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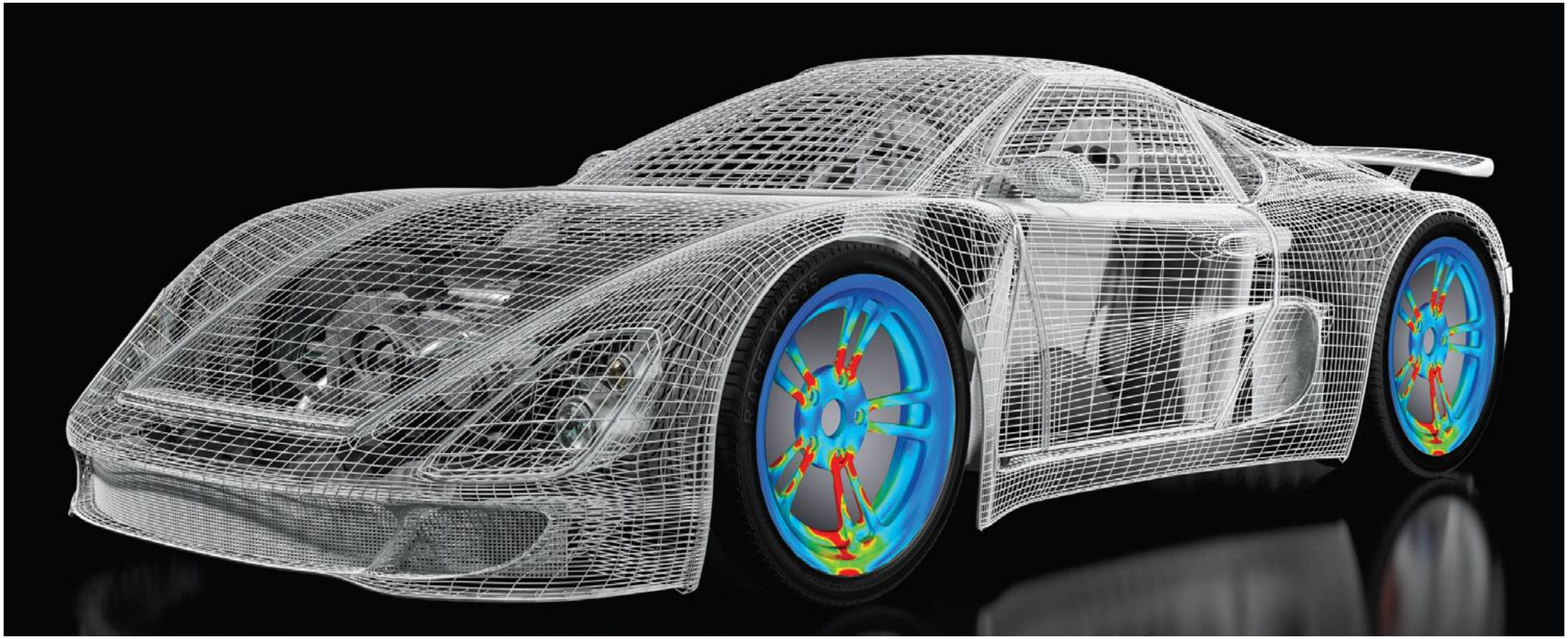
AI Topology optimization



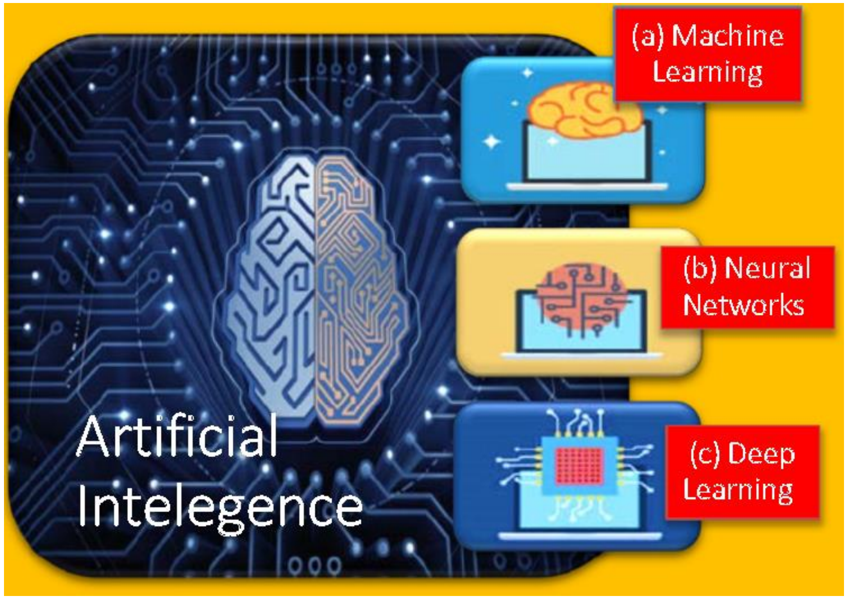
Braverman Arik

Agenda

- What is Artificial Intelligence (AI) and Deep Learning For CFD?
- Machine Learning
- Difference Between Artificial Intelligence and Machine Learning
- Machine Learning
- Artificial Neural Networks (ANNs)
- Machine Learning in Fluid Dynamics
- Optimization Procedure
- Pump Project
- Pump Project Optimization
- Pump Project-Model Parametrization
- The Future of ANNs for Fluids Modelling

Artificial Intelligence (AI) and Deep Learning For CFD

- Every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it.
- Anything from a computer program playing a game of chess, to a voice-recognition system
- AI can be classified into the following :
  - Machine Learning
  - Neural Networks
  - Deep Learning



Machine Learning

- Machine learning is a type of Artificial Intelligence (AI) that provides computers with the ability to learn without being explicitly programmed.
- Machine learning focuses on the development of computer programs that can change when exposed to new data.
- It has given us self-driving cars, practical speech recognition, effective web search, and a vastly improved understanding of the human genome.
- Instead of extracting data for human comprehension as is the case in data mining applications machine learning uses that data to detect patterns in data and adjust program actions accordingly.

Machine Learning

- Machine learning algorithms are often categorized as being supervised or unsupervised.
- Supervised algorithms can apply what has been learned in the past to new data. Un-supervised algorithms can draw inferences from datasets.
- Facebook's News Feed uses machine learning to personalize each member's feed.
- The software is simply using statistical analysis and predictive analytics to identify patterns in the user's data and use to patterns to populate the News will be included in the data set and the News Feed will adjust accordingly.
- Machine learning (ML) is an algorithms that process Scope of Artificial Intelligence and extract information from data.
- They are linked to learning processes and are categorized as supervised, semi-supervised, or unsupervised

Difference Between Artificial Intelligence and Machine Learning

- Artificial Intelligence (AI) is a smart computer program
- It can be a pile of statements or a complex statistical model.
- Usually, when a computer program designed by AI researchers actually succeeds at something like winning at chess.
- Machine learning is a subset of AI.
- Machine learning is a development of self-learning algorithms.
- Machine learning uses statistics (mostly inferential statistics) to develop self-learning algorithms.
- Artificial Intelligence is a science to develop a system or software to mimic human to respond and behave in a circumstance.
- AI has defined its goal into multiple chunks. Later each chuck has become a separate field of study to solve its problem.

Difference Between Artificial Intelligence and Machine Learning

- The ML algorithms attempt to optimize along a certain dimension
- Different outputs/guesses are the product of the inputs and the algorithm.
- Artificial Neural Networks (ANN) keep on measuring the error and modifying their parameters until it can't achieve any less error. They are, in short, an optimization algorithm.
- AI mimics natural intelligence to solve complex problems and enables decision making
- Machine learning, on the other hand, is about improving and maximizing performance by means of self-learning algorithms.
- Both of them require large databases from which to learn: the more the high-quality data that becomes available.
- The better the results, hence the close connection of AI and ML to Big Data.

Deep Learning

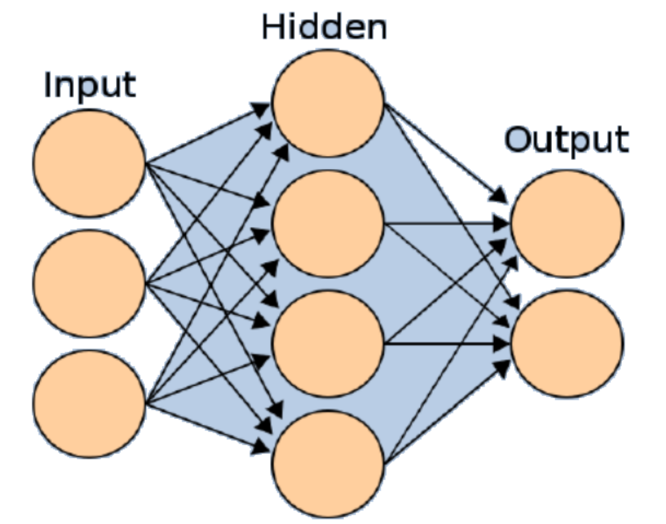
- The artificial neural networks (ANN) have discrete layers, connections, and directions of data propagation.
- The first layer individual neurons, passes the data to a second layer. The second layer of neurons does its task, and so on, until the final layer and the final output is produced.
- Each neuron assigns a weighting to its input; how correct or incorrect it is relative to the task being performed.
- The final output is then determined by the total of those weightings.

Deep Learning

- The neural network's task is to conclude whether this is a stop sign or not.
- It comes up with a "probability vector," based on the weighting. then tells the neural network whether it is right or not.
- Deep Learning is a technique for implementing Machine Learning.
- Deep Learning has enabled many practical applications of Machine Learning and by extension the overall field of AI
- Deep Learning breaks down tasks in ways that makes all kinds of machine assists seem possible, even likely. Driverless cars, better preventive healthcare, even better movie recommendations, are all here today or on the horizon.

Artificial Neural Networks (ANNs)

- If the combined incoming signals are strong enough, the neuron becomes activated and the signal travels to other neurons connected to it.
- Such systems can be trained from examples in a traditional computer program.
- Neural networks have been used to solve a wide variety of tasks, like computer vision and speech recognition, that are difficult to solve using ordinary rule-based programming.
- Typically, neurons are connected in layers, and signals travel from the first (input), to the last (output) layer.
- Modern neural network projects typically have a few thousand to a few million neural units and millions of connections



Artificial Neural Network (ANN)

