Using Parametrized Propeller Data for Training Neural Networks

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Fluid Dynamics and Ship Theory

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Agenda

1. Introduction
2. Propeller data
3. Neural network
4. Autoencoder
5. Conclusion and Outlook

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Introduction

- Accelerate the propeller design process
- Design with AI increasing
- Research for usage of ML in propeller design
- Genetic algorithms, regression trees, combinations of SVM and GA, NNs …
- Research about necessary data amount for NNs missing

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Propeller data

Flowdiagram

CAESES → StarCCM+ → Neural Network

CAESES
- Generate parametrized geometries
- Automatic CAD file generation

StarCCM+
- Calculate OWC for geometries automatically
- Output OWC and pressure distribution

Neural Network
- Use generated data as training data
- Different dataset sizes

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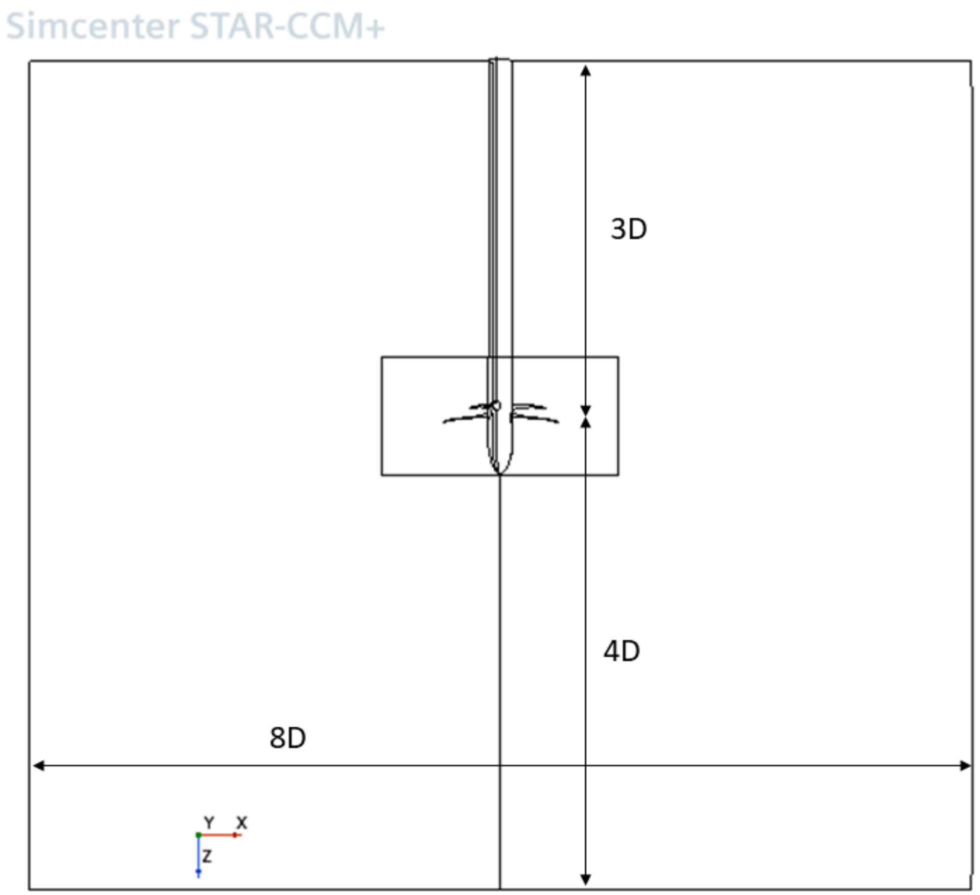
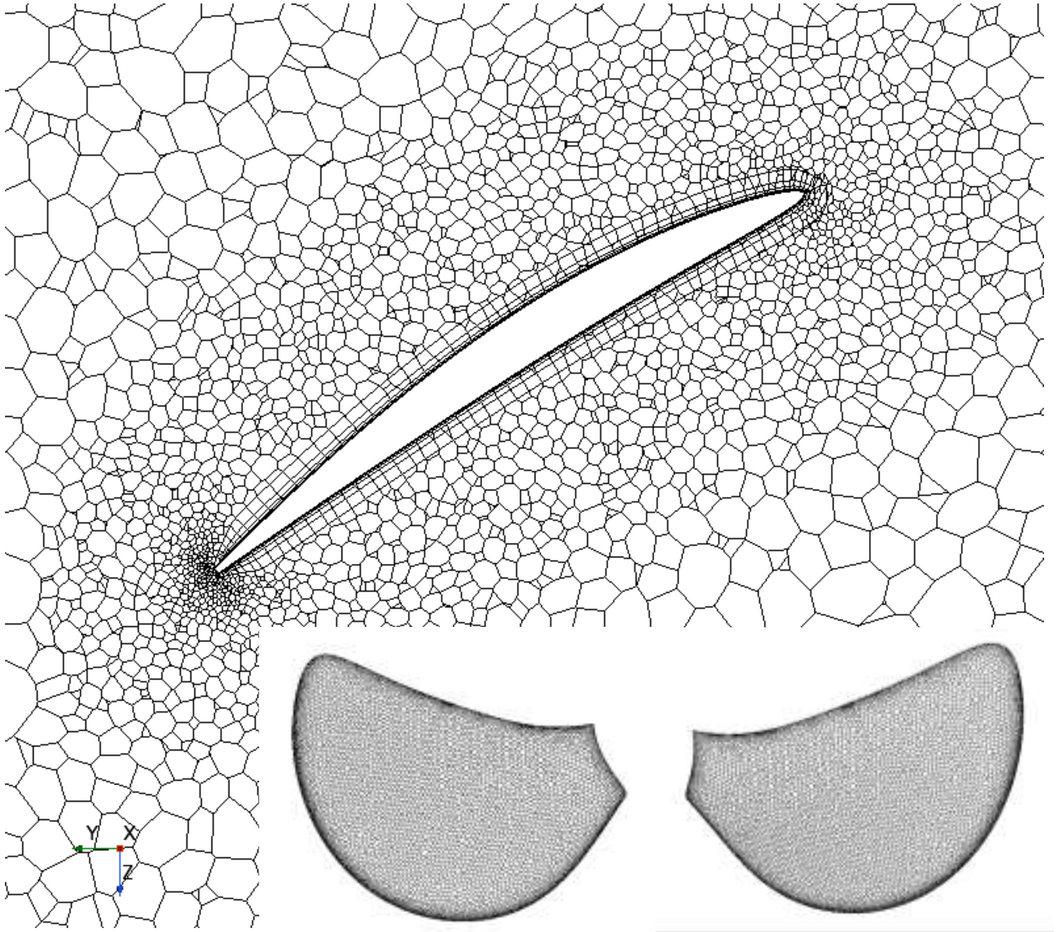
Propeller data

