Robust Optimisation

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The following slides were presented during the VSC Day organised in Brussels on the 4th of June 2019. If you have any question, don't hesitate to contact me by email (fcontino@vub.ac.be). You can also find more information about our research on the following website: http://burn-research.be

Robust Design Optimisation: challenges to find optimum under uncertainties

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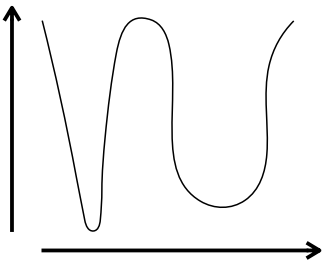

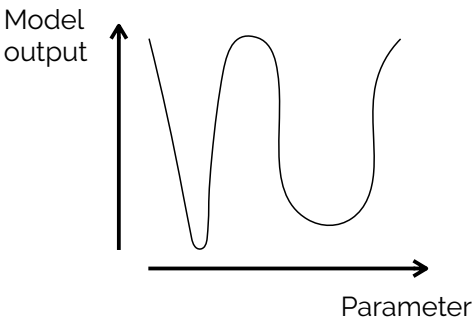

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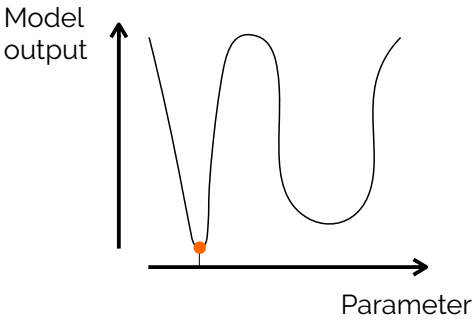
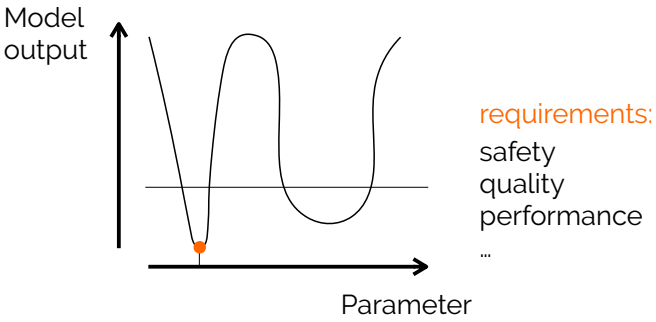
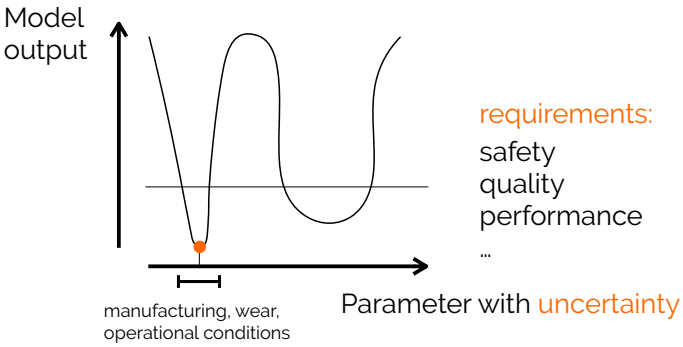

Model output
Parameter

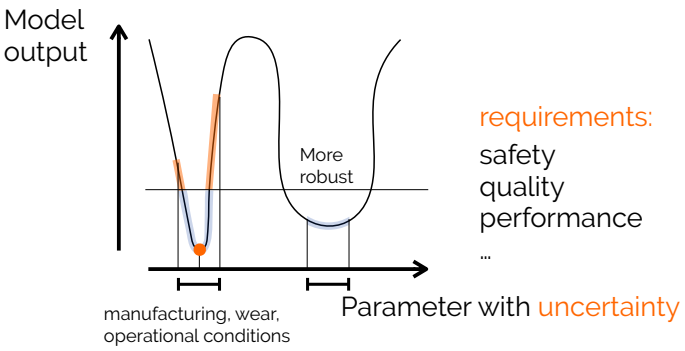
3


Model output
Parameter
requirements:
safety
quality
performance
...