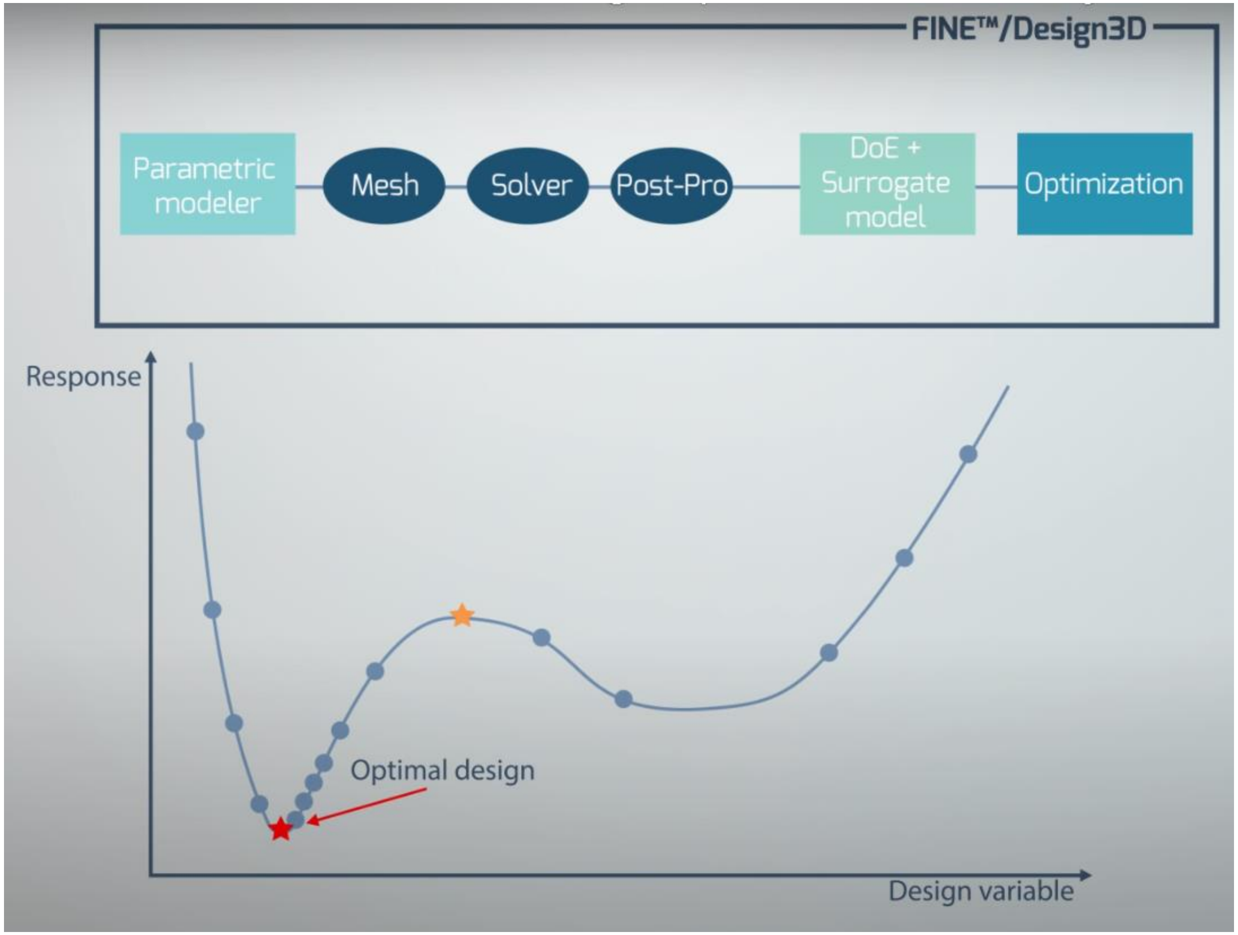
Artificial Neural Networks (ANNs)

- The signals and state of artificial neurons are real numbers, typically between 0 and 1.
- The signal must surpass the limit before propagating.
- Training typically requires several thousand cycles of interaction
- The goal of the neural network is to solve problems in the same way that a human would
- Dynamic neural networks are the most advanced, in that they dynamically can, based on rules, form new connections and even new neural units while disabling others.

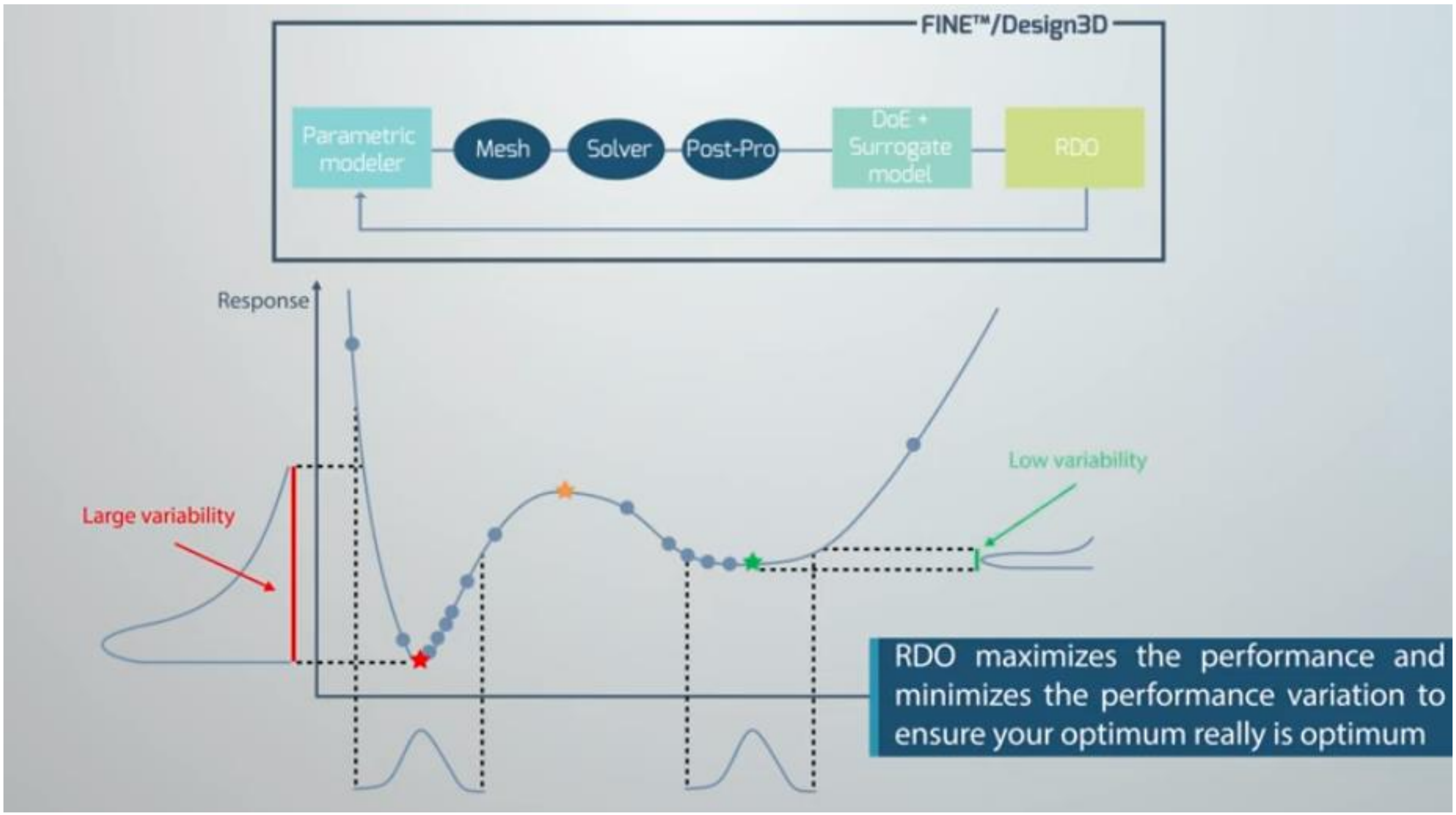
Machine Learning in Fluid Dynamics

- Fluid flows are very popular in modern engineering and in the life sciences.
- Particularly unsteady aerodynamic forces and moments inspired engineering design principals.
- Improving efficiency, maximize thrust and lift, and increase maneuverability.
- The applications presented herein encompass a variety of problems such as cylinder drag minimization, neural net modeling of the near wall structures, enhanced jet mixing, and parameter optimization in turbine blade film cooling.
- Maximal Wall Shear Stress (MWSS)

Optimization Procedure



Optimization Procedure



Optimization Procedure

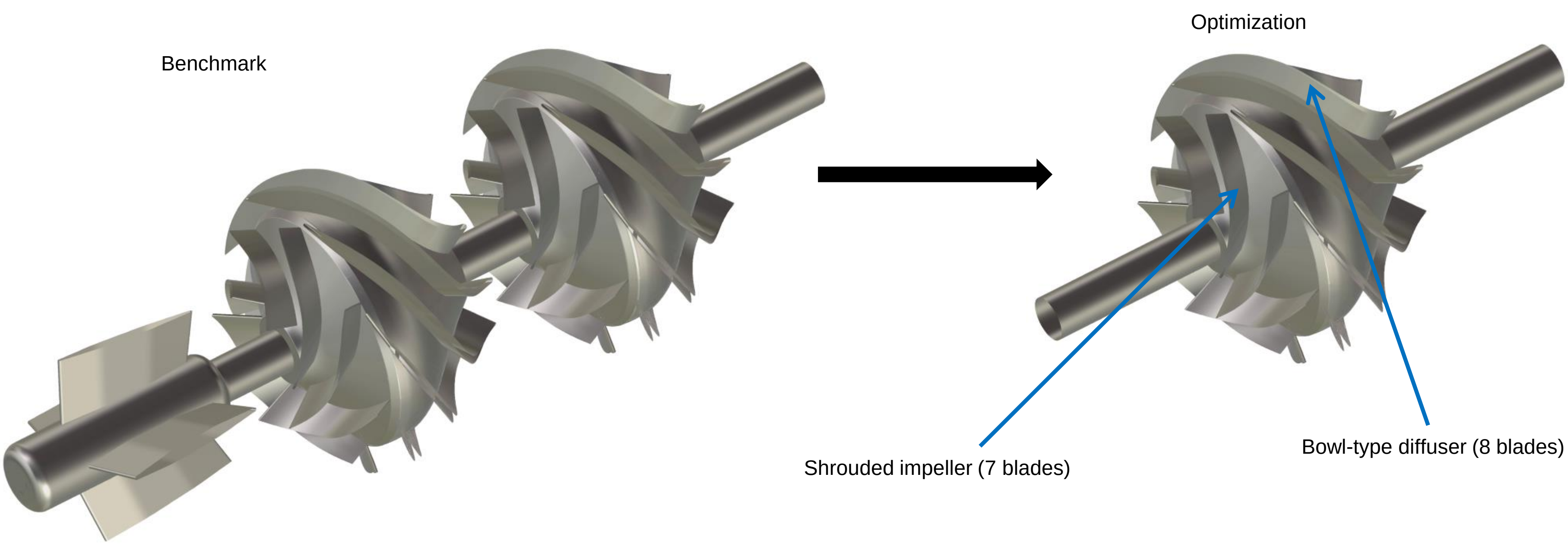
- DOE helps to design an experiment that provides you with more information and minimal work

- DOE available in FINE™/Design3D:

  - Full factorial
  - Fractional factorial
  - Central composite
  - Box-Behnken
  - Plackett-Burman
  - Rechtschaffner
  - Latin hypercube
  - D-optimal

