Multidisciplinary Design Optimization and Analysis of an Open Rotor Stage: Part 1

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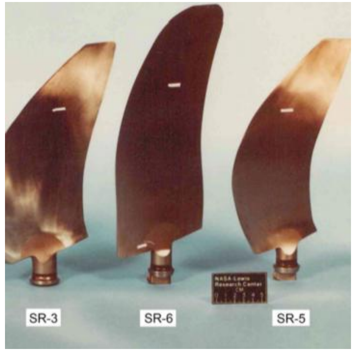

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Presentation Outline

1. Introduction and Background of Optimization Methods using the Tail Cone Thruster (TCT)
   – Brief discussion of TCT work using surrogate modelling
   – Bayesian Optimization of the TCT

2. Structural Optimization of the Open Rotor Stage

Design Variables and Geometry Generation

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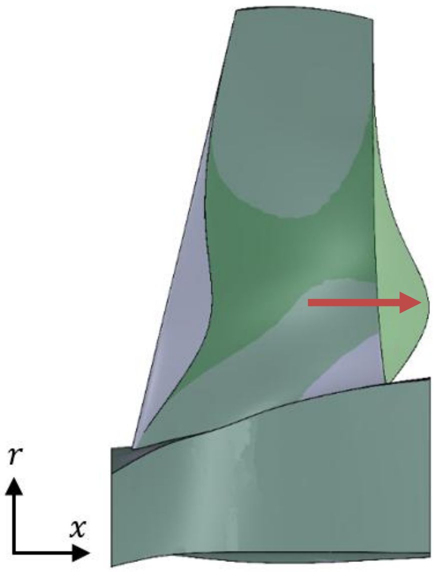
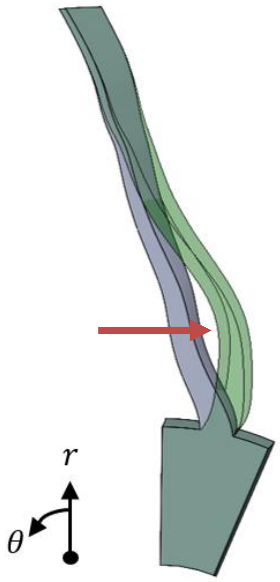
Design Variables and Geometry Generation

- Designs generated using T-Blade3.
- Lean $\Delta\theta$ and Sweep ($\Delta m'$) control points are the focus of presented work.
  - These are placed at specified locations along the blade span
- Analyses are conducted using Ansys Mechanical



Axial Sweep ($\Delta m'_{25}$)

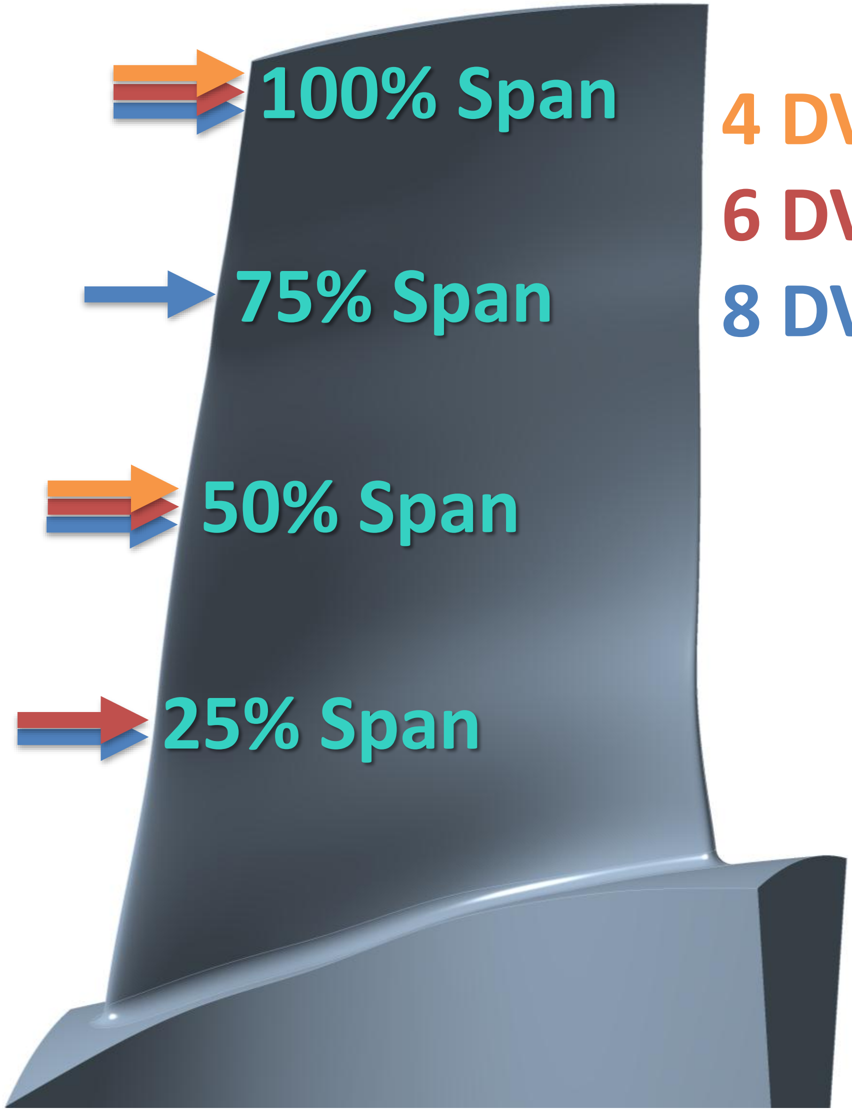


Tangential Lean ($\Delta\theta_{25}$)

141,400 Elements

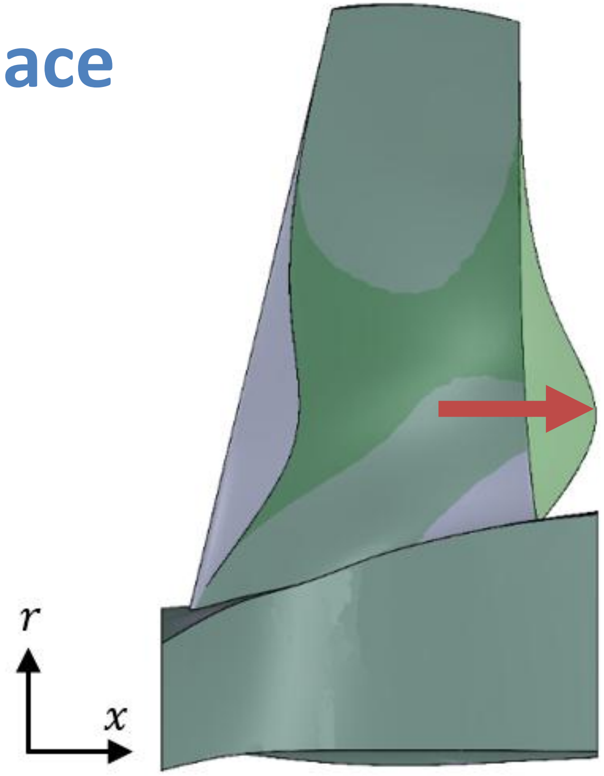
Mesh used for Optimization

Design Space

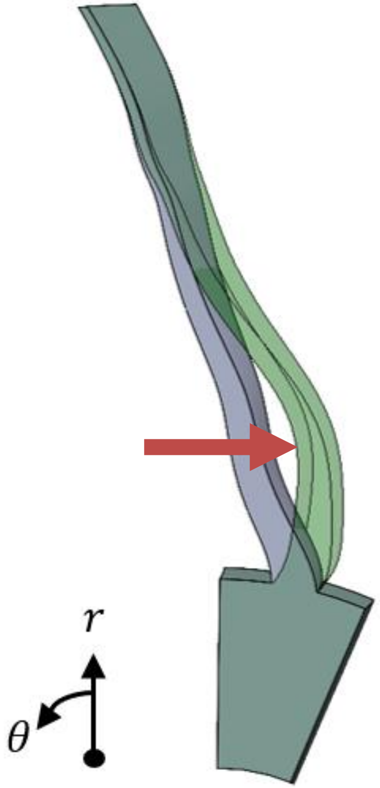


4 DV Space
6 DV Space
8 DV Space

All variables range: (-0.17,0.03)



Axial Sweep ($\Delta m'_{25}$)



Tangential Lean ($\Delta\theta_{25}$)

Baseline Model

- The material is titanium (Ti-6Al-4V (Grade 5))
- Results are presented in terms of the Margin of Safety (MS)

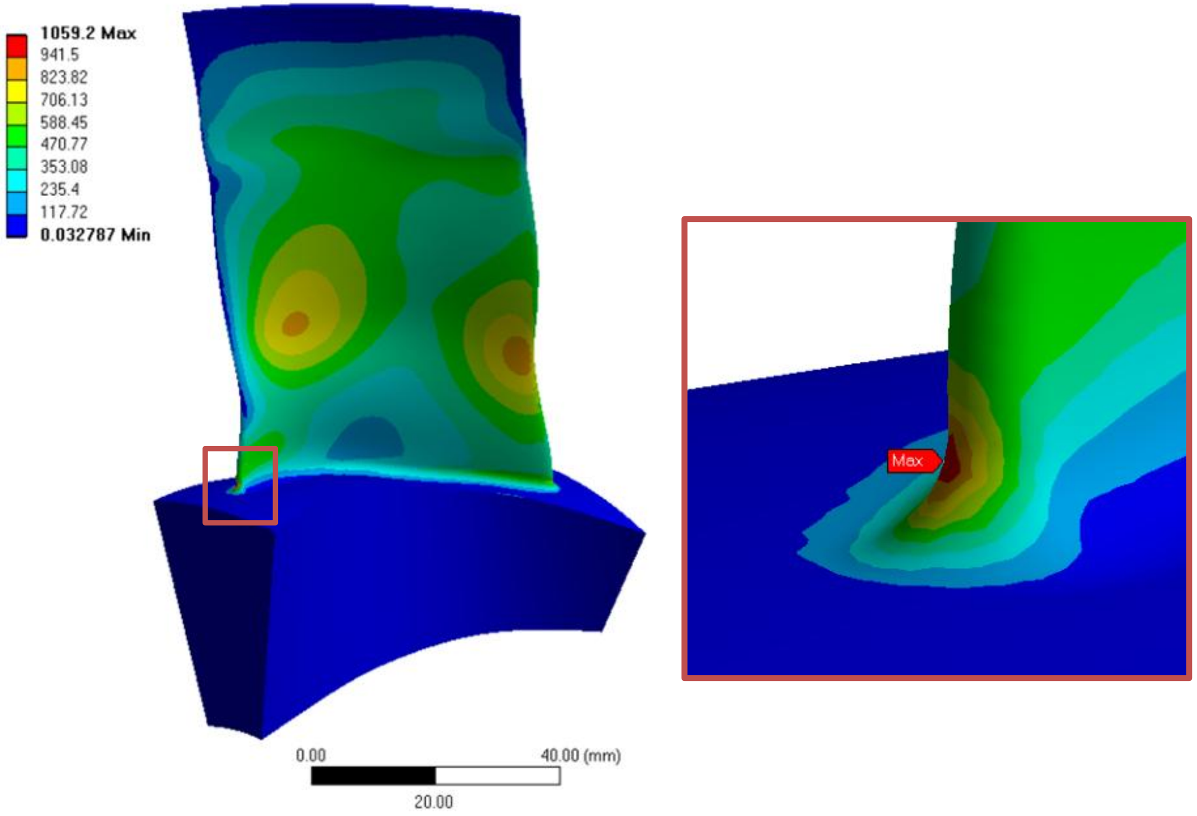
$$\mathrm{MS} = \frac{\text{Yield Strength}}{1.1 \cdot \text{Max Stress}} - 1$$

- The objective in the current study is limited to maximizing MS.
- The baseline structure is the Tail Cone Thruster 7-28-3
  - Designed at the University of Cincinnati

Material Properties of Ti-6Al-4V (Grade 5)

Density [kg/m^3]	4430
Young's Modulus [Pa]	1.14E+11
Poisson's Ratio	0.33
Tensile Yield Strength [Pa]	1.10E+09

$$\mathrm{MS}_{\mathrm{baseline}} = -0.0545$$



Motivations for Non-Gradient Based Methods

- Early work on TCT optimization had difficulty with a significant number of simulations failing, which caused issues with gradient methods.
  - This has been largely resolved.
- Additionally, the design space was found to be noisy and with local MS maxima.
- The implement Bayesian optimization method can be restarted at any point and use data from previous runs.

