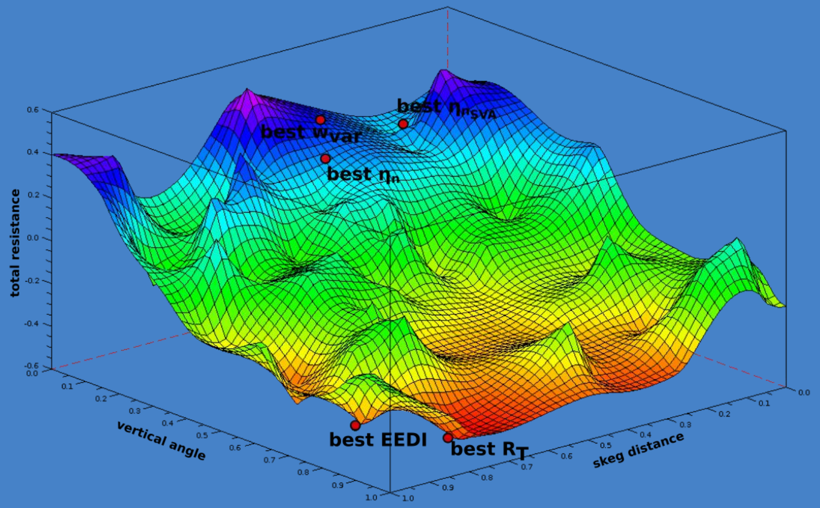
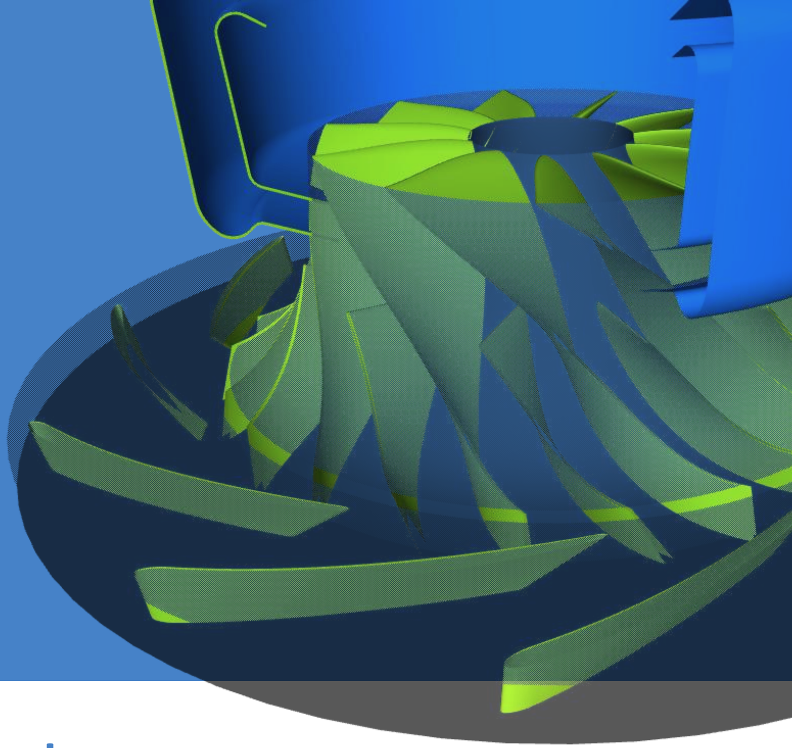




Strategies for the Massive Acceleration of Complex Fluid-Dynamic Shape Optimizations

FRIENDSHIP SYSTEMS

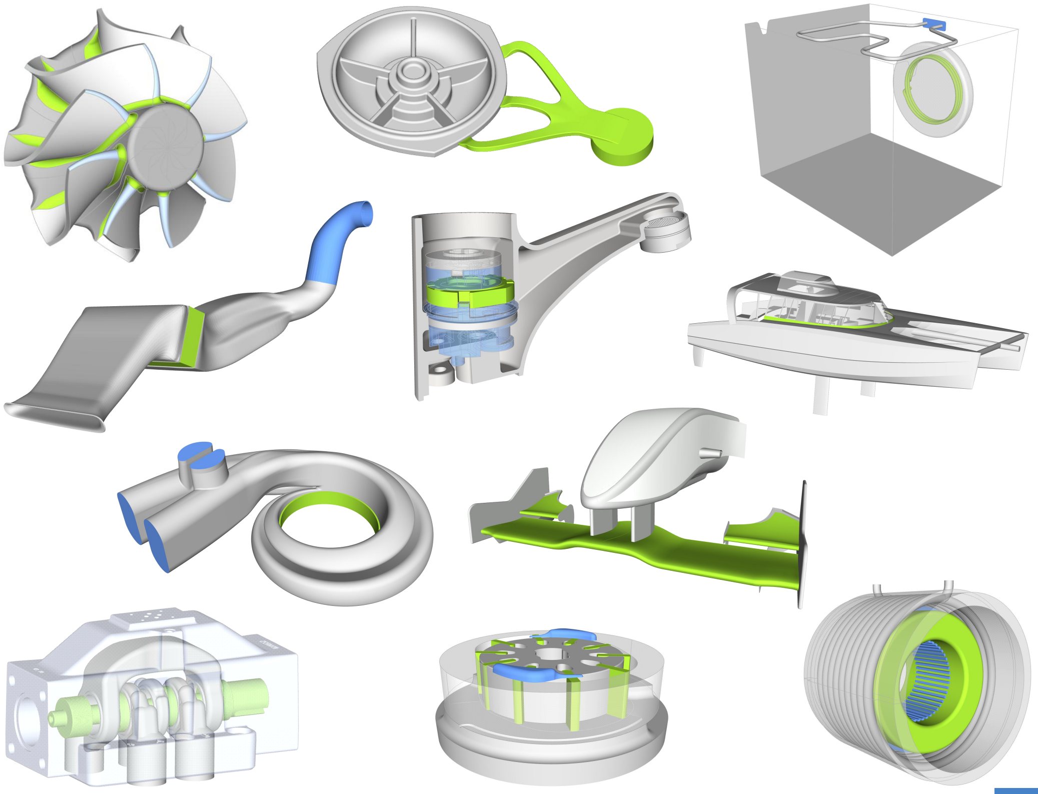
Motivation | The Need for Optimization

- Laws and regulations, as well as tough competition in the market, demand a very high level of performance in modern engineering design
- Old processes (manual iteration: CAD → Grid generation → Solving → Post-processing) are:
  - Time consuming → increases development costs
  - Can lead to improved, but not optimized, results → failure to meet targets