4


Model output
manufacturing, wear, operational conditions
Parameter with uncertainty
requirements:
safety
quality
performance
...

5



6

Challenge of robust optimisation: curse of dimensionality

Cost robust optimisation = Cost uncertainty quantification X Cost optimisation

Need for HPC

The curse of dimensionality is the major challenge of robust optimisation. We combine the cost of uncertainty quantification and the cost of optimisation.

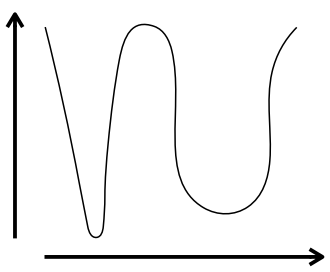
7

Robust Design Optimisation: challenges to find optimum under uncertainties

Framework
- Optimisation
- Uncertainty Quantification

Examples
- Heat exchanger
- Rapid Compression Machine
- Airfoil

Challenges in HPC
- Change of paradigm



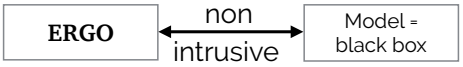
The ERGO framework: reliable, efficient and non-intrusive

DAKOTA Explore and predict with confidence. Similar framework as Dakota (Sandia) and includes our latest developments

ERGO
ἔργο

Engineering
Robust
Global
Optimisation

Model to be optimised is considered as a black box



ERGO is a light wrapper written in Python

9

To tackle the challenge of the curse of dimensionality we are combining efficient methods for uncertainty quantification and optimisation. In the perspectives, we'll see even more advanced methods we will use as a continuation of this study.
The framework interact in a non-intrusive way with the model considered as a black box.

The latest optimisers are included in the framework

Metaheuristic (no assumptions)

Particle swarm optimisation
Cuckoo, Firefly
Genetic, …

Gradient based (also using adjoint)

Sequential Least Squares Programming
Broyden–Fletcher–Goldfarb–Shanno (BFGS)

10

Gradient based are quasi-Newton methods (quasi because it uses an approximation of Jacobian or Hessian) where the next point in the search for the optimum is obtained based on the Jacobian to find where the gradient of the function is zero.

The latest optimisers are included in the framework

Hybrid

Fusion of metaheuristic methods
Metaheuristic + Gradient-based

Very good at global search

Very good at local search

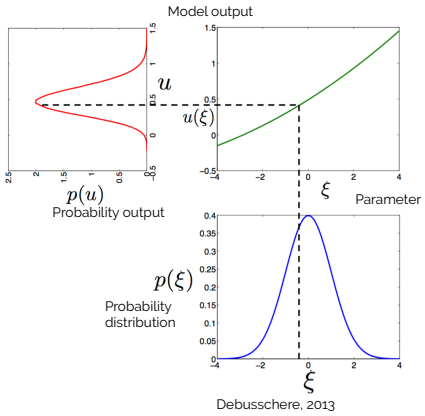
11

We use polynomial chaos expansion for uncertainty quantification

uncertainty in output

↑

uncertainty in parameters

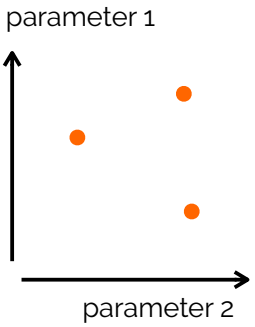


Debusschere, 2013

12

To represent the uncertainty on the model's output as a response to the parameters' uncertainty, we use polynomial chaos expansion.

