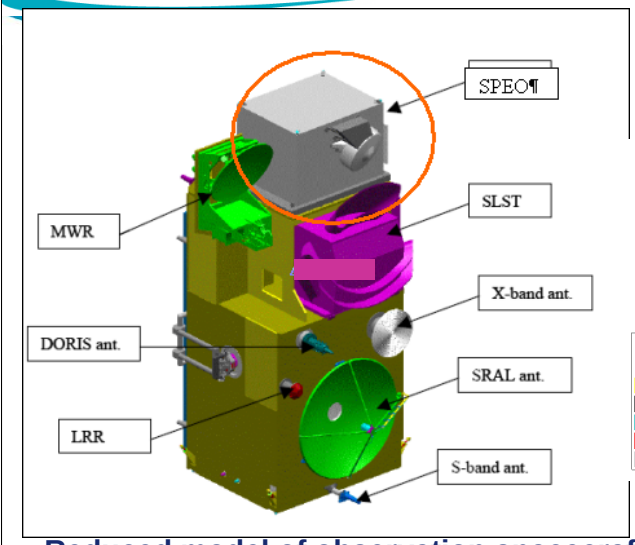
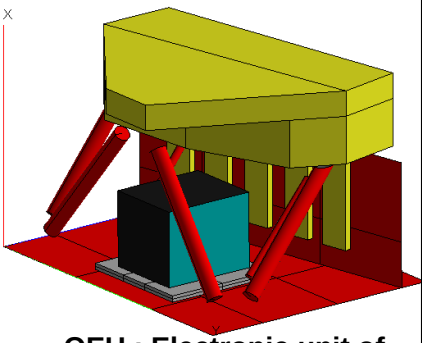
Stochastic approach for uncertainty analysis

The model





OEU : Electronic unit of observation instrument

Reduced model of observation spacecraft :

- ESATAN, ESARAD (radiative) , CORATHERM (conductive)
- 280 nodes
- Sensitivity/uncertainty on OEU unit

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Stochastic approach for uncertainty analysis

Objectives

Compare effects of concurrent inaccuracies and confidence level (*stochastic approach*) versus cumulative inaccuracies and margin (*deterministic approach*)

1- Calculate the $T_{max\ OEU}$ corresponding to various X percentile (μ+3σ, μ+2σ, median), i-e the $T_{max\ OEU}$ obtained by X % of total runs

2 - Compare it to $T_{Max\ design}$ and to design margin (10°C) taken in the deterministic approach

$Tmax_{design}$ = 40 °C

T_{calcul} (Nominal case) = 30°C

Margin (deterministic approach) = 10°C

Temperature LIMITS	OPERATIONAL						
	Min			Max			Min
Element designation	Q	A	D	D	A	Q	Start up
OEU	-30	-20	-10	+40	+50	+60	-30

NB : We add to $T_{max\ stochastic}$ a 3°C margin for systematic error not taken into account in probabilistic process (modeling error, …)

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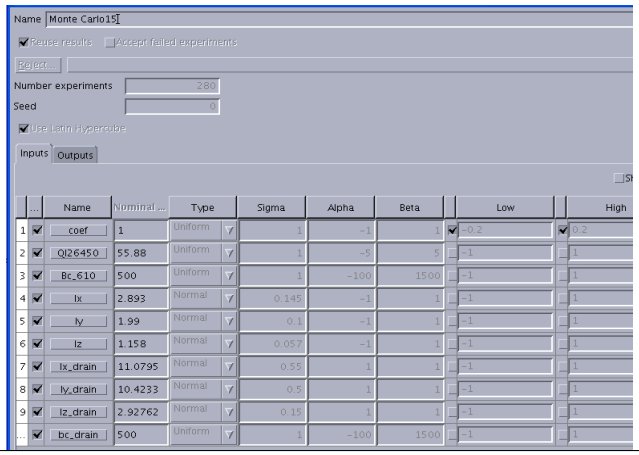
Stochastic approach for uncertainty analysis

Workplan and data

Sensitivity/uncertainty on OEU unit

- Design exploration : identification/confirmation of most influent parameters
- Uncertainty propagation with two stochastic approaches :
  - MCS on analysis and MCS on metamodel
- Calculation case : Hot operational in steady and transient
- 10 initially selected parameters and distribution probability law

OEU dissipation
GLs OEU/drainplate
GRs OEU / ambiance
GLs drainplate / -X panel
$\lambda_{x,y,z}$ –X panel
$\lambda_{x,y,z}$ drainplate