- Automation can:
  - Shorten development times and reduce design cycles
  - Increase knowledge about product’s behavior
  - Lead to better and optimized designs

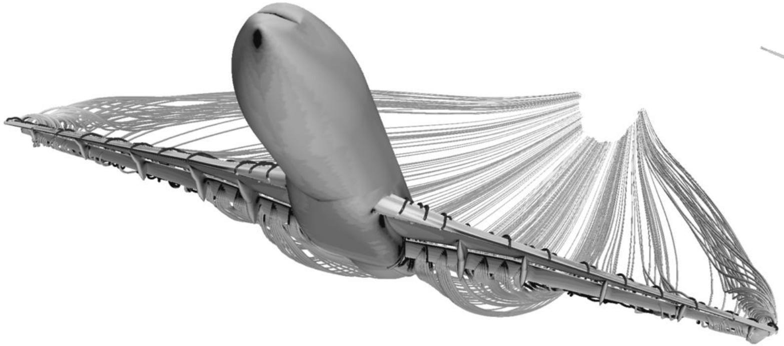
Motivation | Complex Problems

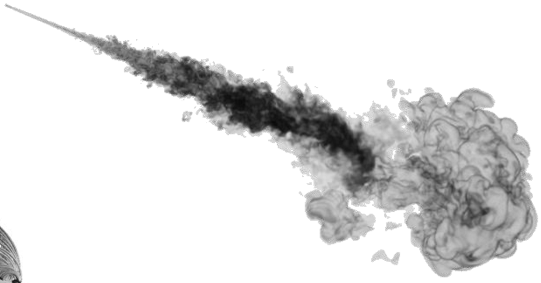
- Complex models
  - Usually, a high number of parameters defines a parametric model
  - Way too much effort to involve all of them in a conventional optimization process
  - Often, the designer selects a small number of parameters based on experience and engineering judgment
    - This reduces the design space for the optimization
    - The designer might not have enough experience to make a good selection
    - Especially difficult if the model was created by someone else

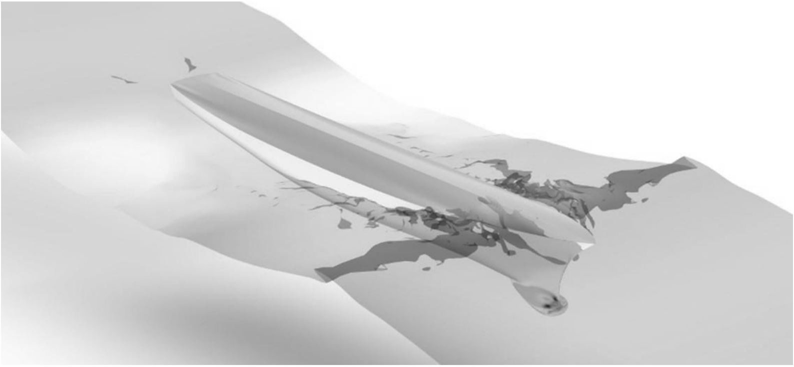


Motivation | Complex Problems

- Complex simulations
  - High cell count
  - Complex physics
  - Many operating points



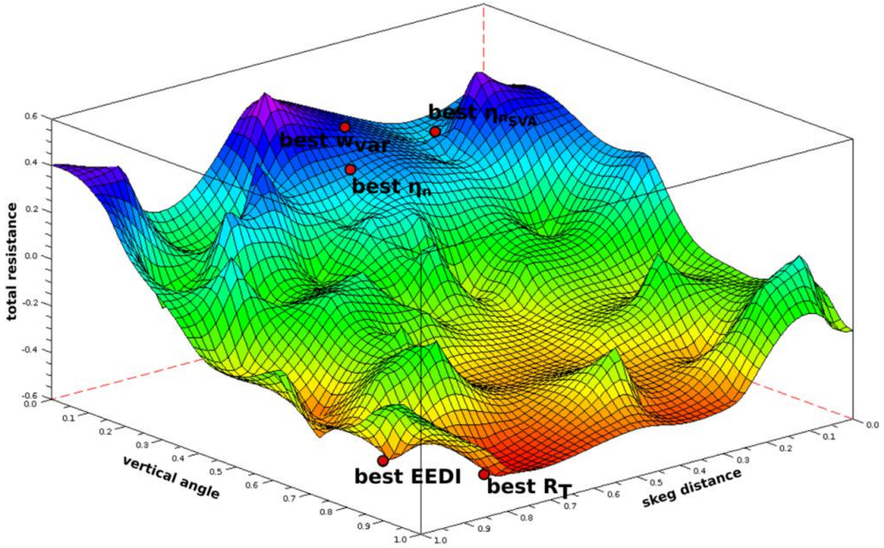




Strategies | Surrogate Based Optimization

Surrogate Based Optimization

- Replace CFD computations with a surrogate model based on a database of previous CFD results
- Process:
  - Run a systematic geometry evaluation and analyze with CFD
  - Generate the surrogate model
  - Optimize on the surrogate model
  - Verify optimization results with CFD and, if needed, update the surrogate model