According to the optimization problem, a DOE can be better than another one

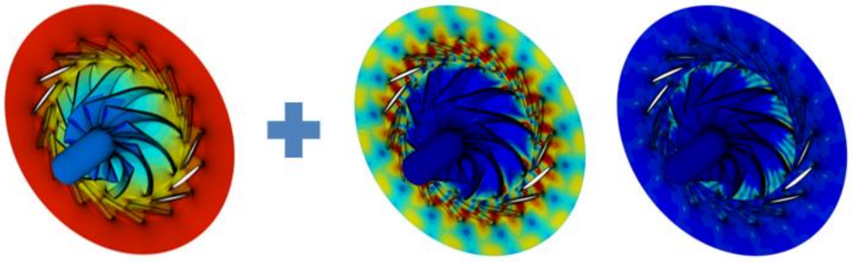
Pump Project



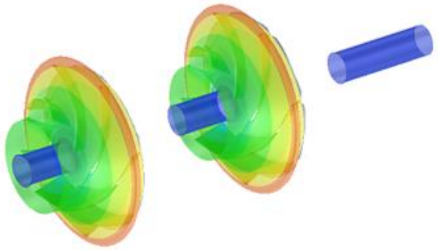
Pump Project

Numerical settings for NLH computations

$$U(\vec{r},t)=\overline{U}(\vec{r})+\sum U'(\vec{r},t)$$



Time averaged solution *Harmonics*



Rotating walls

Non-rotating walls

Pump Project

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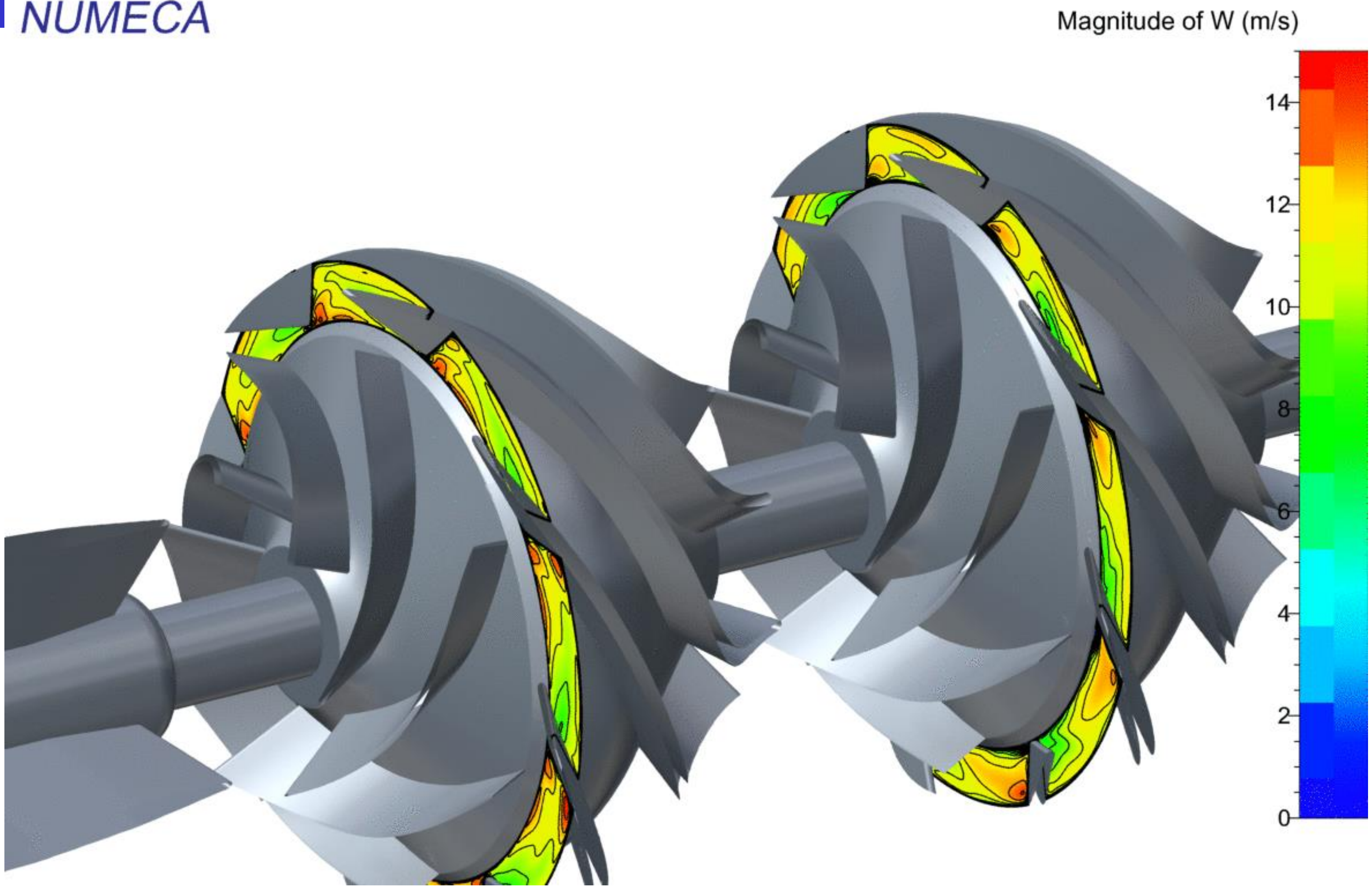
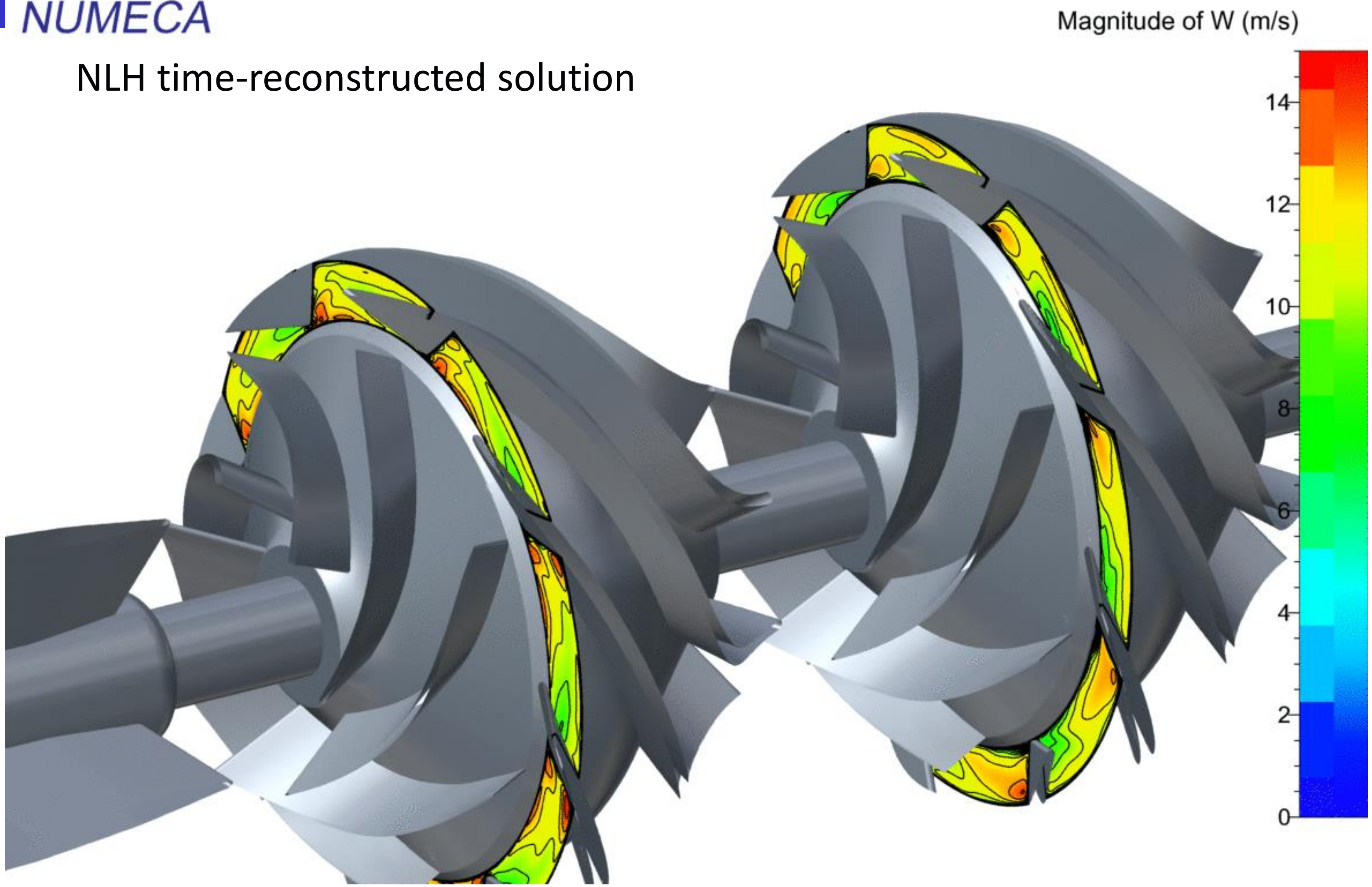


Pump Project Unsteady flow analysis

NUMECA

NLH time-reconstructed solution



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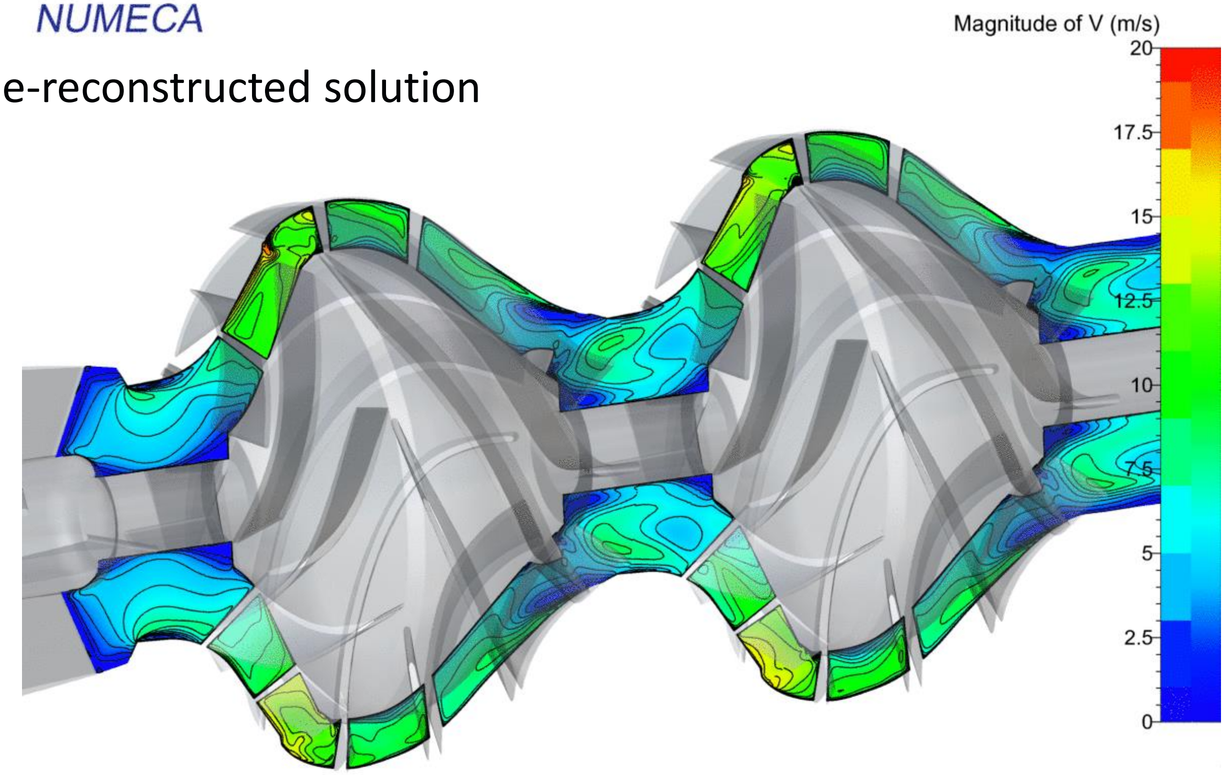
Pump Project Unsteady flow analysis

NUMECA

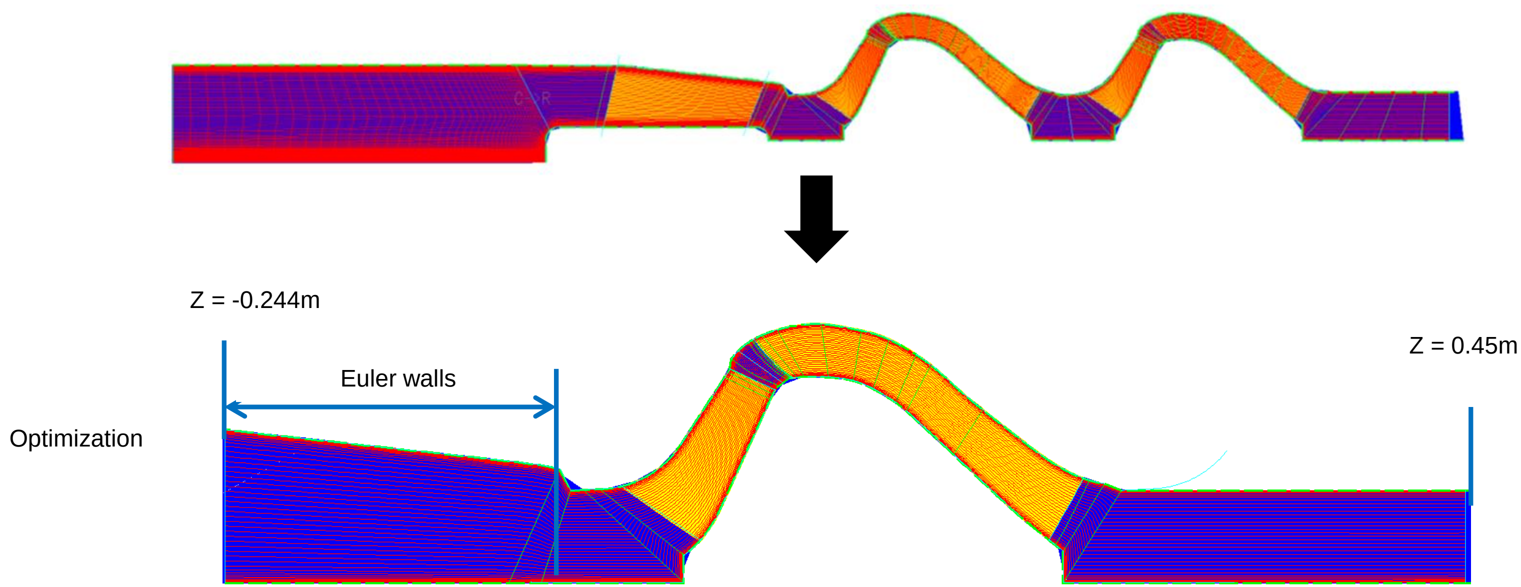
NLH time-reconstructed solution



Results of the NLH can be visualized as fully unsteady, allowing the engineer the visualization of disturbances in the flow, as well as flow fluctuations and instabilities