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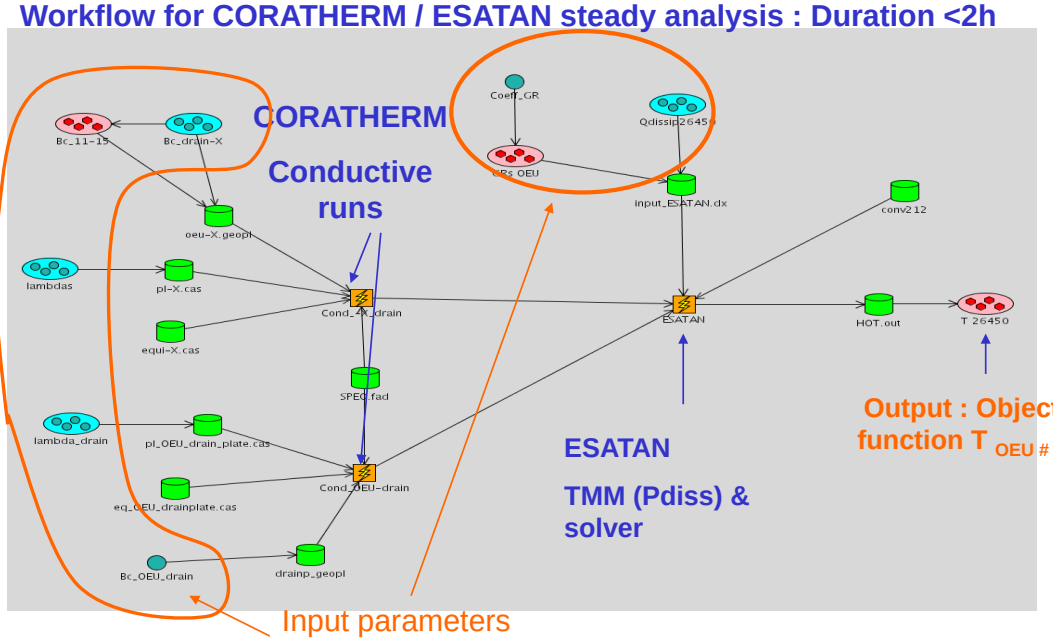
Stochastic approach for uncertainty analysis

Integration in OPTIMUS, steady state workflow

Workflow for CORATHERM / ESATAN steady analysis : Duration <2h



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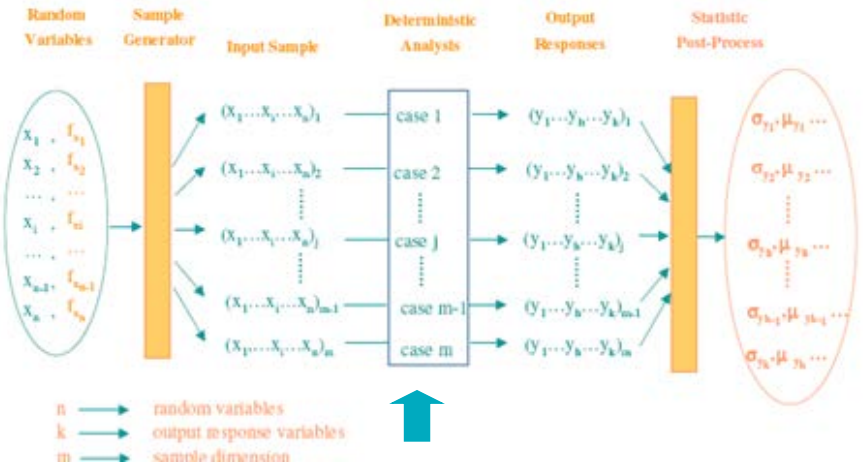
Stochastic approach for uncertainty analysis

Simulation and metamodeling approach

Orthogonal DOE (Placket Burman) allow to reduce number of input factors (4 vs 10) in a limited time



RSM (quadratic polynomial) instead of analysis code allow to save most of analysis time

