Design-space reduction with super parameters for faster optimization

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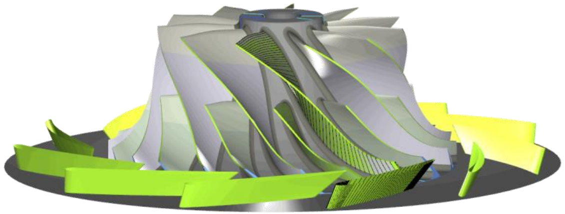
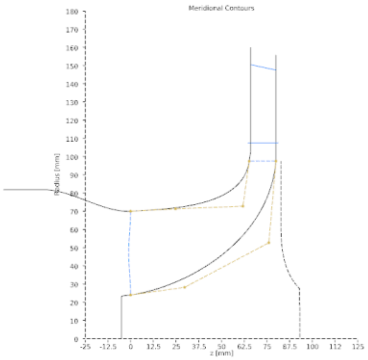
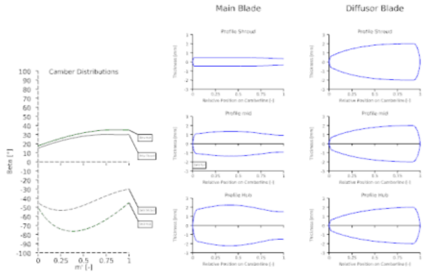
Advanced Turbomachinery Design (GAMMA)

Contents

- Motivation for parameter reduction
- Karhunen-Loève Expansion (KLE) for design space reduction
  - Idea
  - Simple examples
  - Process
- Massive parameter reduction in compressor optimization
- Conclusions

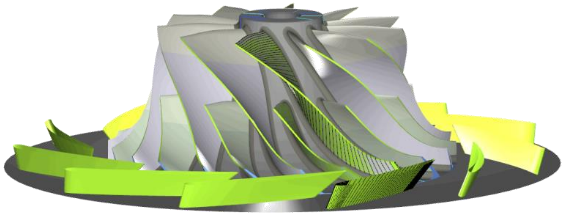


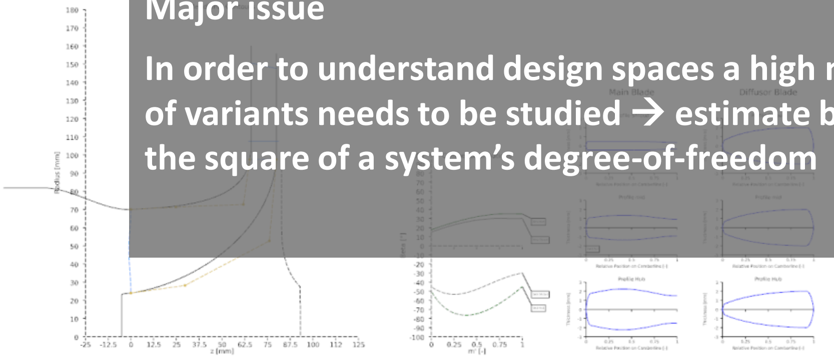




Motivation for massive parameter reduction

- Problem:
  - Optimization of parametric models with many free design variables requires many simulations
  - Number of designs required ~ (number of free variables)^2
- Aim:
  - Reduction of the number of free variables
    - → Reduce the design space further
    - → Substantial speed-up in simulation-driven design (SDD)
- Application:
  - Design task with many free variables
  - Design tasks with long (resource-intensive) simulations

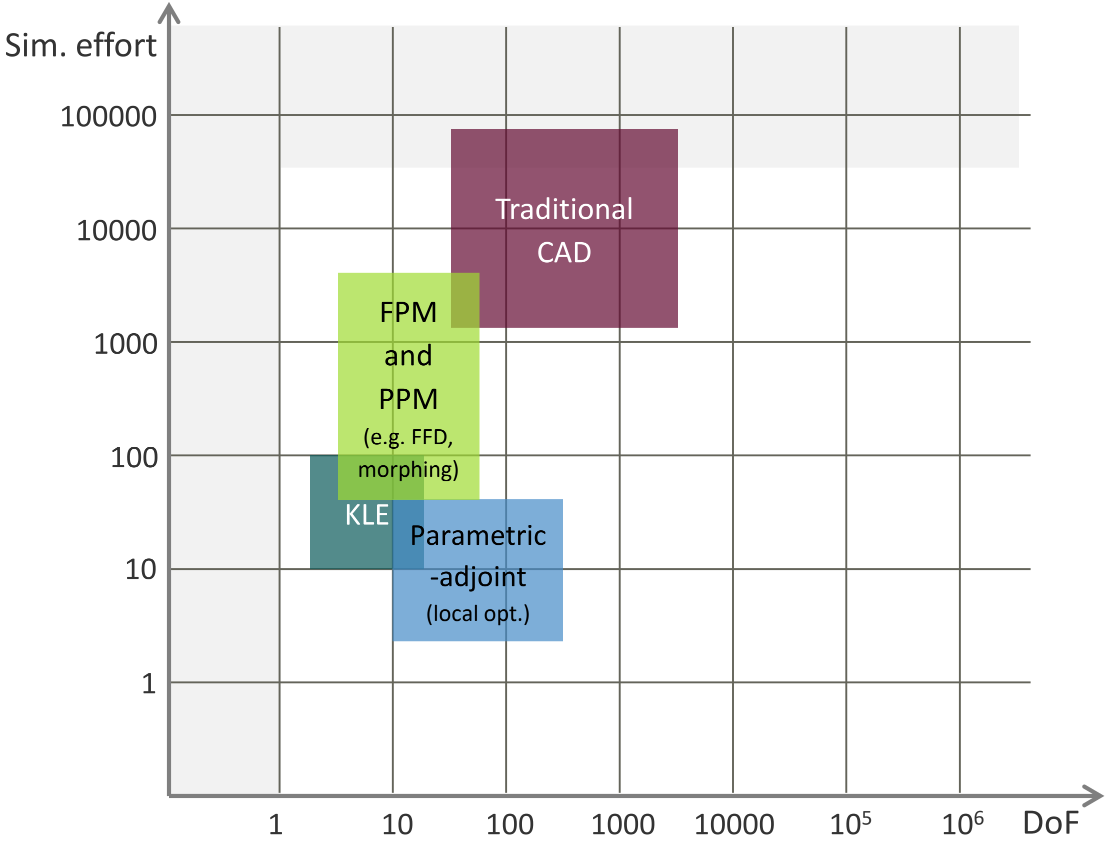




Major issue

In order to understand design spaces a high number of variants needs to be studied → estimate being the square of a system's degree-of-freedom

Motivation


Sim. effort
100000
10000
1000
100
10
1
1
10
100
1000
10000
10^5
10^6
DoF
Traditional
CAD
FPM
and
PPM
(e.g. FFD,
morphing)
KLE
Parametric
-adjoint
(local opt.)

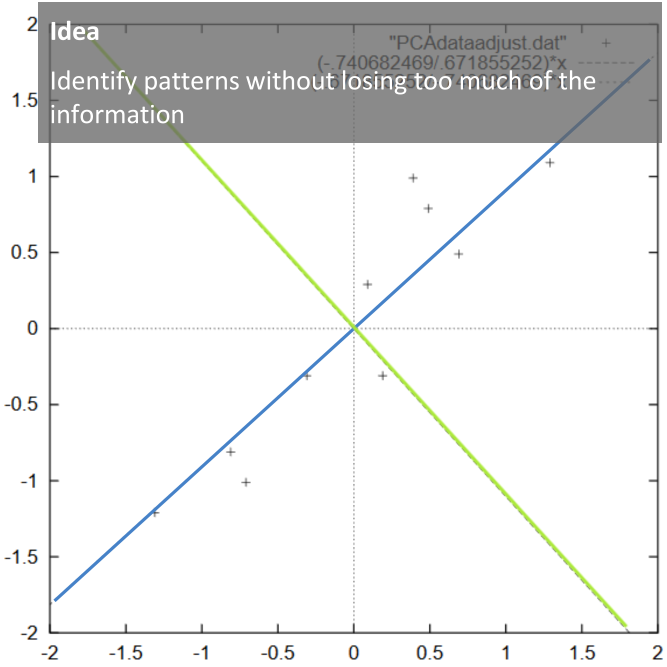
Design-space reduction by Karhunen-Loève Expansion (KLE)

Karhunen-Loève Expansion (KLE)

- Principle components analysis
  - A large number of statistical variables are being replaced by an approximation with a reduced number of linear combinations of orthogonal basis functions
  - Modes relate to “super parameters”
  - Decorrelation of data (as far as possible)
- Benefits
  - Check quality of a parametric model
  - If needed and possible reduce number of free variables (further)
- Aim
  - Finding an optimal basis of orthonormal functions
  - Optimality condition refers to the geometric variance retained by the new basis functions

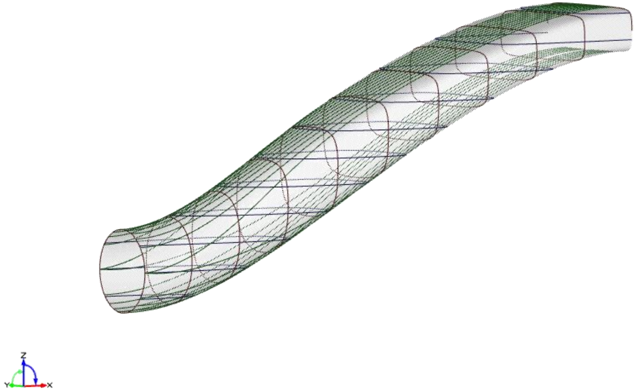
Idea

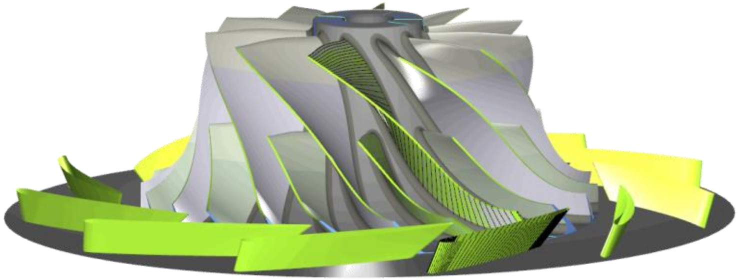
Identify patterns without losing too much of the information

