Automatic Design of ORC Turbine Profiles Using Evolutionary Algorithms

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Design of ORC turbines

Turbomachinery design demands systematic procedures

ORCs push towards non-conventional turbomachinery (load, efficiency, compactness)

Semi-empirical criteria lack of reliability in non-conventional contexts

High-fidelity CFD crucial in non-conventional turbomachinery R&D

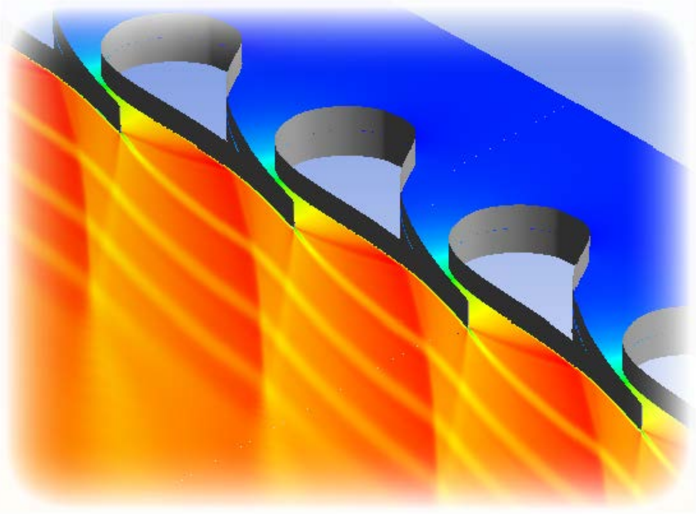
Automatic CFD-based design package required

Evolutionary design strategy coupled with:

geometric **parametrization** methods

experimentally validated **CFD model**

surrogate models



Outline

- Evolutionary Shape Optimization
- Bricks
  - ✓ Parametrization model
  - ✓ CFD model
  - ✓ Surrogate model
- Optimization Strategy Layouts
- Exercise of Design
- Robust Design
- Conclusions

Evolutionary Shape Optimization

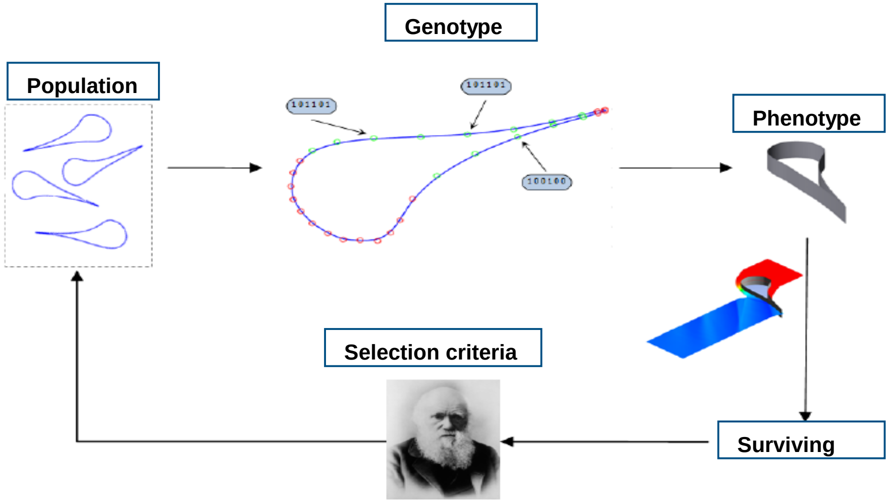
- **Shape Optimization**: to minimize an OF using geometry as design parameters

- Stochastic **Evolutionary** Optimization (inspired by Evolution Theory):
  - ✓ Direct: no need of problem inversion, only need direct CFD tools
  - ✓ Heuristic: requires statistical relevance (→ high cost)

- Combined with **surrogate models** to tackle computational cost

- Non-dominated Sorting **Genetic Algorithm**:
  - ✓ 200 generation
  - ✓ 70% of crossover
  - ✓ 2% of mutation
  - ✓ elitism