Latin Hypercube Sampling and Surrogate Modelling Approach

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Surrogate Training and Optimization Process

A thorough accounting of this work is provided in our 2025 Aviation Paper:

- *Structural Optimization of Turbomachinery Rotors: A Study of Machine Learning Surrogate Models*

- Sample size impact on sampling accuracy.
- Comparison of Random Forest and Neural Network (Multi-Layer Perceptron, MLP) Models.
- Investigation on the impact of design space size on surrogate accuracy.

Step 1: Choose a Design Space

↓

Step 2: Sample the Space with LHS

↓

Step 3: Evaluate Each Point in the Sample with FEA

↓

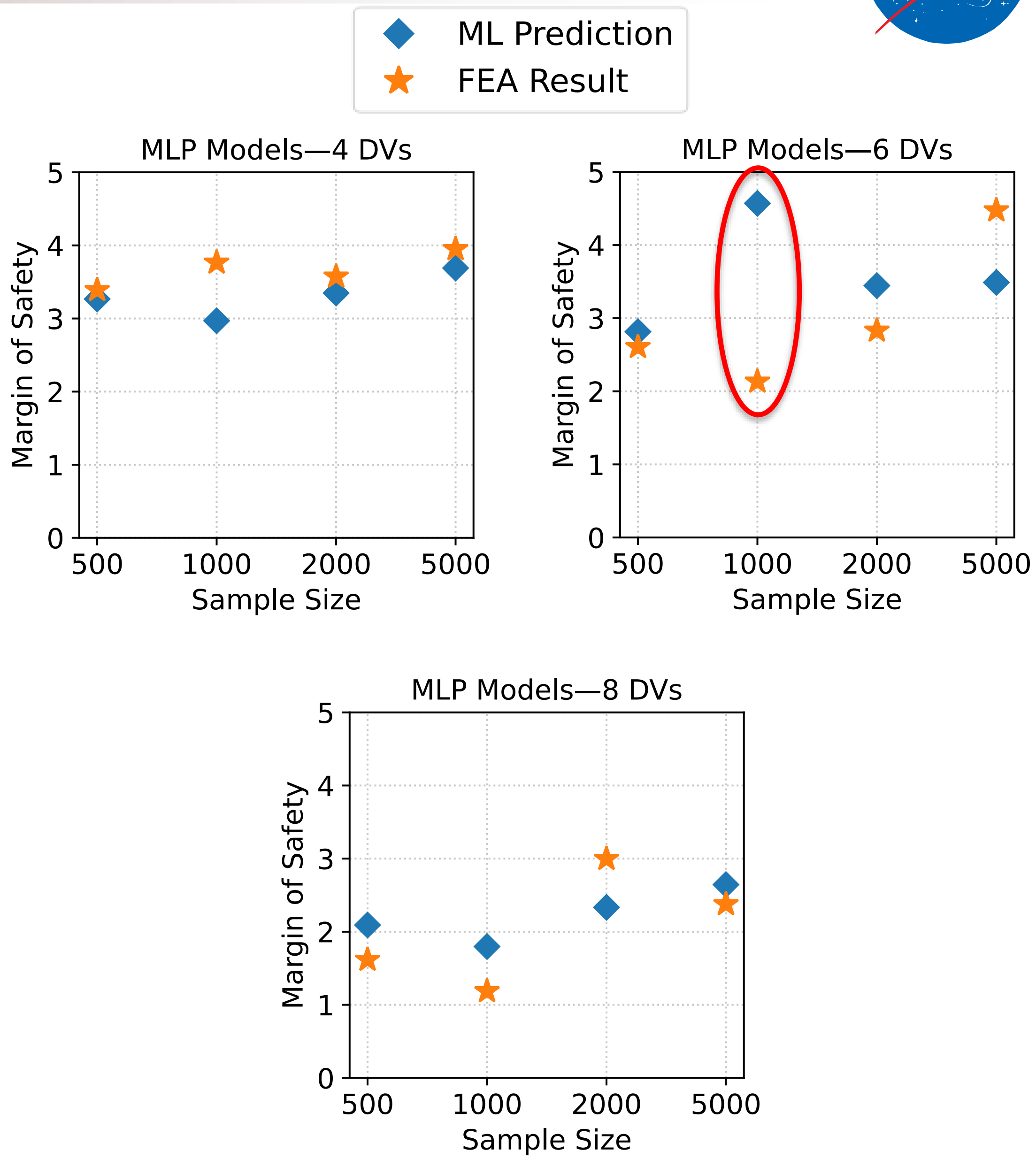
Step 4: Train a Machine Learning Model with the Data

↓

Step 5: Conduct Optimization on ML Surrogate Model

Optimization Results

- The surrogate models trained in the space with 4 DVs produced the most consistent results
- However, they were unable to achieve the performance of the best result from 6 DVs.
  - This may be a limitation of having too few design variables.
- The model training with 1000 samples suffered from extrapolation issues.
  - During the optimization, the process pushed the design to the edge of the design space, which was much poorer performing than predicted.
- For the 8 DV space, the surrogate models suffers from the ‘curse of dimensionality’
  - The best MLP models for the 8 DV space underperformed compared to the worst performing MLP model from the 4 DV space.



Bayesian Optimization

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Bayesian Optimization Basics

Surrogate Model

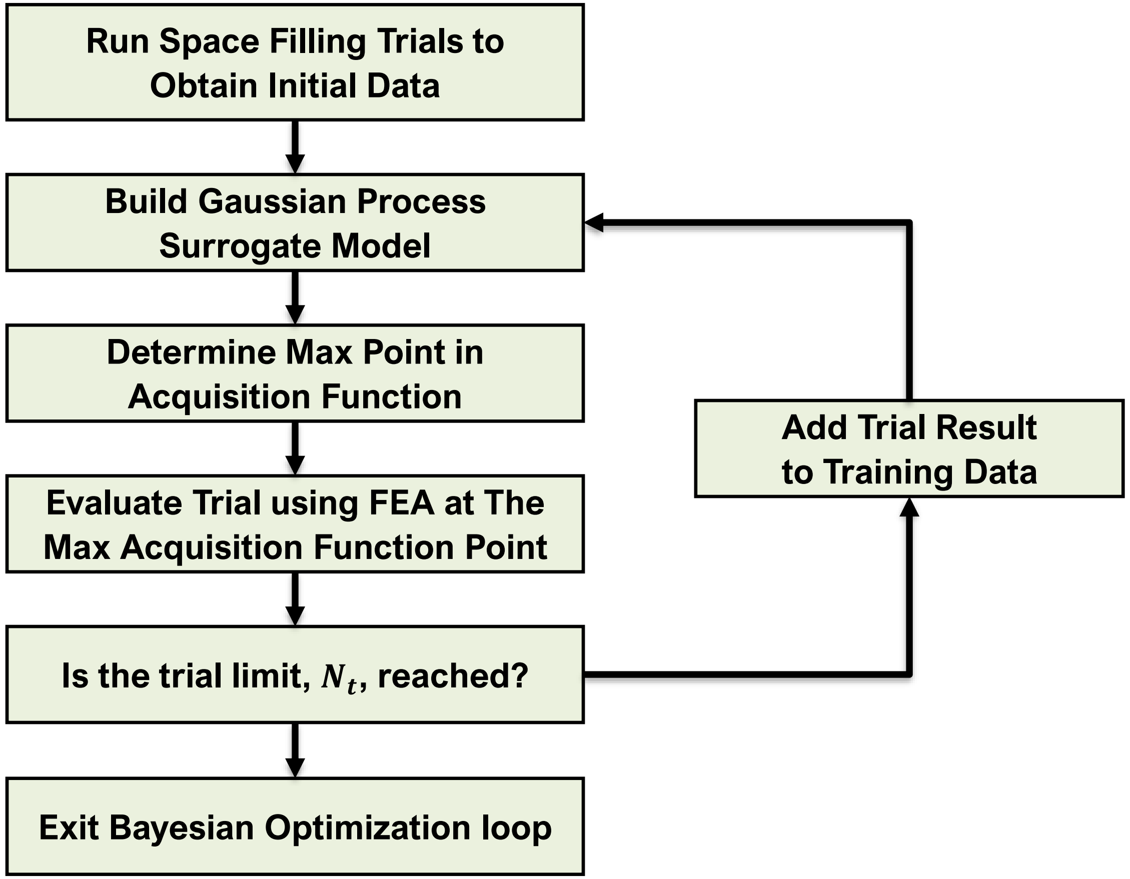
- Gaussian Process Regression Model

Surrogate Returns

- **Mean Value**
  - The best estimate of the functions value based on existing samples.
- **Standard Deviation**
  - An estimate of uncertainty based on existing samples.