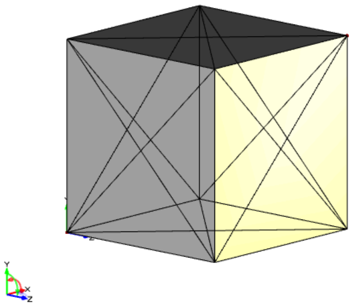


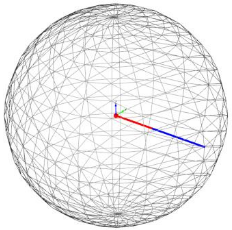
Source: Lindsay I. Smith (2002) A Tutorial on Principal Components Analysis

Examples



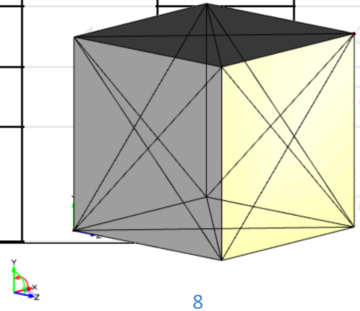






Variability reached by super parameters

		Modified sphere	Cuboid	HVAC duct
Number of free variables of the original CAD model (DoF)		2*	3	14
Number of Sobol variants used for KLE		100	100	1000**
Variability reached with 1st super parameter	1	100.0 %	35.83 %	83.84 %
Variability reached with 1st and 2st super parameters	2	–	69.28 %	92.06 %
Variability reached with the first three super parameters	3	–	100.0 %	[illegible]
Variability reached with the first four super parameters	4	–	–	97.44 %
Variability reached with the first five super parameters	5	–	–	98.51 %
Variability reached with the first 10 super parameters	10	–	–	99.72 %
Number of super parameters needed to reach more than 95 % variability		[illegible]	[illegible]	3
Number of super parameters needed to reach more than 99 % variability		[illegible]	[illegible]	7
Ratio of number of free variables of the original CAD model and number of KLE variables needed to reach 95 % variability *[square]*		[illegible]	[illegible]	67 [illegible]



Cuboid

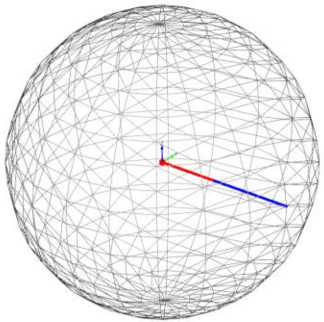
All CAD variables are completely independent ⇒ KLE does not give any benefit

Variability reached by super parameters

		Modified sphere	Cuboid	HVAC duct
Number of free variables of the original CAD model (DoF)		2*	3	14
Number of Sobol variants used for KLE		100	100	1000**
Variability reached with 1^{st} super parameter	1	100.0 %	35.83 %	83.84 %
Variability reached with 1^{st} and 2^{st} super parameters	2	–	69.28 %	92.05 %
Variability reached with the first three super parameters	3	–	100.0 %	[illegible]
Variability reached with the first four super parameters	4	–	–	[illegible]
Variability reached with the first five super parameters	5	–	–	[illegible]
Variability reached with the first 10 super parameters	10	–	–	[illegible]
Number of super parameters needed to reach more than 95 % variability		1	3	
Number of super parameters needed to reach more than 99 % variability		1	3	
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]*	

Modified sphere with $x_1 + x_2 = r$

CAD variables are completely redundant $\Rightarrow$
KLE diagnoses dependencies



Variability reached by super parameters

		Modified sphere	Cuboid	HVAC duct
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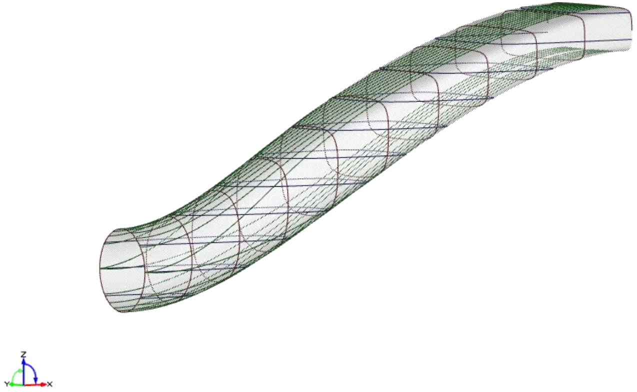
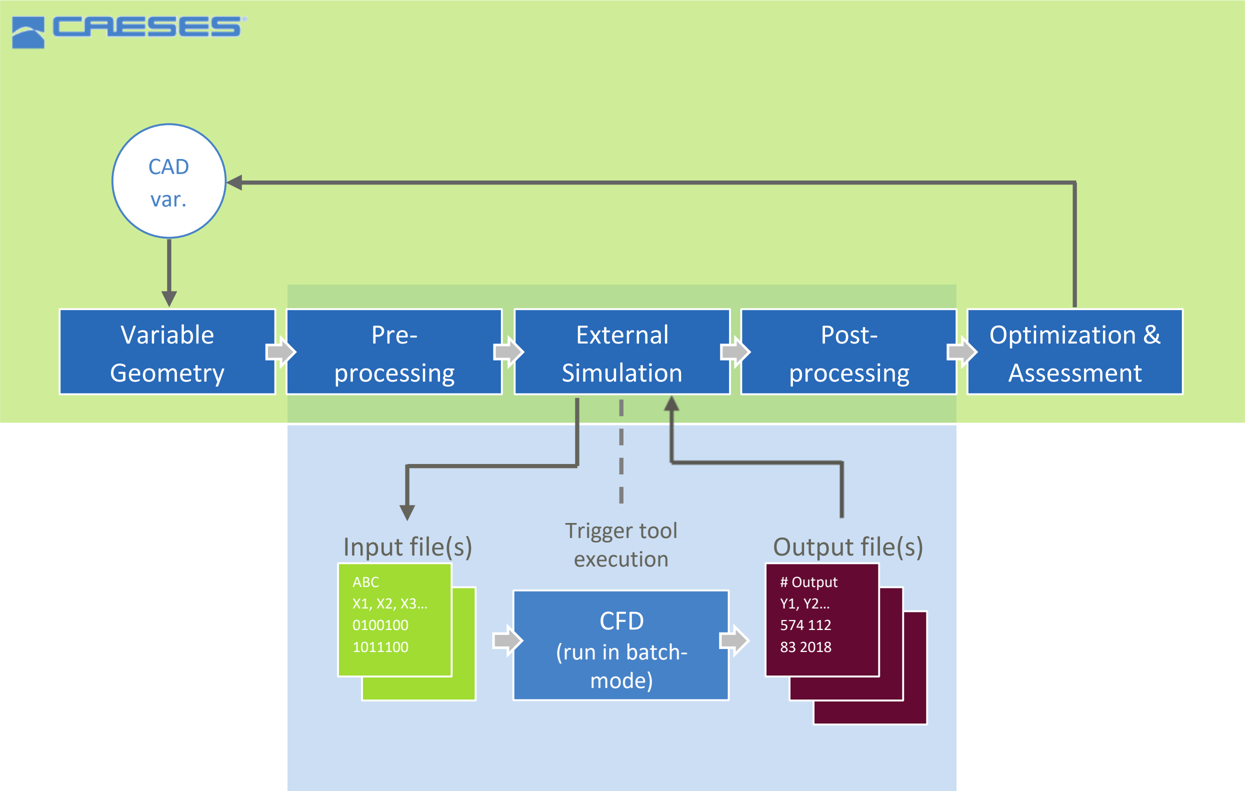
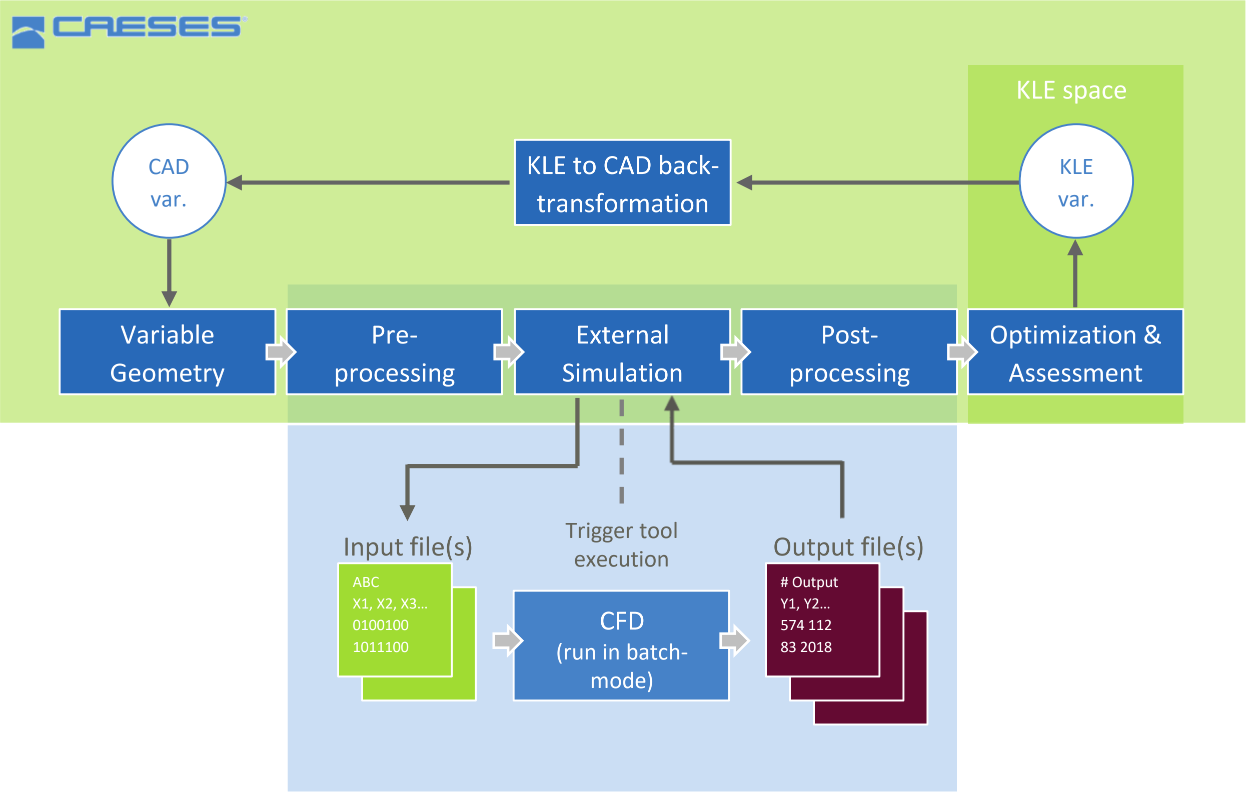
Number of Sobol variants used for KLE		100	100	1000**
Variability reached with 1^{st} super parameter	1	100.0 %	35.83 %	83.84 %
Variability reached with 1^{st} and 2^{st} super parameters	2	–	69.28 %	92.05 %
Variability reached with the first three super parameters	3	–	100.0 %	**95.76 %**
Variability reached with the first four super parameters	4	–	–	97.44 %
Variability reached with the first five super parameters	5	–	–	98.51 %
Variability reached with the first 10 super parameters	10	–	–	99.72 %
Number of super parameters needed to reach more than 95 % variability		1	3	3
Number of super parameters needed to reach more than 99 % variability		1	3	7
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]*