GA SCHEMATIC



Briks

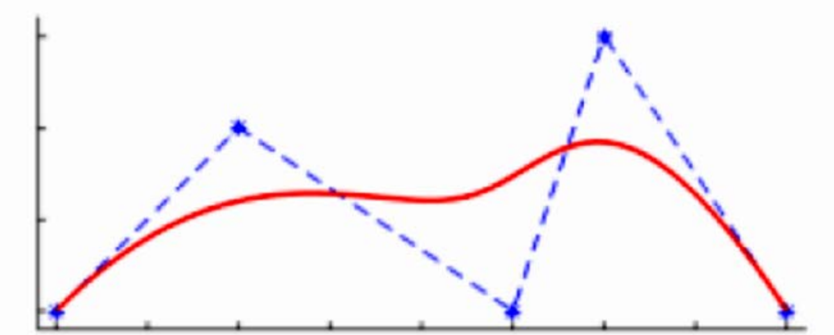
Blade geometry parametrization

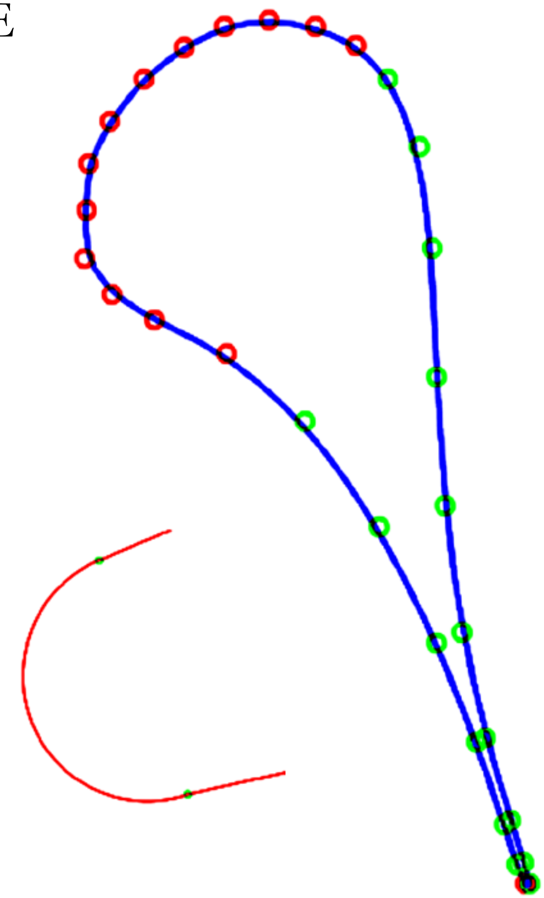
- Concept: blade geometry as succession of regular lines identified by **Control Points**
- **B-Spline** cubic lines: C^2 smoothness, identified by 4 CPs, computed recursively
- Degrees of **freedom**: impose passing by CPs, circular TE

$$x(u) = \sum_{j=0}^{L} d_j N_j^n(u)$$

$$N_j^k(u) = \frac{u - u_{j-1}}{u_{j+k-1} - u_{j-1}} N_j^{k-1}(u) + \frac{u_{j+k} - u}{u_{j+k} - u_j} N_{j+1}^{k-1}(u)$$

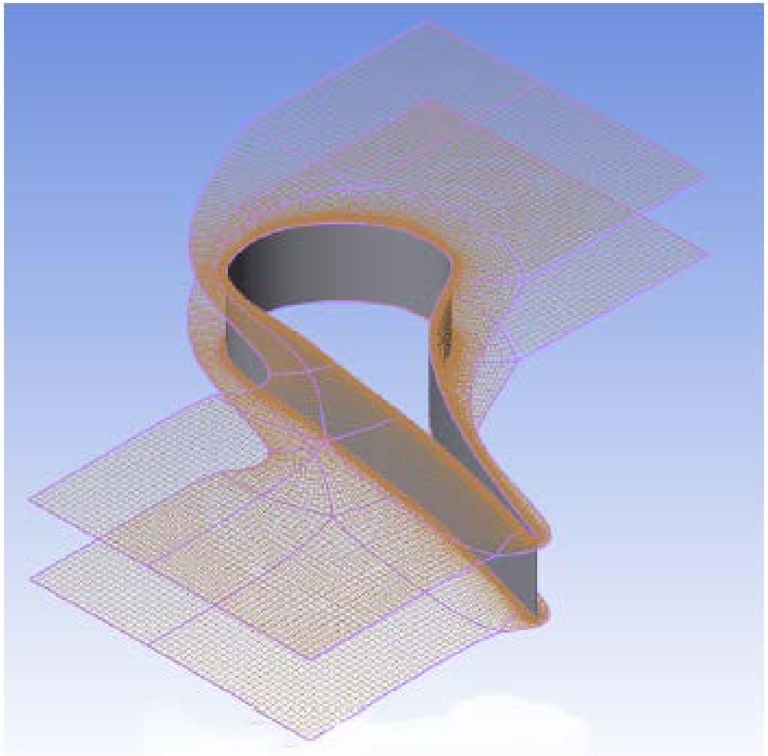
$$N_j^0(u) = \begin{cases} 0 & \textit{if} \quad u_{j-1} \leq u < u_i \\ 1 & \textit{if} \quad \textit{otherwise} \end{cases}$$





Briks
CFD model

- High-fidelity blade-to-blade flow model
- Quasi-3D steady flow model
- Hexahedral grids with 50 ÷ 400 kcells
- Solver: Finite Volume ANSYS-CFX, with:
  - . **HR methods** for inviscid fluxes
  - . centred scheme for diffusive terms



- Turbulence model: **k-ω SST** with near-wall boundary layer solution (wall $y^+ \sim 0.1$)
- **Real gas model** implemented via **Look-Up-Table** approach; LuT constructed using a generalized thermodynamic library
- Flow model **validated** against experiments (Persico et al., 2012, ASME J. Turbomach.)

Briks
Surrogate model

- 10^4 OF evaluations required by GA, CFD runs are expensive

  → **surrogate models** to speed-up convergence

- Surrogate: analytical function that mimics the 'response surface', being:
  - ✓ highly **flexible**
  - ✓ initially **tunable**
  - ✓ **adjustable** via a learning process

- **Re-tuning** of the surrogate model
  - ✓ Initial interpolation on a data-base (DOE)
  - ✓ GA only applied to the interpolated surrogate model
  - ✓ Improvement of data-base and re-interpolation close to the optimum

- **Kriging** surrogate model used (suitable for highly irregular data distributions):

Optimization Strategy: Local vs Global

- ✓ Initial CFD-based DOE for response sampling
- ✓ Surrogate function interpolated and minimized

Local 'trust region' method

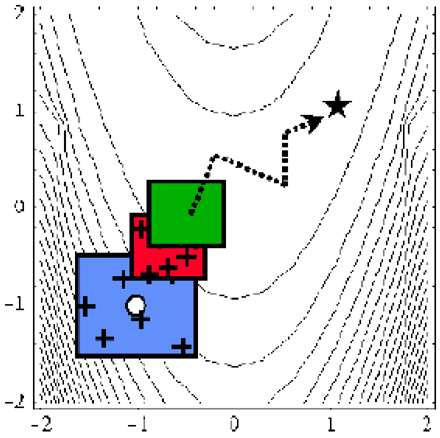
- ✓ Trust region reliability checked by trust ratio

$$\rho^k = \frac{f(x_c^k) - f(x_{opt}^k)}{\tilde{f}(x_c^k) - \tilde{f}(x_{opt}^k)}$$