The total cost includes the sampling for optimisation and UQ

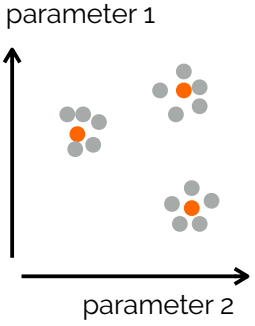


The optimiser explores the space of parameters to find an optimimum

13

While the optimiser search for the optimum in the parameters' space, it requires statistics (mean and variance) as multi-objective

The total cost includes the sampling for optimisation and UQ



The optimiser explores the space of parameters to find an optimimum

UQ module needs additional points to compute statistics

14

These statistics are provided by sampling in the region of the sample using the polynomial chaos. Sampling based on Sobol sequence. S. Abraham et al., JCP, 2017.

We use polynomial chaos expansion for uncertainty quantification

Model approximated by polynomial chaos expansion

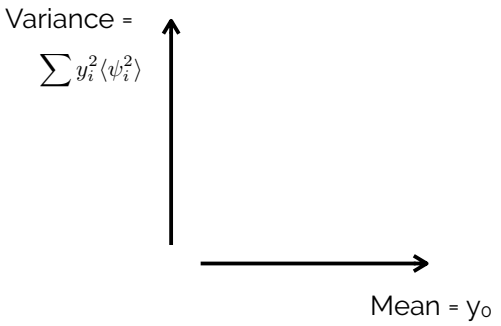
$$\text{Model output} \quad u(\xi) \approx \sum y_i \psi_i(\xi)$$

- $u(\xi)$: Uncertain parameter(s)
- $\psi_i(\xi)$: Orthogonal polynomials
- y_i: Unknown coefficients to be found with samples = simulation results

Polynomial chaos expansion is a sort of local surrogate model used to represent the model output. It is based on a series of orthogonal polynomials where the coefficients are the unknowns and require simulations.

15

Mean and variance of the objective are given directly by Polynomial Chaos



The advantages of polynomial chaos are the faster convergence compared to methods such as Monte Carlo, and the the easy recovery of the mean and variance based on the coefficients of the polynomials.

16

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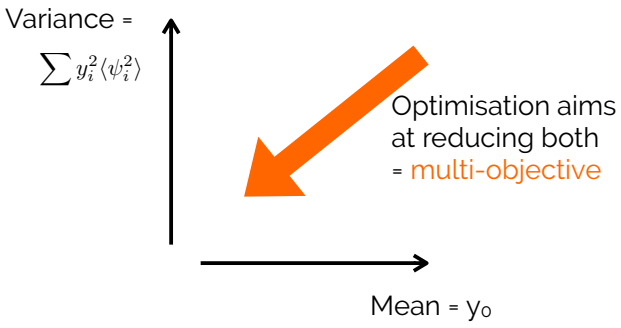

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17

Robust Design Optimisation: challenges to find optimum under uncertainties

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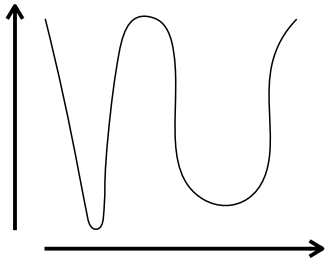
- Rapid Compression Machine
- Airfoil

