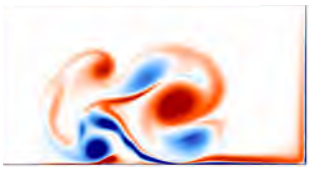
Robust Optimization: application to rapid compression machines

F. Contino, P. Tsirikoglou, S. Abraham, G. Ghorbaniasl

The following slides were presented during the 2-day meeting organised at Politecnico di Milano the 22-23 of February 2018. If you have any question, don't hesitate to contact me by email (fcontino@vub.ac.be). You can also find more information about the Euforia framework on the following website: http://euforia-web.eu/

Robust Optimization: application to rapid compression machines

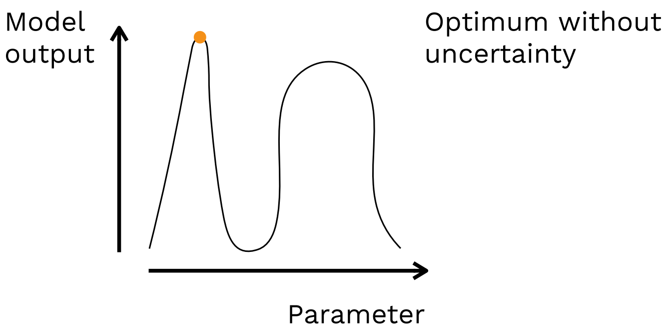
Francesco Contino
Panagiotis Tsirikoglou
Simon Abraham
Ghader Ghorbaniasl
Vrije Universiteit Brussel



22/2/2018

fcontino@vub.be

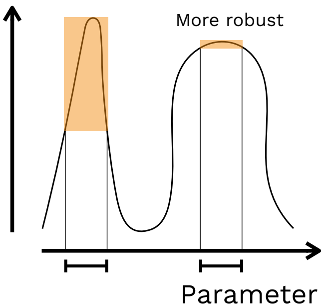
Deterministic optimization only gives the optimum of the model



Robust optimization takes uncertainty into account

When taking uncertainty for the parameter, the range of output of the model can be large in the region of the optimum. This means that the average across the uncertainty might be higher elsewhere.

Model output



In practice, parameters have uncertainty

Different ranges of model output

Challenge of robust optimization: curse of dimensionality

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

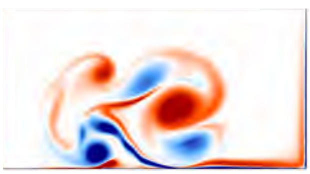
Cost robust optimization	=	Cost UQ	X	Cost optimization

Robust Optimization: application to rapid compression machines

Rapid Compression Machines

Euforia network

Robust optimization results

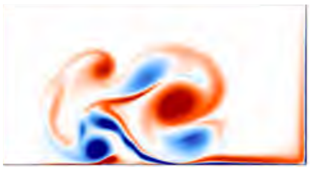


Robust Optimization: application to rapid compression machines

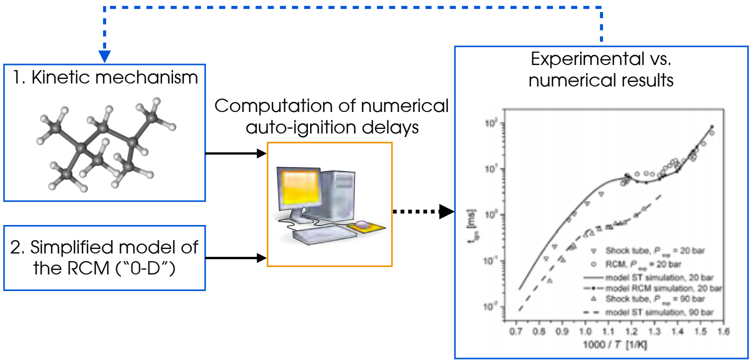
Rapid Compression Machines
Working principles
Why optimizing it?