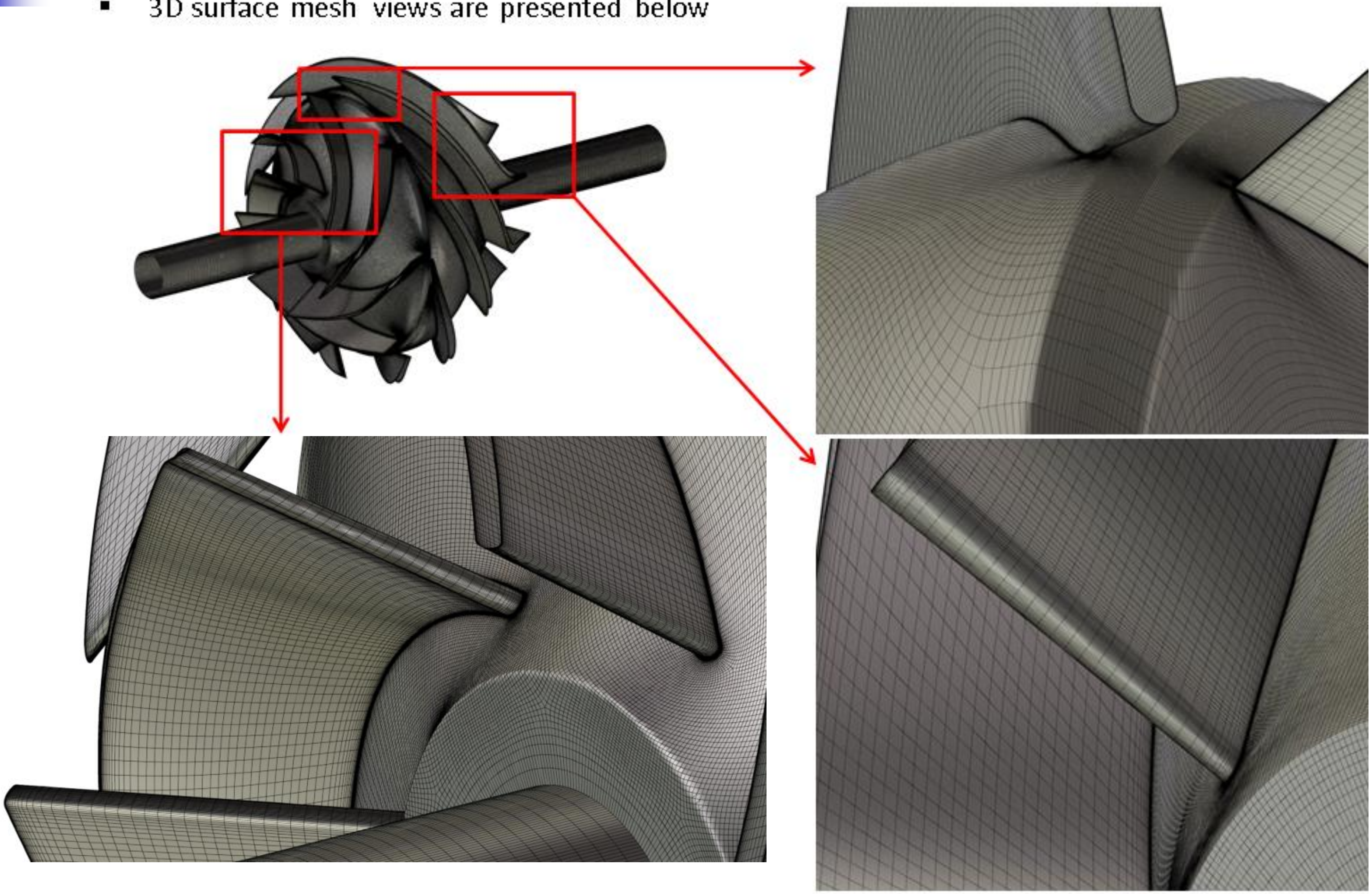
Pump Project

- The was mesh generated with the following modifications:
  - Inlet struts and second stage erased from the initial mesh
  - For the inlet :
    - Axial extension keeping shroud shape
    - Simplification of the hub with straight axial extension for the low radius part
    - Extended parts (hub/shroud) will be Euler walls



Pump Project-Meshing

- 3D surface mesh views are presented below



Pump Project-Meshing

	Number of points	Negative cells	Min orthogonality [deg]	Max aspect ratio [-]	Max expansion ratio [-]
Impeller	2 624 350	0	24	991	2.72
Diffuser	2 190 695	0	15	2611	1.85
Entire mesh	**4 815 045**	**0**	**15**	**2611**	**2.72**
Criteria		**= 0**	**>15-20**	**<3000**	**<3**

Pump Project-Case Setup

<u>Fluid</u>

Water described as a incompressible flow. The properties used are identical to those set-up during the benchmark

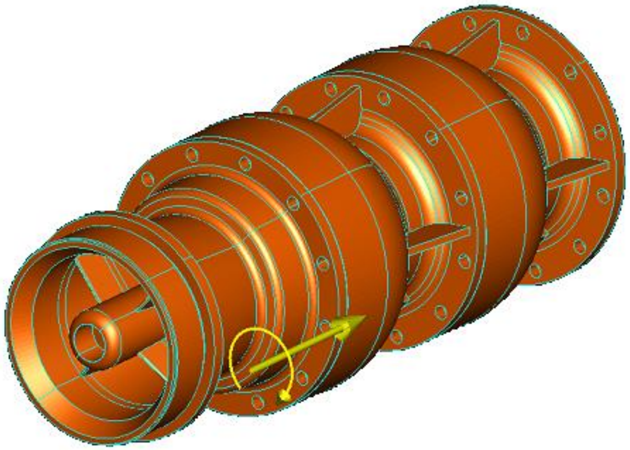
<u>Models</u>

Simulations will be 3DNS with Spalart-Allmaras, one-equation Low Reynolds turbulence model with a target y+ = 1.

<u>Boundary conditions</u>

<u>Inlet</u>: Total conditions are imposed:

- Pt = 101 325 Pa
- Tt = 293 K
- Turbulent Viscosity = 0.0001 m^2/s
- Velocity direction = Axial



Pump Project-Model Calculation

$$Head = \frac{p_{t2} - p_{t1}}{\rho g}\,[m] \qquad \eta = \frac{(p_{t2} - p_{t1})\dot{m}}{\rho \omega T}\,[\%] \qquad P_{hp} = \frac{T\,\omega}{745.7}\,[hp]$$

Where:

p_{t2} is the total pressure at the outlet of the CFD domain

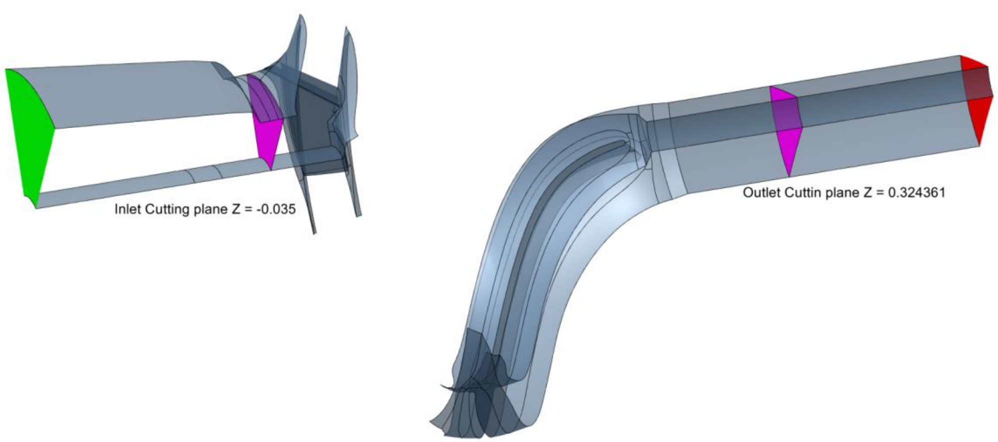
p_{t1} is the total pressure at the inlet of the CFD domain

$\dot{m}$ is the mass flow rate

ρ is the fluid density

ω the rotational speed

T the torque blade-fluid



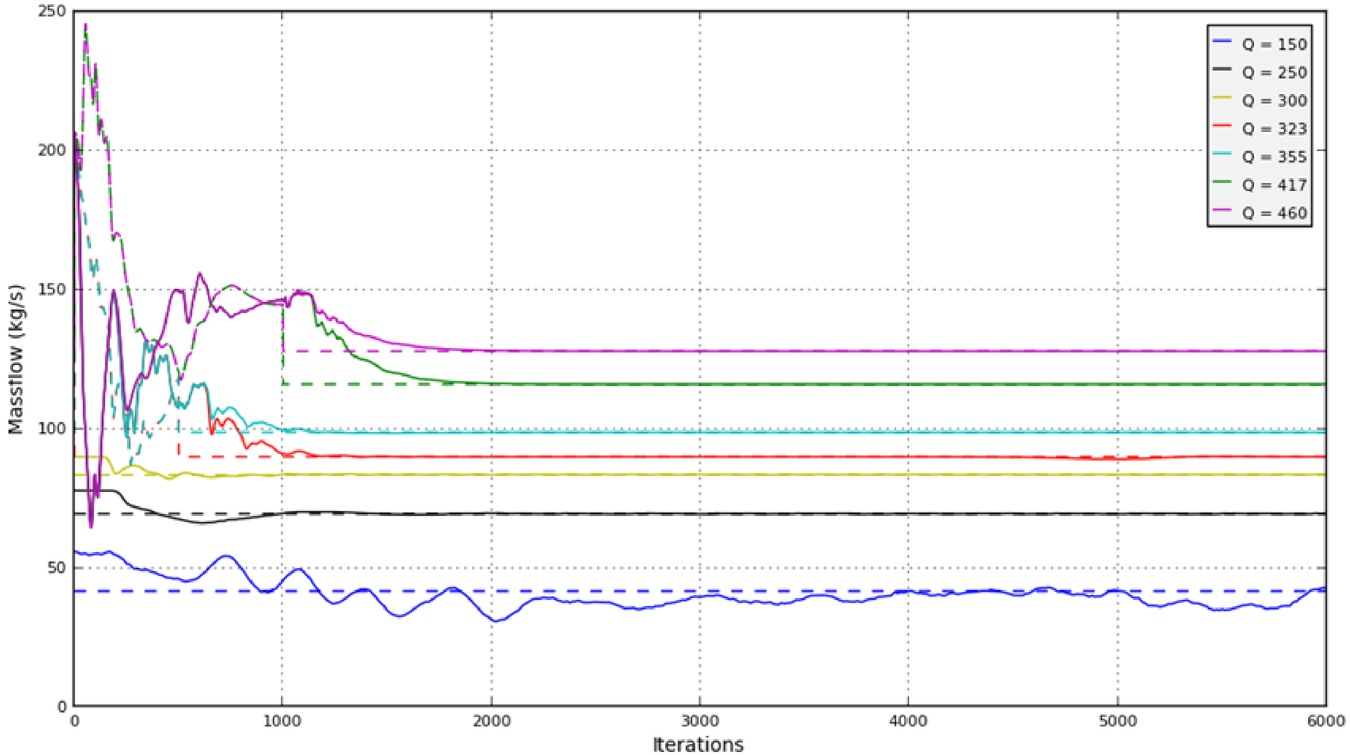
Pump Project-Model Calculation

The performance curve is created modifying the massflow at the outlet to cover the whole range before surge. The following values have been used:

- Qv = 460 m3/h → Ok
- Qv = 417 m3/h → Ok
- Qv = 355 m3/h → Ok
- Qv = 323 m3/h → Ok
- Qv = 300 m3/h → Ok
- Qv = 250 m3/h → Small oscillations (0.1% on the massfow)
- Qv = 150 m3/h → Strong oscillations (10% on the massflow)
- Qv = 100 m3/h → Divergence of the simulation (surge)

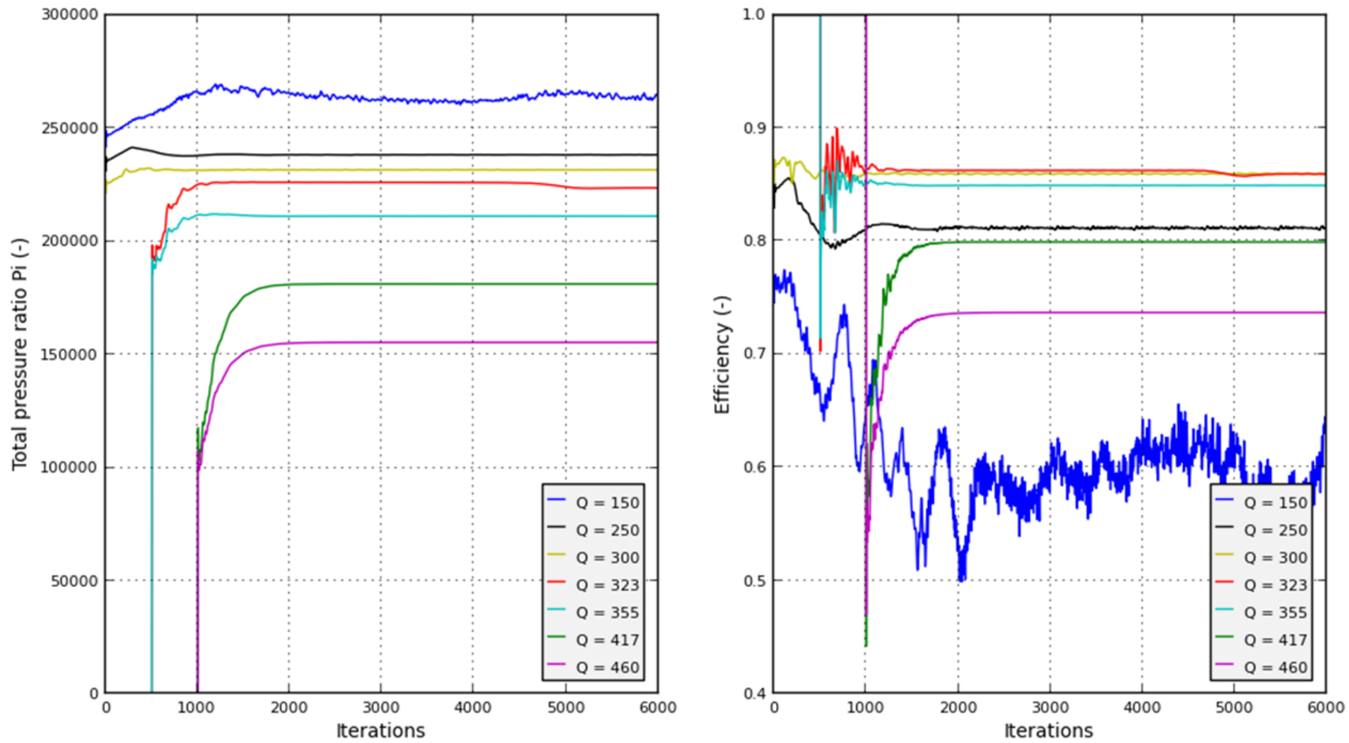
Pump Project-Model Simulation

Seven simulations have been run to compute the performance curve. Except for the point close to the surge, the convergence is excellent. The mass flow is presented below.



Pump Project-Model Simulation

The global quantities are also converged.



Pump Project-Model Simulation

Single stage post-processing			
Qv [m3/h]	Head [m]	Efficiency [%]	P [hp]
248	25.6	85.4	27.1
280	25.4	89.1	29.2
309	24.7	89.7	31.0
324	23.8	89.0	31.7
356	22.3	87.9	32.9
380	21.2	86.7	34.0
418	19.3	83.7	35.2
461	16.8	78.3	36.1

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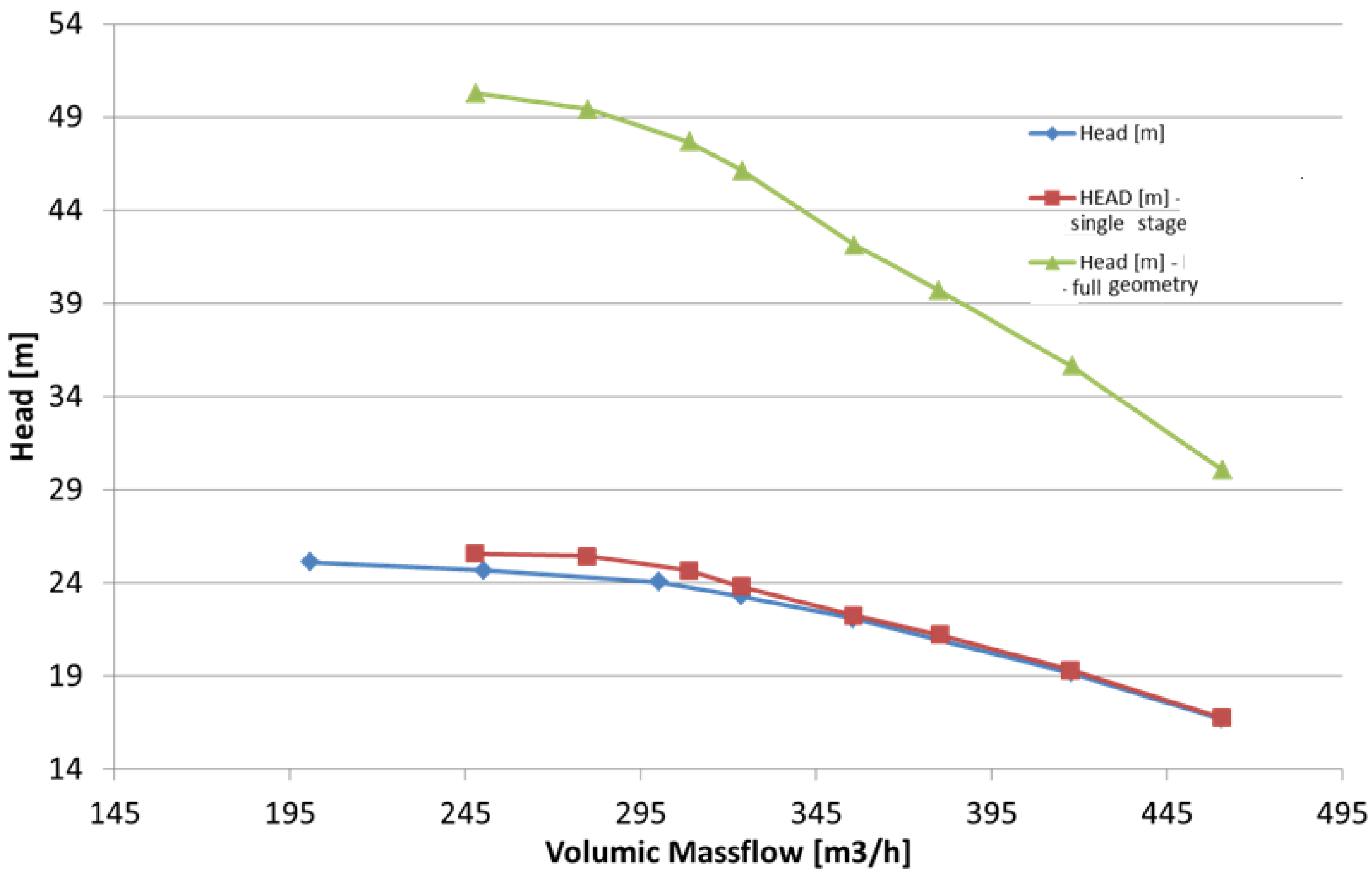
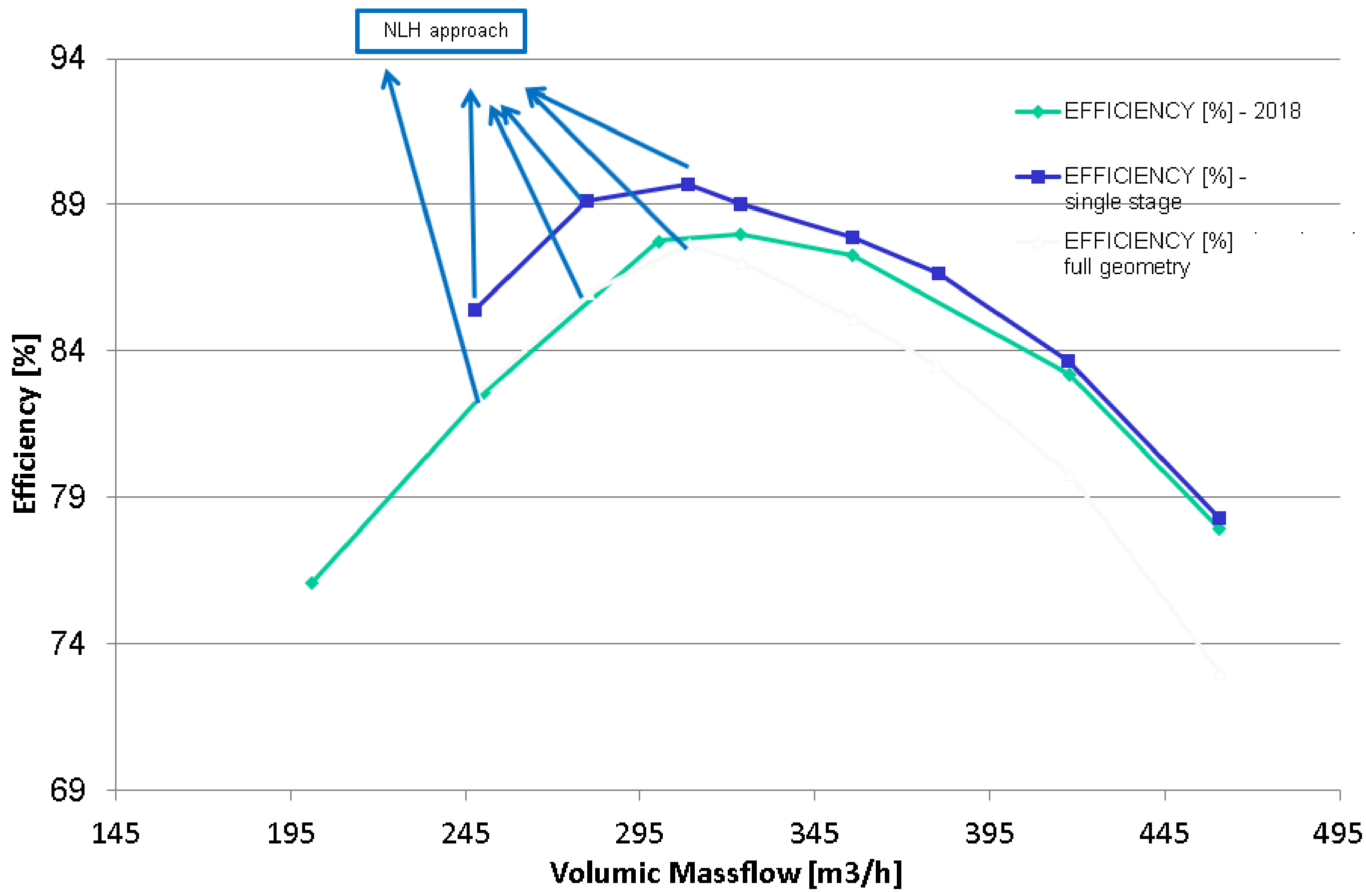
Pump Project-Model Simulation