Challenges in HPC
- Change of paradigm



Robust design of heat exchanger involves many parameters

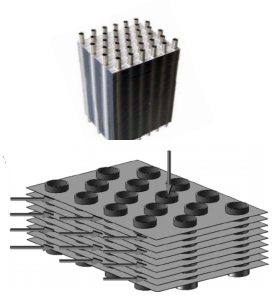


Plate finned tube heat exchanger

minimise
1. Pressure drop
2. Total volume
3. Air mass flow

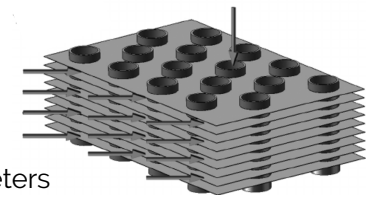
constraint: frontal area

19

Robust design of heat exchanger involves many parameters

Design parameters

Tube diameter (x2)
Tube distance (x2)
Fin thickness
Fin distance

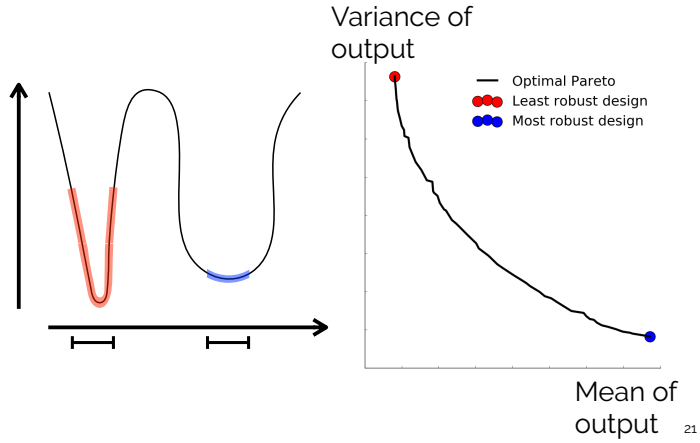


Operational parameters

Air temperature
Water temperature
Air velocity

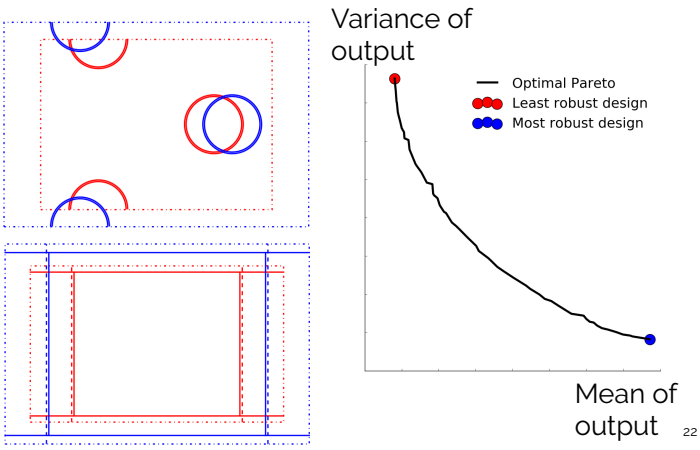
20

Robust Design empowers the engineer with the mean/variance trade-off



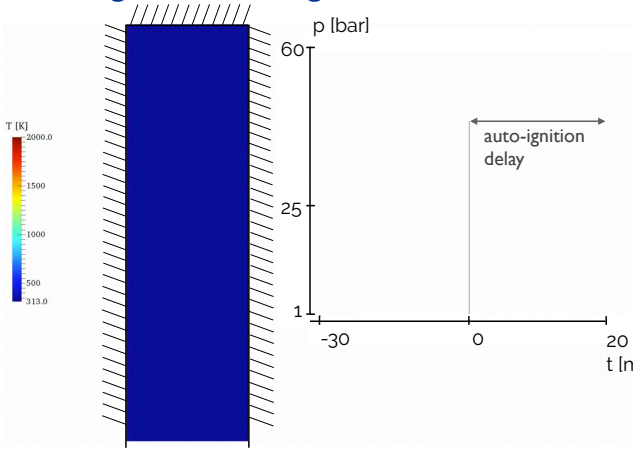
21

Robust Design empowers the engineer with the mean/variance trade-off



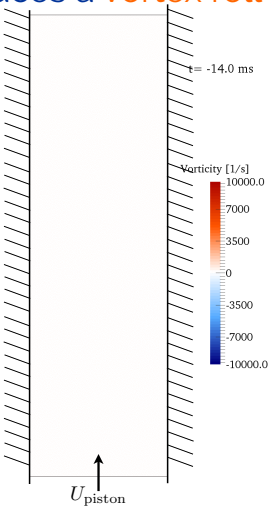
22

RCMs enable the analysis of auto-ignition in engine-like conditions



Robust Optimisation can also be applied in the context of research tools

Flat piston induces a vortex roll-up



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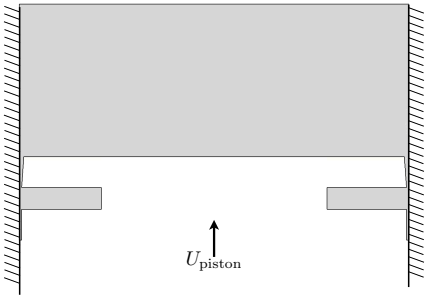
All RCMs implement crevices (instead of a flat piston) to absorb this vorticity.