Euforia network

Robust optimization results

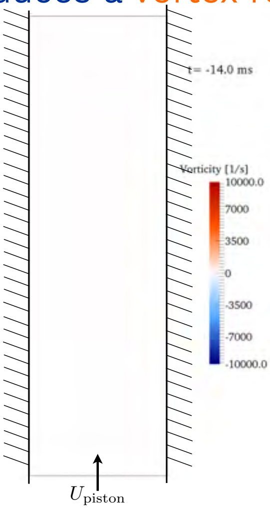


Experimental data used to validate chemical kinetic mechanisms

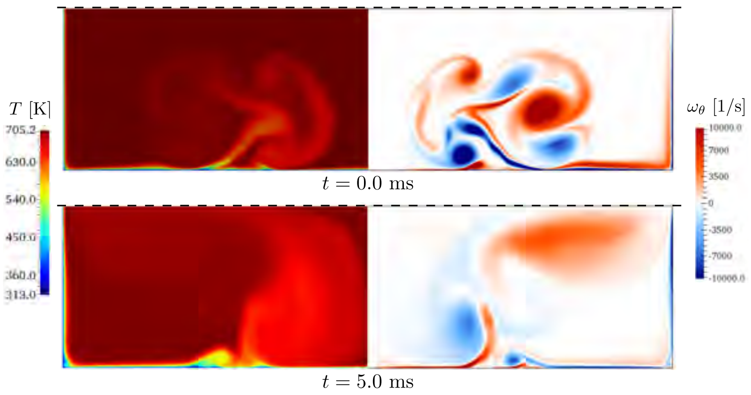


The 0-D model makes an intrinsic part of the validation process used by the researchers.

Flat piston induces a vortex roll-up

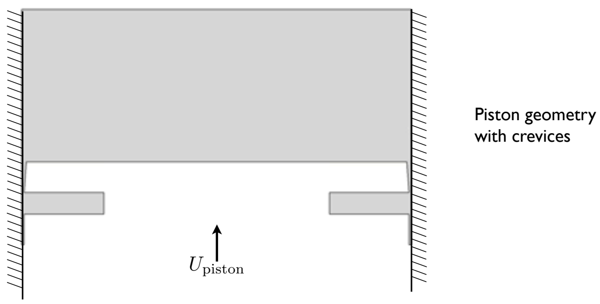


Flat piston induces a vortex roll-up and inhomogeneous temperature



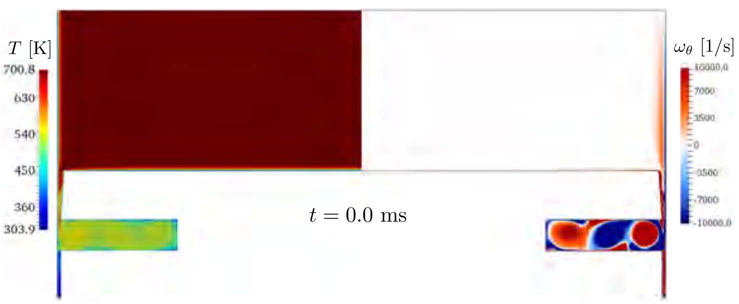
The vortex roll-up comes from the vorticity present at the wall and being scraped by the piston.

To prevent vortex roll-up, piston designed with crevices



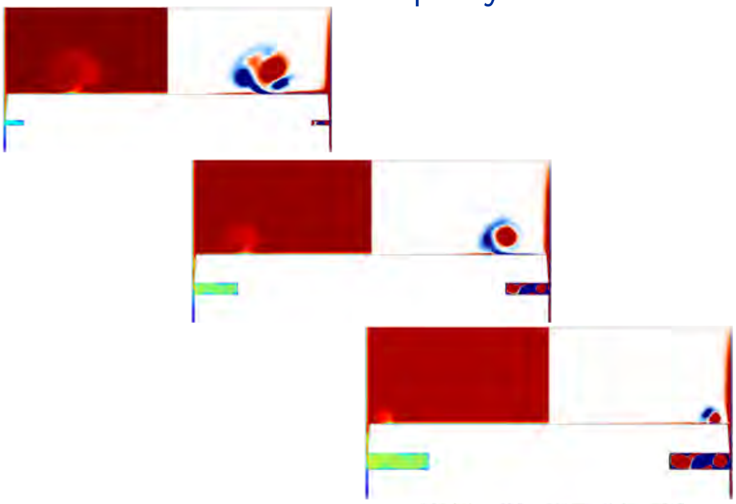
All RCMs implement crevices (instead of a flat piston) to absorb this vorticity.