CFD setup





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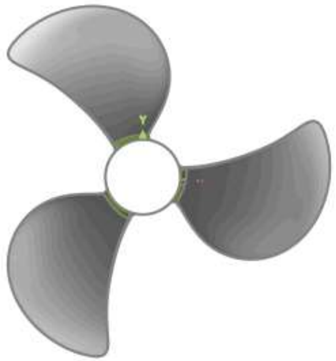
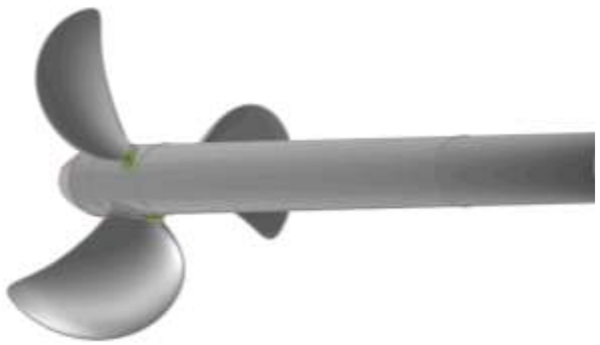
Propeller data

Geometry parameters

Parameter	Min	Max
Chord - Hub	0.25	0.4
Chord - Delta	0.0	0.2
Camber	0.01	0.06
Pitch - Base	0.9	2.0
Pitch - Delta	0.05	0.3
Skew	0.1	0.35
Number of blades	3	*6*