- ✓ If reliable ($\rho^k > 0.5$), trust region shink
- ✓ CFD-based DOE in new trust region

…

→ Trust region collapses on optimum



Global 'training' method

- ✓ Optimum checked by CFD
- ✓ New CFD value added to data-base
- ✓ Surrogate re-interpolated

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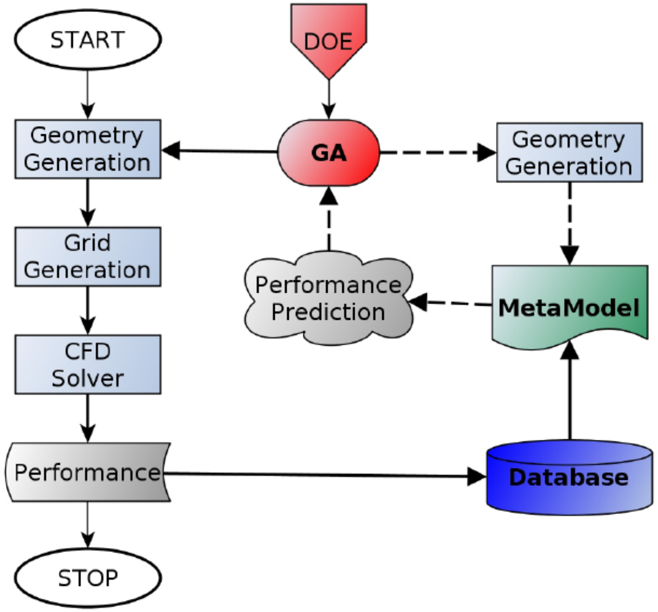
→ Surrogate minimum approaches optimum



Exercise of Design
Test case

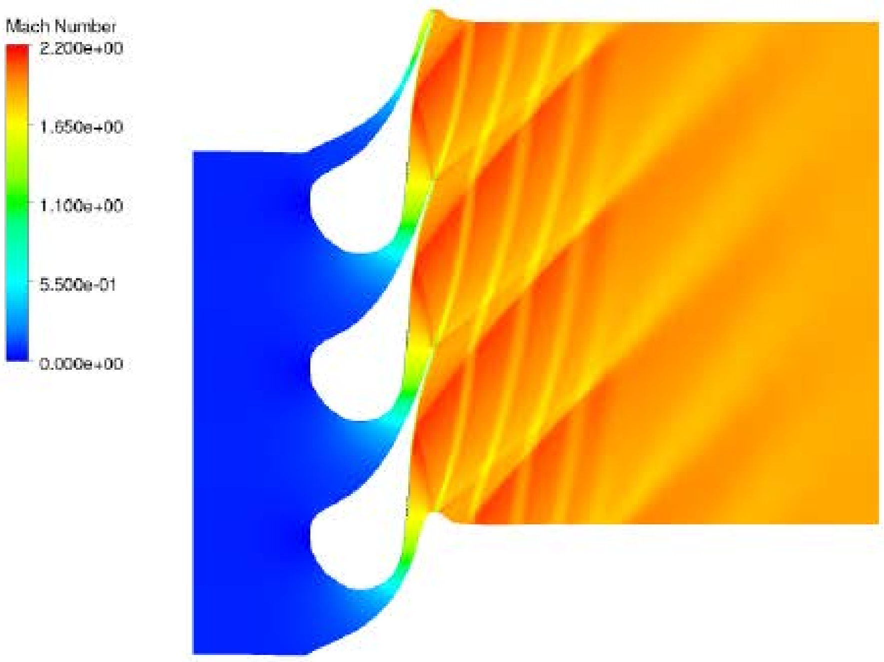
Supersonic converging-diverging cascade (M = 2.1) for axial ORC turbine (MDM)

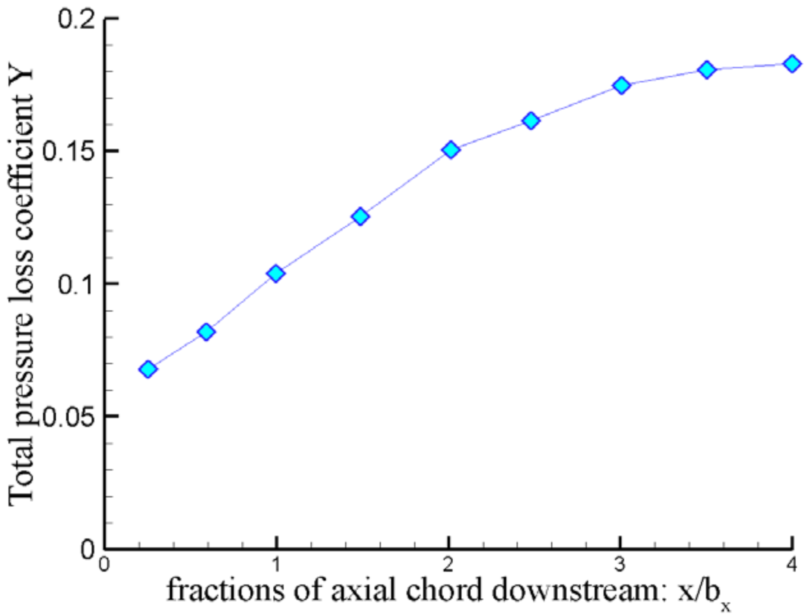
Baseline configuration:

Strong shocks generated on Suction Side and on TE (fishtail)

Weaving wake trace due to huge circumferential pressure gradients

→ dramatic raise of loss due to shock mixing downstream (and impact on rotor?)