With crevices, the temperature field is uniform



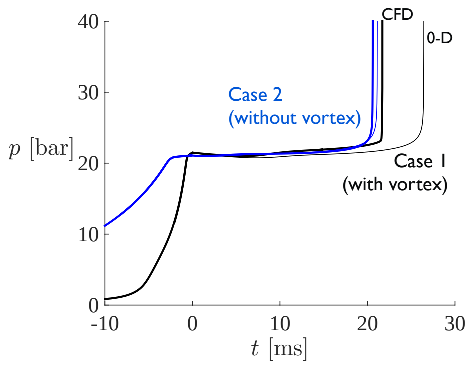
Thanks to the crevice, the temperature field is homogeneous.

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.

The vortex roll-up induces significant deviation from the 0-D model



Crevices should be adequately designed otherwise experiments with and without badly designed crevices might not highlight the right problem.

Objective of the optimization: no vortex while being adiabatic

Crevices big enough

but compression ratio fixed (r_V = 17)

Adiabatic core big enough

but risk of vortex due to speed

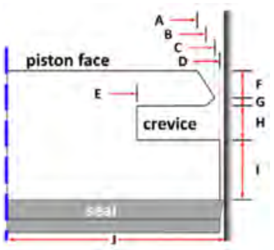
Objective: non-dimensional speed

$$obj = \frac{U_{vortex} \cdot t_{compression}}{L_{stroke}}$$

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

The find the best objective, we will investigate different geometries, using the the parametrization of Goldsborough et al. (PECS, 2017)

We optimize the geometry and the compression stroke properties



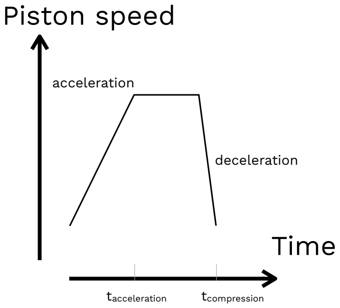
Goldsborough et al., 2017

Geometric parameters to be optimized

Geometrical uncertainty: 1%

Aside from the geometry, one of the important features is the compressions stroke. We have parametrized it using three main steps: acceleration, constant speed, and braking. While the uncertainty for the geometry was 1%, the uncertainty on the stroke is much higher (often not being measured accurately): 10%.

We optimize the geometry and the compression stroke properties



Stroke profile based on three steps

Three opt. parameters: acceleration, deceleration, $t_{acceleration}/t_{compression}$

Stroke length optimized with comp. ratio constant

Stroke uncertainty: 10%

Robust Optimization: application to rapid compression machines

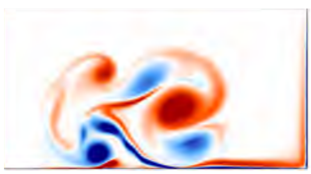
Rapid Compression Machines

Euforia network

Uncertainty Quantification

Optimization methodology

Robust optimization results



The Euforia framework: reliable, efficient and non-intrusive

Similar framework as Dakota (Sandia) and includes our latest developments
-UQ method
-surrogate-based optimizers

Euforia is a light wrapper written in Python

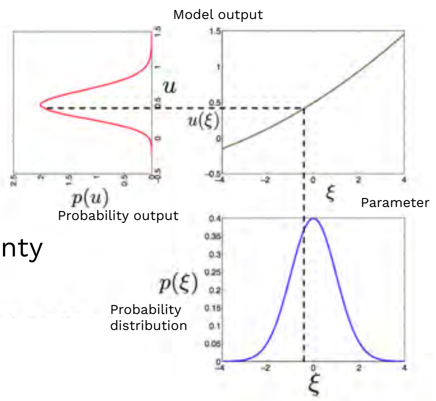
Model to be optimized is considered as a black box

Euforia ⟷ OpenFOAM

To tackle the challenge of the curse of dimensionality we are combining efficient methods for uncertainty quantification and optimization. In the perspectives, we'll see even more advanced methods we will use as a continuation of this study.