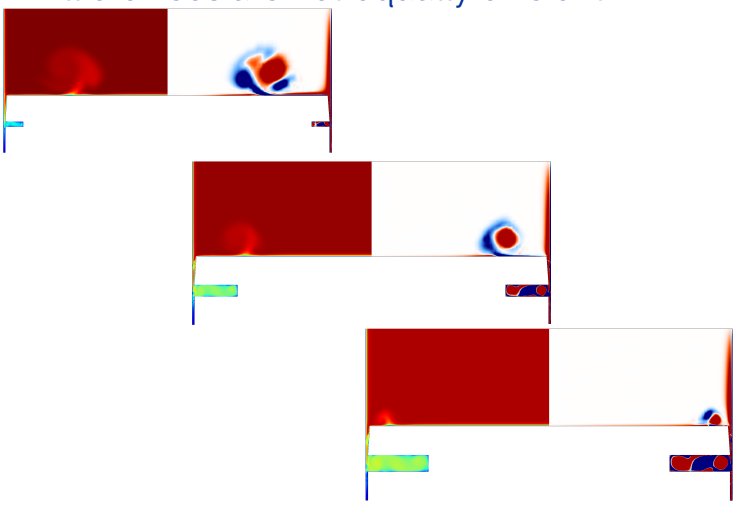
To prevent vortex roll-up, piston designed with crevices



Piston geometry with crevices

25

All crevices are not equally efficient



One of the biggest problems for experimentalist is that the presence of crevices does not guarantee the absence of vortex roll-up.

Objective of the optimisation: no vortex while being adiabatic

Objective: minimise vortex

Crevices big enough

but compression ratio fixed (r_V = 17)

Adiabatic core big enough

but risk of vortex due to speed

The main objective of the optimisation is therefore not to have a vortex. But obviously, it should also have a fast compression to keep an adiabatic core.

27

For this reference case, the cost is still very expensive

Full polynomial chaos
order 2, 9 uncertain parameters
requires 110 samples

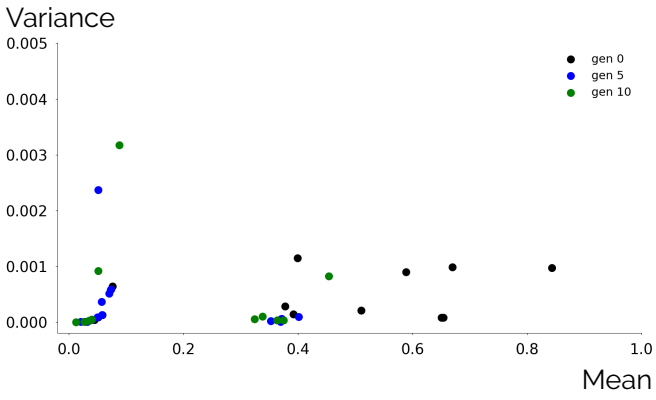
Optimisation is based on
full CFD model for all samples