Standard process



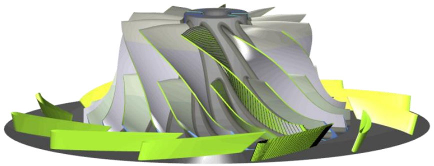
Process with KLE



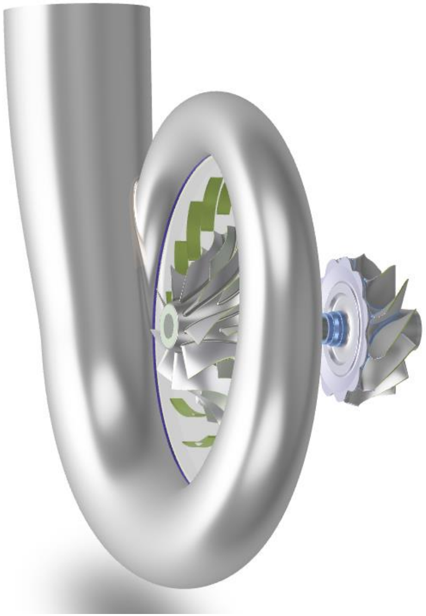
KLE for compressor optimization

Parametric Model of a Turbocharger

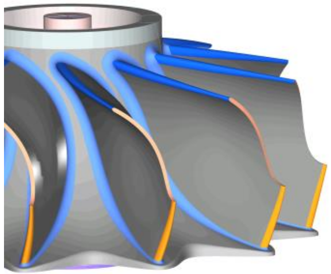
Impeller + Diffuser
Compressor



Volute Compressor



Radial turbine

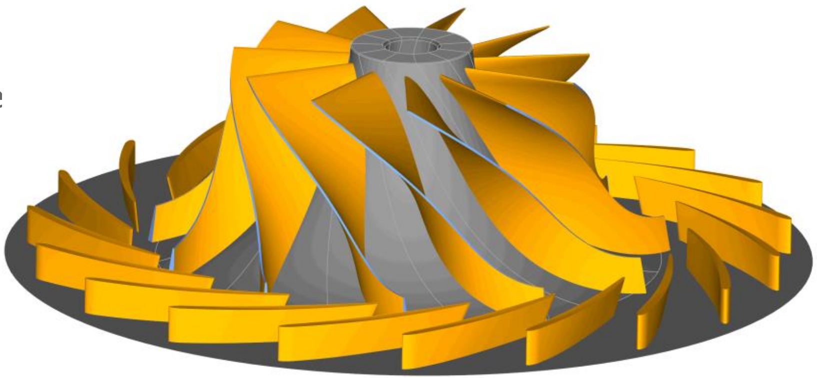


Axial turbine

Compressor Component – Impeller and Diffuser

- **Geometry created in CAESES:**
  - D_Out: 195mm
  - No splitter blades
  - 11 impeller blades
  - 19 diffuser blades
- 16 design variables for the main blade
- 10 design variables for the diffuser vane

- **Target:**
  - Increase efficiency
- **Constraint:**
  - Pressure ratio > 2.1
  - Convergence

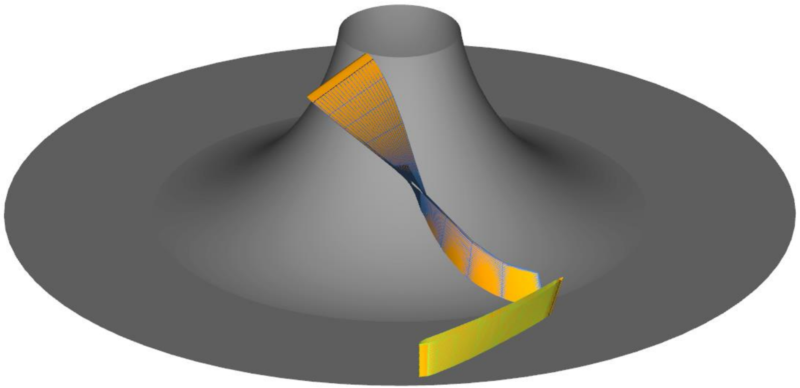


Design Variables

	Design Variable	Lower	Value	Upper
1	ANGLE_HUB	-10	0	10
2	ANGLE_SHROUD	-10	0	10
3	MID_SHIFT_DELTA	-2	0	2
4	MID_SHIFT_POS	0.3	0.5	0.8
5	BETA_HUB_LE	40	45	50
6	BETA_HUB_TE	45	50	55
7	BETA_SHROUD_LE	25	30	35
8	BETA_SHROUD_TE	40	41.7	50
9	BETA_TanFactor_HUB_LE	0.4	0.5	0.6
10	BETA_TanFactor_HUB_TE	0.4	0.5	0.6
11	BETA_Tan_HUB_LE	-45	-45	-35
12	BETA_Tan_HUB_TE	-65	-60	-55
13	BETA_TAN_SHROUD_LE	-15	-10	-5
14	BETA_TAN_SHROUD_TE	-40	-35	-30
15	THETA_DELTA_SHROUD_LE	-10	-2	0
16	THETA_DELTA_SHROUD_TE	-10	0	10
17	Diff_BETA_HUB_LE	17	19	25
18	Diff_BETA_HUB_TE	28	37	44
19	Diff_BETA_SHROUD_LE_Delta	-4.5	-2	3.5
20	Diff_BETA_SHROUD_TE_Delta	-5	-1	8
21	Diff_BETA_Tan_HUB_LE	-30	-20	-10
22	Diff_BETA_Tan_HUB_TE	-7.5	0	10
23	Diff_BETA_Tan_SHROUD_LE	-30	-20	-10
24	Diff_BETA_Tan_SHROUD_TE	-10	10	20
25	Diff_THETA_DELTA_SHROUD_LE	-15	-3	8.5
26	Diff_THETA_DELTA_SHROUD_TE	-5	0	5

Building a KLE model

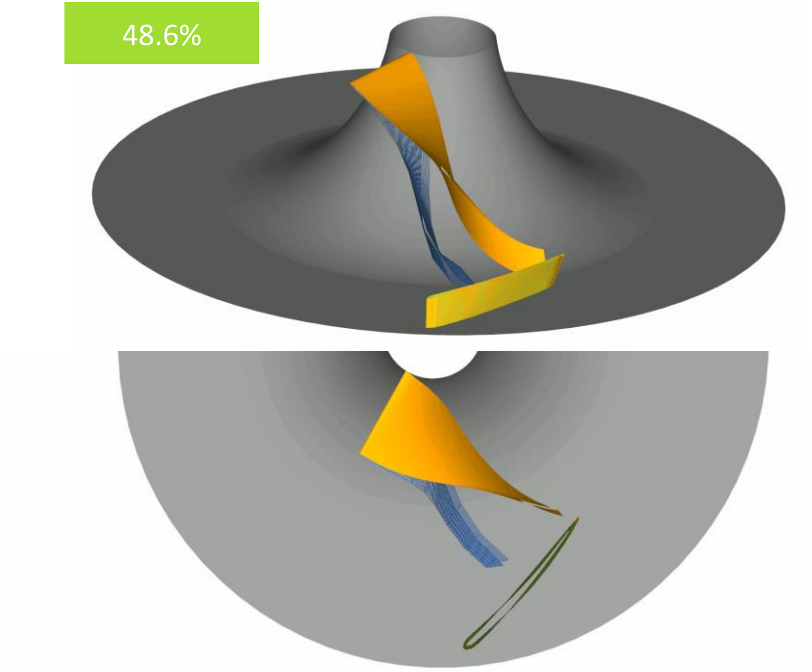
1) Build a parametric model (as usual)
2) Produce an ensemble of variants (DoE)
   - ➢ Same topology, different geometry
3) Determine KLE → Generate the KLE model
4) Decide how many KLE variables shall be used
5) Optimize in KLE space
   - Generate new variant in KLE space
   - Back-transform from KLE space to CAD space and analyze (and repeat)