Strategies | Parametric Adjoint Optimization

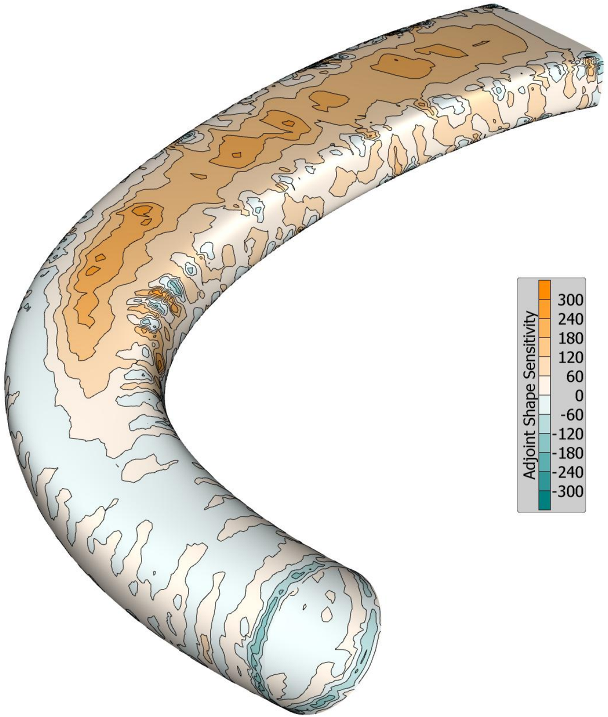
CAESES®

Adjoint Analysis Results

- In shape optimization: shape sensitivity (change of objective function *J* due to normal displacement of cells on the design boundary)

$$\frac{\partial J}{\partial n_k}$$

- A positive shape sensitivity means that the boundary should be moved in positive normal direction
- A negative shape sensitivity calls for boundary movement in negative normal direction



How to Use the Adjoint Sensitivities

- Adjoint shape sensitivity values can be used to displace the surface cells directly and to morph the shape, e.g. in a CAD independent approach
- Downside is that the shape changes cannot easily be fed back into the design workflow, geometry constraints (e.g. for production) may be violated

→ *Solution: map shape sensitivities to CAD model parameters*

Sensitivity for CAD parameter α_i

Normal displacement of model boundary due to CAD parameter change: „design velocity“

$$\frac{\partial J}{\partial \alpha_i} = \sum_k \frac{\partial J}{\partial n_n A_n} \frac{\partial n_k}{\partial \alpha_i} A_k$$

Adjoint shape sensitivity

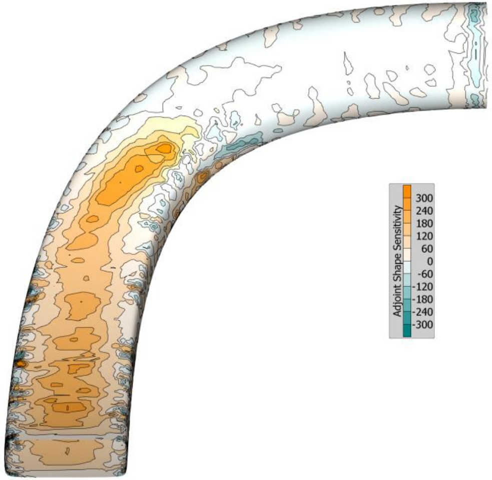
Local cell size

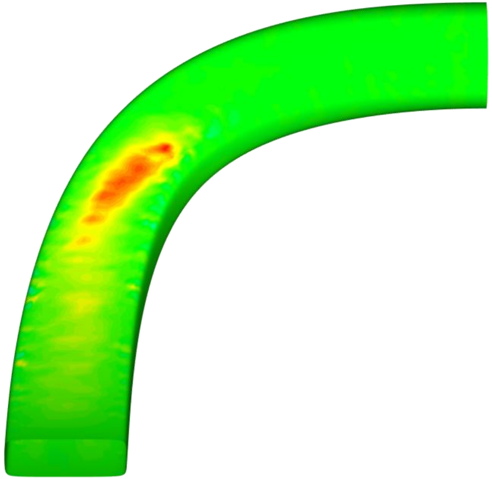
Parametric Adjoints

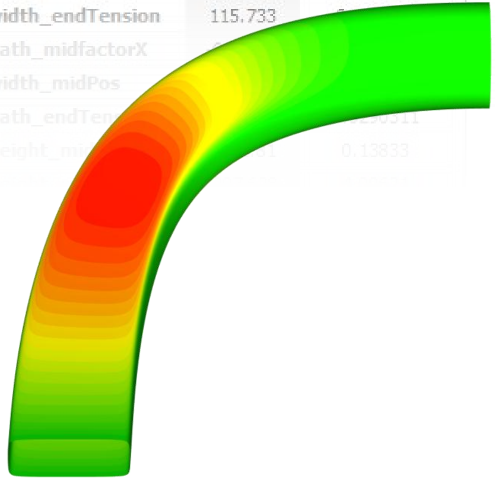
- Connecting to information about parameter influence on shape leads to sensitivities for all design parameters

pictures: Sensitivities

	Sensitivity	Variation Delta
width_mid	-41.2465	3.99853
path_midfactorZ	1388.89	0.0208482
path_startTension	562.865	0.0419241
height_startTension	3119.02	0.242158
path_midfactorY	233.01	0.0402543
width_endTension	115.733	[illegible]
path_midfactorX	[illegible]	[illegible]
width_midPos	[illegible]	[illegible]