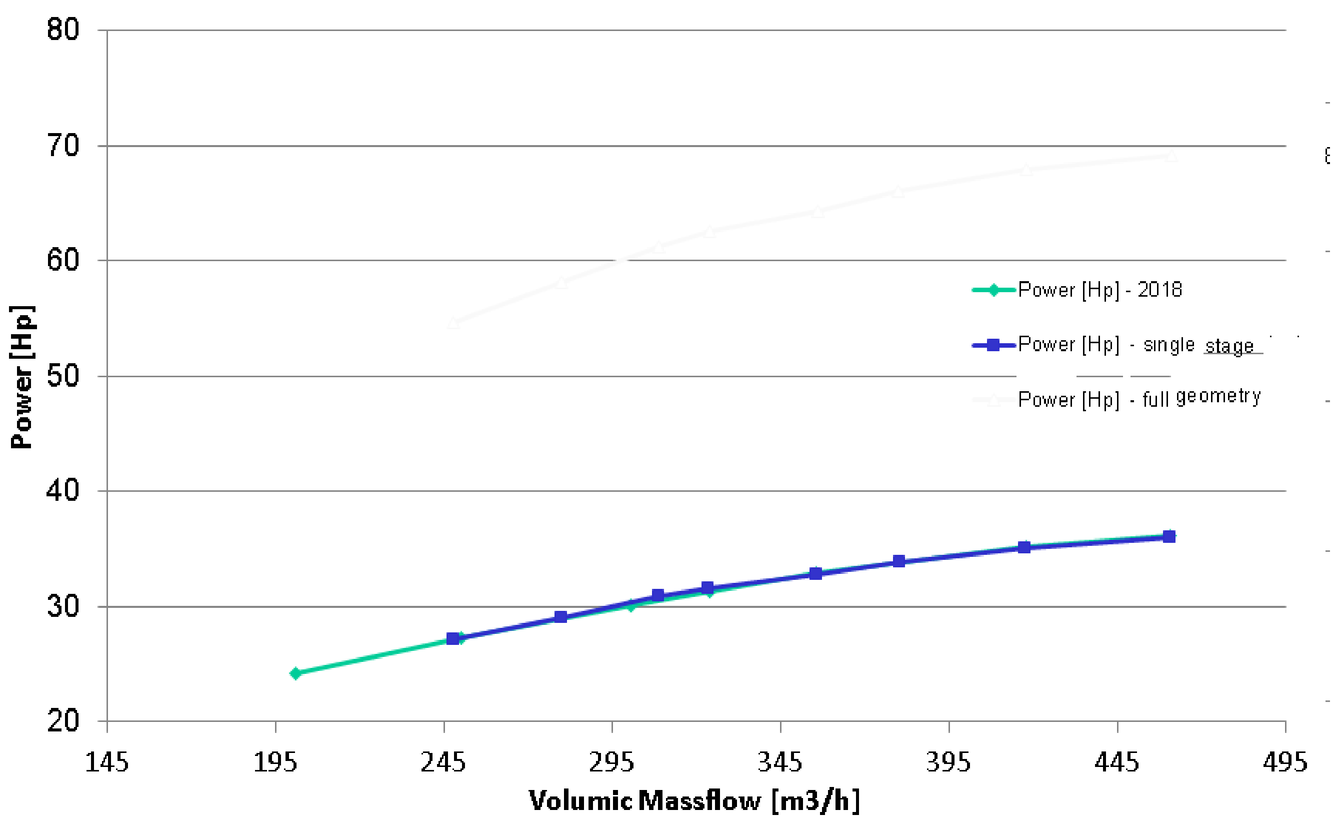
Pump Project-Model Simulation

The evolution of the Efficiency is presented below.

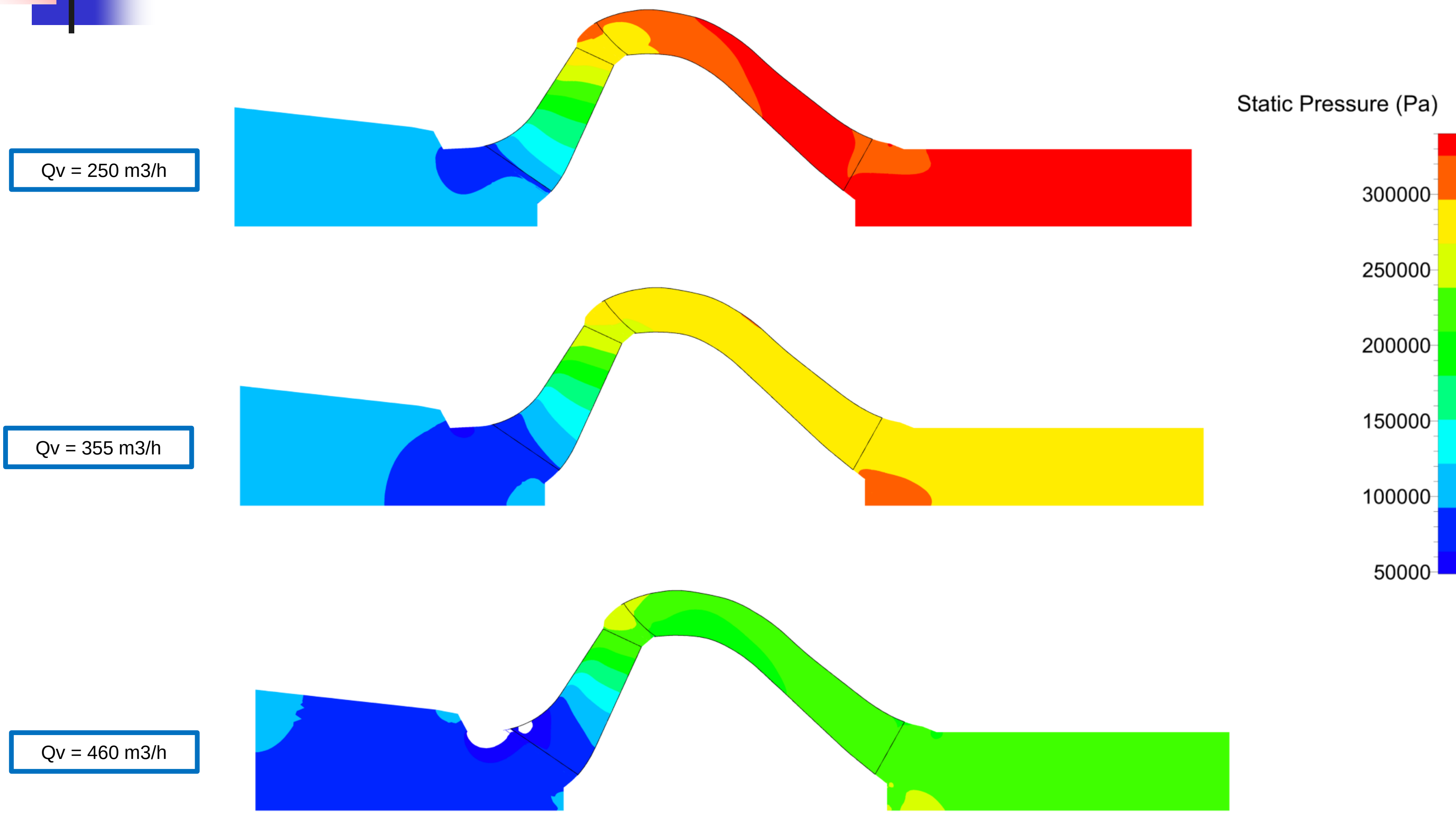


Pump Project-Model Simulation

The evolution of the Power is presented below.



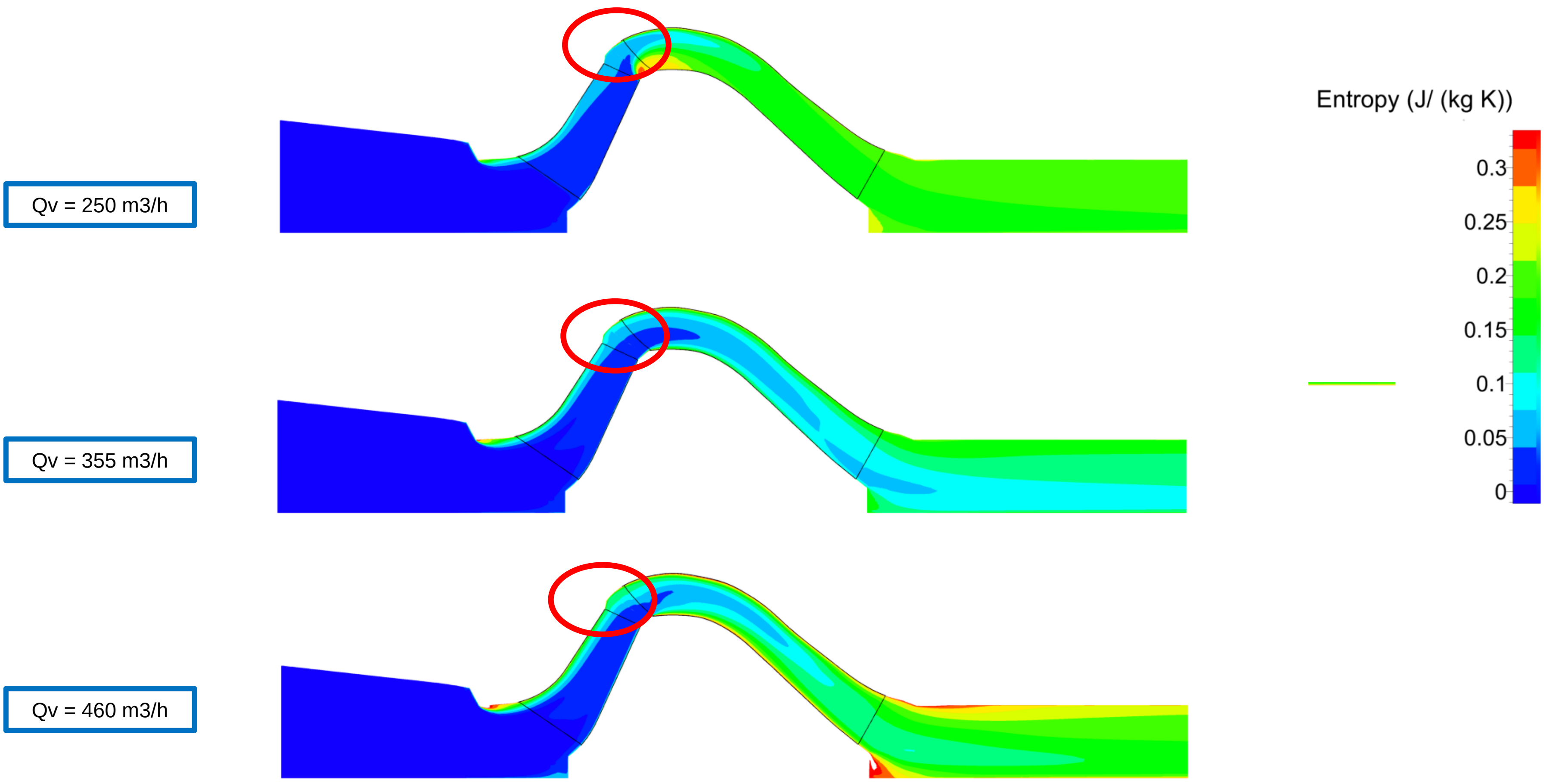
Pump Project-Model Simulation Static pressure