First and second KLE modes

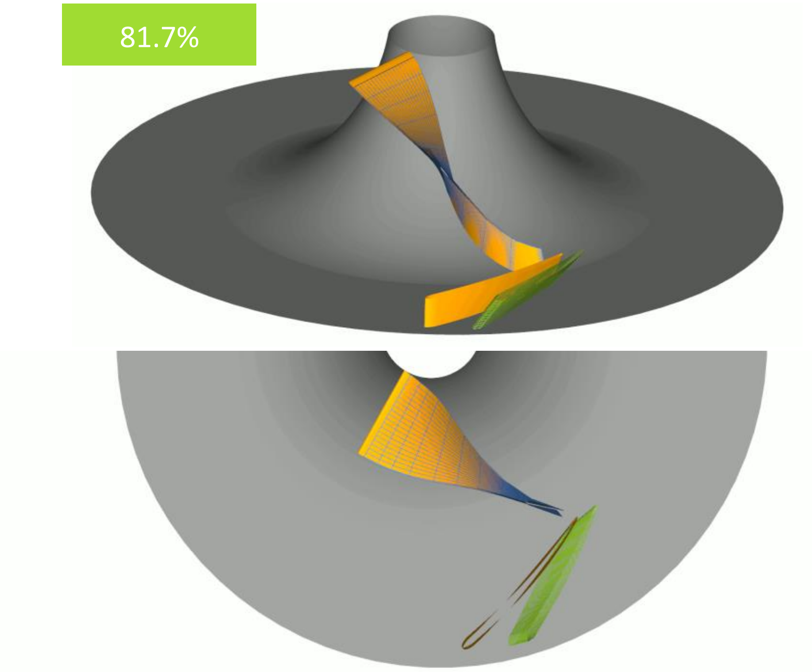
KLE mode 1 – main blade

48.6%



KLE mode 2 – diffuser

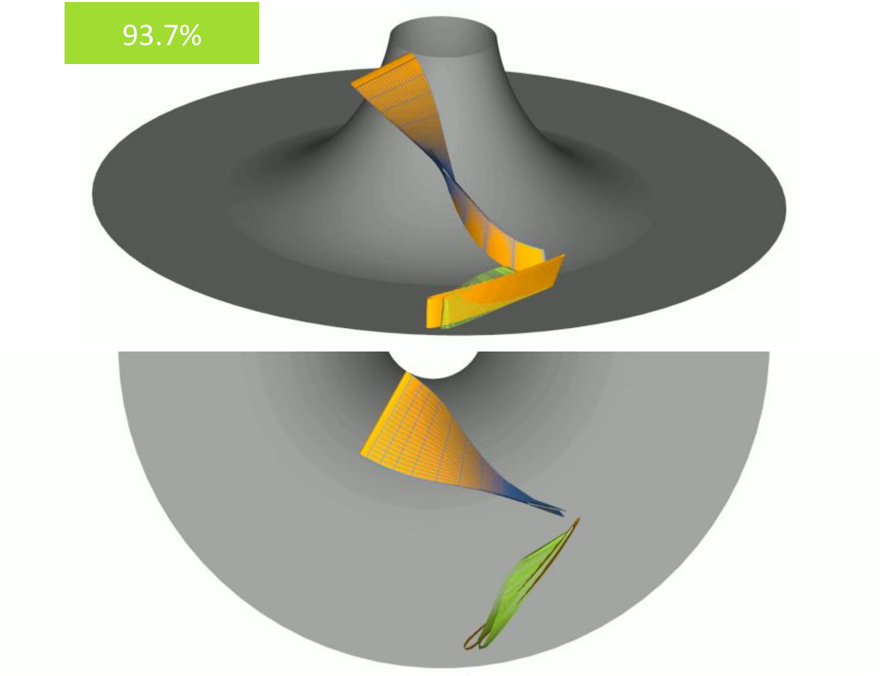
81.7%



Third and fourth KLE modes

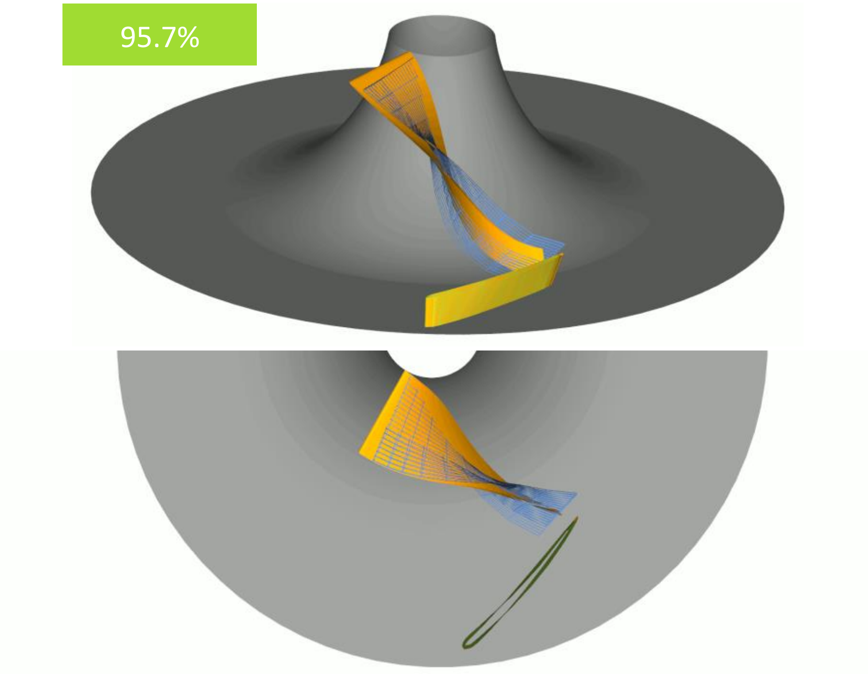
KLE mode 3 – diffuser

93.7%



KLE mode 4 – main blade

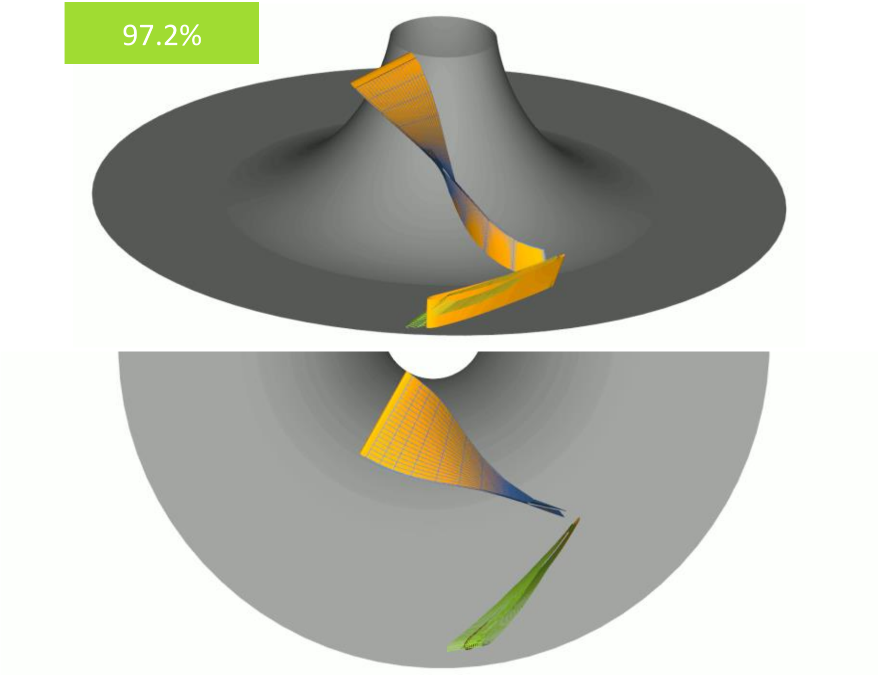
95.7%



Fifth and sixth KLE modes

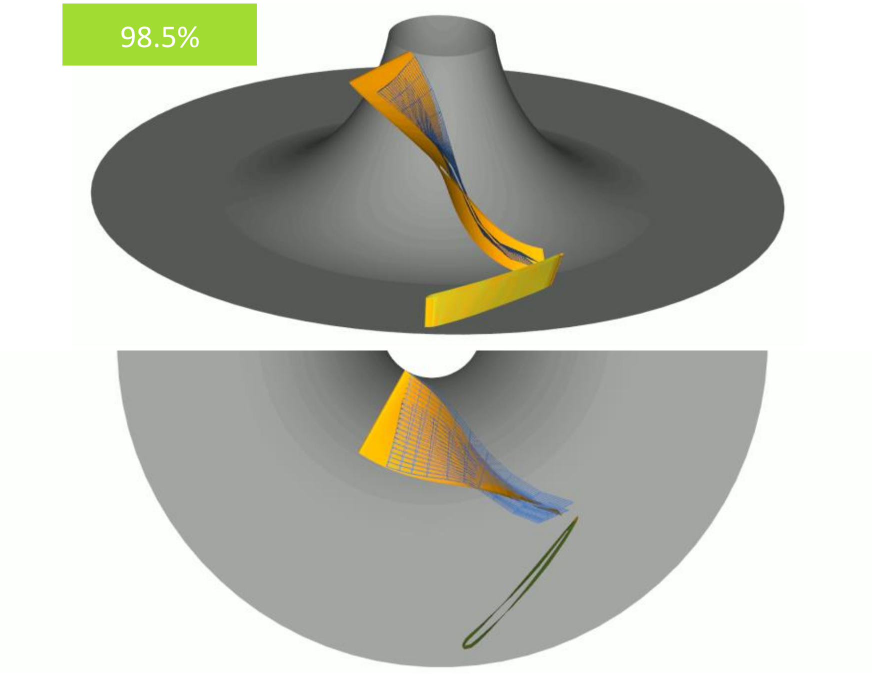
KLE mode 5 – diffuser

97.2%



KLE mode 6 – main blade

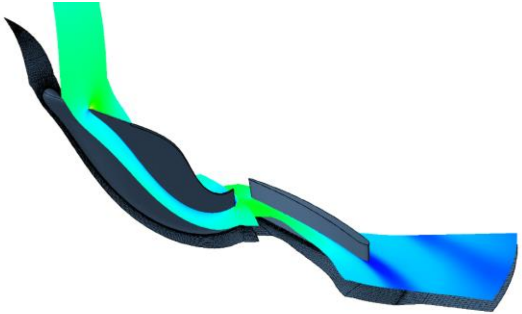
98.5%

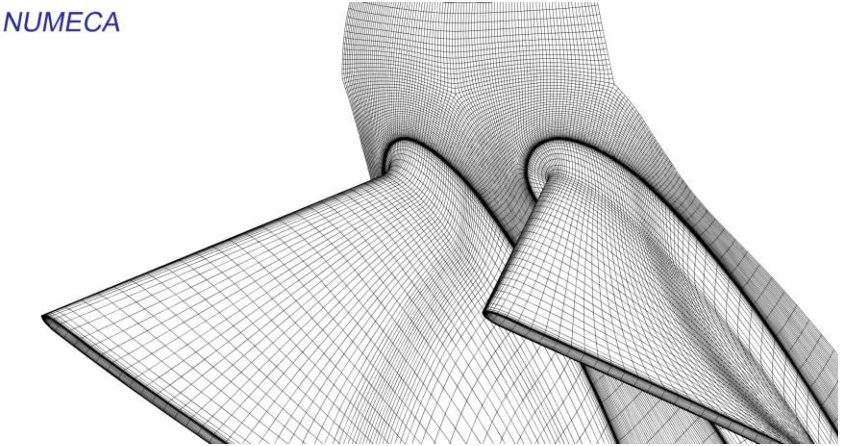


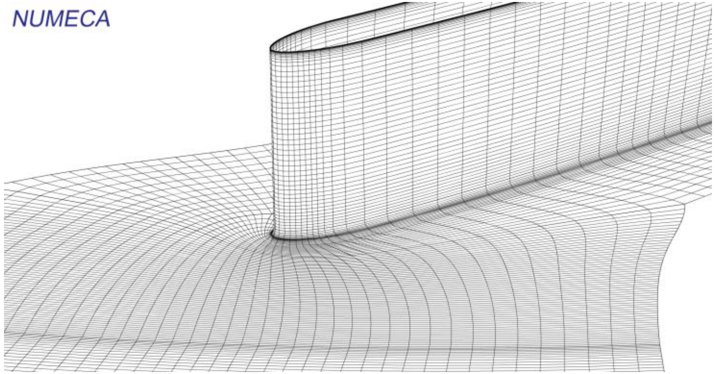
Compressor Component – CFD setup

- NUMECA Software:
  - AutoGrid5™ for hexahedral grid generation
  - FINE™/Turbo for CFD computation