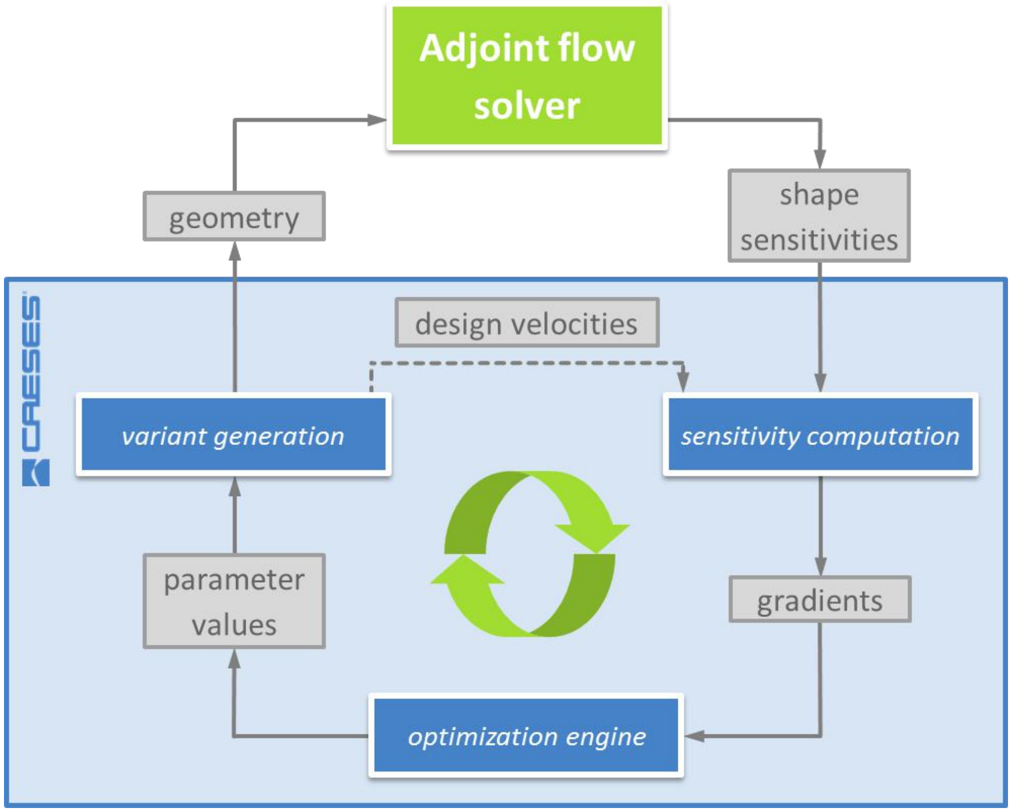




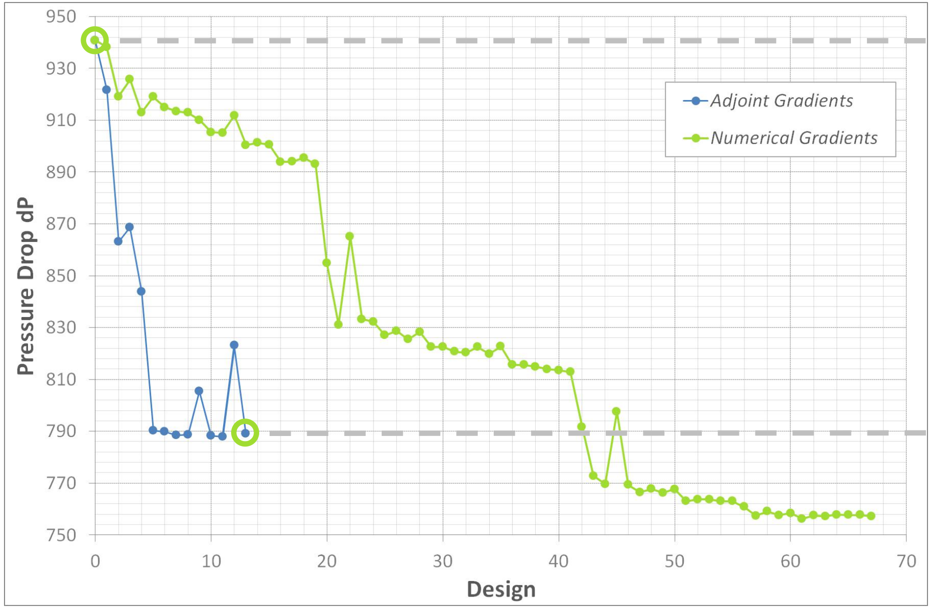


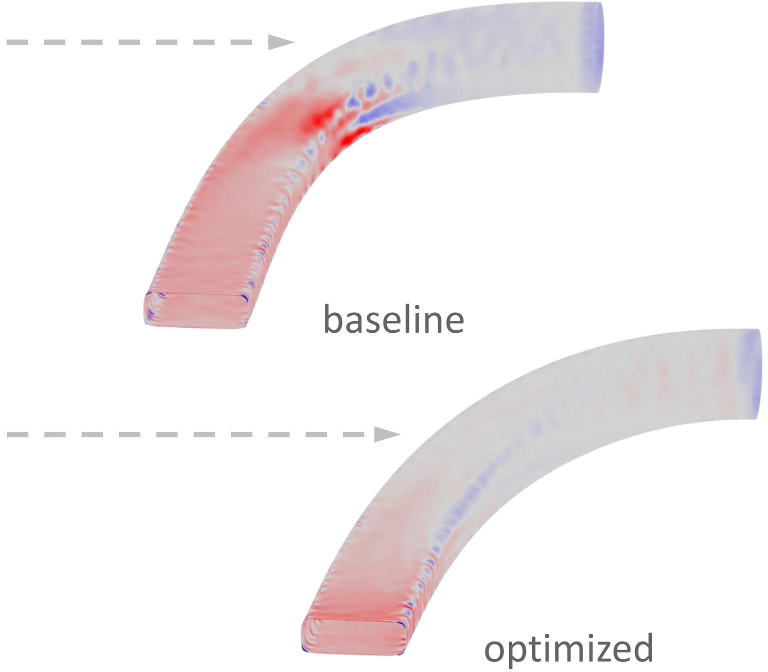
adjoint shape sensitivity → product ← design velocity