Next Point Selected by Maximizing

- **Acquisition Function**
  - Using the mean and standard deviation, an acquisition function is formulated. This function is then maximized to determine the next point to sample.
  - Exploration means high weighting of uncertainty
  - Exploitation means high weighting of mean value



Acquisition Functions

- Posterior Mean
  - $\mathrm{PM}(x) = \mu(x)$

Used for high exploitation after the space has been explored

- Upper Confidence Bound
  - $\mathrm{UCB}(x) = \mu(x) + \beta\sigma(x)$

Used for exploration early in the optimization process

- Expected Improvement
  - $\mathrm{EI}(x) = \begin{cases} (\mu(x) - f^+ - \xi)\Phi(Z) + \sigma(x)\phi(Z), & \sigma(x) > 0 \\ 0, & \sigma(x) = 0 \end{cases}$
  - $Z = \frac{\mu(x) - f^+ - \xi}{\sigma(x)}$

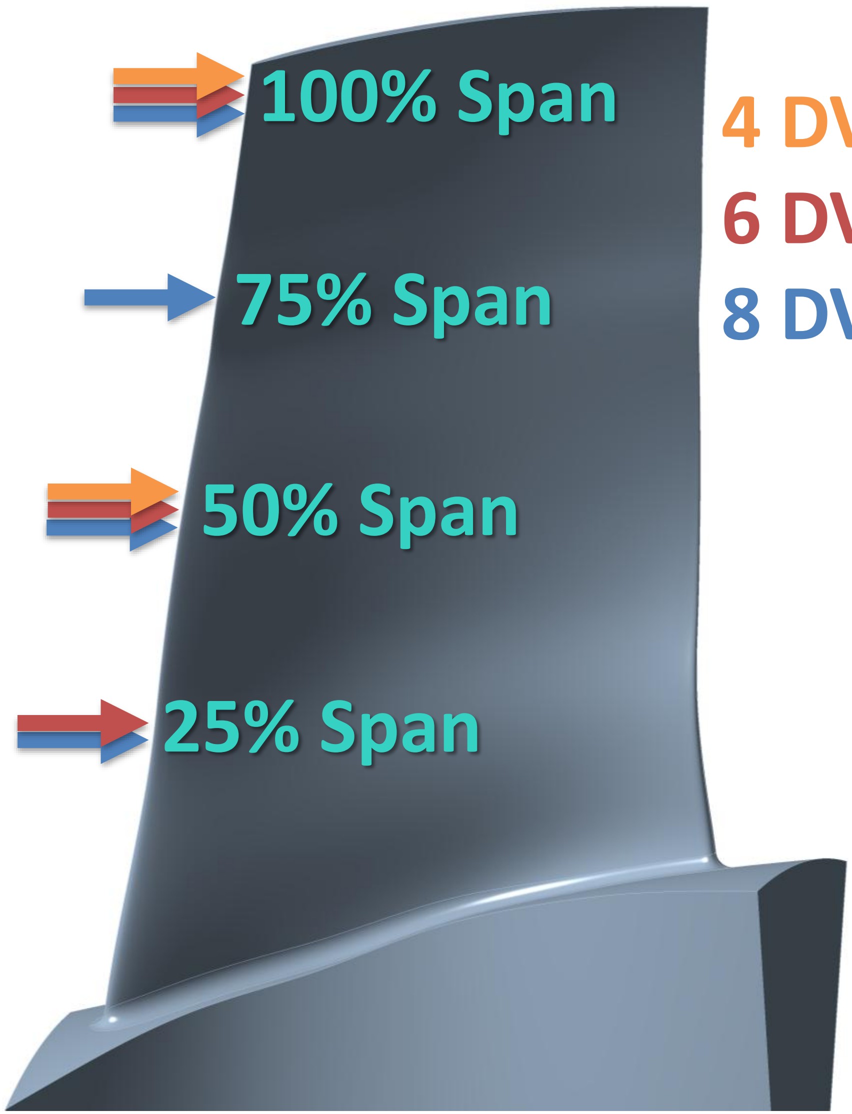
Used as an intermittent step between exploration and exploitation

f^+: current best design
$\Phi(Z)$: cumulative distribution function (CDF) of the standard normal distribution
- The probability that the prediction exceeds the current best

$\phi(Z)$: probability density function (PDF) of the standard normal
- The weighting from uncertainty

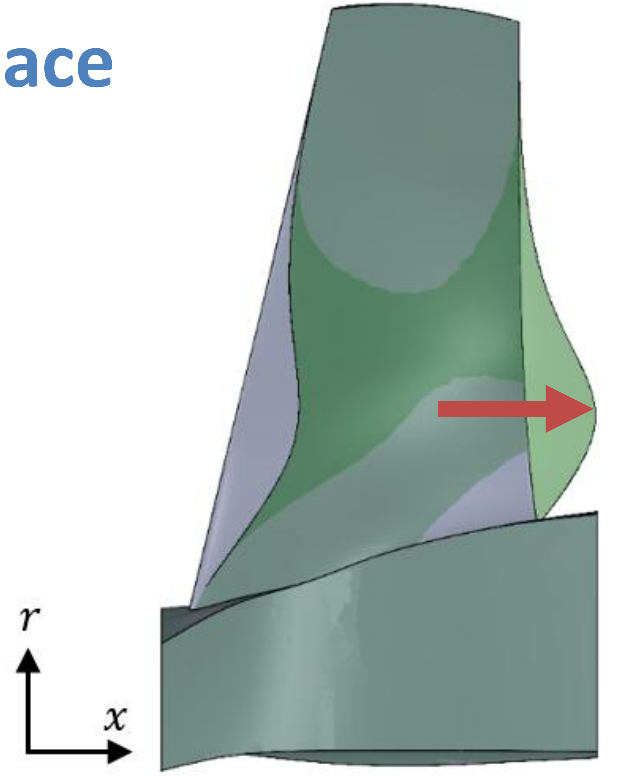
ξ: The exploration parameter
- if $\xi > 0$: the process penalizes exploitation and encourages exploration
- Ax allows only $\xi = 0$

Bayesian Design Space (Same as ML Surrogate Model)

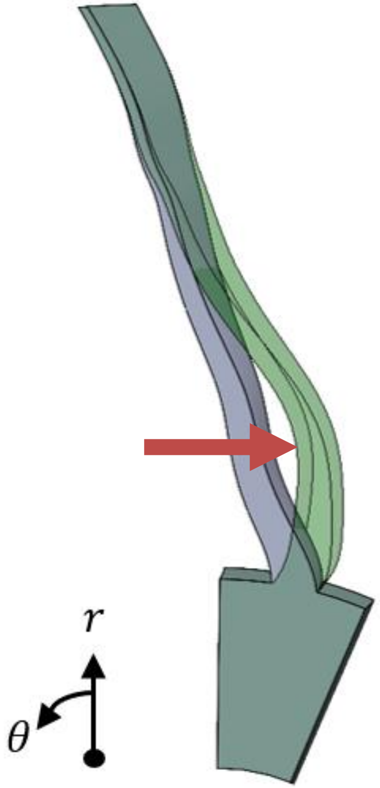


4 DV Space
6 DV Space
8 DV Space

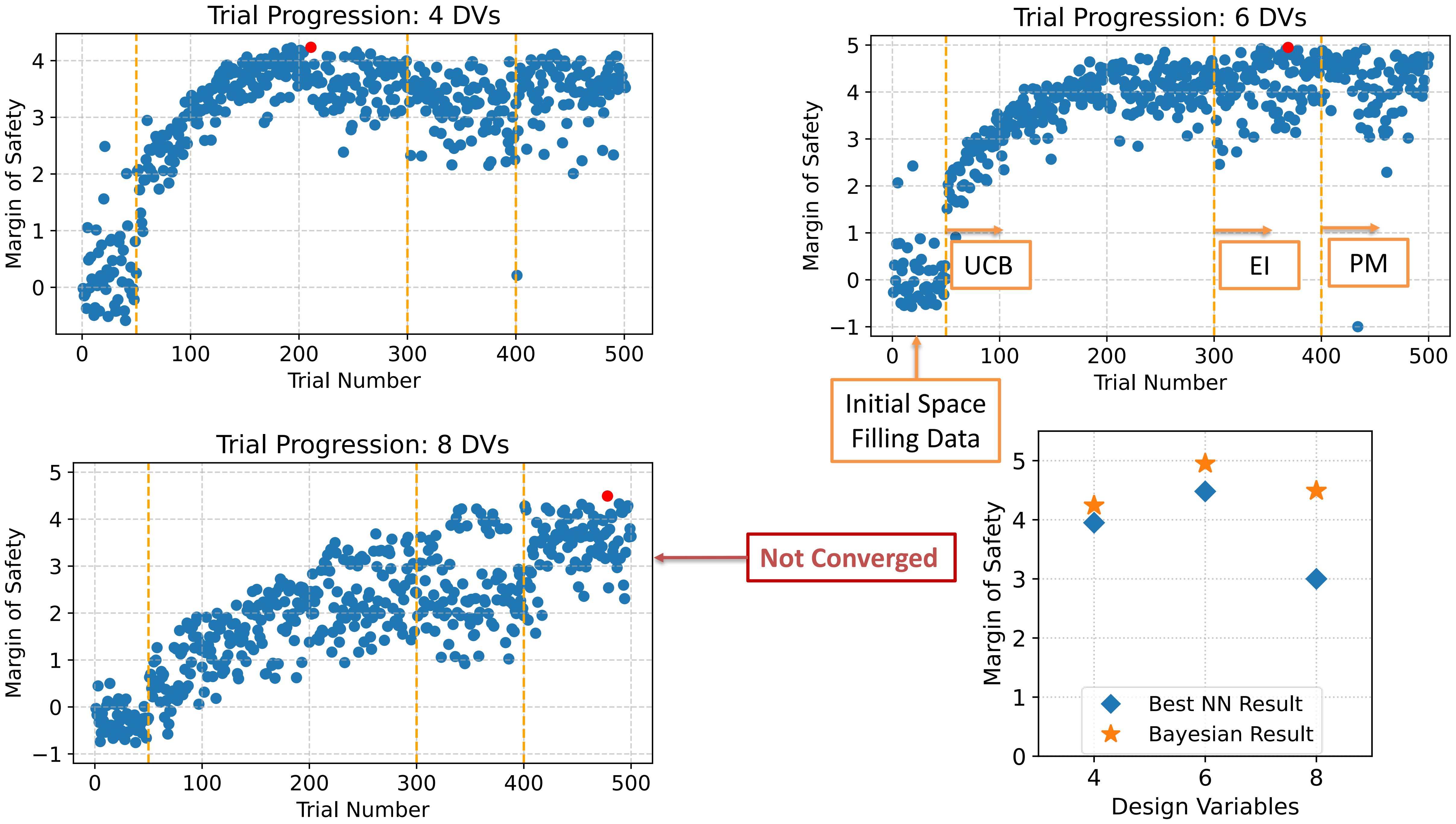
All variables range: (-0.17,0.03)



Axial Sweep ($\Delta m'_{25}$)

