RL for Aerodynamic Shape Optimization

AIrFoil – Increasing the Efficiency of Air Source Heat Pumps

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Introduction

In the research project AIrFoil[1] an international consortium works on improving Air Source Heat Pumps by leveraging a new design concept involving **homogenization of the airflow before the heat exchanger**. This produces

- less noise, and in turn
- the ability to increase the ventilator rotational speed, leading to
- a more efficient heat transition at the heat exchanger of the air source heat pump.

How much the concept improves low noise or efficiency can be chosen by the user.

Method

The homogenization is produced by inserting a flow rectifier into air flow before the heat exchanger. We follow the approach of continuous interpretable aerodynamic shape optimization (ASO) with

- **Reinforcement Learning (RL)** with a geometry **model** $\mathrm{M}: \Theta \to \Theta$ for the incremental changes of the geometric parameters: $\mathrm{M}(\theta) = \Delta\theta$
- an interpretable geometry parametrization based on the airfoil parameters **PARSEC** [2].

The strategy to be learned by RL is when to freeze some parameters from the 11 PARSEC + 3 camber dimensions [6] to fewer degrees of freedom to increase the performance to a feasible calculation speed of the full configuration's optimization.

1st Results

We observe that

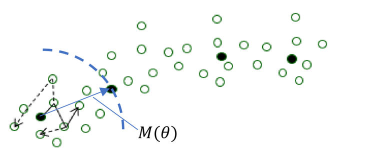
- the different representations of the PARSEC parametrization ($Z(x) = \sqrt{x}p(x)$ with a order 5 polynomial $p(\cdot)$) given by different ways of writing the polynomial (roots, coefficients, PARSEC – parameters [2]) can be used to freeze some degrees of freedom along the optimization procedure,
- which is useful for the performance speed of the remaining optimization,
- and renders physical insight in terms of the interpretable PARSEC design parameters.

In a simple 2-D **Example** a redirection of a flow-field can be achieved with only 2 parameters (roots of the polynomials) without Camber line parameters. It is the foundation for a 3-D design procedure and significantly contributes to coping with the 'curse of dimensionality'.

The images on the right show a linear interpolation between optimization results for different inflow angles (red=high, blue=low). This is needed for the blades of the rectifier in the full configuration.

Reinforcement Learning for accelerated interpretable Aerodynamic Shape Optimization

Objective: Optimal $\Delta\theta$ *and* optimal optimzation-strategy
States: $S = \Theta$, **Actions**: $A = \{\Delta\theta_i\}$, **Policies**: $\{\pi_i(\cdot\,|\theta)\}$
Return: $R(\theta, \hat{G}(\cdot,\theta), \{\theta_0^{(i)}\}_i)$ is estimated from the analytical estimate $\hat{G}$ of the reward. The actions in the *i*-th step allow freezing single state variables to decrease number of dimensions.
Use actions as sensitivites in θ's to *explain* most important adaptions, used in changing policies.



Scaling: Use two scales – One for larger parameter-adaptions between CFD-calculations, and one for local optimization (mesh-level). RL is performed in the cells (dashed blue line) of the larger scale.

$$\theta \in \mathbf{\Theta} \subset \boldsymbol{R}^d, \qquad x \in \mathbf{X} = \boldsymbol{R}^3 \backslash \boldsymbol{B} \subset \boldsymbol{R}^3 \qquad u \in C^2(\mathbf{X} \times \mathbf{\Theta}, \boldsymbol{R}^3)$$

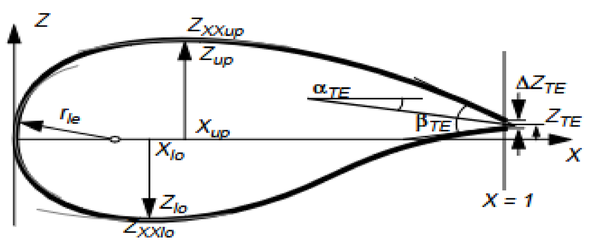
$$u_i(x, \theta + \Delta\theta) = u_i(x,\theta) + \langle \Delta\theta, \partial_2\, u_i(x,\theta)\rangle + \frac{1}{2!}\langle \Delta\theta, d_2^2 u_i(x,\theta)\Delta\theta\rangle + O(\Delta\theta^3)$$

Reward: $G(\Delta\theta) = \frac{u_1(x,\theta+\Delta\theta)}{|u(x,\theta+\Delta\theta)|}$

Estimate by surrogate: $\hat{G}(\Delta\theta) = \frac{\hat{u}_1(x,\theta+\Delta\theta)}{|\hat{u}(x,\theta+\Delta\theta)|}$ estimating gradient $\widehat{\partial_2 u}(x,\theta)$.