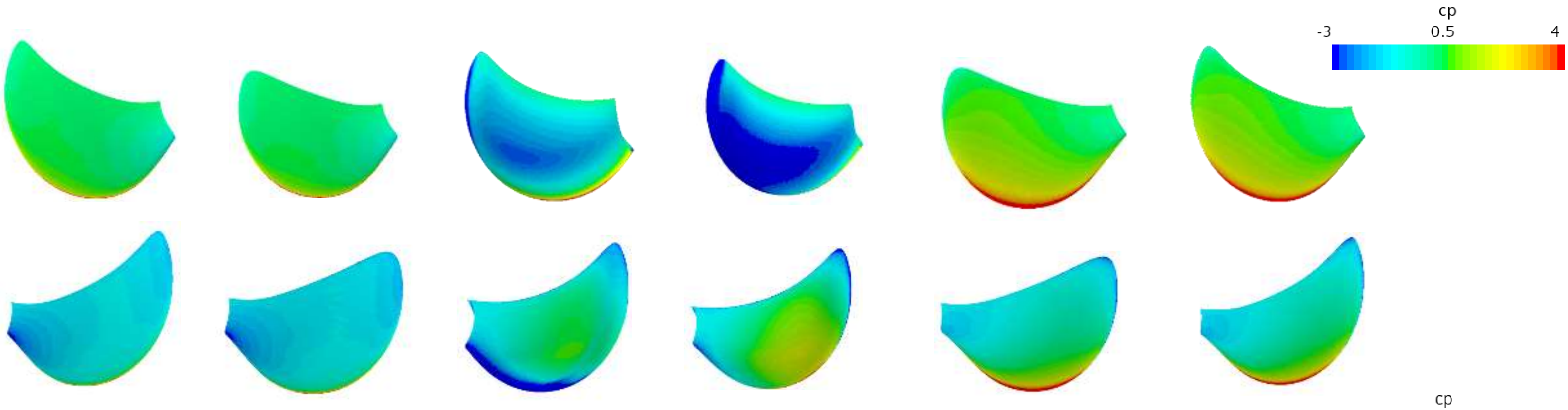
- Check for outliers using k-means-clustering
- Cut efficiency values above 1 and below 0
- Four dataset sizes: 100, 500, 1000 and 3000