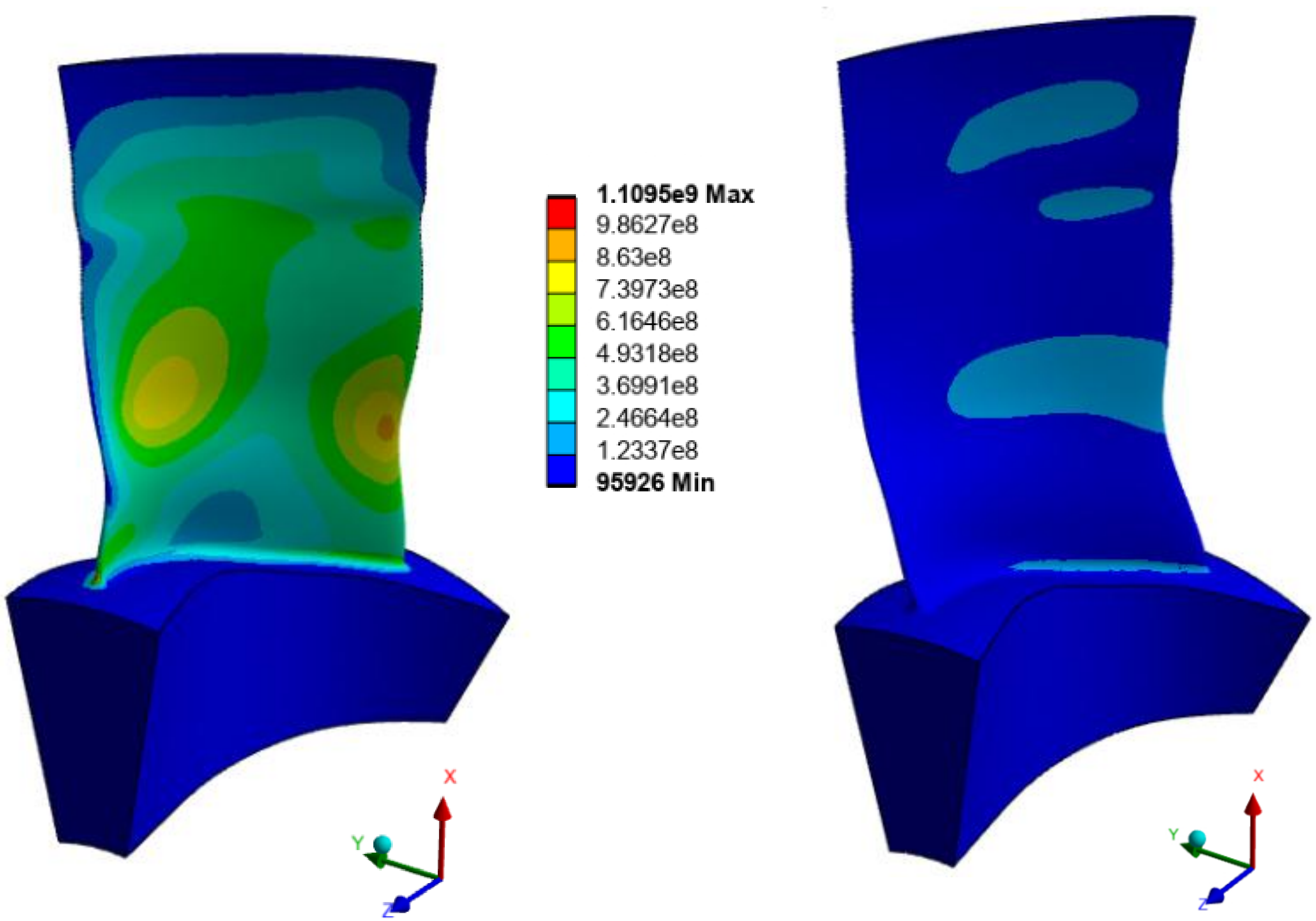


Tangential Lean ($\Delta\theta_{25}$)


Trial Progression: 4 DVs
Margin of Safety
Trial Number
Trial Progression: 6 DVs
Margin of Safety
Trial Number
UCB
EI
PM
Initial Space Filling Data
Trial Progression: 8 DVs
Margin of Safety
Trial Number
Not Converged
Margin of Safety
Design Variables
Best NN Result
Bayesian Result

Baseline vs Optimized: Von-mises Stress Contours

Baseline Design | **Optimized Design (6 DVs)**



Open Rotor

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N-OPEN-1 Optimization

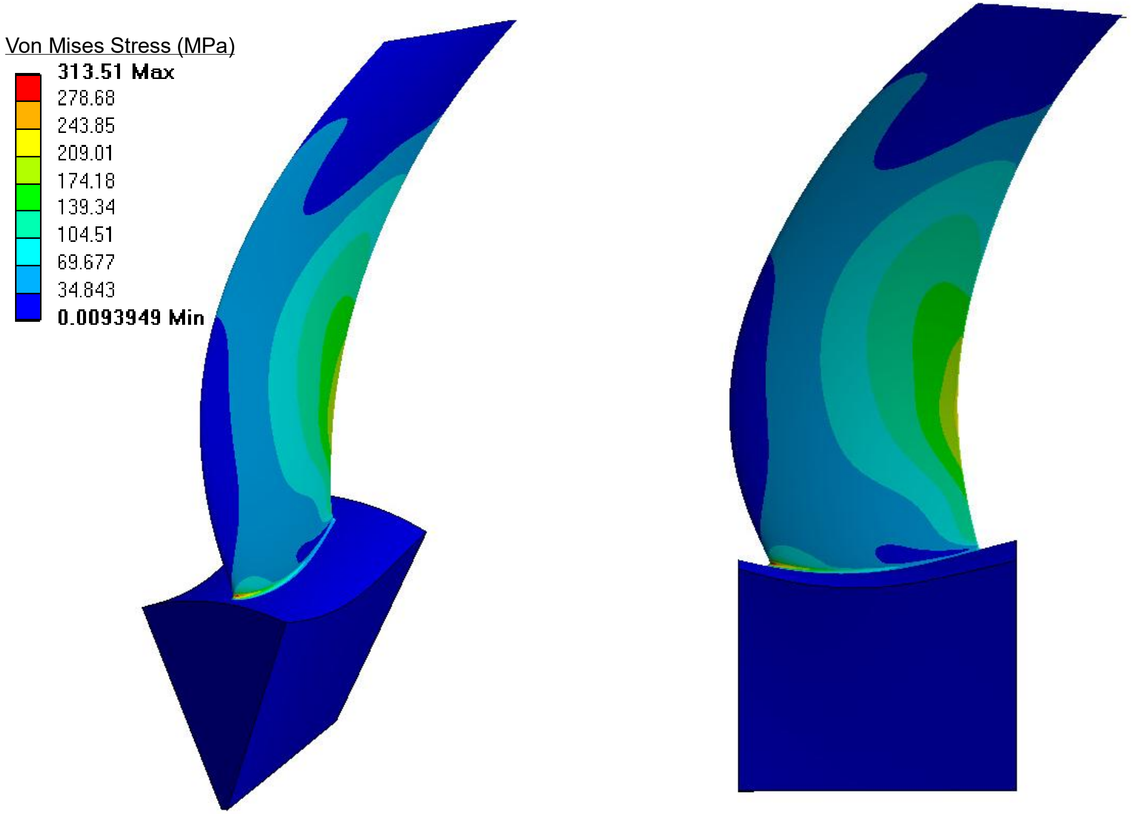
- The N-OPEN-1 design was aerodynamically optimized for cruise conditions using a wedge model to consider structural constraints.
  - Work presented at 2026 ASME Turbo Expo
    - *Design of an Open Rotor Stage*

- This model used as the structural constraint was optimized at takeoff speed, but not at takeoff pitch.

- Additionally, no pressure load was applied to the structural model.

- AL 7075-T6 was chosen as the material.

AL 7075-T6	
Density (ρ) [kg m^{-3}]	2810
Elastic Modulus (E) [GPa]	71.7
Poisson's Ratio (ν)	0.33
Tensile Yield Strength (σ_y) [MPa]	503