Around 10 000 CFD simulations
on 60 cores: 2 days

This will be the reference for
future research

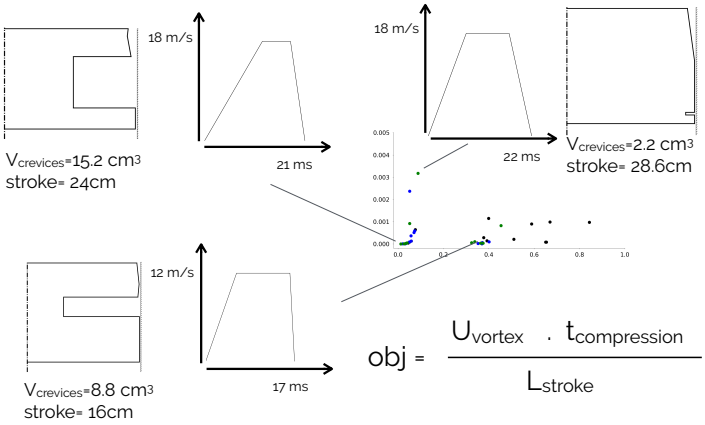
We use this case as a demonstration for more advanced techniques to reduce the computation cost. Therefore, the current simulations were based on full polynomial chaos and CFD for every sample.

Variance and mean are are non-confronting objectives



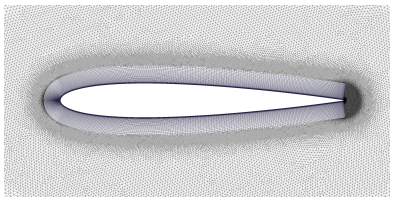
Reducing the mean also helps reducing the variance of the objective.

Variance and mean are are non-confronting objectives



Here are some geometries and compression stroke properties corresponding to some points in the objective space.

Airfoil robust optimisation: aerodynamics and aeroacoustics



Start from NACA0012

Geometry with 6 parameters

Optimise for noise and aerodynamics

Optimising for noise leads to no lift, optimising for lift makes a lot of noise

Aerodynamics:
C_L/C_D = 85
Noise > 80 dB

Aeroacoustics:
$C_L/C_D < 0$
Noise : 69 dB

Both: (weighted objective)
C_L/C_D= 67
Noise : 71 dB

33

Robust optimisation: work in progress

Main drivers of uncertainty:
- mean flow
- source motion
- tip Mach number
- airfoil thickness

Next step: run robust optimisation

34

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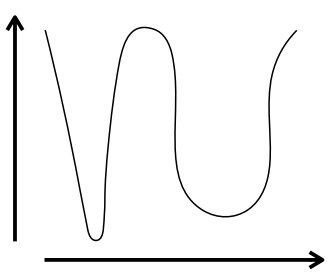
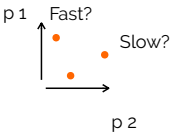
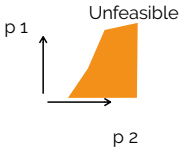
Challenges in HPC
Change of paradigm



Typical optimisation explores unexpected regions



High number of parameters difficult to predict all combinations



Large region with limited knowledge some might be unfeasible

Challenge: constraints handling

36

Robust optimisation is explorative and could lead to issues with the model: taking more time to provide a solution or searching in regions of parameter space that are unfeasible.

Many simulations is load intensive but different from one big simulation

Cost robust optimisation = Cost uncertainty quantification X Cost optimisation

Thousands of simulations — Easy to parallelise

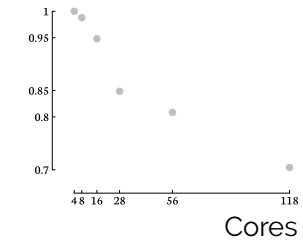
Different computational costs — Balancing issues

37

Although having many simulations to run seems easy to parallelise–no communication needed–in practice we had balancing issues because of the synchronicity of the robust optimisation.

Load balancing limits the efficiency

Efficiency
(strong scaling)



Many cores end up waiting for the last one to finish

38

Change of paradigm suggested by HPC team and literature

One job in the queue:
load imbalance

Thousands of jobs in the queue:
management?

Potential solution HPC side:
running program taking advantage of free computational resource

Potential solution literature:
asynchronous optimisation

39

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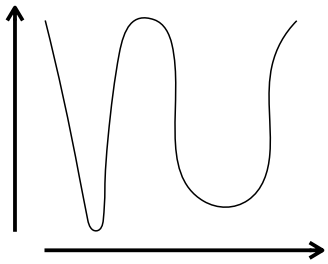

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