Exercise of Design
Procedure

Objective Function

Standard deviation of static pressure half a chord downstream of the TE

→ Minimize shock, shock mixing loss, flow disuniformity in stator-rotor gap

Design Space

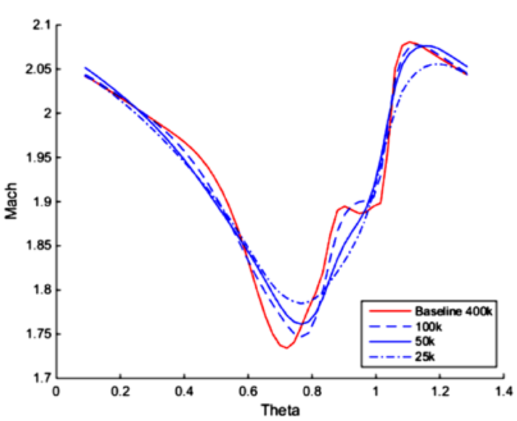
Parametric study on CP number and design space initially performed

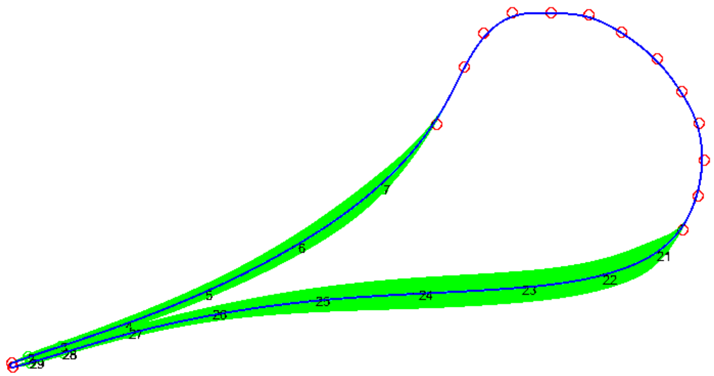
15 movable CPs in the rear blade section both on PS and SS

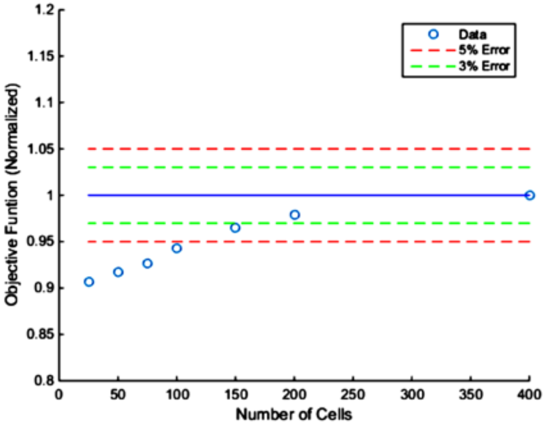
Computational Cost

grid dependence analysis to reduce the cost of CFD run

→ low fidelity (100 kc) optimization, high fidelity (400 kc) validation

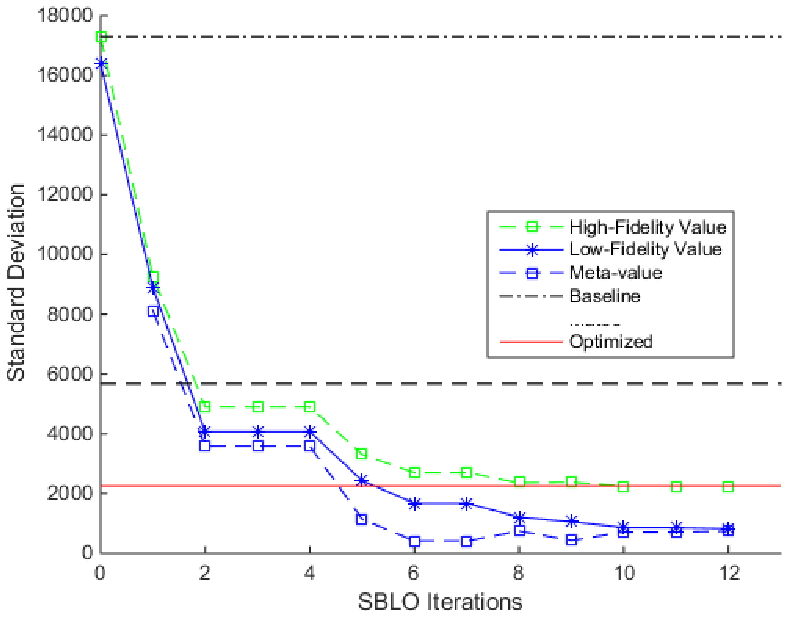




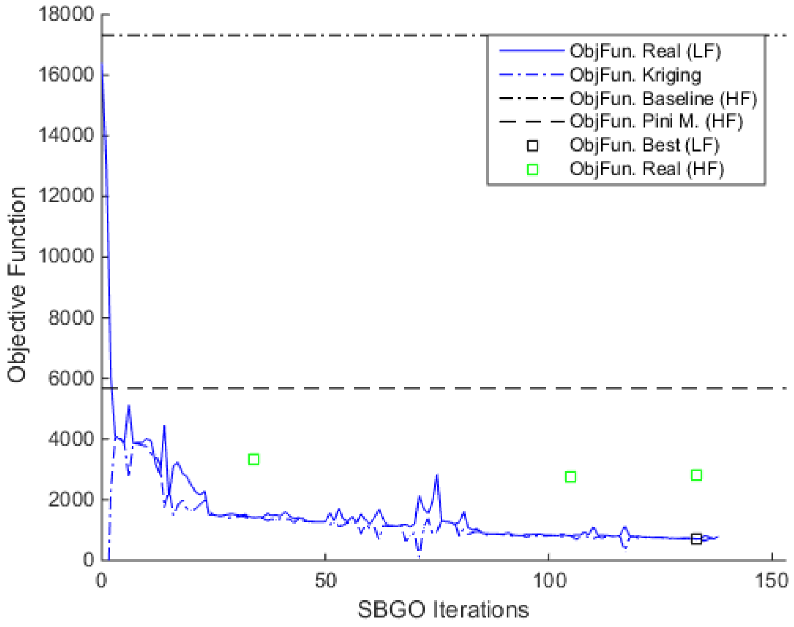


Exercise of Design
Convergence history

Local



Global



Convergence attained by both methods → nearly identical min OF (and blade!)