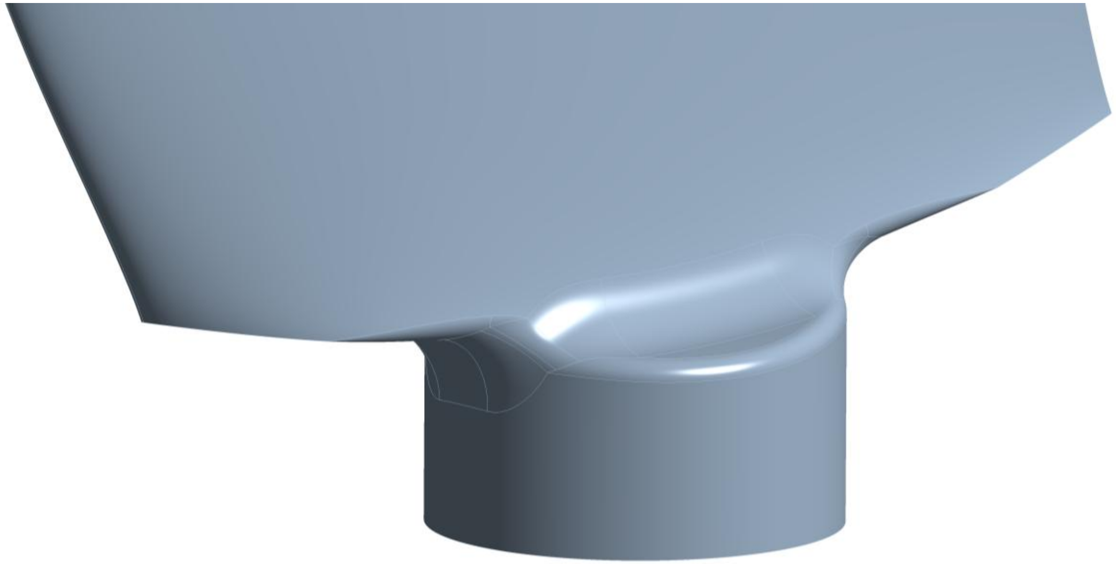


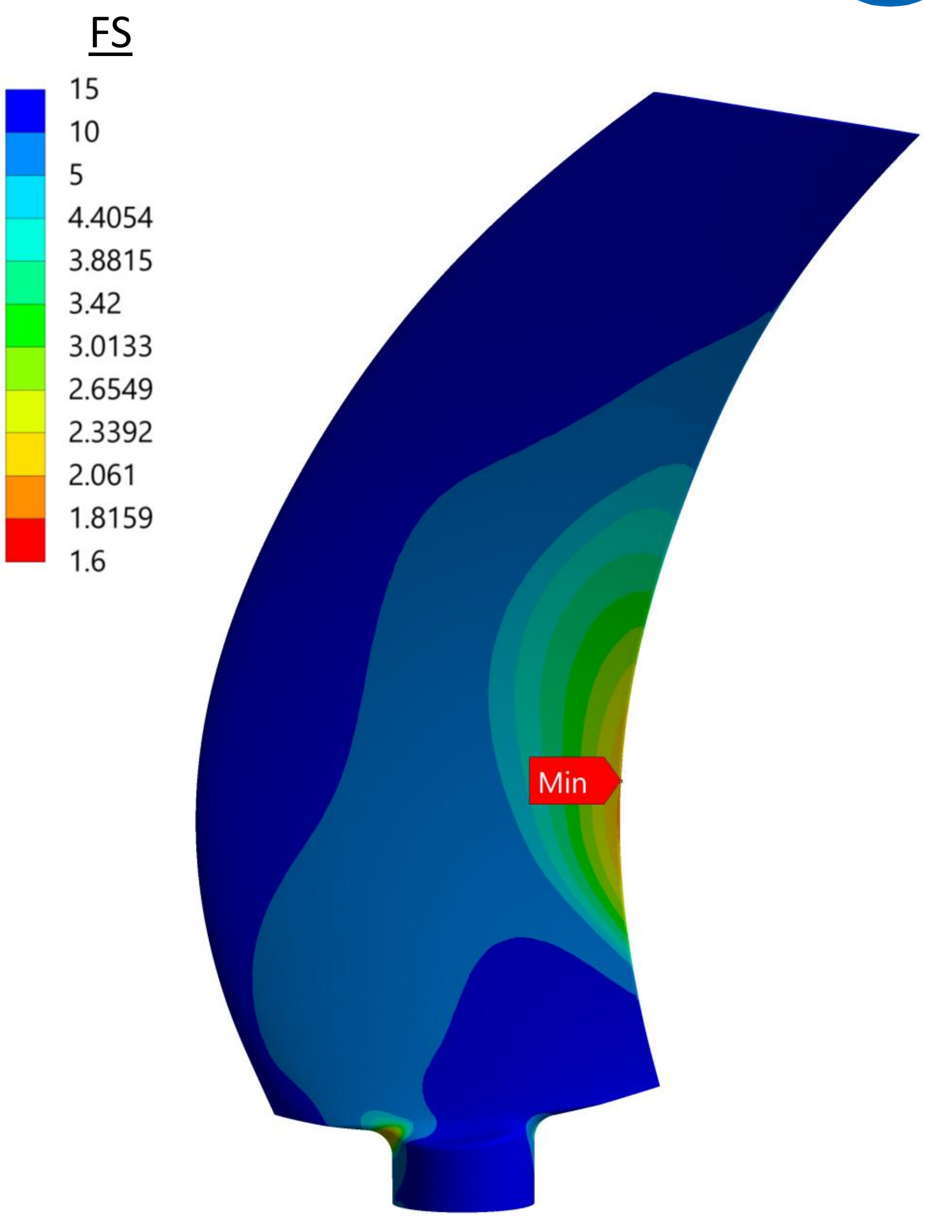
Shank Model

- The initial shank model was adapted from the N-Open-1 design by thickening the lower part of the blade span.

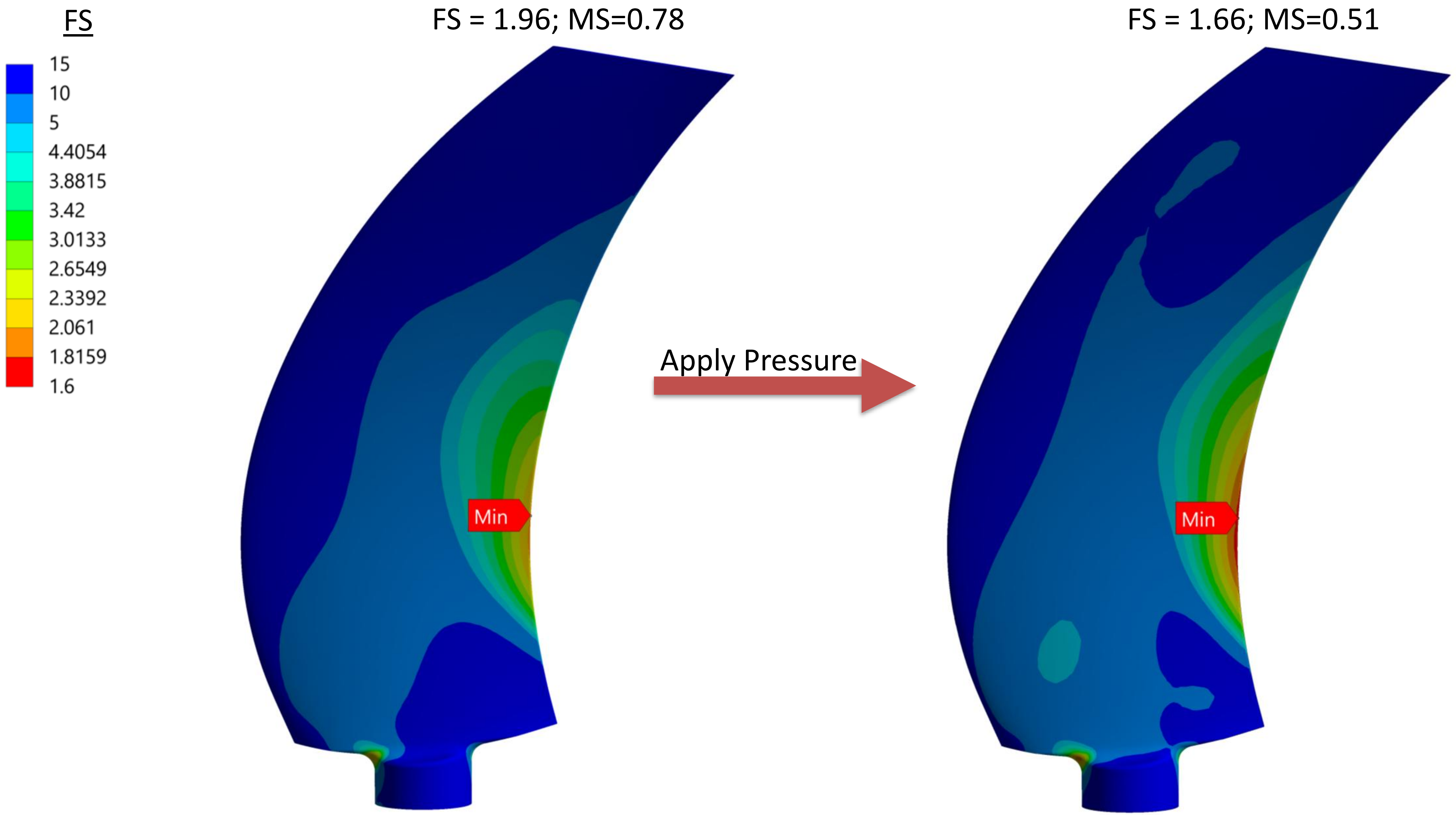
- The FEA automation now includes pitching and pressure load capability.