We use polynomial chaos expansion for uncertainty quantification

For a given uncertainty in the parameters we obtain uncertainty in the output



Debusschere, 2013

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

We use polynomial chaos expansion for uncertainty quantification

Model approximated by polynomial chaos expansion

Model output — $u(\xi) \approx \sum y_i \psi_i(\xi)$

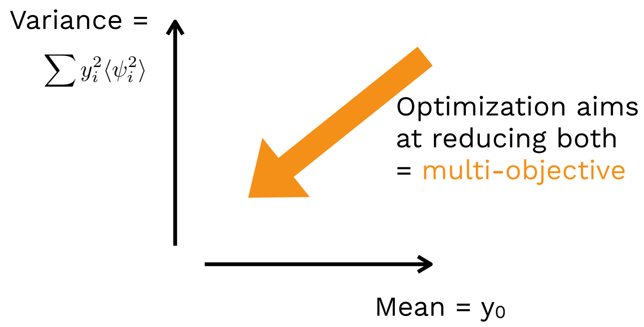
Uncertain parameter(s)

Orthogonal polynomials

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.

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.

Optimization based on Cuckoo search coupled with specific sorting criterion

Cuckoo search: mimics cuckoos flying around to lay eggs

Survival of eggs in good nests
=good model solution

Fly following Levy distribution
=many small steps for every big one

Non-dominated
Sorting by crowding distance
(from NSGA-II)

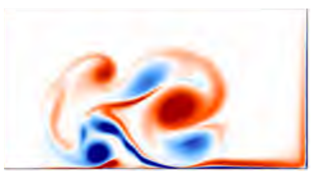
We used one of the available optimizers, namely Cuckoo search. It is based on the (aggressive) breeding behavior of the Cuckoo birds and the foraging path of animals. They fly using a Levy distribution which includes many small steps (for local exploration) for every big step (for global exploration).

Robust Optimization: application to rapid compression machines

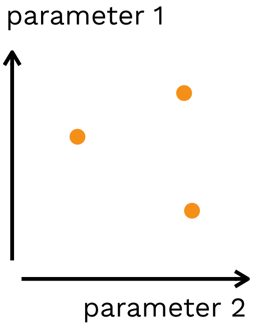
Rapid Compression Machines

Euforia network

Robust optimization results
Computational cost
Pareto front



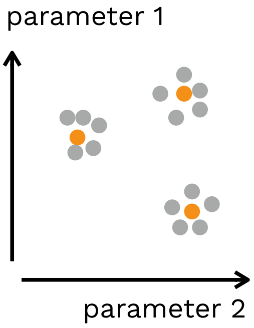
The total cost includes the sampling for optimization and UQ



The optimizer explores the parameters' space to find an optimimum

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

The total cost includes the sampling for optimization and UQ



The optimizer explores the parameter space to find an optimimum

UQ module needs additional points to compute statistics

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.

For this reference case, the cost is still very expensive

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

Optimization is based on full CFD model for all samples

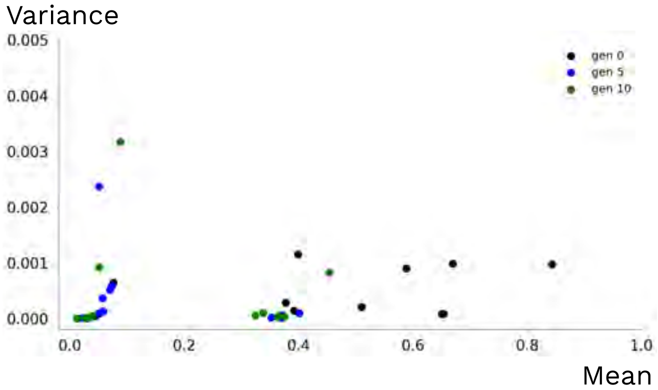
Around 10 000 CFD simulations on 60 cores: 2 days

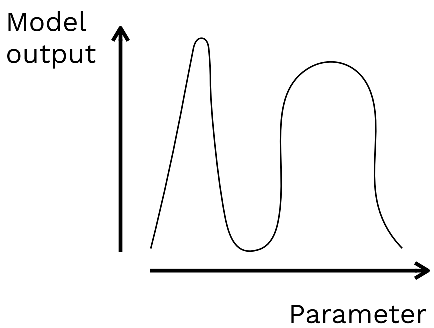
This will be the reference for future research (see perspectives)