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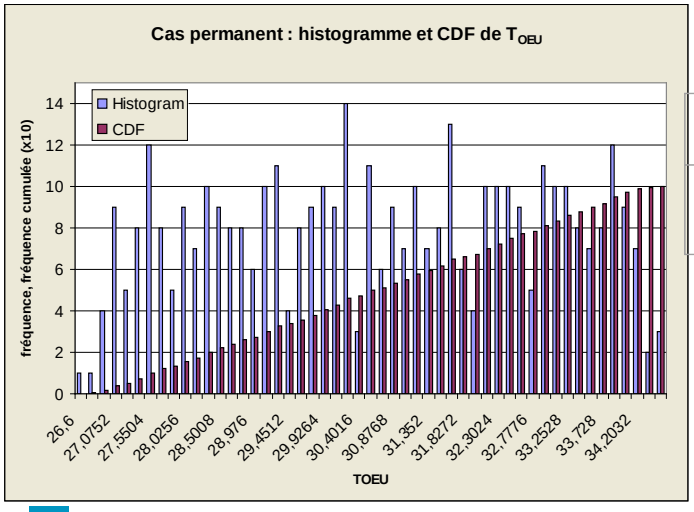
Stochastic approach for uncertainty analysis

Results with MCS on simulation (400 runs, 9 hours CPU)

CDF calculation and percentiles at 50% (median) , 97.7% (μ+2σ) et 99.85% (μ+3σ)



	P99.85	P97.7	P50
OEU Temp (C) 400 runs	37.5	37.1	33.6

Vs T_{marged} TAS = $T_{max\ design}$ =40 °C

➔ **The margin was overestimated with deterministic approach**

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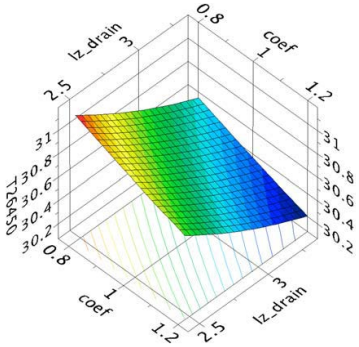
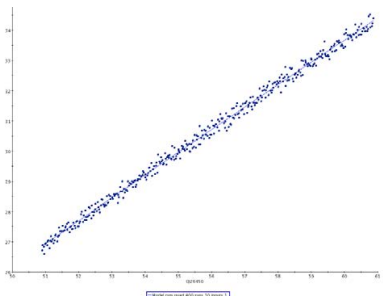
Stochastic approach for uncertainty analysis

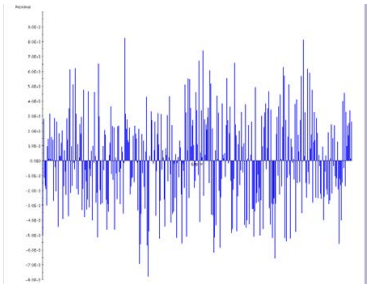
MCS on metamodel : RSM validation and meaning (2/2)



3D view of RSM



2D plot : RSM vs simulation



Error RSM/simulation

MCS on Metamodel Vs MCS on Simulation : comparison

Identical statistical results !!

	P99.85	P97.7	P50	CPU time
T0EU on simulation	37.5	36.9	33.6	9h
TOEU on RSM	37.5	36.9	33.6	25 mn

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Stochastic approach for uncertainty analysis

Conclusions (1/2)

- In the chosen test case the stochastic method pointed out that design margin taken was overestimated

➔ Successful effect of competitive inaccuracies instead of cumulative ones

- SM allow to evaluate the probability to stay below a design limit temperature starting from dispersion laws associated to input variables

➔ In this case we obtain a probability of 99.85% to stay below 37.5°C for OEU whereas traditional margin philosophy give Tmax = 40°C

- About OPTIMUS : High level of integration of various computation codes and great interest for easy parallelisation of computation

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Stochastic approach for uncertainty analysis

- **Conclusions (2/2)**
  - Strength and user-friendliness of reference method : MCS with Latin hypercube DOE
    - But it can be too much time consumer when used through direct simulation code
  - Meta-modeling technique (Design of Experiment & Response surface) allow to save great part of calculation time vs reference MCS method
    - !! Require validation of metamodel
  - Whatever the approach (simulation or metamodel) stochastic method is useful to size thermal design when it's marginal, but it's still questionable if an optimized less conservative design is always achieved through this method.
    - The distribution law of the design parameters variation around their nominal values could affect the method. Even if it was not an issue here.

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Summary

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Global conclusion

- Stochastic and statistical methods are globally useful for improving thermal engineering activity
  - Deeper design exploration, powerful optimisation methods
- Meta-modeling methods are successful to save significant part of analysis time
- But a particular attention shall be paid to the validation of the metamodel before any use of it for optimisation, sampling, …
- OPTIMUS was revealed well adapted to our needs
  - Large panel of design exploration & optimisation methods, powerful pre-post processing, user friendly GUI, easy integration of various applications (CORATHERM, ESATAN, THERMICA, …)

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Thank you for your attention,

Any question ?