$$FS = \frac{\text{Yield Strength}}{\text{Max Stress}}$$

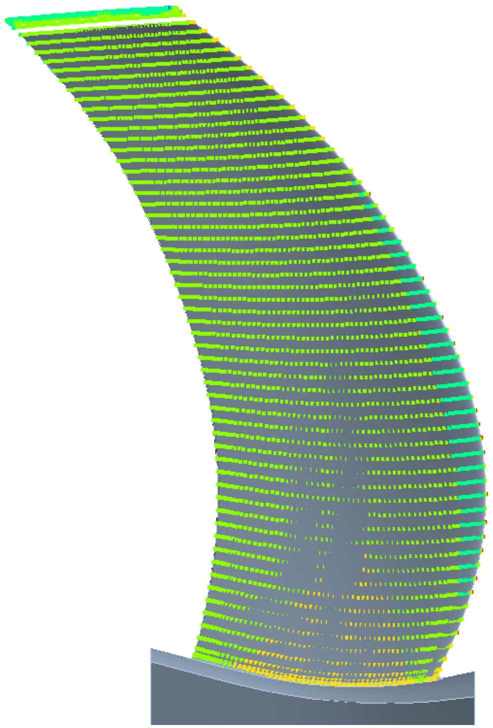




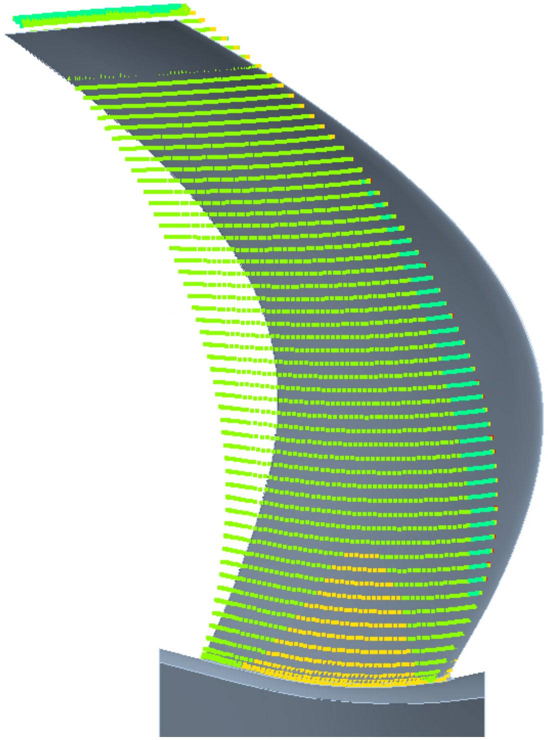
Applying Takeoff Pressure Load



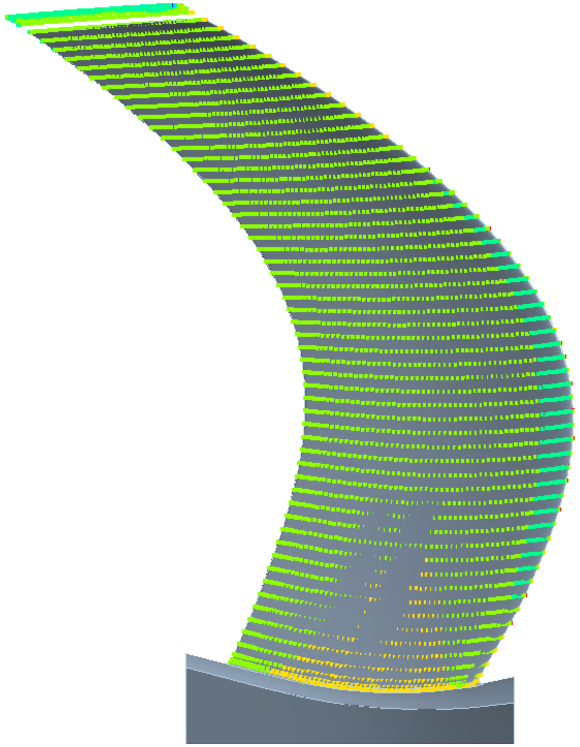
Transform Load Tool



Baseline Design with
Baseline Pressure load



Trial Design with
Baseline Pressure load

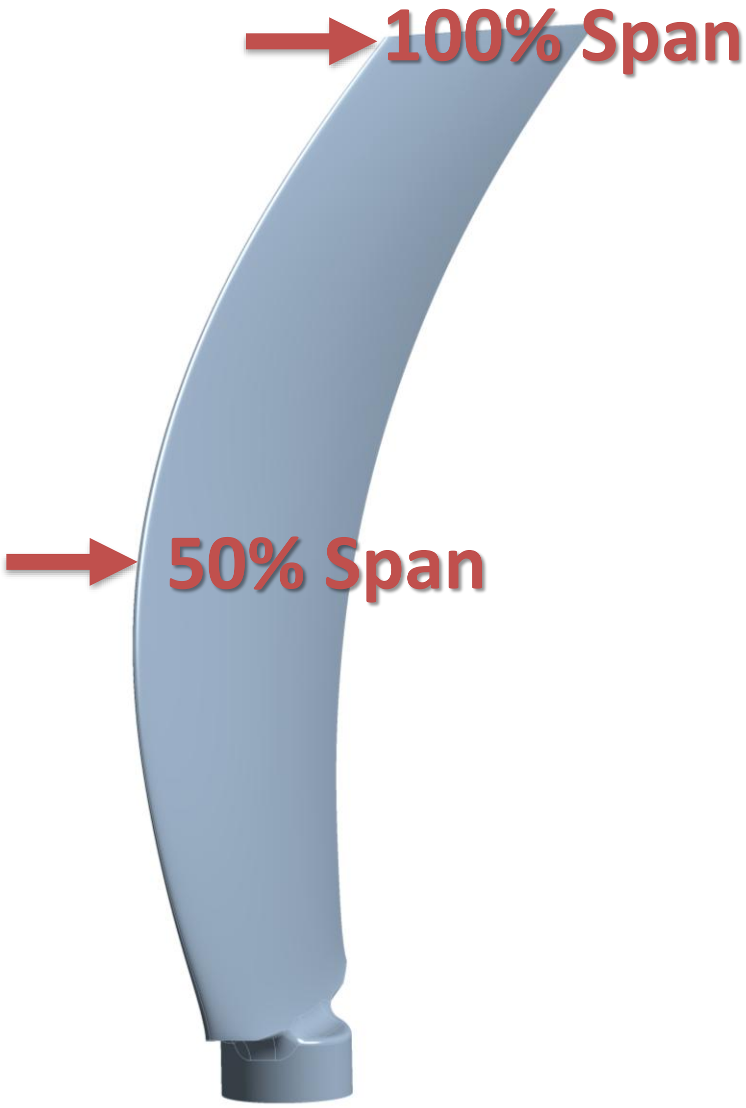


Trial Design with
Transformed Pressure load

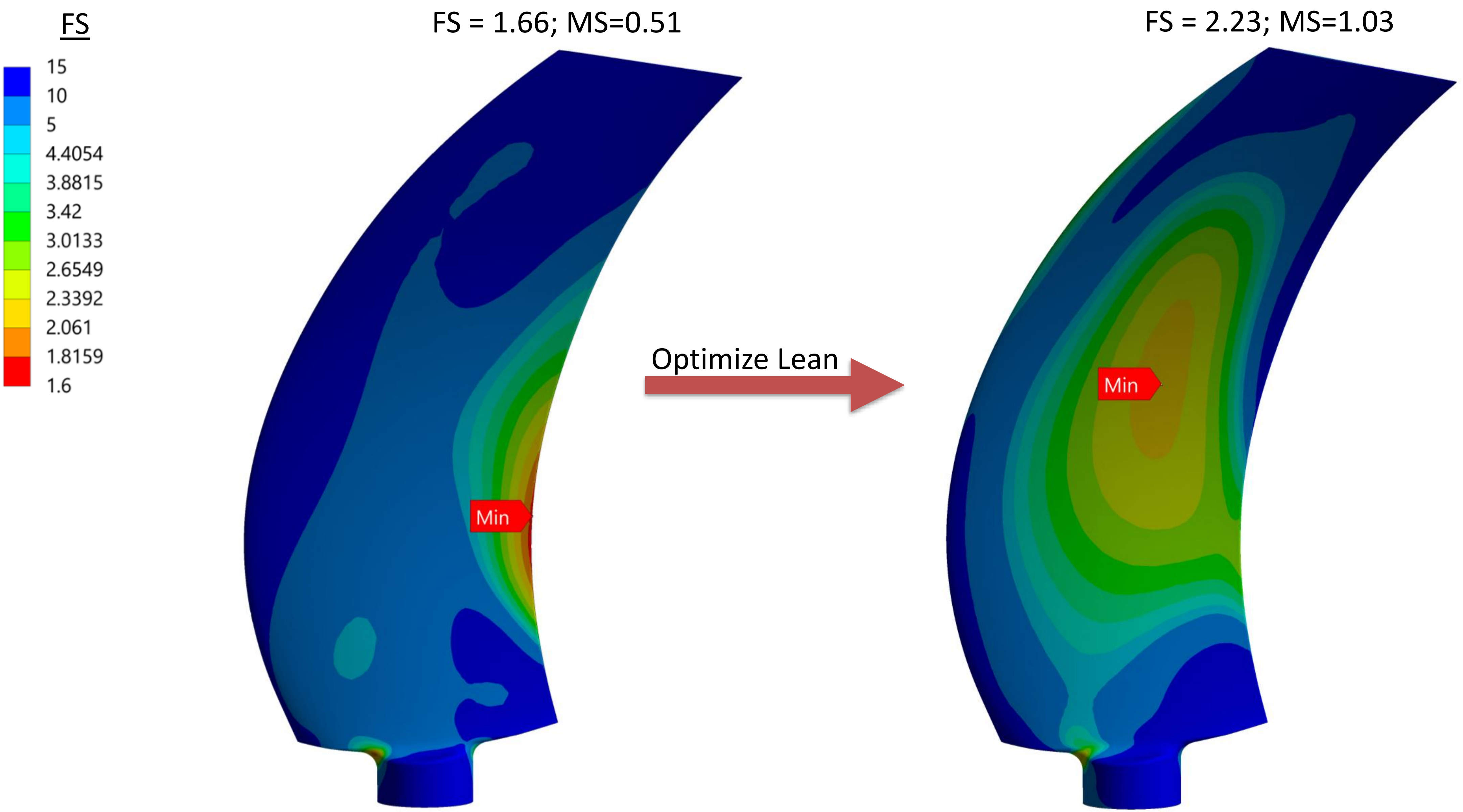
Lean Optimization

- Using the pressure loading from N-Open-1, tangential lean optimization was conducted using two control points.
  - 50% and 100% span

- The pressure load was applied during the optimization using the load transformation.
  - This assumption eliminated the need to run a CFD simulation for each FEA run.



Lean Optimization Result

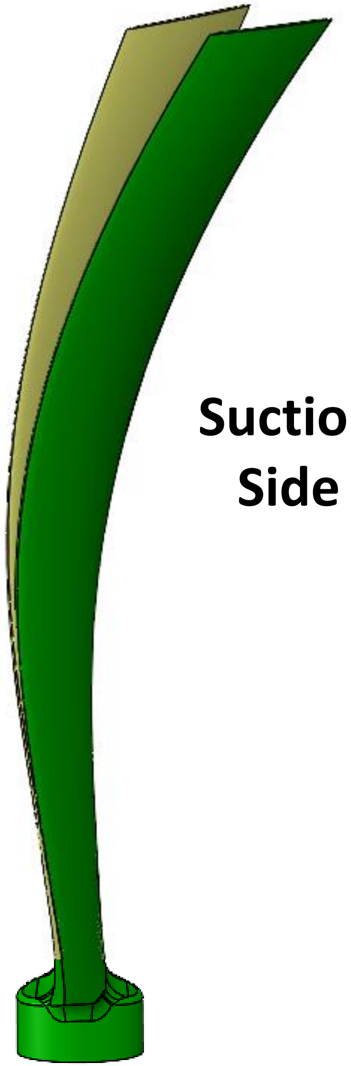


Geometry Changes

Baseline Geometry

Lean Optimized Geometry

Pressure Side

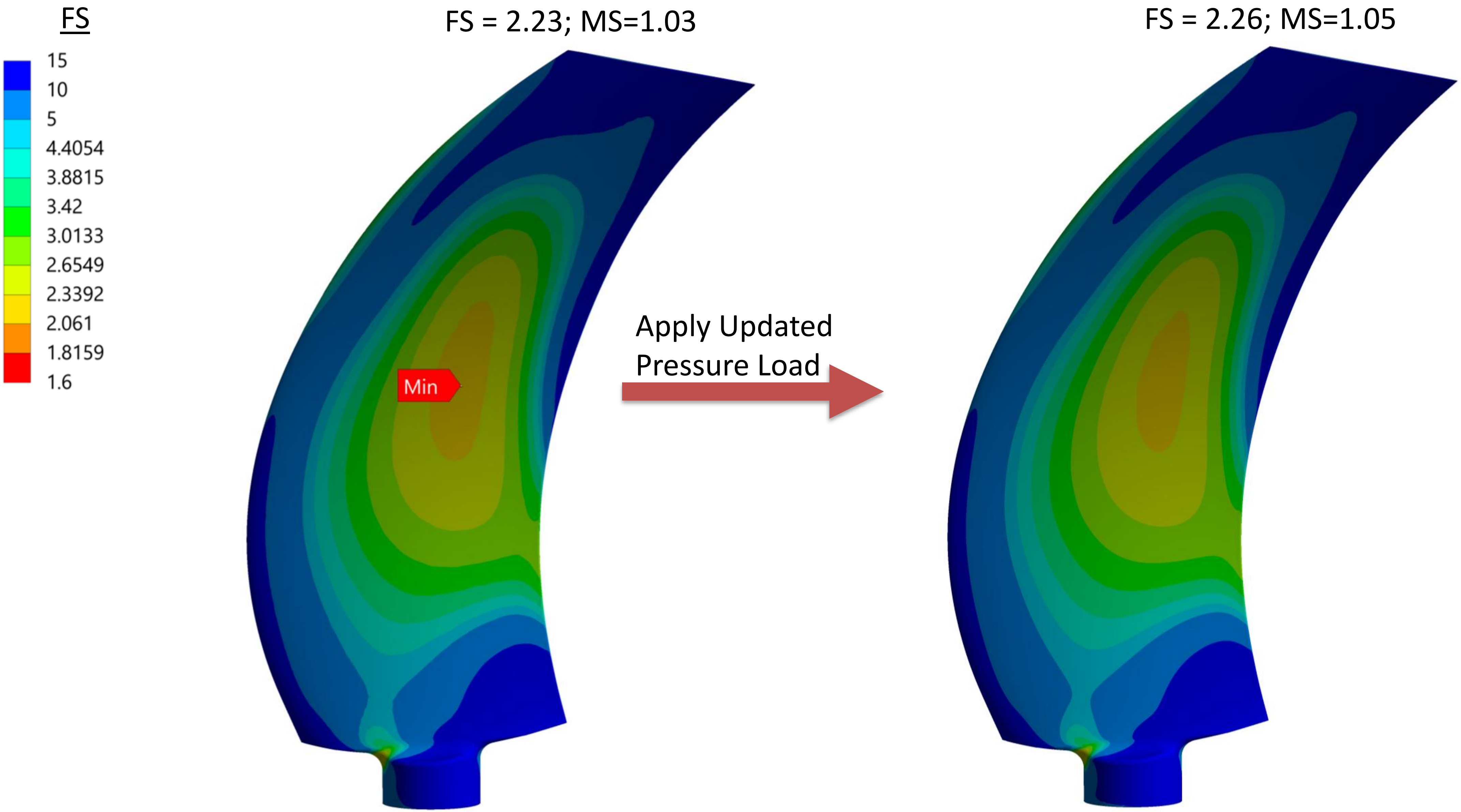


Suction Side

Pressure Assumption Impact

FS = 2.23; MS=1.03

FS = 2.26; MS=1.05



Next Steps

- The current work showed the importance of including the aerodynamic pressure when conducting structural optimization.