Process Automation



Optimization Process



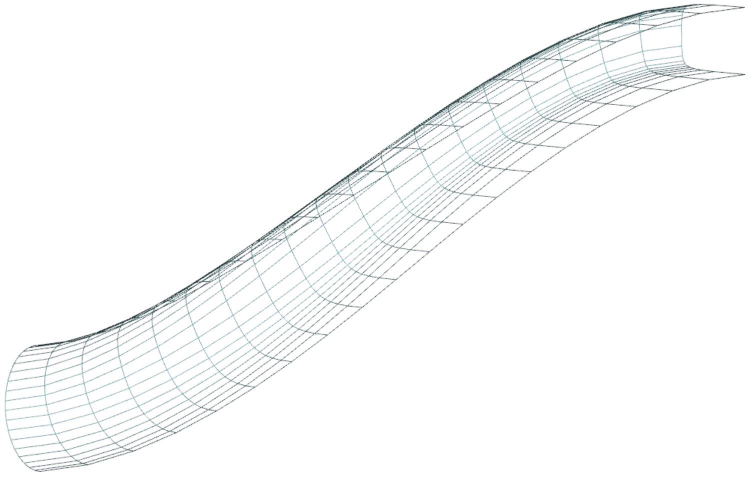


- Using the gradient information from the adjoint CFD leads to a much faster convergence of the optimization

Strategies | Principal Component Analysis

Principal Component Analysis

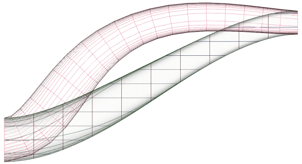
- Design space dimensionality reduction based on principal component analysis (Karhunen-Loève Expansion, KLE)
  - Maps data from an original space of *p* parameters to a new space of *p* parameters (modes or super parameters) which are uncorrelated over the dataset



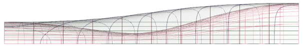
Variation of original parameters

Principal Component Analysis

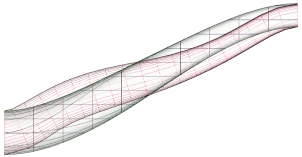
- Design space dimensionality reduction based on principal component analysis (Karhunen-Loève Expansion, KLE)
  - Maps data from an original space of *p* parameters to a new space of *p* parameters (modes or super parameters) which are uncorrelated over the dataset
  - Back transformation to generate geometry variants when optimizing in the reduced design space based on linear interpolation



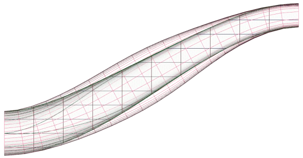
1st mode



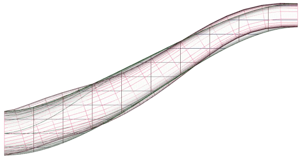
2nd mode



3rd mode



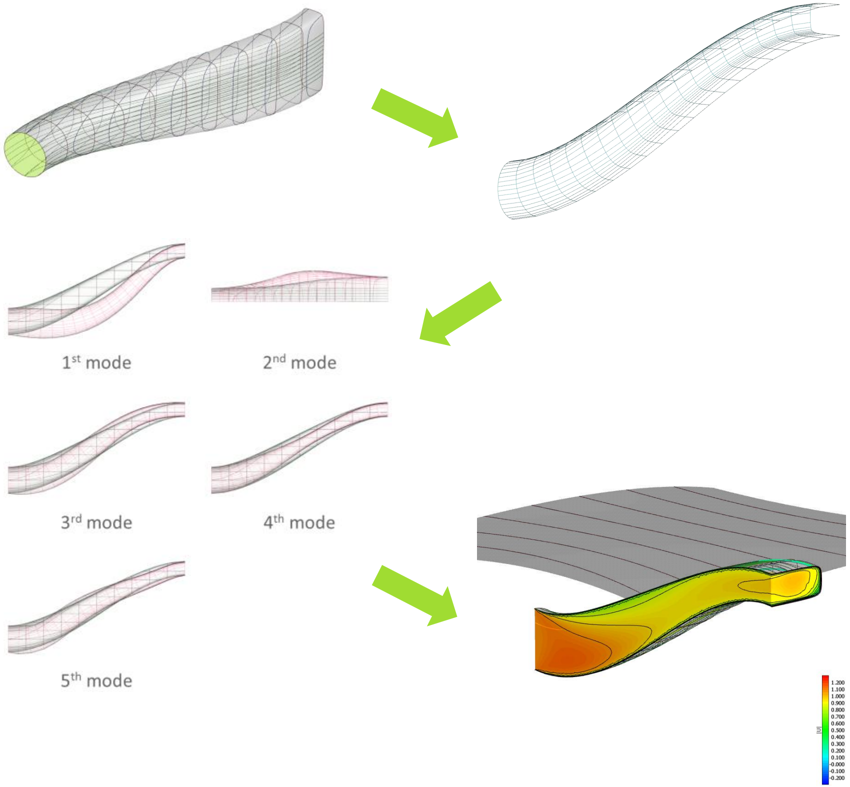
4th mode



5th mode

Process

- Build a parametric model (as usual)
- Produce an ensemble of variants (DoE)
  - Same topology, different geometry
- Determine KLE
- Decide if KLE variables shall be used
- 1 If no, optimize in CAD space (as usual)
  - Generate new variant in CAD space and analyze (and repeat)
- 2 If yes, optimize in KLE space
  - Generate new variant in KLE space
  - Back-transform from KLE space to CAD space and analyze (and repeat)