Pump Project-Model Simulation Entropy

Entropy in pitch-averaged views

More losses in the outlet of the impeller for the case close to the surge



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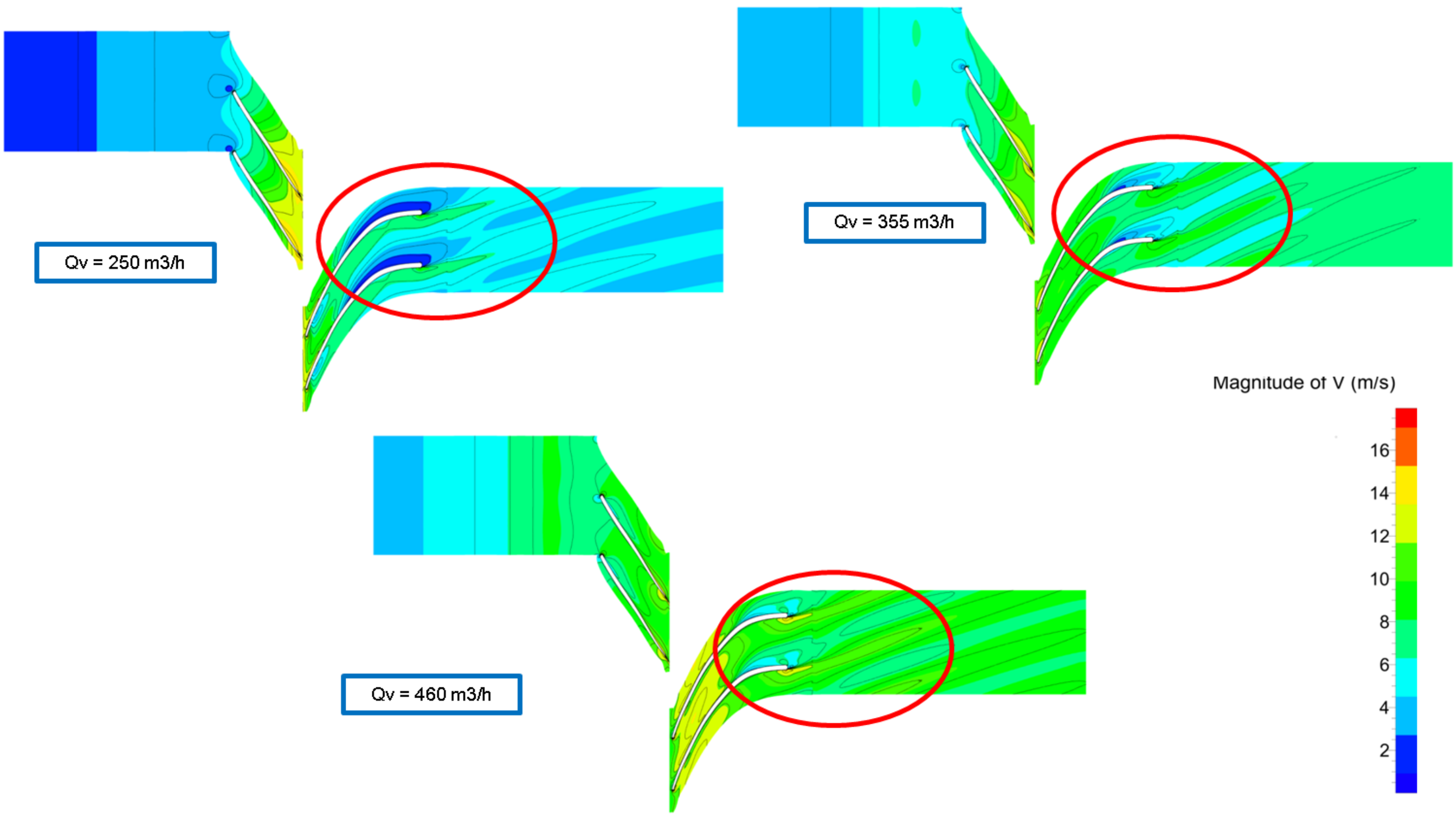
Pump Project-Model Simulation Blade to Blade Velocity

Magnitude of speed in a blade-to-blade view at 50% of the span

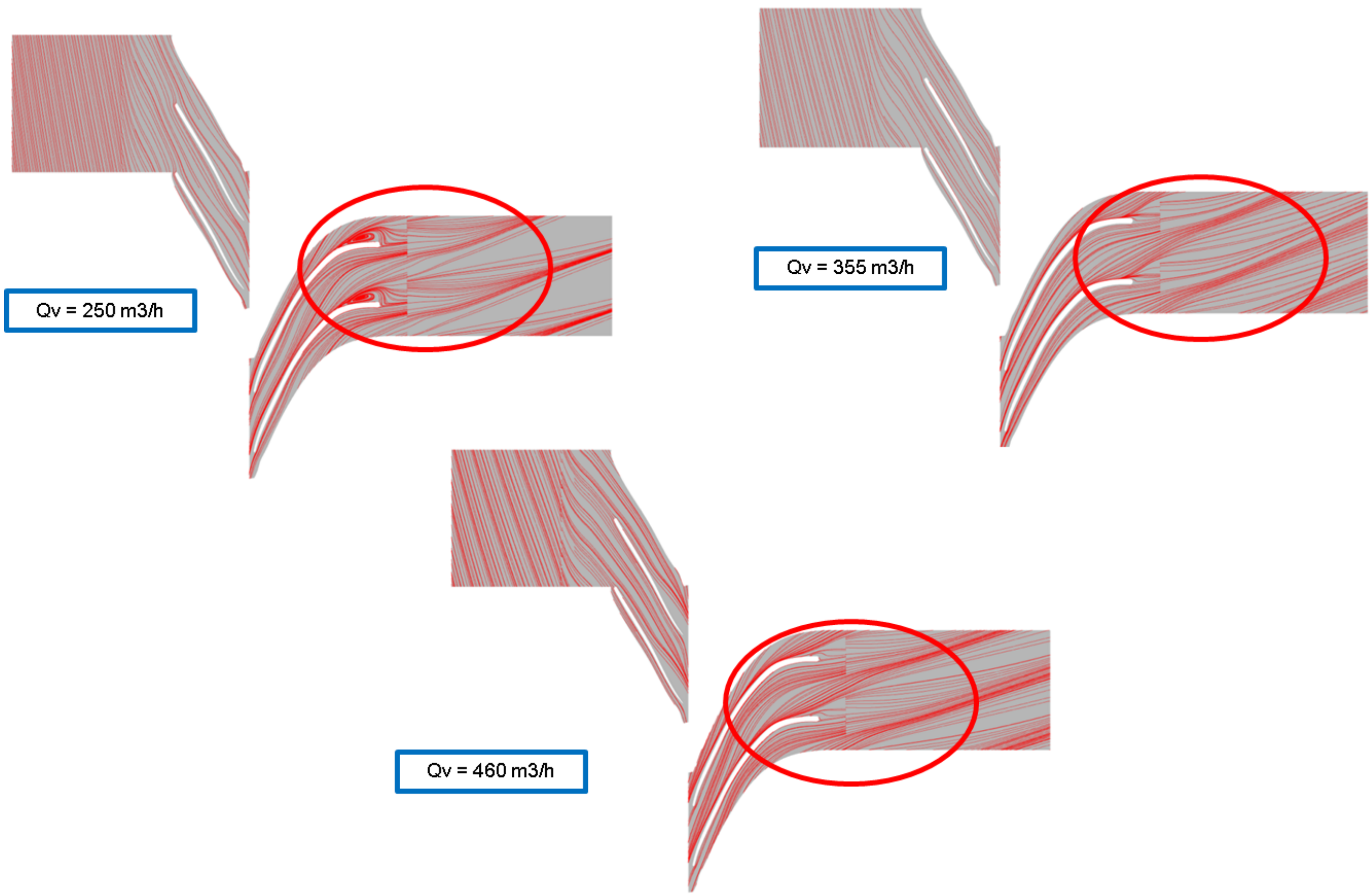
We can see the additional low speed area for the point close to the surge



Pump Project-Model Simulation Blade to Blade Streamline

Relative streamlines in a blade-to-blade view at 90% of the span

We can see the recirculation on the diffuser blades for the point close to the surge

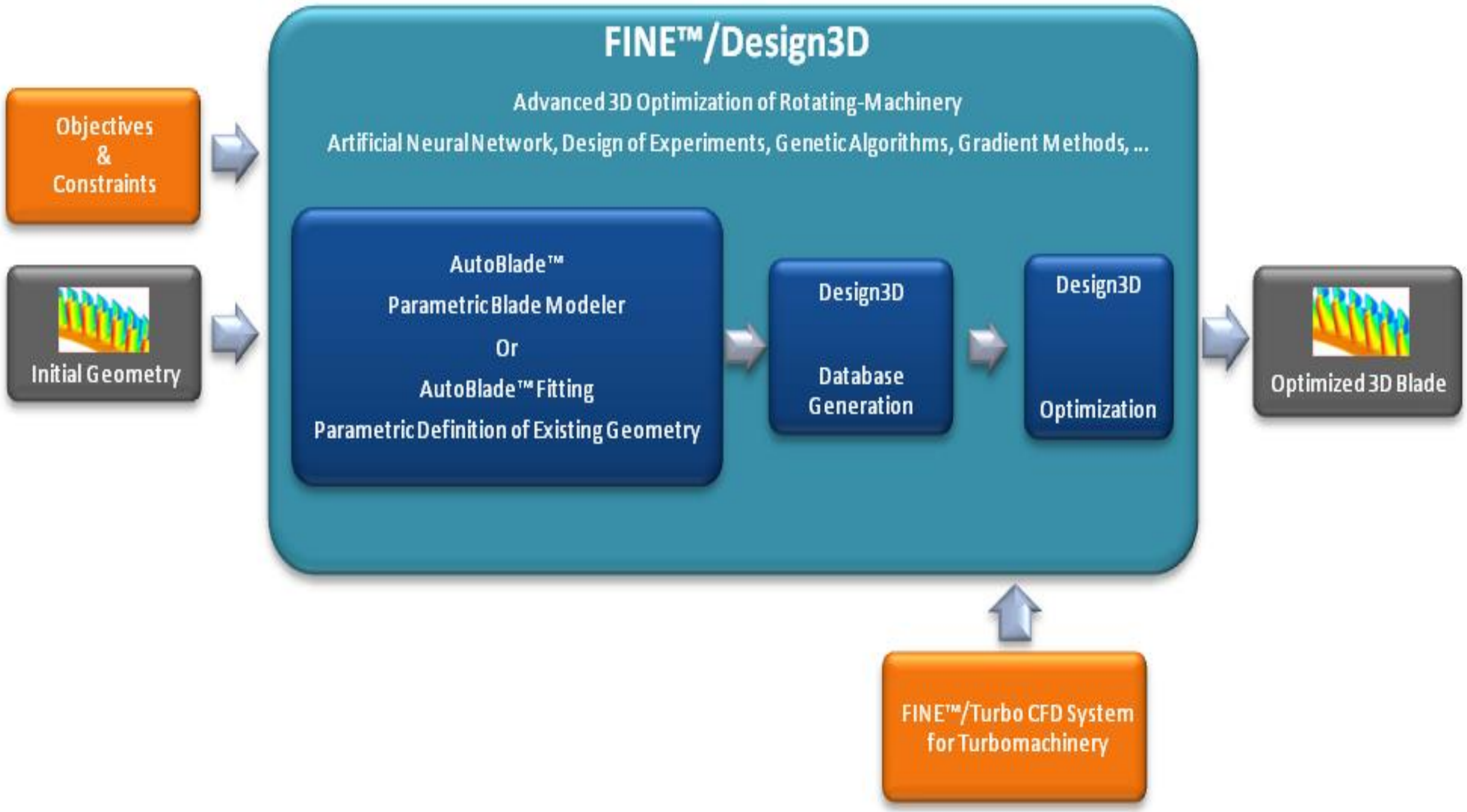


Pump Project-Model Parametrization

- The goal of the parameterization is to replace the real geometry by a parametrical model representing:
  - The hub
  - The shroud
  - The 3D blade
- For that purpose, mathematical objects such as Line/Bezier/B-spline curves are used
- The difficulty of the parameterization is to use the « good » number of parameters to:
  - have a good capture of the initial geometry
  - Avoid a too large number of parameters that will lead to a heavy and costly optimization process.
- The parameterical model will be used as an input for the optimisation process (see following slide)
- AutoBlade™ from NUMECA is use to manage the paramétrisation process

Pump Project-Model Parametrization

- The methodology is provided below. We are currently defining the parametric model.