- It also showed that it is possible to utilize the baseline pressure load by altering its position using a radial basis function.

- The next steps in this work is the coupling of aero and structural optimizations, which will be presented in the following timeslot.

- For a more in-depth discussion on Bayesian optimization, please see our SciTech 2027 Papers:
  - *Bayesian Optimization Applied to Turbomachinery Structural Optimization*
  - *Aero-Structural Optimization of the Open Rotor Stage Design (N-OPEN)*

Questions?

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TCT Mesh Study

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Mesh Refinement on Baseline Design

Coarse

141,400
Elements

Medium

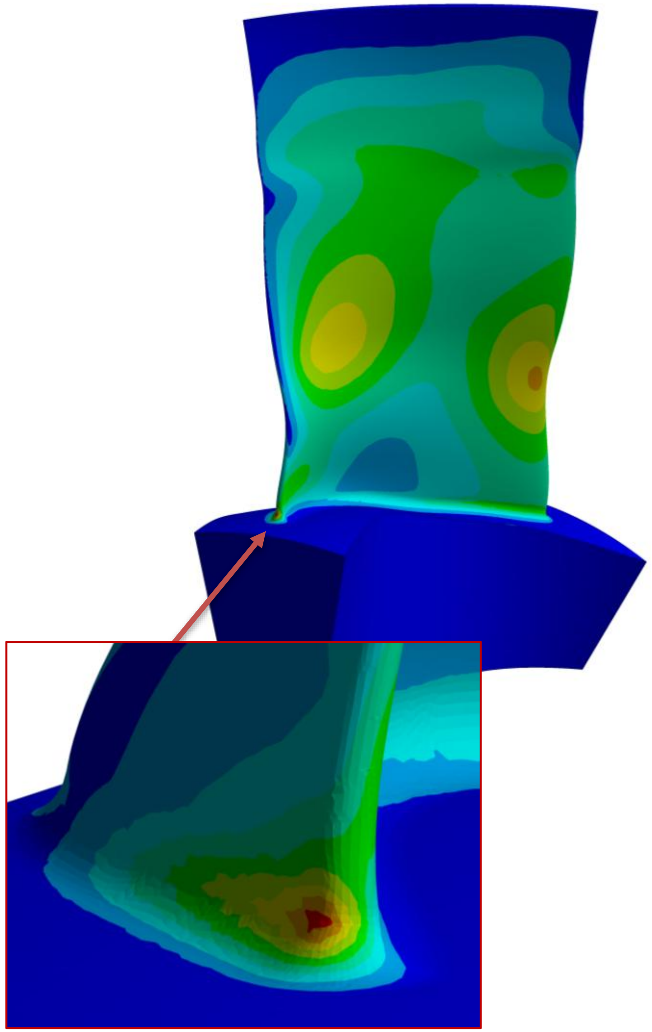
953,980
Elements

Finest

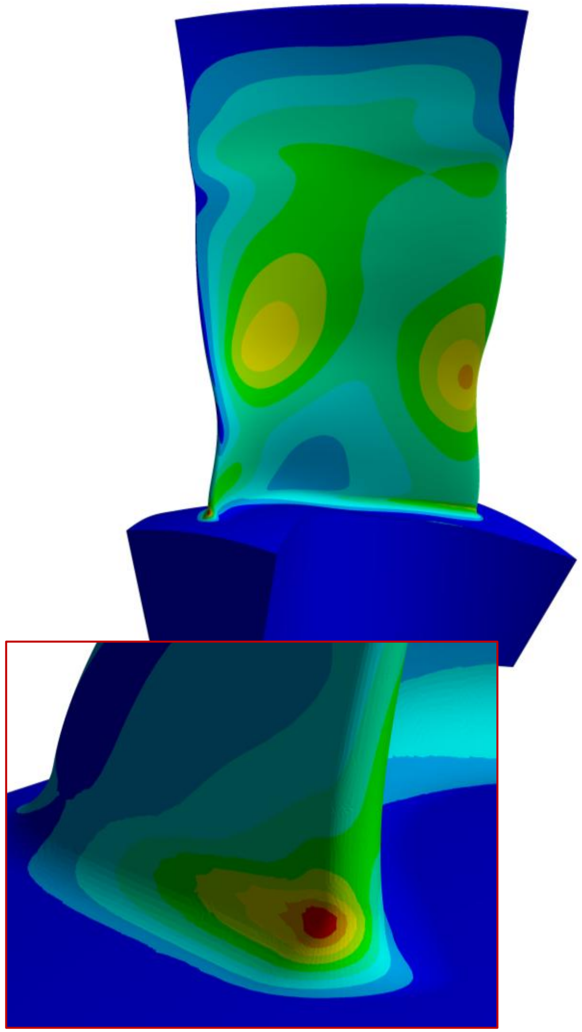
6,932,500
Elements

Mesh Refinement on Baseline Design

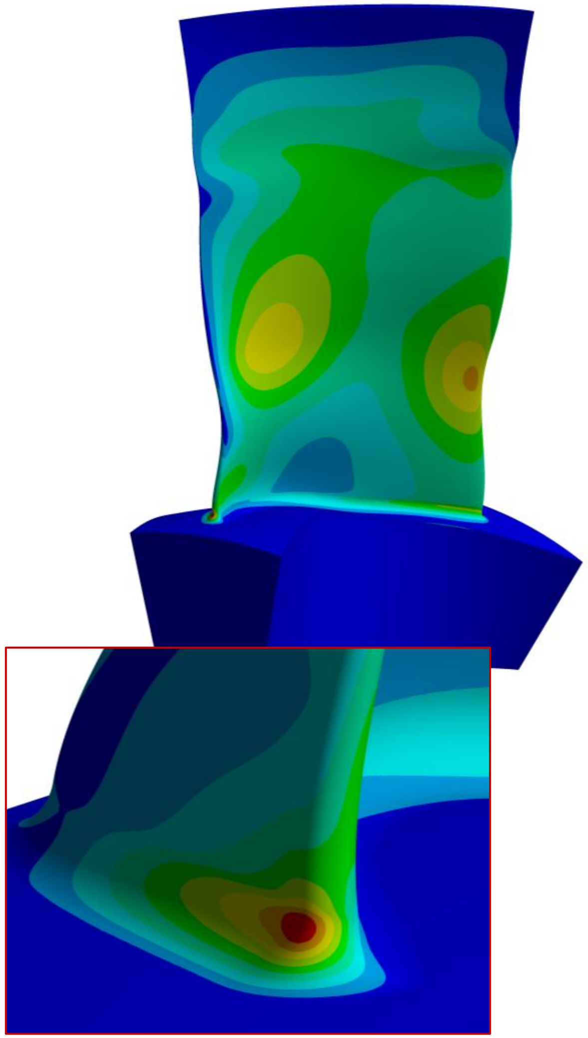
Max Stress:
1,077 Mpa
-3.33% vs. finest



Max Stress:
1,110 Mpa
-0.33% vs. finest



Max Stress:
1,114 MPa

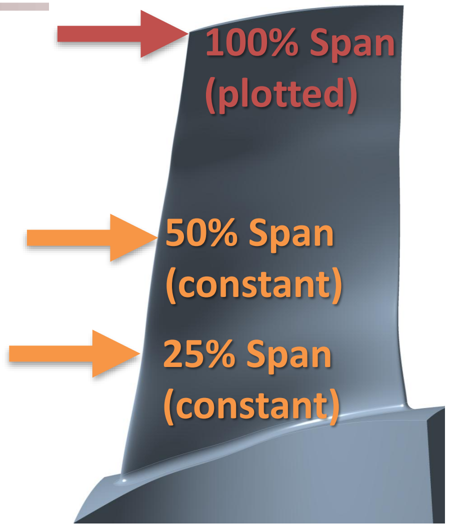


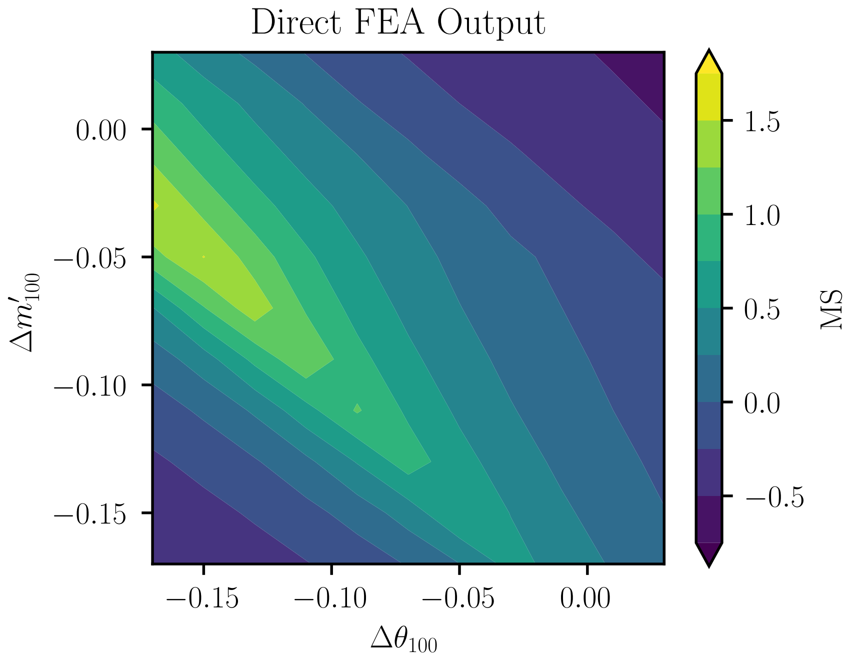
Design Space Visualization

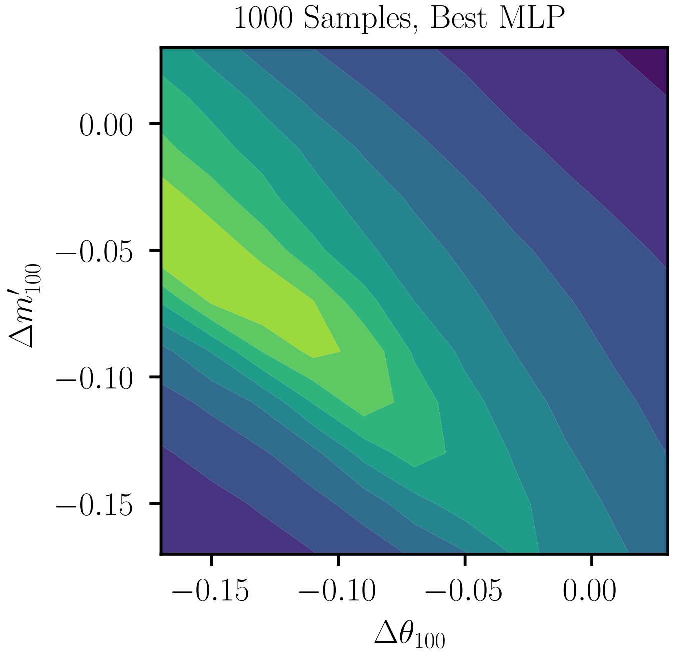
- The plots are a 2D slice of the six-dimensional design space.
  - Direct FEA Output
  - MLP model trained with 1000 samples
  - RF model trained with 1000 samples