- Setup:
  - Revolutions per min: 37,000
  - Mass flow rate: 1.35kg/s

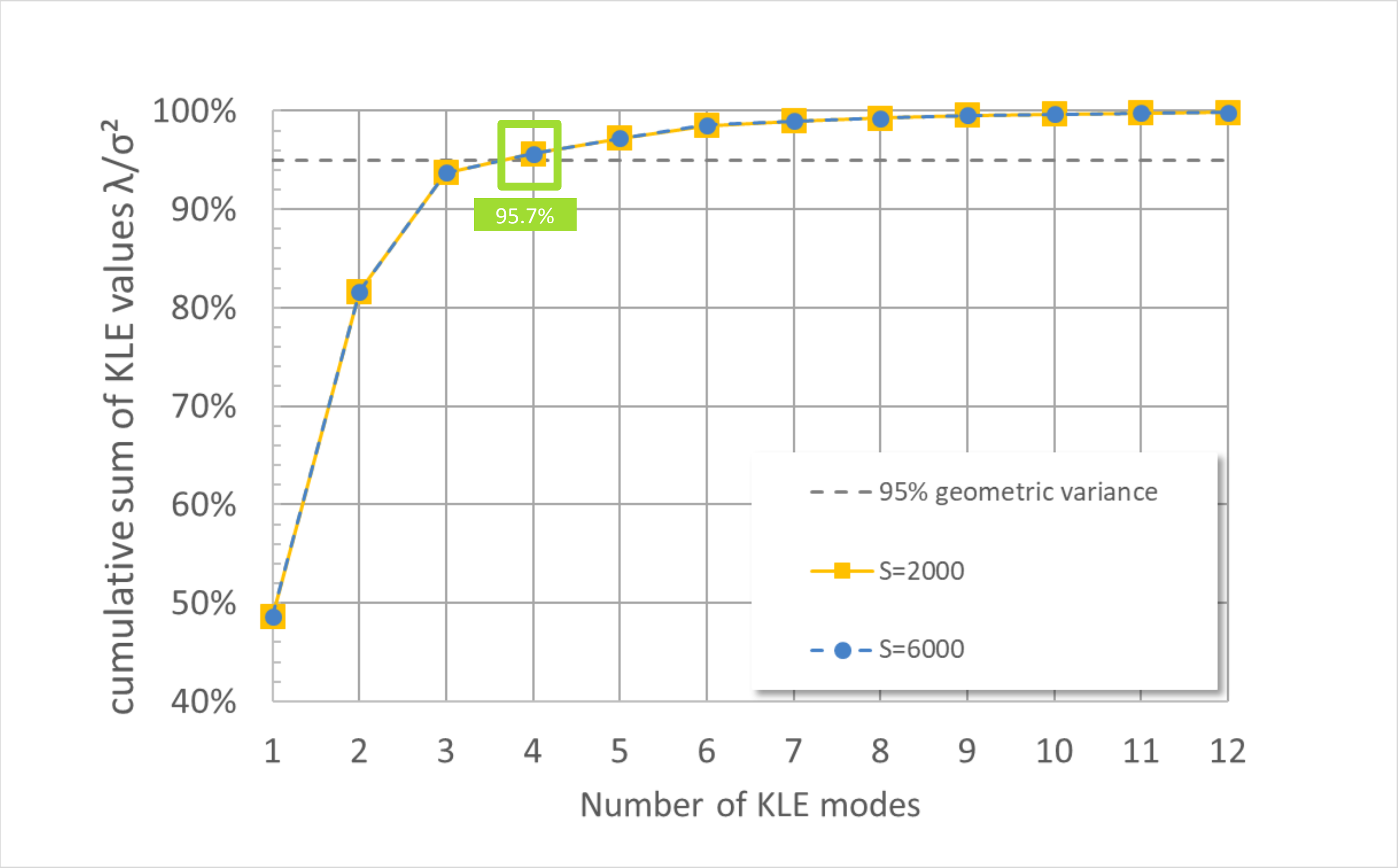




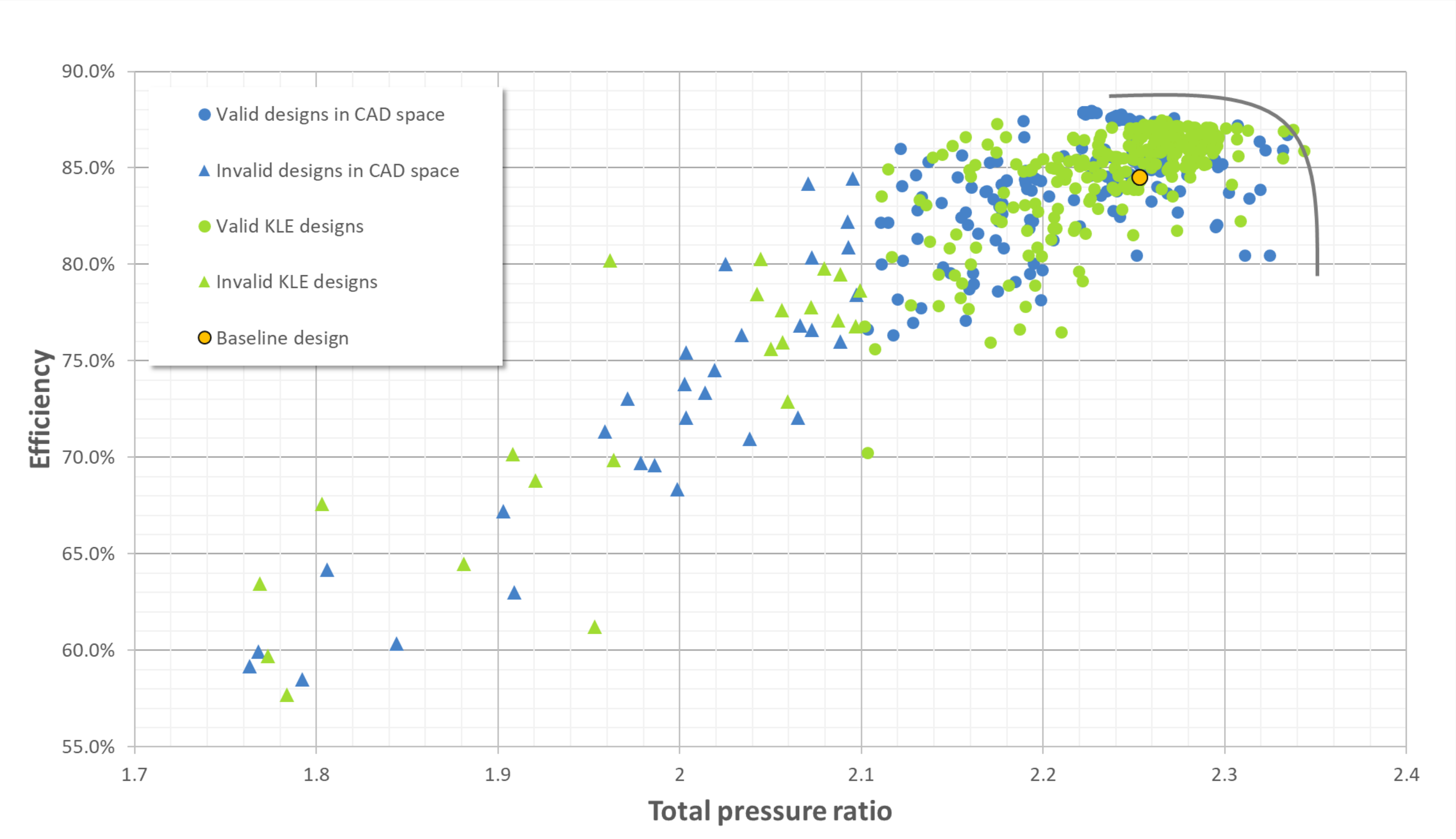


Optimization in KLE space

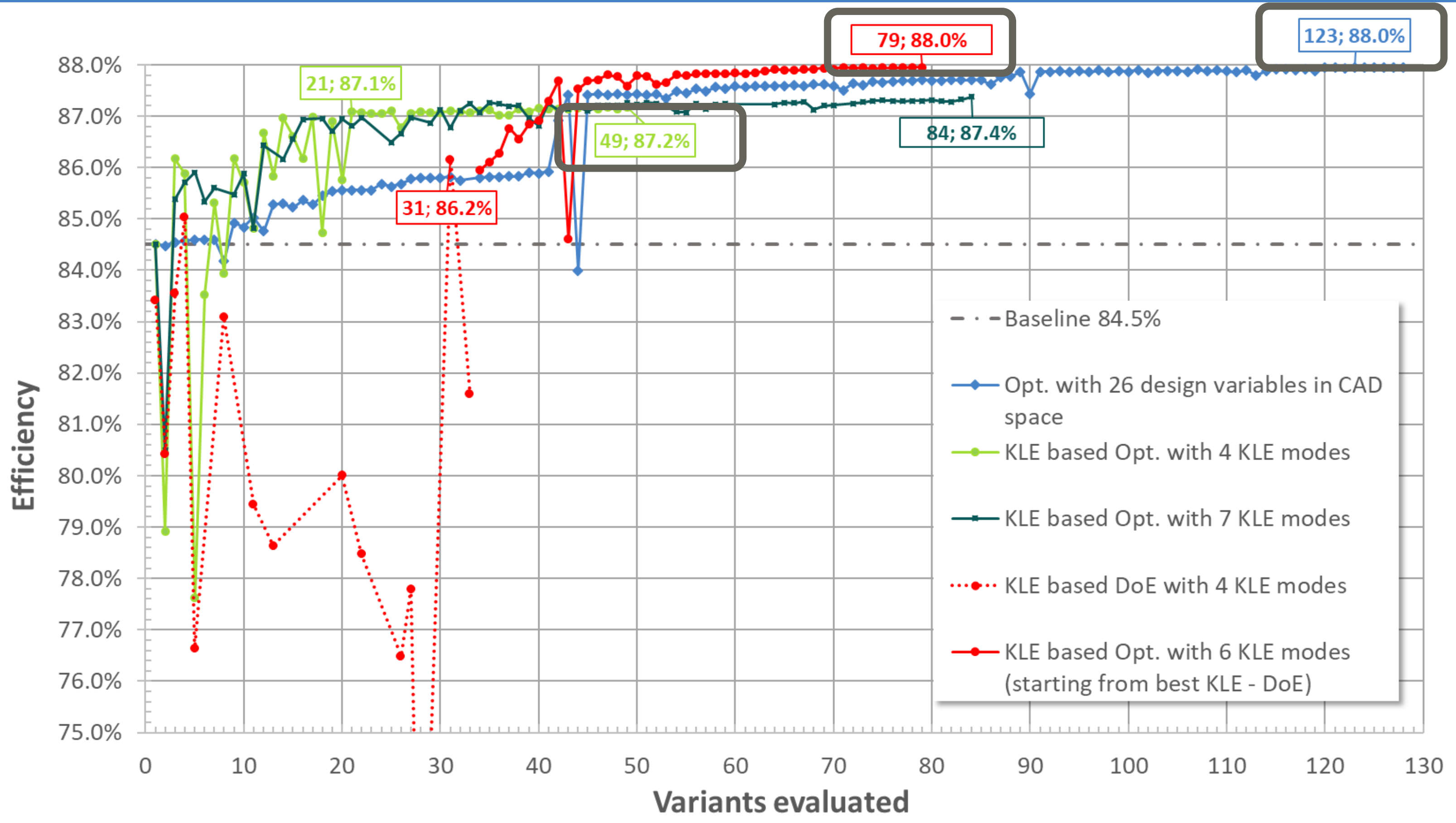
Variability with each KLE mode



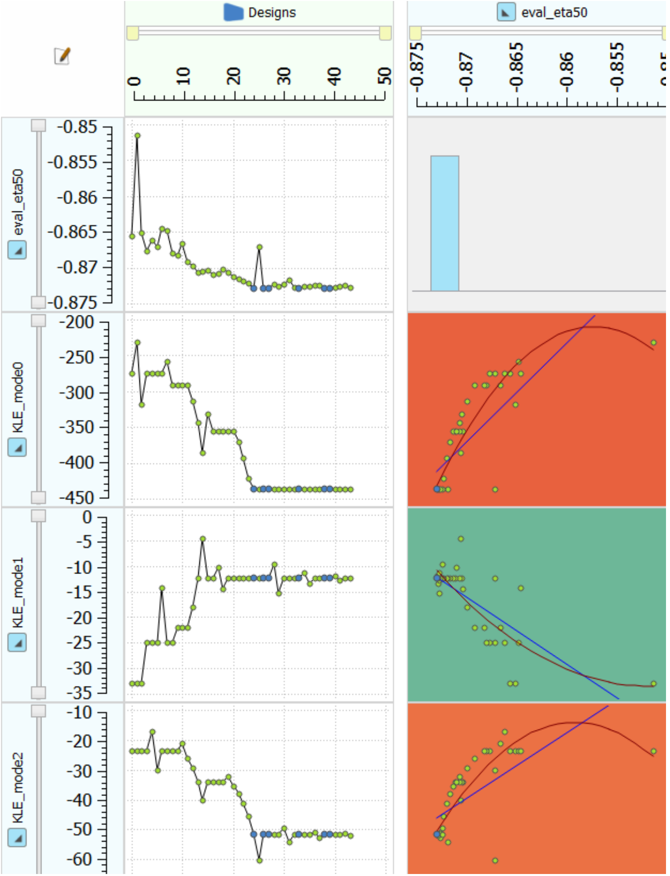
Results for total pressure ratio and efficiency



Optimization history for the compressor



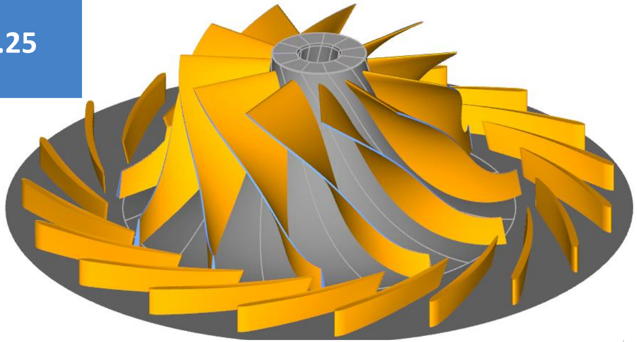
Optimization in KLE space

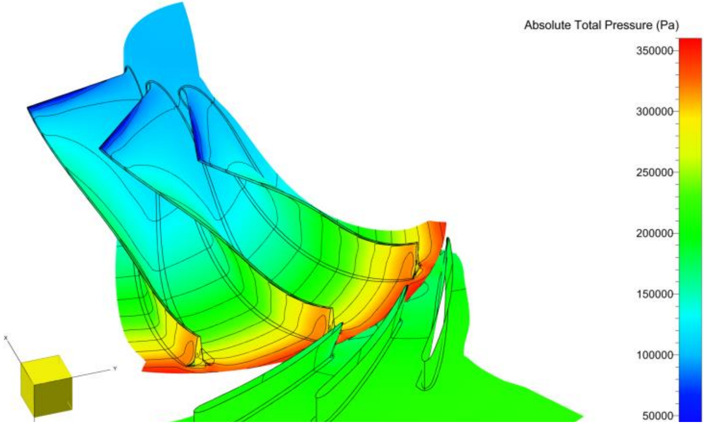


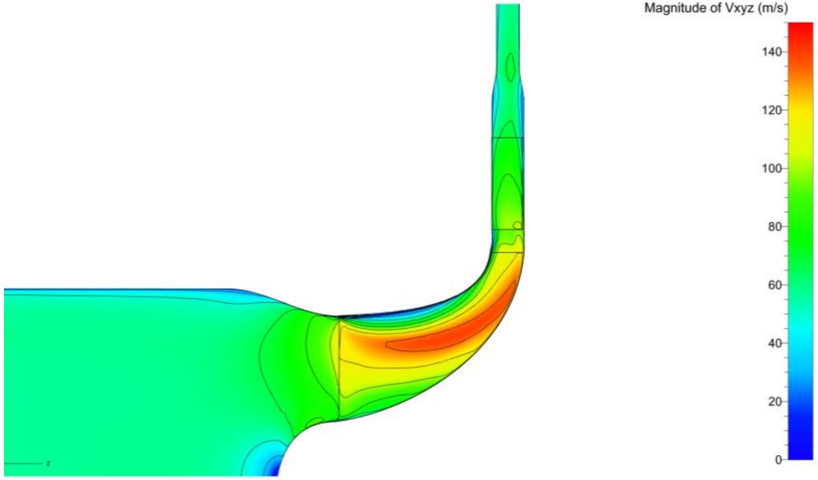
- Optimization in **CAD space** with **26 design variables** for comparison
  - Starting from the baseline design
  - **128 variants** evaluated with **3.5%** improvement
- Optimization in **KLE space** with **4 KLE modes**
  - Starting from the baseline design
  - **49 variants** evaluated with **2.7%** improvement
- Optimization in **KLE space** with **6 KLE modes**
  - Starting from the best DoE result (4 KLE modes)
  - **79 variants** evaluated (33 DoE + 46 Opt. designs)
  - 1.7% + 1.8% = **3.5%** improvement