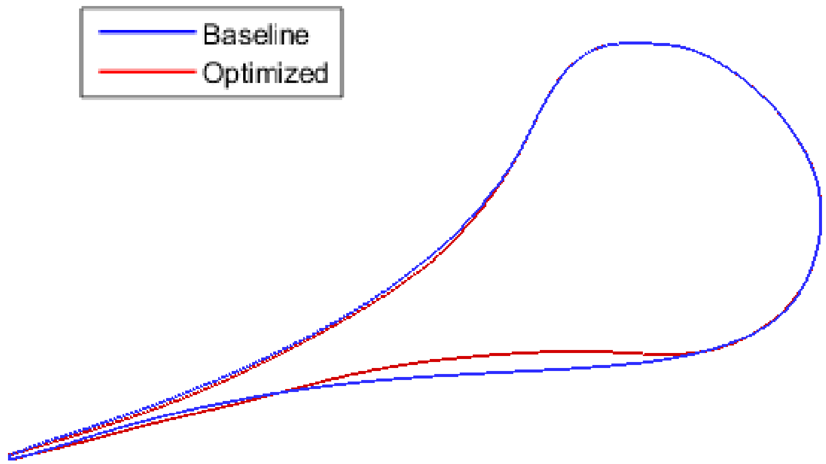
Global-Cost ≈ 20 h (16 proc. Cluster); Local-Cost ≈ 3 × Global-Cost

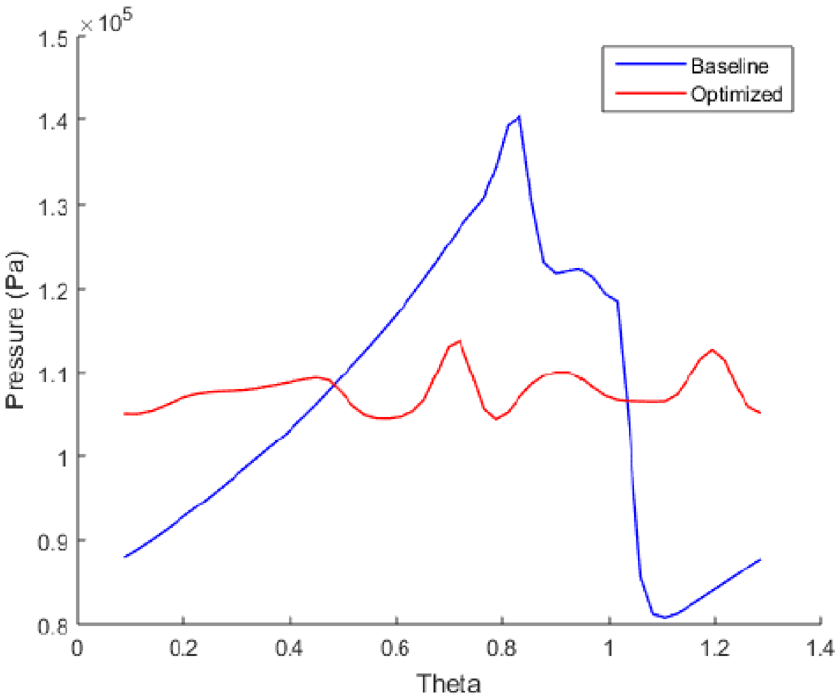
LF optimization proved to be reliable when verified in HF (very well matched trend)

Optimization Results
Outcome

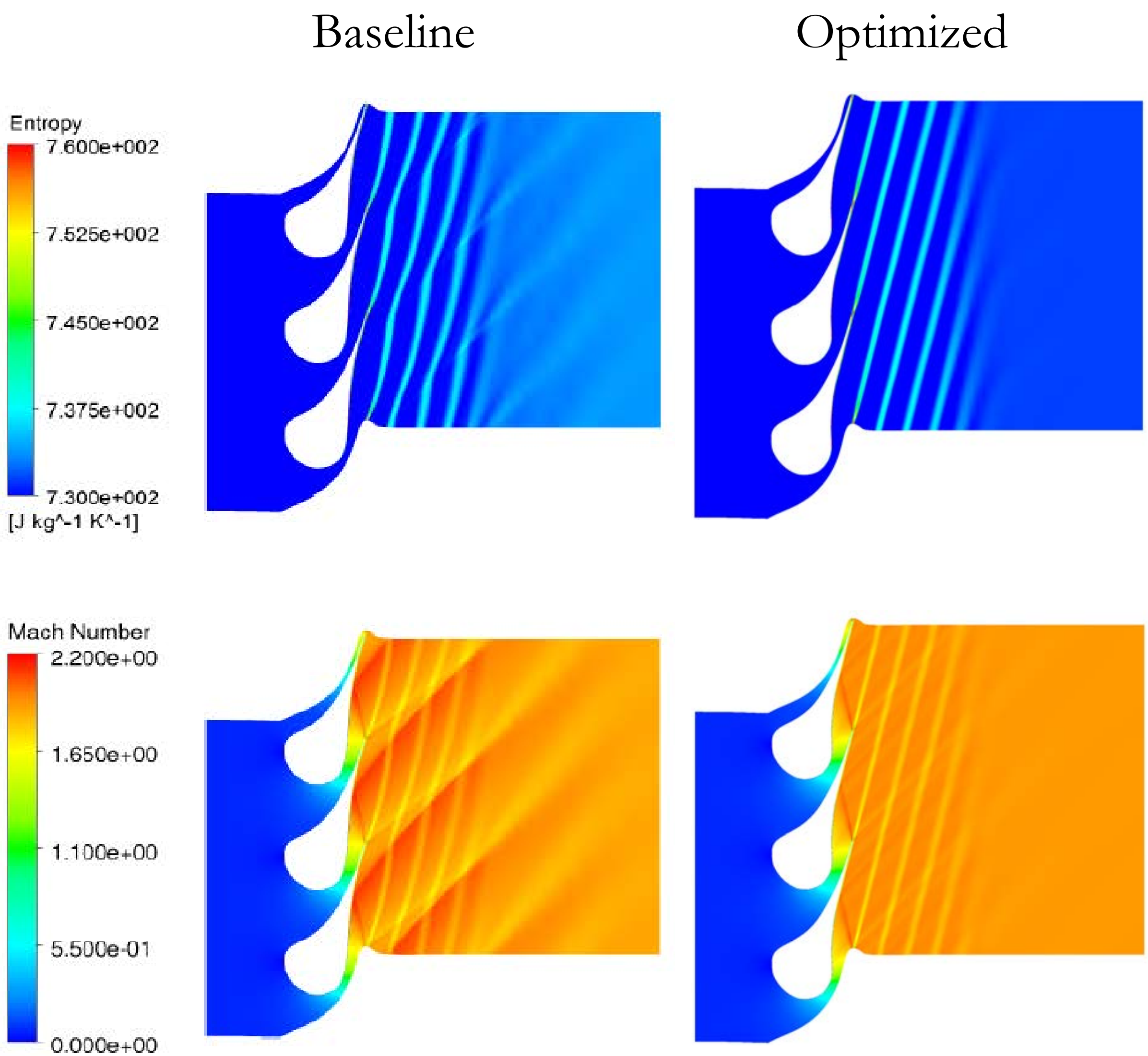
Optimized configuration → Nearly uniform Pressure downstream