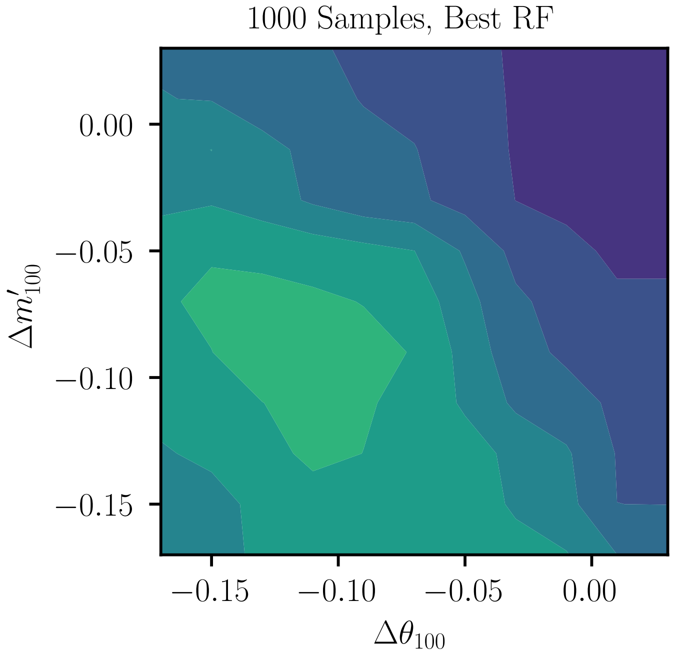
- The MLP model shows excellent capability of recreating the space
  - Random forest struggles.

- Other evaluations included in the full paper were consistent with these results.









Surrogate Modelling Conclusions

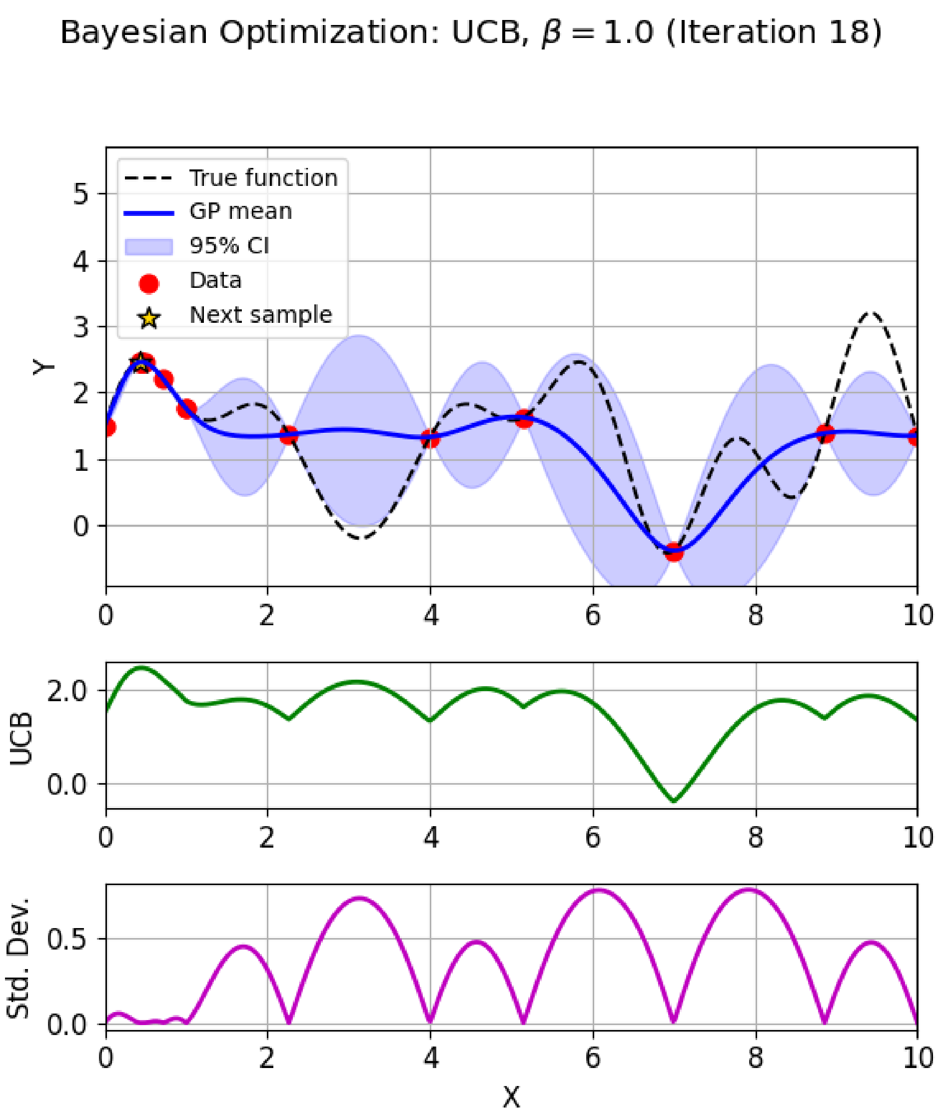
- Neural Network models consistently outperformed RF models.
- Despite superior accuracy, some MLP models experienced extrapolation issues during optimization, predicting unrealistic optima at the edges of the design space.
- Accuracy significantly declined with increased dimensionality (curse of dimensionality).
  - This resulted in poorer performance in design optimization for the 8 DV space.
- As a next step in this research, focus will be shifted to Bayesian Optimization methods, which avoid spending excessive resources in regions of poor performance.

Bayesian Optimization

- Bayesian optimization is a more effective method of selecting points to build the surrogate model.
  - Recall that in the previous section, the method characterized the entire design space equally, spending many resources in regions with poor performance.
- **Focuses sampling in areas of high performance or uncertainty**
  - prioritizes regions likely to improve results.
- **Works in high-dimensional spaces**
  - Gaussian process surrogate model works well with up to 15 design variables.
- **Adaptive and data-driven**
  - Surrogate model updates with each new trial.
- **Applicable to various types of design variables**
  - Continuous Variables (range of floating-point numbers)
  - Integer Variables (range of integers)
  - Categorical Variables (labels without inherent order)
    - For example: red, green, blue
    - Material selection is a good example of a categorical variable that could be used in turbomachinery design.

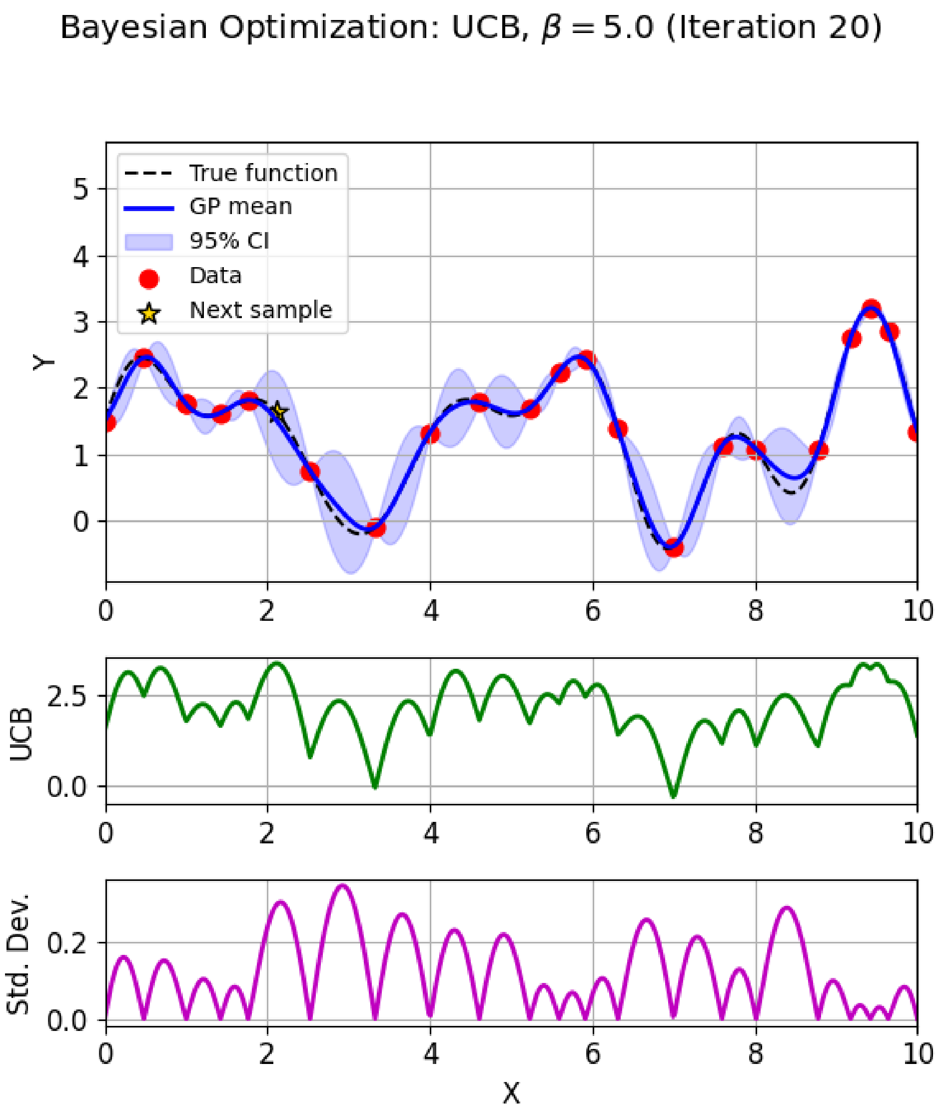
Acquisition Function: Upper Confidence Bound

- The following two examples will showcase the effect of the β parameter on space exploration.
- First, consider the case to the right with $\beta = 1.0$.
- This case becomes stuck in a local maxima.
  - Due to low weighting of uncertainty
  - Repeatedly provides that point as the next trial.
  - After Iteration 17, it is completely stuck.
- This highlights the detriment of not favoring exploration enough.



Acquisition Functions: Upper Confidence Bound

- With $\beta = 5.0$, the UCB function becomes much more exploratory.
- At iteration 12, the best point in the range is proposed as a trial.
- At iteration 20, one can that this approach is highly exploratory.
- Note that there is a detrimental effect of setting β too high in that more resources may be spent in regions of low performance.
- My testing has shown that for the structural optimization problem, $\beta = 5.0$ provides a good balance of exploration.



Open Rotor Stage Mesh Study

Element Count	5.7.8.13 (No Pressure)
120206	1.964
784904	1.981
5530651	1.977

Element Count	5.7.8.13 (With Pressure)
120206	1.651
784904	1.664
5530651	1.664

Element Count	5.7.8.14 (Pressure Load)
121969	2.2314
793421	2.2312
5569812	2.2311