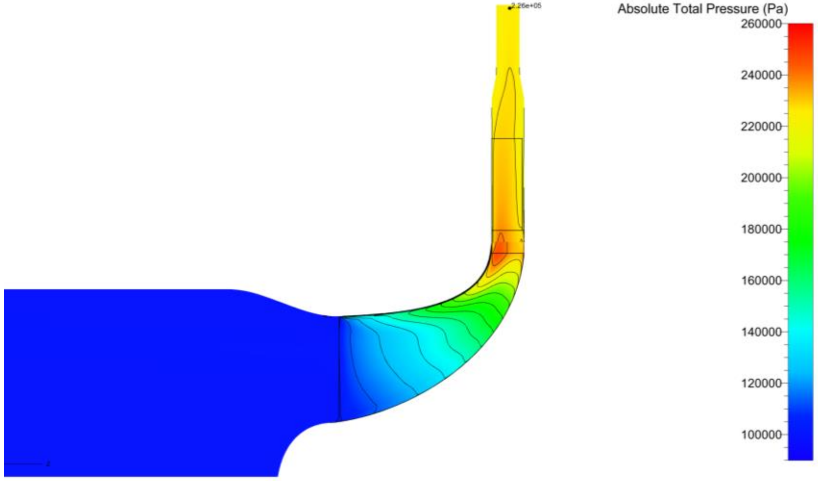
Baseline

Efficiency	84.5 %
Pressure Ratio	2.25



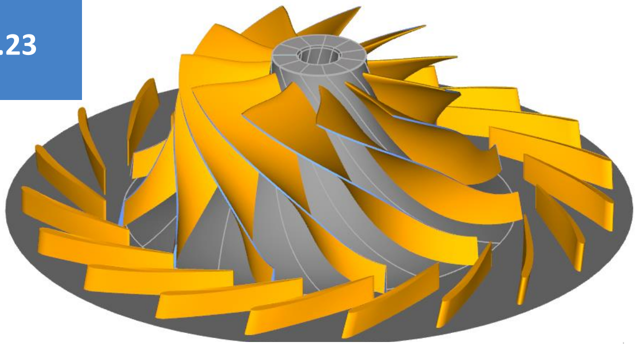


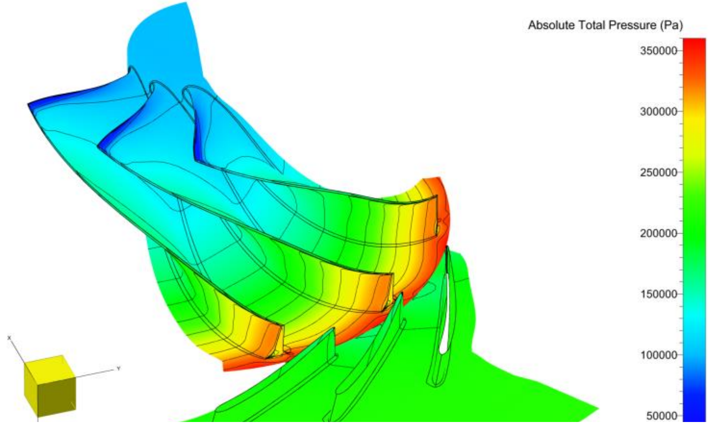


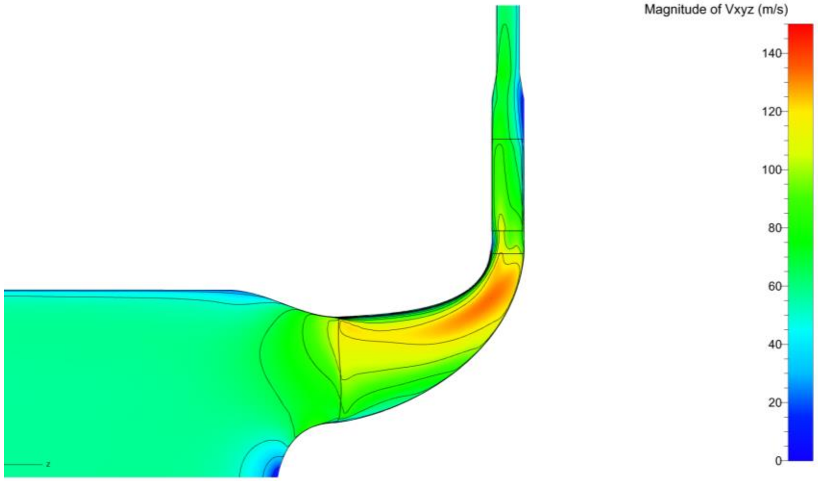


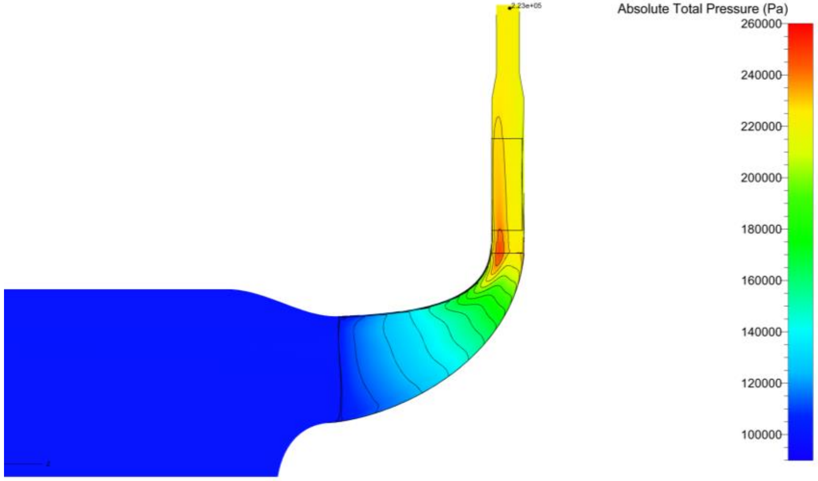
Des 123 – Best Opt. With 26 Design Variables

Efficiency	88.0 %
Pressure Ratio	2.23



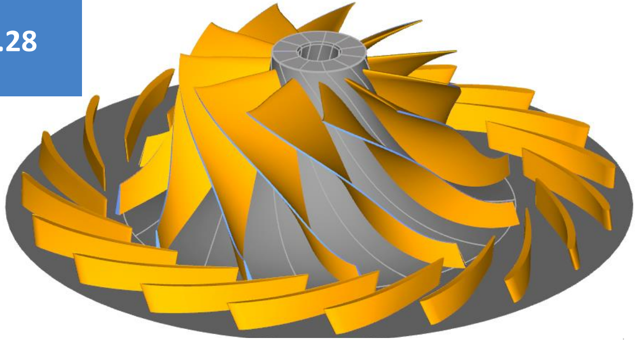


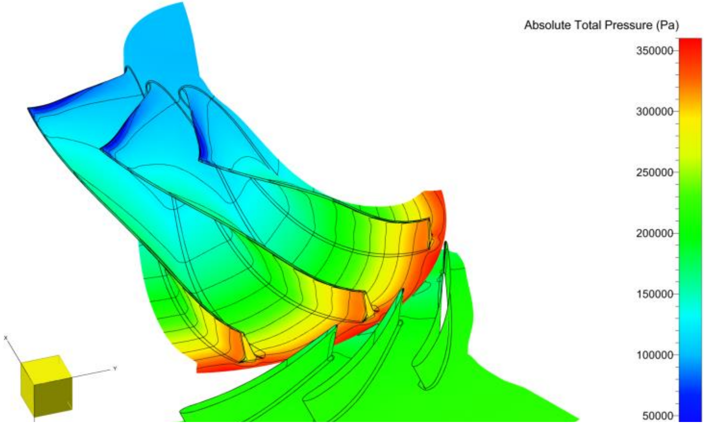


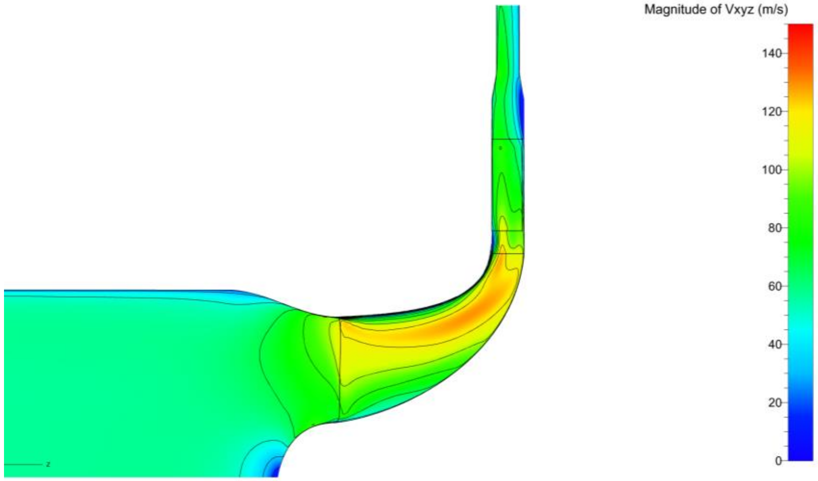


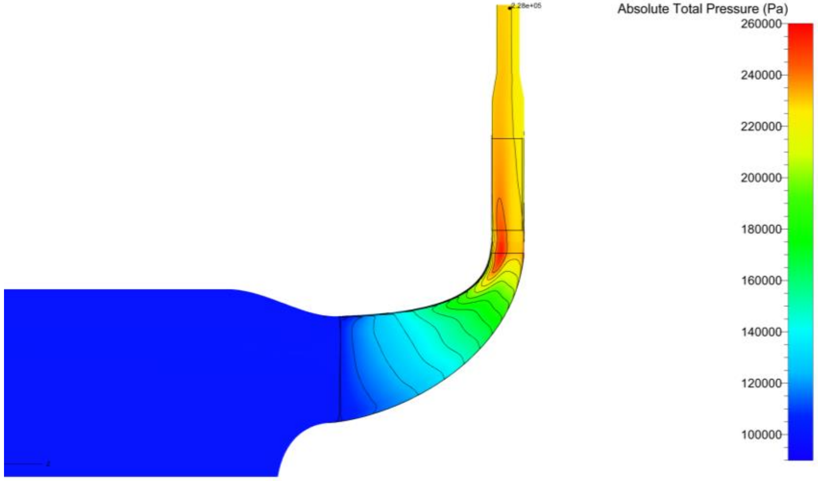
Des 049 – Best KLE based Opt. with 4 KLE modes