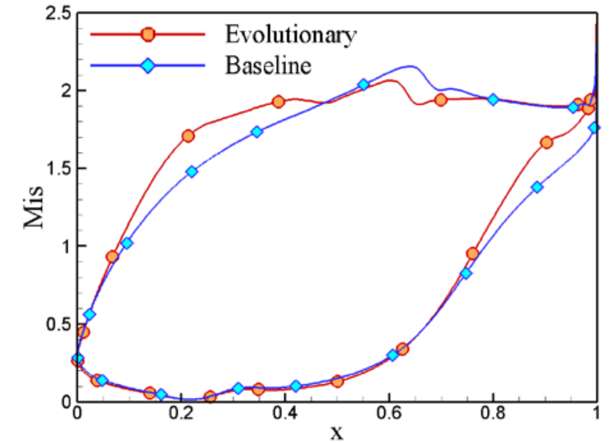
Enhanced divergence → Dramatic shock reduction

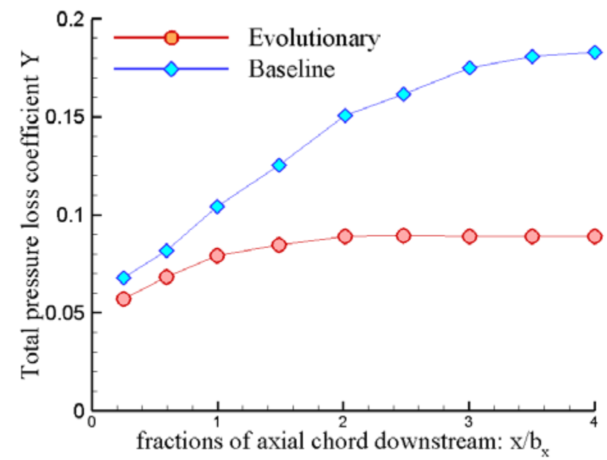




Optimization Results
Flow field and performance





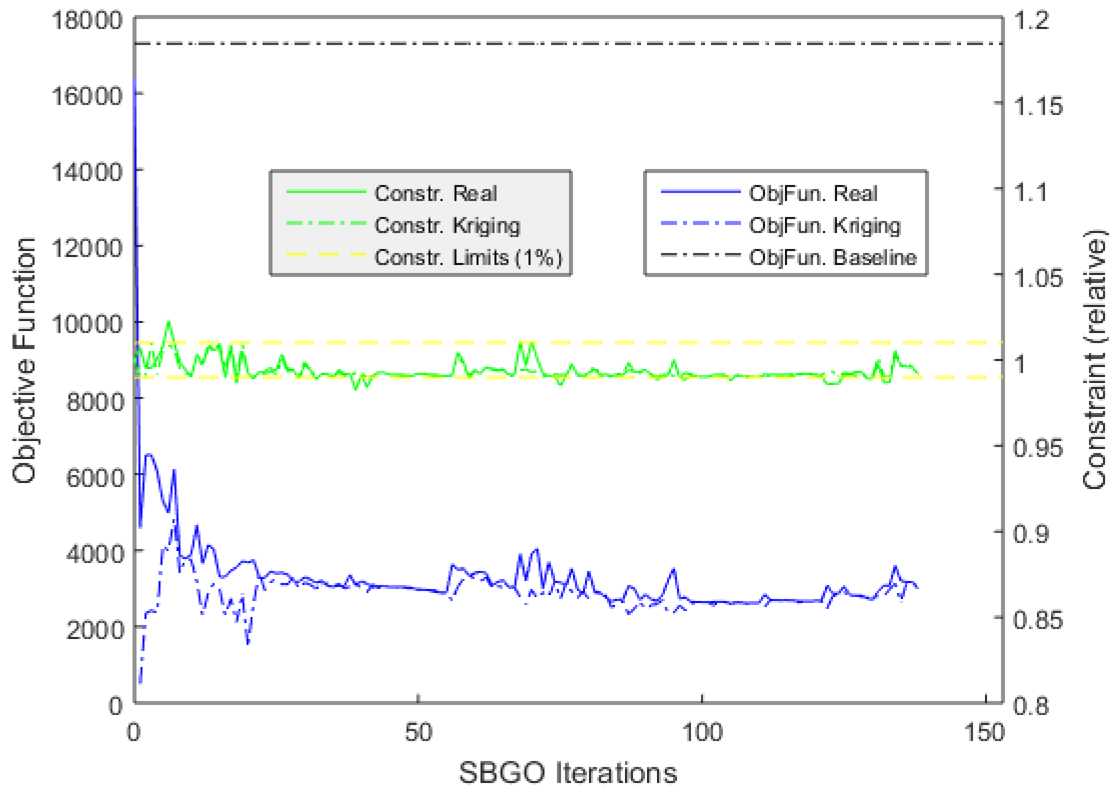


	Baseline	*Evolutionary*
Y	15%	8.9%

Constrained Optimization

1% of flow rate

Convergence history



Surrogate model constructed also for the contrained quantity