Pump Project-Model Parametrization

First, the parameterization of the shroud curves is considered.

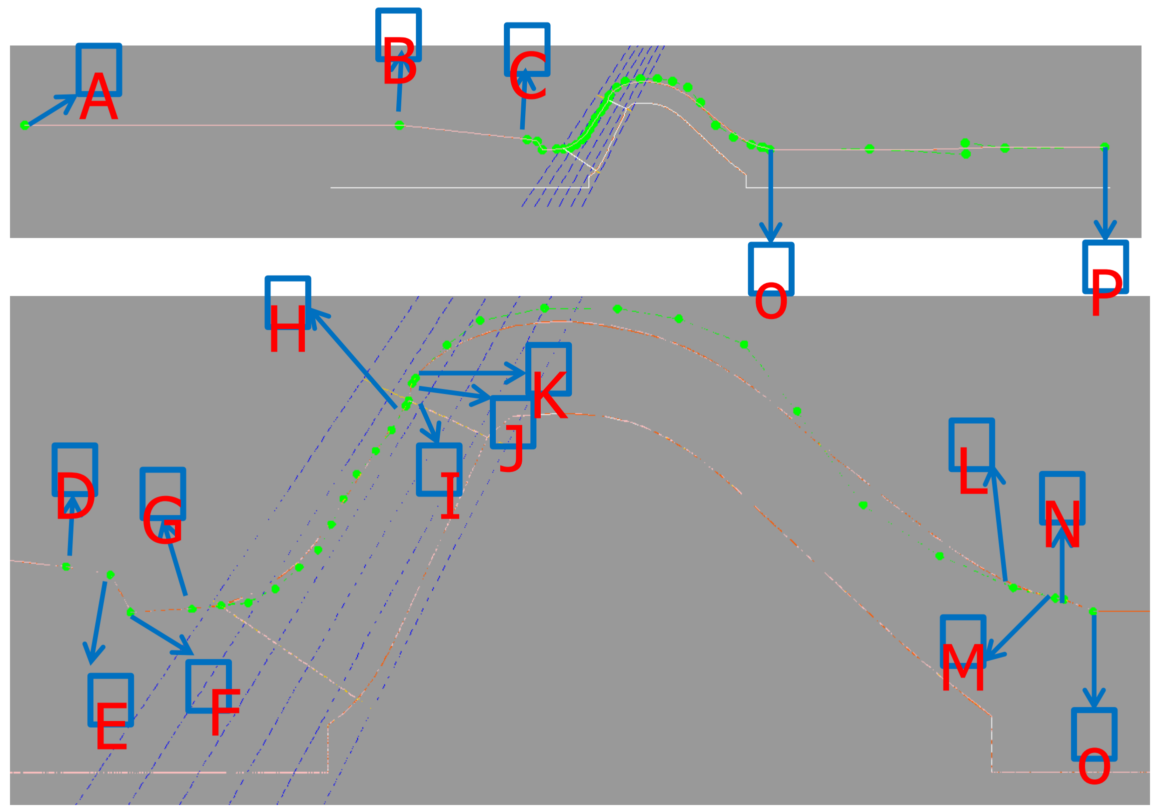
Shroud

The parameterization is presented on the figures based on composite curves :

- A-B/B-C/C-D/D-E/E-F/F-G: Lines
- G-H : Bezier with 12 points
- H-I/I-J/J-K : lines
- G-L : Bezier with 12 points
- L-M/M-N/N-O : lines
- O-P : Bezier with 6 points

The points from the lines are imposed to capture discontinuities from shroud.

The values from Bezier are fitted to get the best capture of shroud curves (see fitting slides)



Pump Project-Model Parametrization

The parameterization of the hub curves is considered.

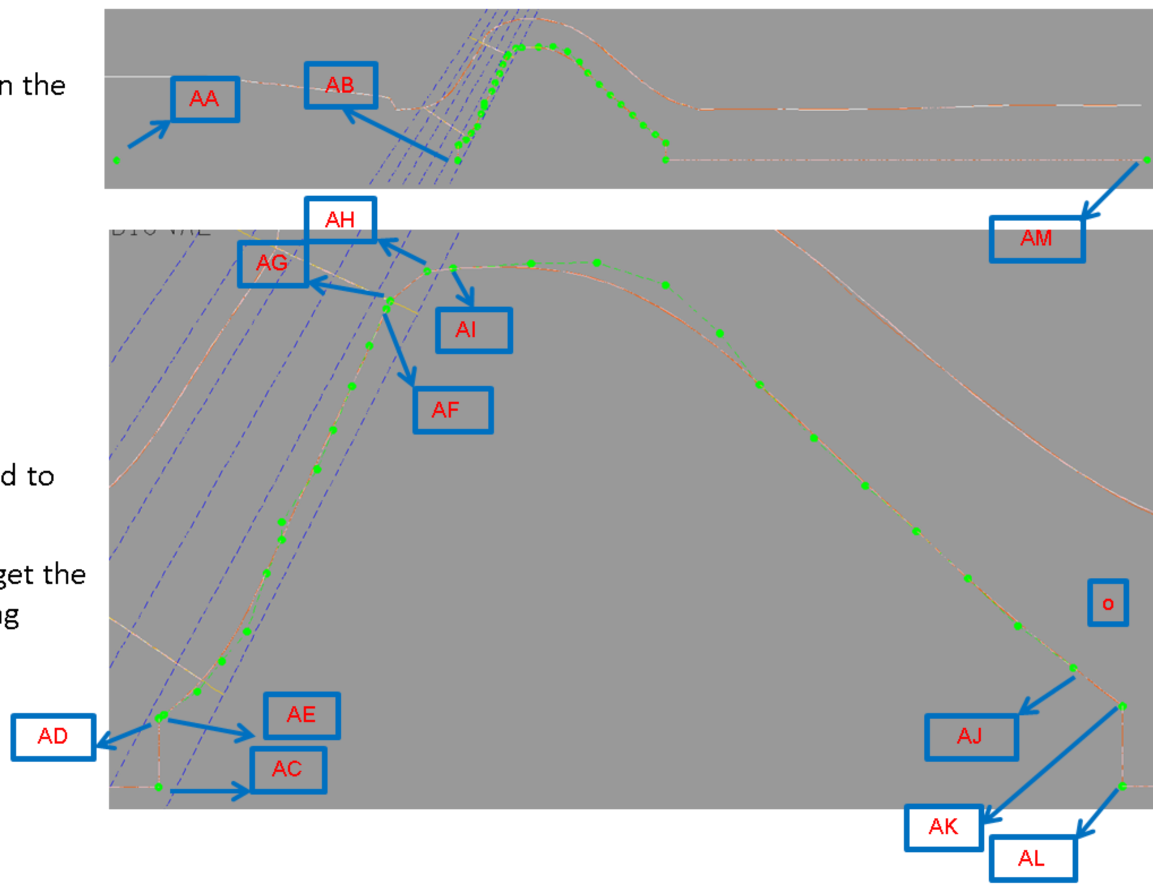
<u>Hub</u>

The parameterization is presented on the figures based on composite curves:

- AA-AB/AB-AC/AC-AE: Lines
- AE-AF : Bezier with 12 points
- AF-AG/AG-AH/AH-AI : lines
- AI-AJ : Bezier with 12 points
- AJ-AK/AK-AL/AL-AM : lines

The points from the lines are imposed to capture discontinuities from hub.

The values from Bezier are fitted to get the best capture of hub curves (see fitting slides)



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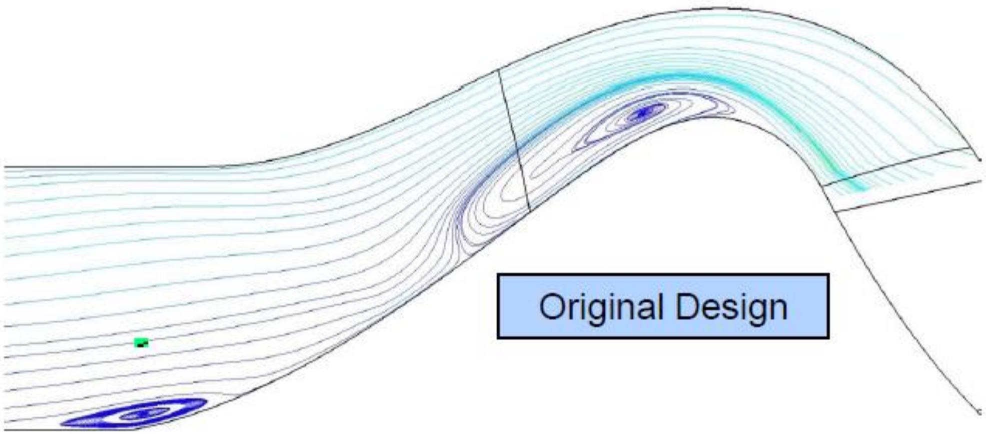
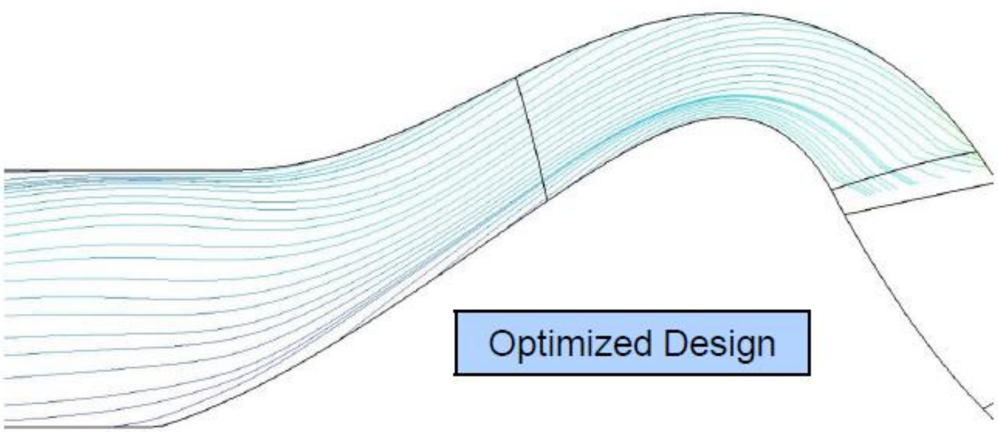
Pump Project-Model Parametrization

Big separation area at hub observed



Separation at hub eliminated at High Capacity



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Pump Project Model Reference-Screening

	Qv = 323		
	Reference	Screening	Variation [%]
Head [m]	23.3	23.6	1.2
Efficiency	88.0	87.6	0.4
P [hp]	31.3	31.8	1.5

	Qv = 355		
	Reference	Screening	Variation [%]
Head [m]	22.1	22.3	1.0
Efficiency	87.3	86.9	0.4
P [hp]	32.9	33.4	1.4

The Future of ANNs for Fluids Modelling

- ANNs will almost certainly have a transformative impact on modelling high dimensional complex systems such as turbulent flows.
- ANNs have challenged by building prediction engines that outperform competing methods
- These two outlooks are centered around the concepts of machine learning and statistical learning.
- Both methodologies have achieved significant success across many areas of big data analytics, the physical and engineering sciences have primarily focused on interpretable methods.
- Despite its successes, significant challenges remain for ANNs. Simple questions remains:
  1. How many layers are necessary for a given data set?
  2. How many nodes at each layer are needed?
  3. How big must my data set be to properly train the network?
  4. What guarantees exist that the mathematical architecture can produce a good predictor of the data?
  5. What is my uncertainty and/or statistical confidence in the ANN output?
  6. Can I actually predict data well outside of my training data?
  7. Can I guarantee that I am not overfitting my data with such a large network?
- These questions remain central to addressing the long-term viability of ANNs.
- The good news is that such topics are currently being intensely investigated by academic researchers and industry (Google, Facebook, etc.) alike.

Thank You!

Big Sucsses