Variability Reached by Super Parameters

		Modified sphere	Cuboid	HVAC duct	RoPAX ferry	SWATH OSV	Compressor component
Number of free variables of the original CAD model (DoF)		2*	3	14	14	27	30
Number of Sobol variants used for KLE		100	100	1000**	3000	3000	3000
Variability reached with 1st super parameter	1	100.0 %	35.83 %	83.84 %	92.38 %	72 %	54.47 %
Variability reached with 1st and 2st super parameters	2	–	69.28 %	92.05 %	**98.33 %**	86 %	89.59 %
Variability reached with the first three super parameters	3	–	100.0 %	**95.76 %**	99.34 %	94 %	94.89 %
Variability reached with the first four super parameters	4	–	–	97.44 %	99.76 %	**96 %**	**96.90 %**
Variability reached with the first five super parameters	5	–	–	98.51 %	99.93 %	98 %	97.57 %
Variability reached with the first 10 super parameters	10	–	–	99.72 %	99.99 %	99 %	99.45 %
Number of super parameters needed to reach more than 95 % variability		1	3	3	2	4	4
Number of super parameters needed to reach more than 99 % variability		1	3	7	3	7	8
Ratio of number of free variables of the original CAD model and number of KLE variables needed to reach 95 % variability *[square]*		2 *[4]*	1 *[1]*	4.67 *[21.8]*	7.5 *[56.3]*	6.75 *[45.6]*	7.5 *[56.3]*

Variability Reached by Super Parameters

		Modified sphere	Cuboid	HVAC duct	RoPAX ferry	SWATH OSV	Compressor component
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Variability reached with the first 10 super parameters	10	–	–	[illegible]	[illegible]	[illegible]	[illegible]
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Ratio of number of free variables of the original CAD model and number of KLE variables needed to reach 95 % variability *[square]*		2 *[4]*	1 *[1]*	4.67 *[21.8]*	7.5 *[56.3]*	6.75 *[45.6]*	7.5 *[56.3]*

Cuboid

All CAD variables are completely independent ⟹ KLE does not give any benefit

Variability Reached by Super Parameters

		Modified sphere	Cuboid	HVAC duct	RoPAX ferry	SWATH OSV	Compressor component
Number of free variables of the original CAD model (DoF)		2*	3	14	14	27	30
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Variability reached with the first 10 super parameters	10	–	–	[illegible]	[illegible]	[illegible]	[illegible]
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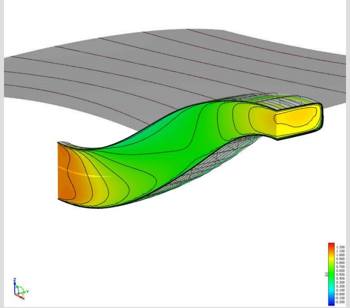
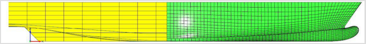
Ratio of number of free variables of the original CAD model and number of KLE variables needed to reach 95 % variability *[square]*		2 *[4]*	1 *[1]*	4.67 *[21.8]*	7.5 *[56.3]*	6.75 *[45.6]*	7.5 *[56.3]*

Modified sphere

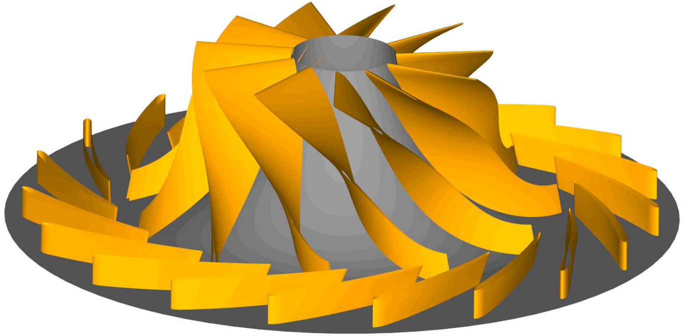
CAD variables are completely redundant ⇒ KLE diagnoses dependencies

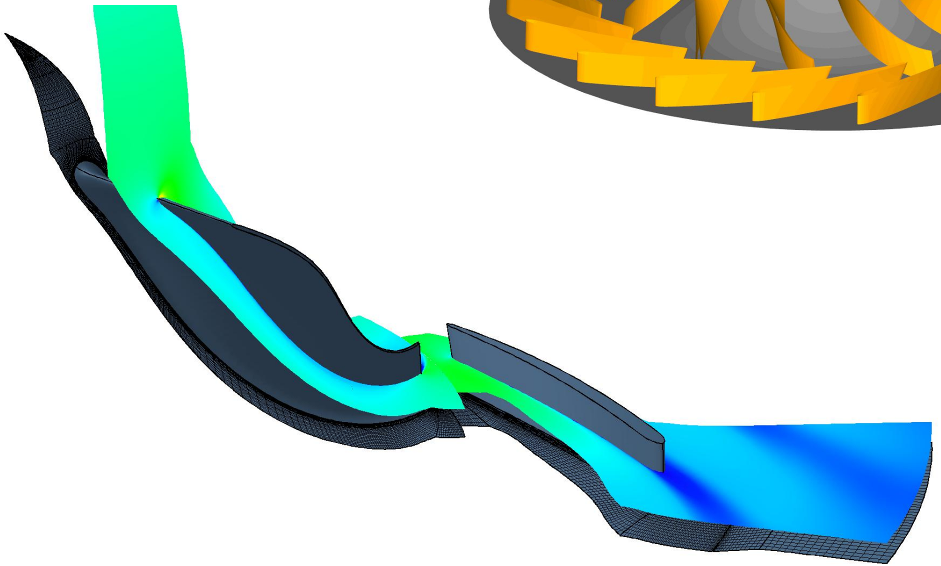
Variability Reached by Super Parameters

	S-Duct	RoPax Vessel
No. of free variables	14	14
Variability with 3 KLE parameters	95%	98%
		

Compressor Test Case

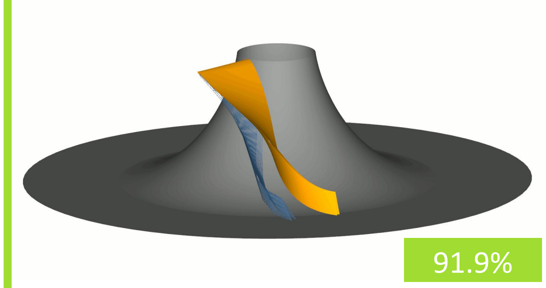
- Geometry:
  - Simplified geometry:
    - D_Out: 195mm
    - No splitter blade
    - NOB impeller: 11
    - NOB diffuser: 19
  - 16 free variables for the description of the main blade
- CFD setup:
  - RPM: 37,000
  - Mass flow: 1.35kg/s