Convergence attained but outcome slightly worst than non-constrained optimization

Non-constrained optimal blade satisfies flow rate contraint by fixed CPs up to throat

→ Geometrical contraint more effective than process contraint (chocked flow)

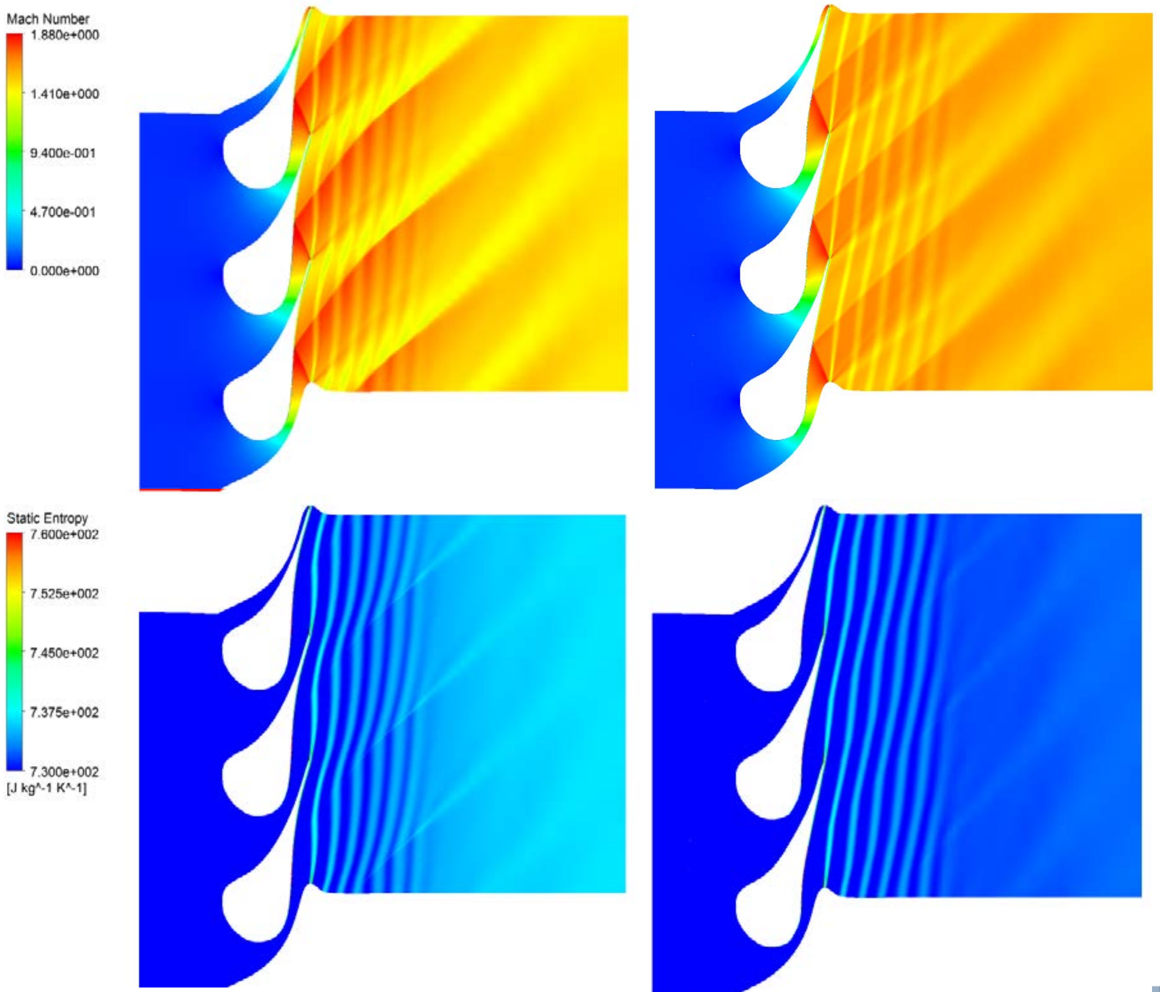
Robust Design

Multi-point Objective Function:

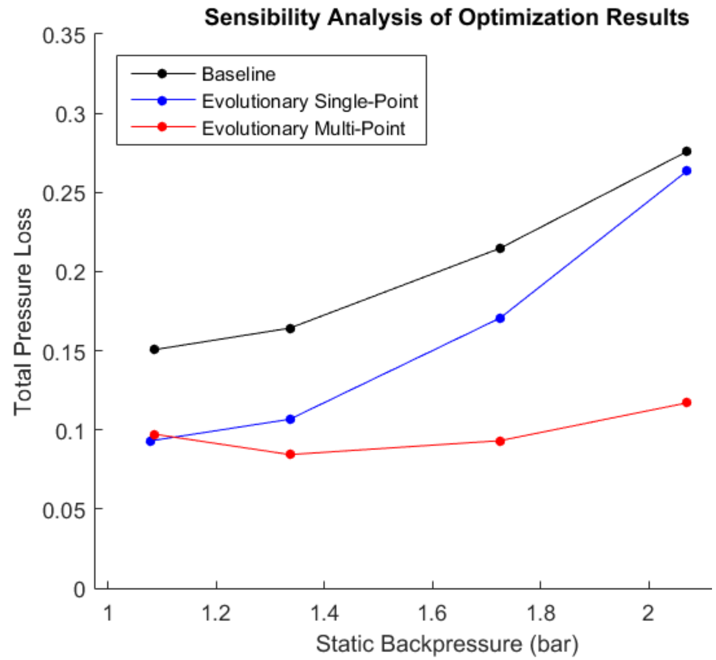
Standard deviation of P combining 2 or 3 operating conditions (possibly weighted)

Baseline Optimized

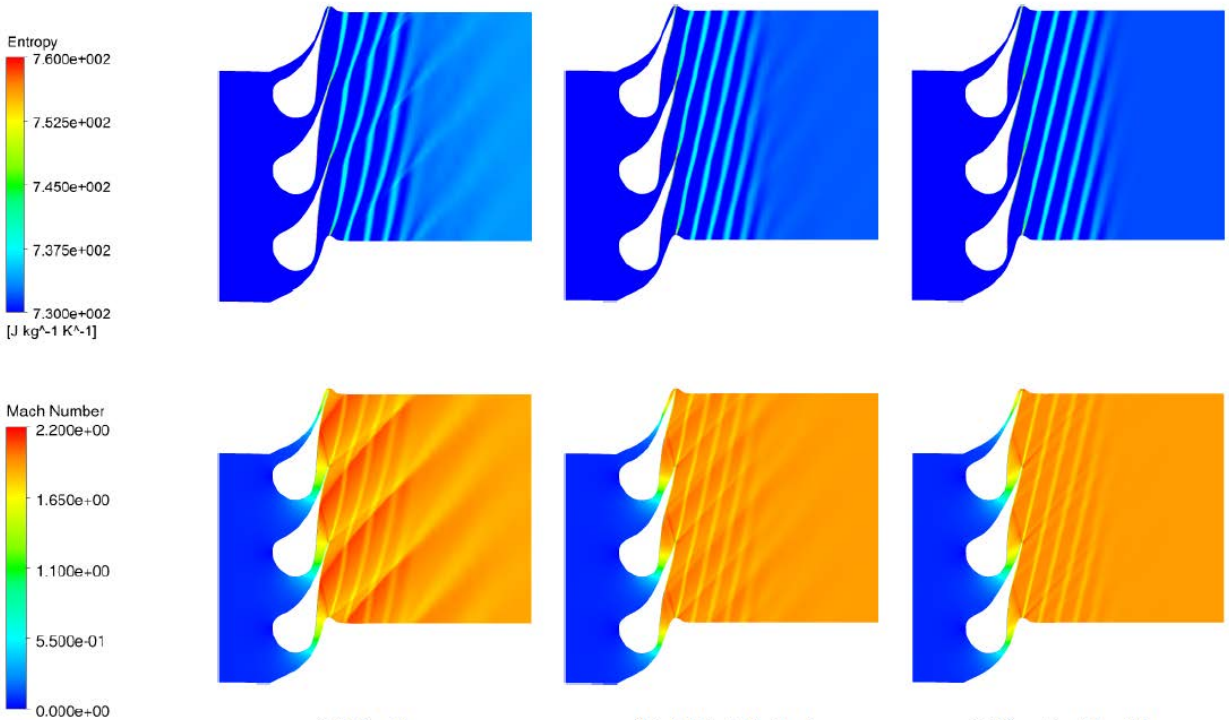
worst scenario ($\beta = 0.5\ \beta_{DES}$)



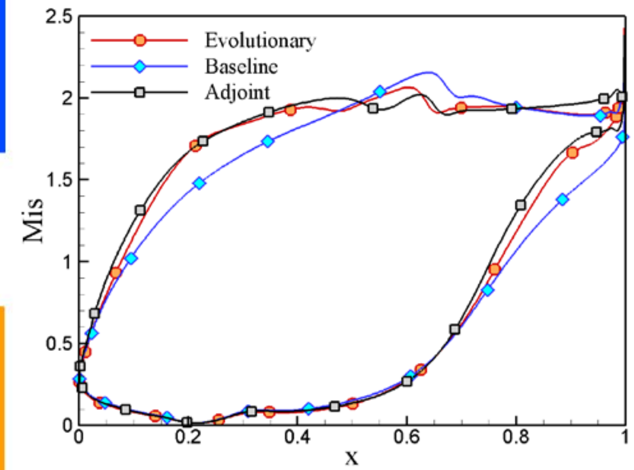
β-loss curves (off-design)



Outcome of Evolutionary Optimization similar to Outcome of Adjoint-based Gradient Optimization



(a) Baseline (b) Adjoint Method (c) Genetic Algorithm



	Baseline	*Evolutionary*	*Adjoint*
Y	15%	8.9%	10.7%

Pini, Persico *et al.*, Adjoint Method for Shape Optimization in Real-Gas Flow Applications, *J. Eng. Gas Turbines Power,* 2015, Vol 137

Conclusions

- High-fidelity methodology for ORC turbine design developed and applied
- Package: genetic algorithm, surrogate model, CFD, geometry parametrization
- Two surrogate-based strategies tested and proved to provide similar outcome
- Successful optimization (40% loss reduction), with 20 h of computational cost
- Constrained optimization developed, even though preventing full minimization
- Successful implementation for robust (i.e., multi-point) design

Thank you!

Any questions?

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