Reduced PARSEC (with fixed roots)

Idea: In PARSEC parametrization use root-factorization representation of polynomial and **fix roots**. Get Interpretation from change in PARSEC-Prmts.



Recipe: (During one cycle)

1. Choose PARSEC-Parameter $\theta \in \Theta$.
2. Calculate Coefficients $\boldsymbol{a^i}, i \in \{1 \dots 6\}$.
3. Find roots x_i of $p(x)$.
4. Observe **stability** of roots.
5. Choose action: If root stable, reduce parameter space by 'fixing' this root. Results in smaller # of dimensions.
6. Calculate resulting parameters $\theta' \in \Theta$.
7. **Interpret** parameter changes $\Delta\theta = \theta' - \theta$.

$$z_{up} = \sum_{i=1}^{n=6} a_{up}^i \cdot x^{i-\frac{1}{2}}, \qquad z_{lo} = \sum_{i=1}^{n=6} a_{lo}^i \cdot x^{i-\frac{1}{2}}$$

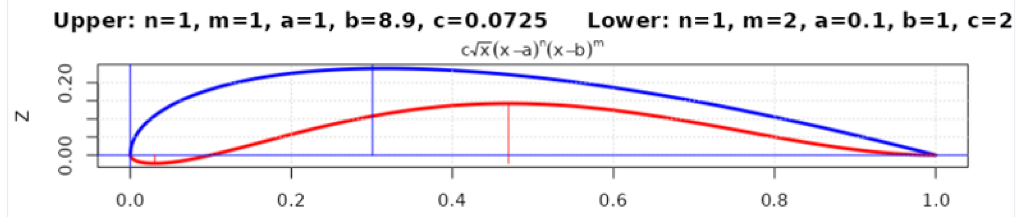
Reduced PARSEC:

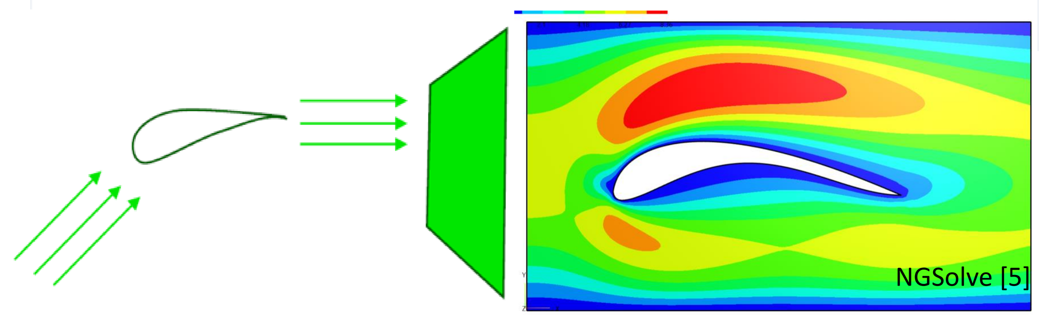
$$Z(x) = \sqrt{x}p(x) = \sqrt{x}c\Pi_{i\in\{1\dots5\}}(x - x_i)$$

Roots x_i plus amplitude c are an equivalent representation. It is useful for *reducing* the number of degrees of freedom.

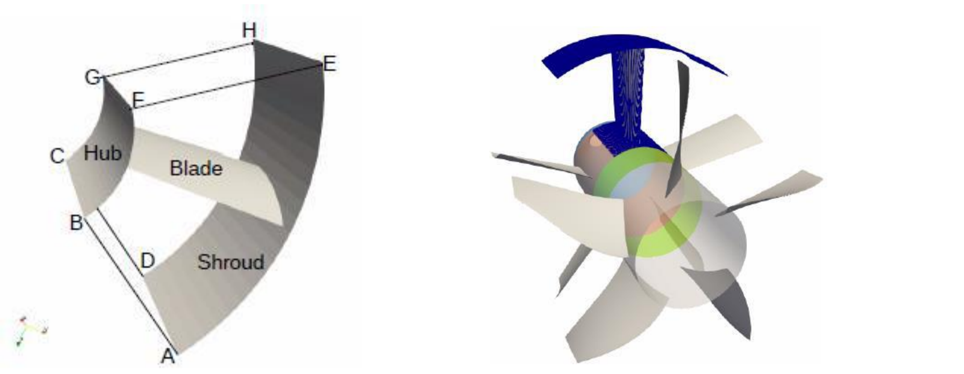
Redirection of flow possible with only two remaining parameters (roots): a_{lower}, b_{upper}