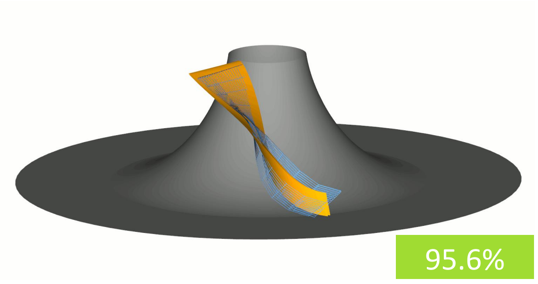


Parameter Reduction

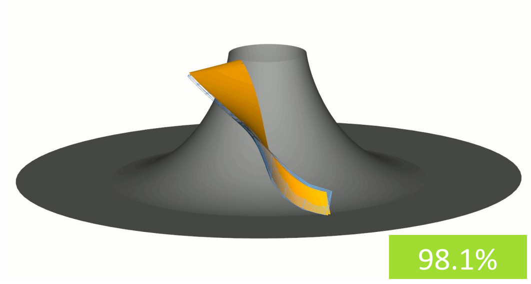
KLE Parameter 0



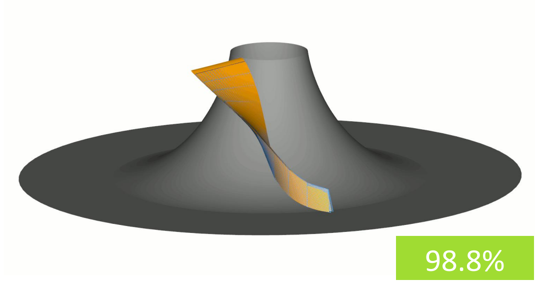
KLE Parameter 1



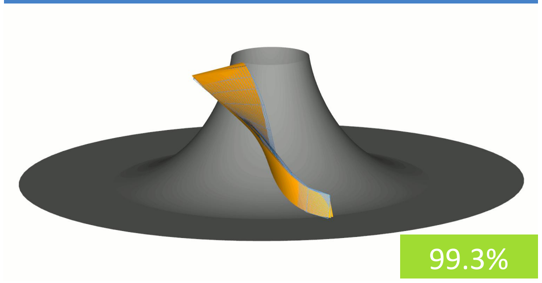
KLE Parameter 2



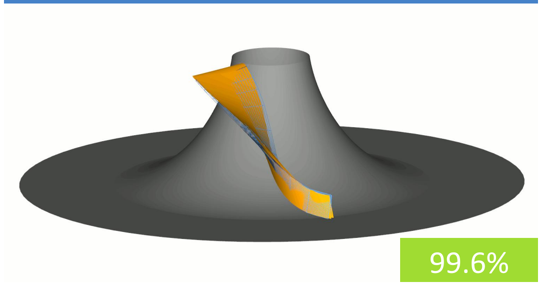
KLE Parameter 3



KLE Parameter 4



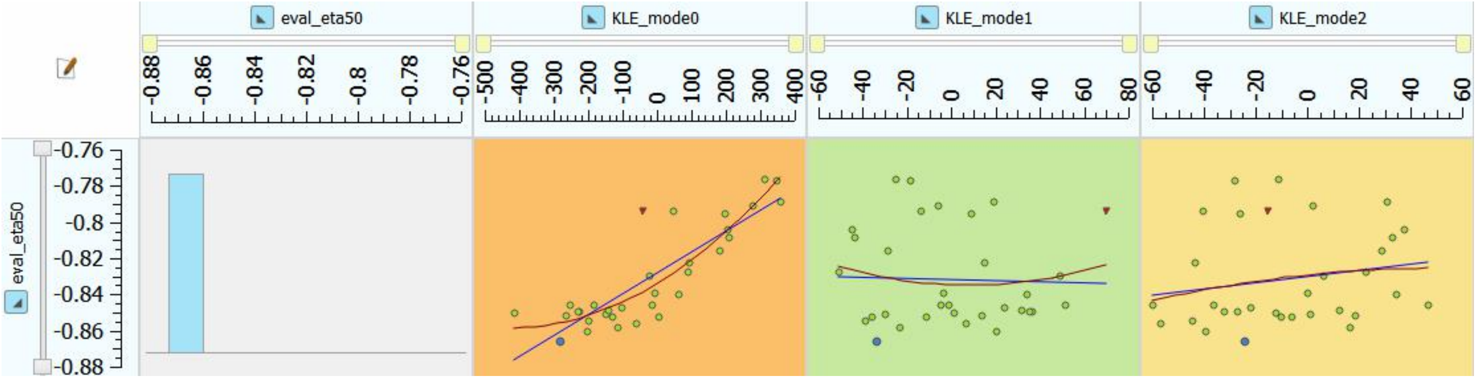
KLE Parameter 4



1st Step | DoE

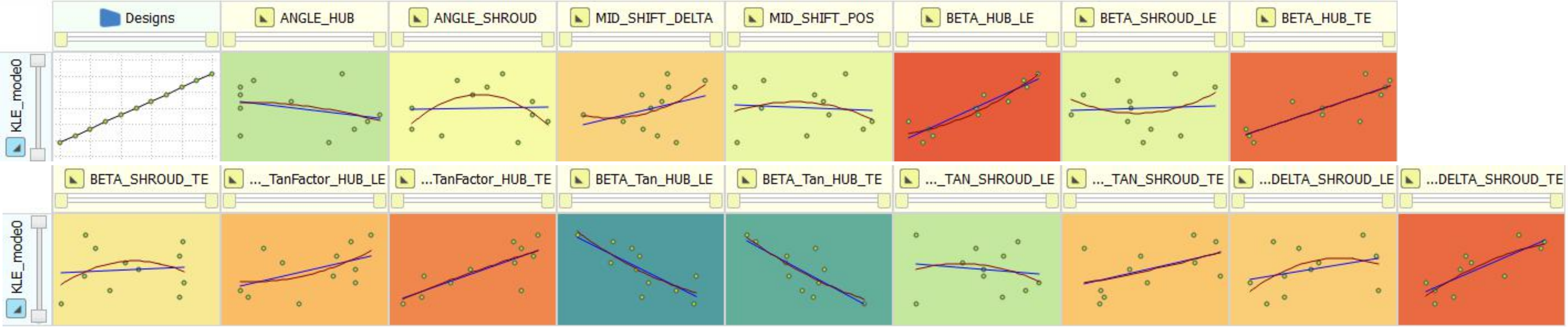
- Preliminary DoE (Sobol)
  - Constraints:
    - Pressure differential = 2.1bar
    - Convergence
  - Objective: efficiency
  - 65 variants

- Results
  - 78% valid designs
  - ~ 3% improvement in efficiency (83.93% → 86.5%)
  - KLE parameter 0 seems to have the biggest influence on the objective function

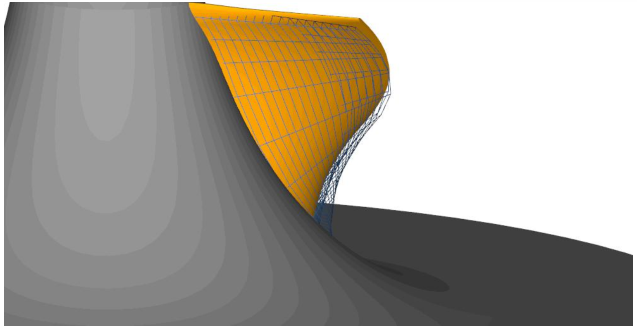


Correlations of Design Parameters