Efficiency	87.2 %
Pressure Ratio	2.28



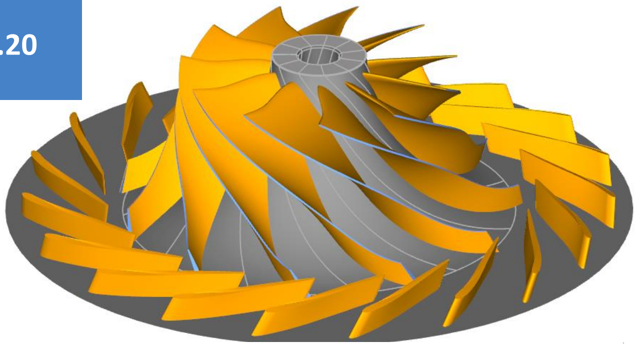


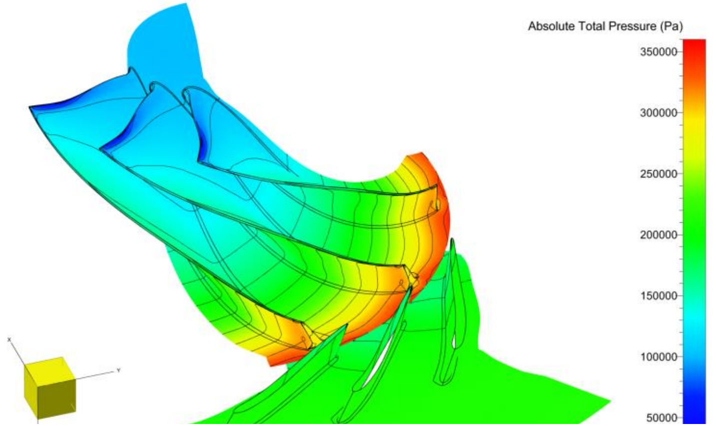


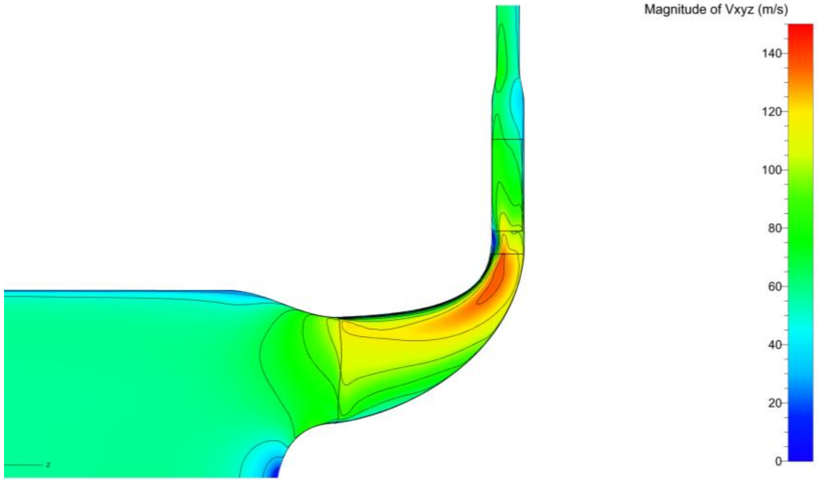


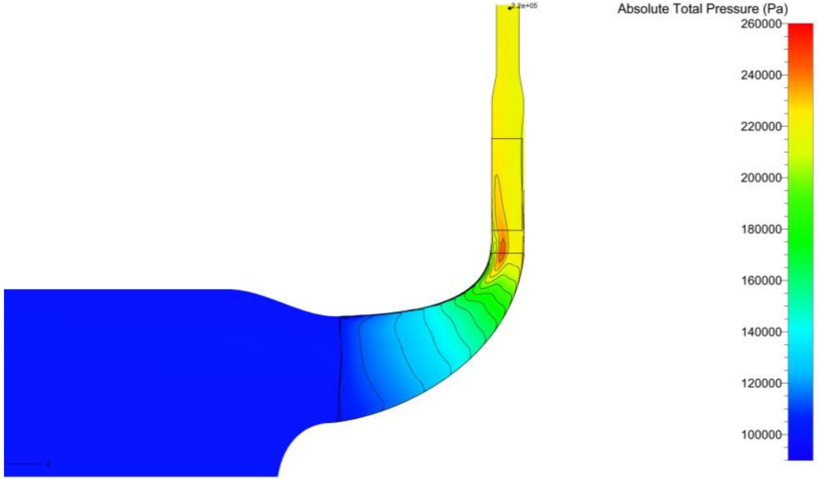
Des 079 – Best KLE based Opt. with 6 KLE modes (best DoE start)

Efficiency	88.0 %
Pressure Ratio	2.20



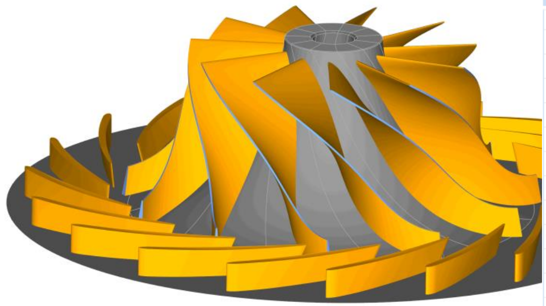


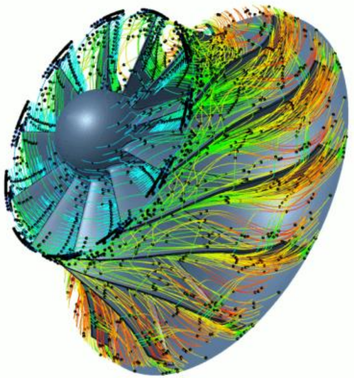




Conclusions

Conclusion



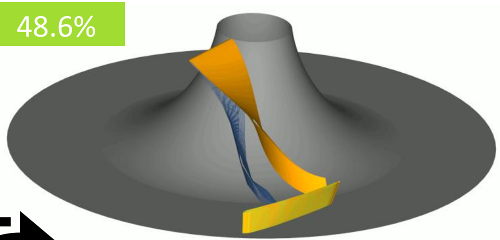


Design Variables

	Design Variable	Lower	Value	Upper
1	ANGLE_HUB	-10	0	10
2	ANGLE_SHROUD	-10	0	10
3	MID_SHIFT_DELTA	-2	0	2
4	MID_SHIFT_POS	0.3	0.5	0.8
5	BETA_HUB_LE	40	45	50
6	BETA_HUB_TE	45	50	55
7	BETA_SHROUD_LE	25	30	35
8	BETA_SHROUD_TE	40	41.7	50
9	BETA_TanFactor_HUB_LE	0.4	[illegible]	0.6
10	BETA_TanFactor_HUB_TE	0.4	[illegible]	[illegible]
11	BETA_Tan_HUB_LE	-45	[illegible]	[illegible]
12	BETA_Tan_HUB_TE	-65	[illegible]	-55
13	BETA_TAN_SHROUD_LE	-15	[illegible]	[illegible]
14	BETA_TAN_SHROUD_TE	-40	-35	-30
15	THETA_DELTA_SHROUD_LE	-10	-2	0
16	THETA_DELTA_SHROUD_TE	-10	0	10
17	Diff_BETA_HUB_LE	17	19	25
18	Diff_BETA_HUB_TE	28	37	44
19	Diff_BETA_SHROUD_LE_Delta	-4.5	-2	3.5
20	Diff_BETA_SHROUD_TE_Delta	-5	-1	8
21	Diff_BETA_Tan_HUB_LE	-30	-20	-10
22	Diff_BETA_Tan_HUB_TE	-7.5	0	10
23	Diff_BETA_Tan_SHROUD_LE	-30	-20	-10
24	Diff_BETA_Tan_SHROUD_TE	-10	10	20
25	Diff_THETA_DELTA_SHROUD_LE	-15	-3	8.5
26	Diff_THETA_DELTA_SHROUD_TE	-5	0	5

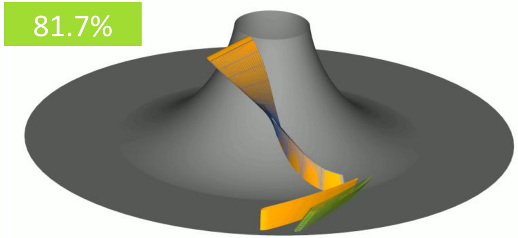
KLE mode 1 – main blade

48.6%



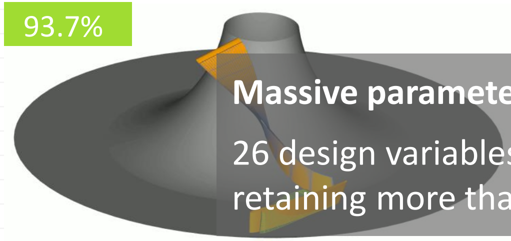
KLE mode 2 – diffuser

81.7%



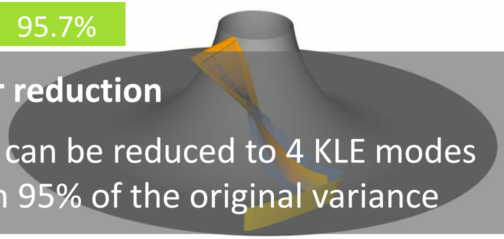
KLE mode 3 – diffuser

93.7%



KLE mode 4 – main blade

95.7%



Massive parameter reduction

26 design variables can be reduced to 4 KLE modes retaining more than 95% of the original variance

Conclusions

- The less free variables to work with the better
- An approach has been developed with which to substantially reduce design spaces made of CAD variables by mapping them into spaces spanned by a different kind of variables, dubbed super parameters
- A back-transformation from KLE to CAD space is needed for complex models
- Massive parameter reduction for faster fluid-dynamic optimization of shapes were shown

- Outlook and future work:
  - Combine parametric-adjoint solutions with KLE (sensitivity analysis)

Promising combination

High-level parametric models with further parameter reduction

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