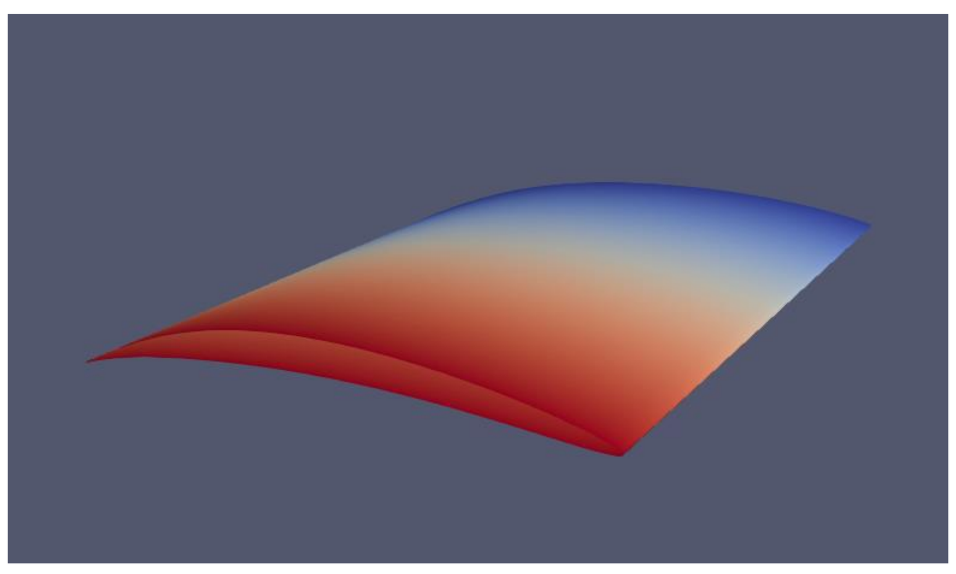
Upper: n=1, m=1, a=1, b=8.9, c=0.0725 Lower: n=1, m=2, a=0.1, b=1, c=2

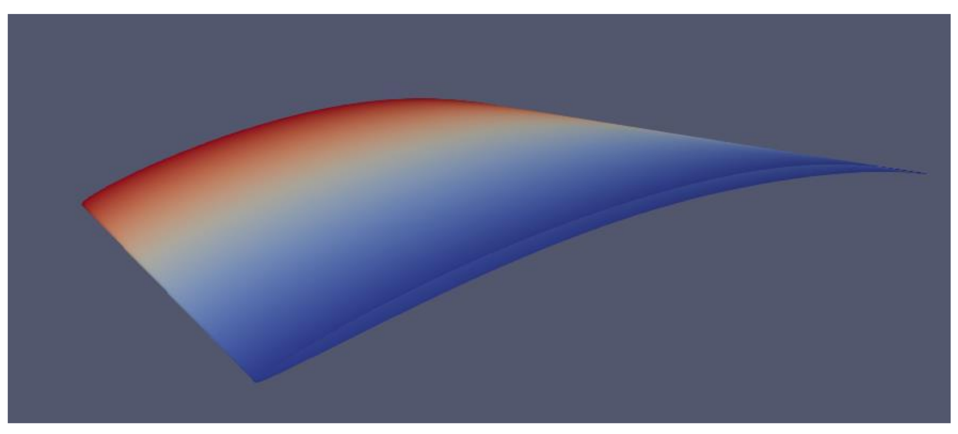




Full 3D Configuration of blade attaching to hub and shroud. Below: Transition of 2D Sections







Conclusion

Reinforcement Learning can be used to

- learn the optimal strategy (policy π^*) for sequentially reducing the number of dimensions of the state space if single roots become stable during optimization process,
- solve sub-optimization tasks like optimal 2-D airfoils to be used in a 3-D design, later (cf. with 'hierarchical' techniques [6]),
- learn the most significant (PARSEC) parameters for the optimizations task by fixing the stable roots.

For the effective use of RL in ASO we find that it is important to start with a parametrization that

1. provides an set of interpretable and independent variables describing the geometric effectively (e.g., Bezier-Parameters are interpretable but strongly correlated [4]),
2. uses a set of actions that allows the reduction of the effective number of degrees of freedom.

References

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[5] Joachim Schöberl, Christopher Lackner, Matthias Hochsteger. NGSolve – Multiphysics Simulation Software, https://ngsolve.org/.

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