- How are the dependencies of the original design variables from KLE parameter 0?
- Variation of KLE parameter 0:

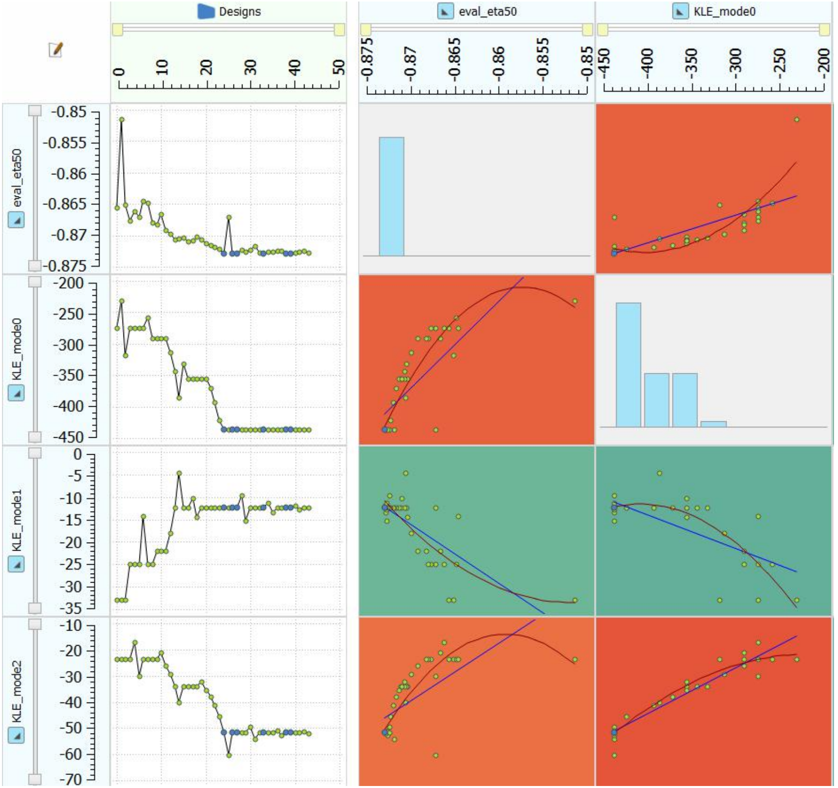


- There are parameters with strong correlations, like *BETA_HUB_LE* and *BETA_HUB_TE*
- Some parameters are more randomly varied



2nd Step | Optimization

- Optimization
  - Starting from best design from preliminary DoE
  - ~ 1% additional improvement (86.5% → 87.25%)



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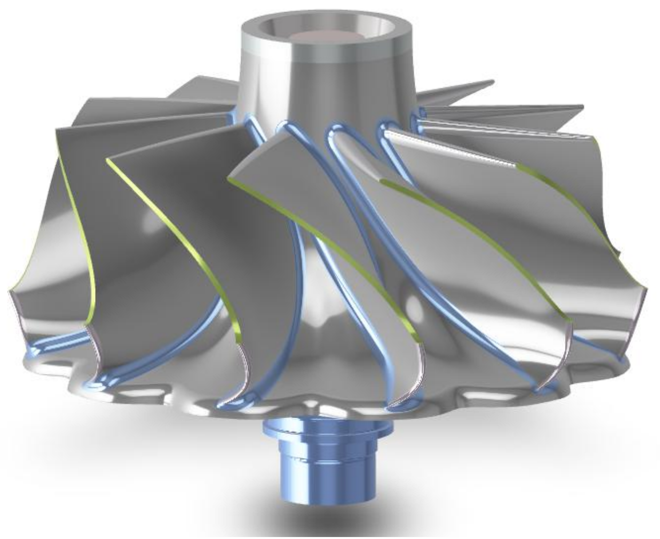
Robust Variable Geometry for Shape Optimization



By using CAESES®, we could massively bring down our turbine design cycle from several months to only a few weeks.

Nicolas Lachenmaier,
Engineer for Fluid Dynamics and Thermal Analysis

Mattia Brenner

brenner@friendship-systems.com

www.CAESES.com