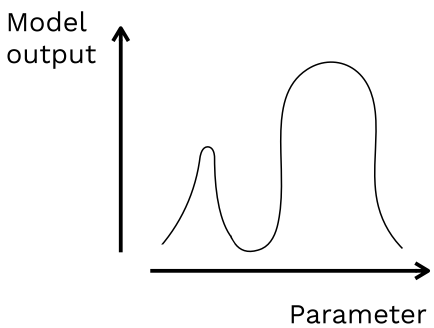
We use this case as a demonstration for more advanced techniques to reduce the computation cost. Therefore, the current simulations were based on full polynomial chaos and CFD for every sample.

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

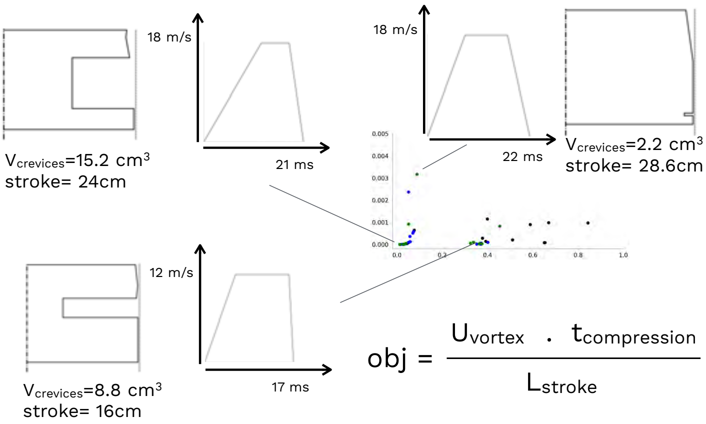
Variance and mean are are non-confronting objectives







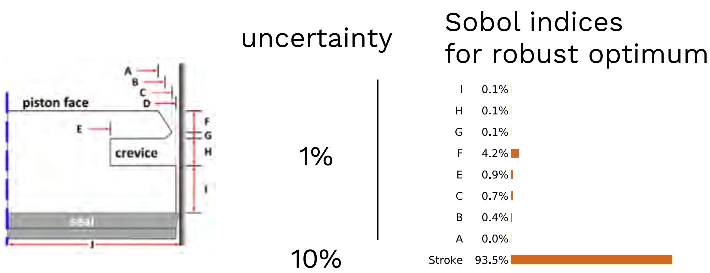
Variance and mean are are non-confronting objectives



$$obj = \frac{U_{vortex} \cdot t_{compression}}{L_{stroke}}$$

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

Using Sobol indices, we compute the sensitivity of the variance



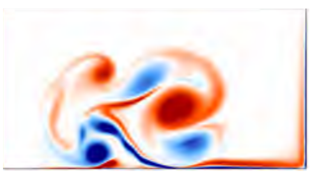
Sobol indices are readily available as a side-product of polynomial chaos. It measures the contribution of each parameter to the variance.

Robust Optimization: application to rapid compression machines

Rapid Compression Machines

Euforia network

Robust optimization results



Next step for this RCM study

Use as reference to further illustrate:

1. Surrogate-based optimization
No need to run CFD for all samples
Expected speed-up: ~10

2. Sparse Polynomial Chaos
Take advantage of sparsity
to reduce number of samples
Expected speed-up: ~2
Abraham et al., JCP, 2017

Next step for robust optimization

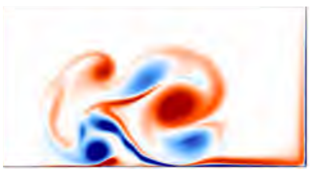
Application to Diesel case

In collaboration with
ICE group @PoliMi

Tier-1 cluster for 3 10^6 core.hours

Robust Optimization: application to rapid compression machines

Francesco Contino
Panagiotis Tsirikoglou
Simon Abraham
Ghader Ghorbaniasl
Vrije Universiteit Brussel



22/2/2018

fcontino@vub.be

Next big developments:

1. Improved Jacobian
2. Quasi-steady state stiffness removal