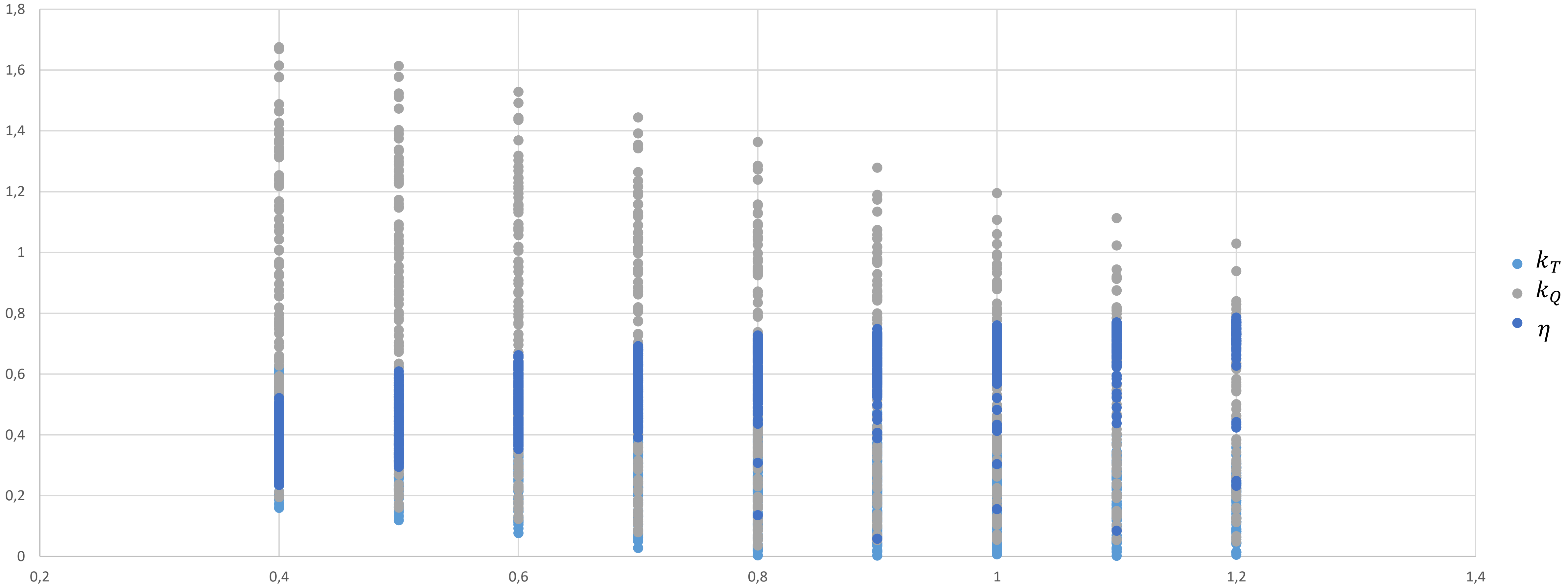
Propeller data

cp on different blade geometries



Propeller data

Open water curve scatterplot



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Neural network

Input and Output

Thrust

Input	Output
Z	J
${k_T}^*$	η
k_Q (variiert)	k_T

Torque

Input	Output
Z	J
${k_Q}^*$	η
k_T (variiert)	k_Q

$$ {k_T}^* = \frac{k_T}{J^2} = \frac{R_T}{\rho D^2 (1-t) v_s^2 (1-w)^2} $$

$$ {k_Q}^* = \frac{k_Q}{J^3} = \frac{\eta_R P_D}{2\pi \rho D^2 v_s^3 (1-w)^3} $$

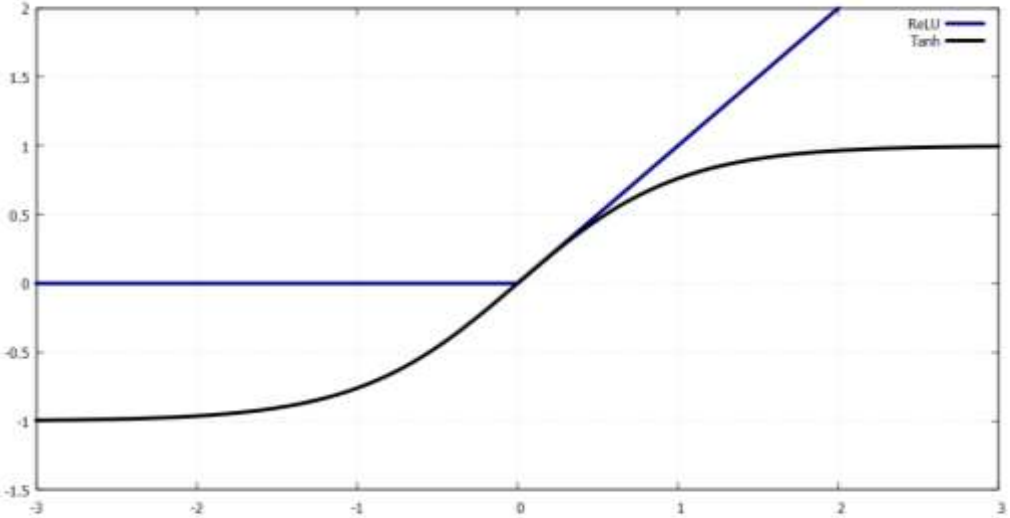
Geometry

Input	Output
J	A_e / A_o
η	P
k_T	chord
k_Q	camber
Z	skew
	cavitation

Neural network

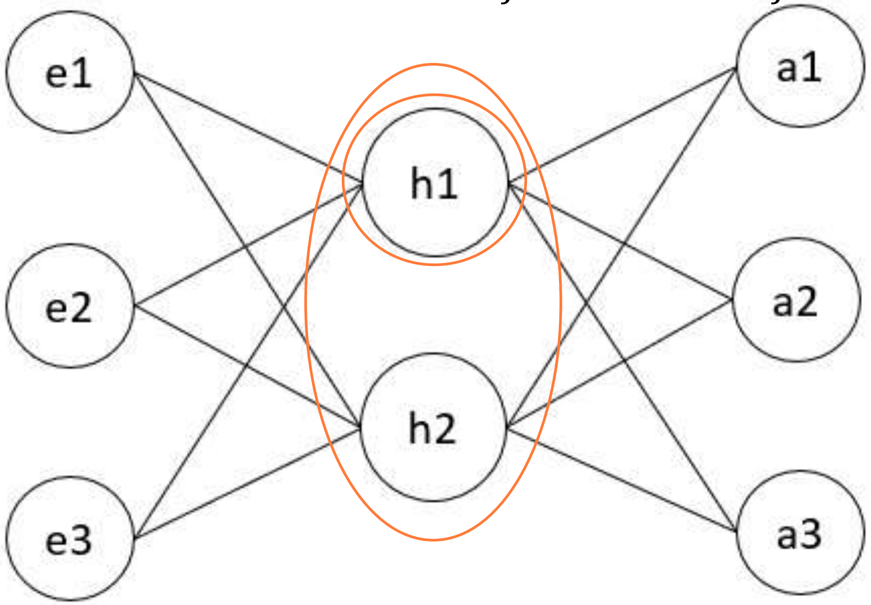
Working principle

- Neural network in PyTorch
- Activation function
- Solver with learning rate
- Number of layers
- Number of neurons



$$a = f(e1 \cdot w1 + e2 \cdot w2 + e3 \cdot w3)$$

$$\Delta w_{ij} = \sigma \cdot e_i \cdot \Delta a_j$$



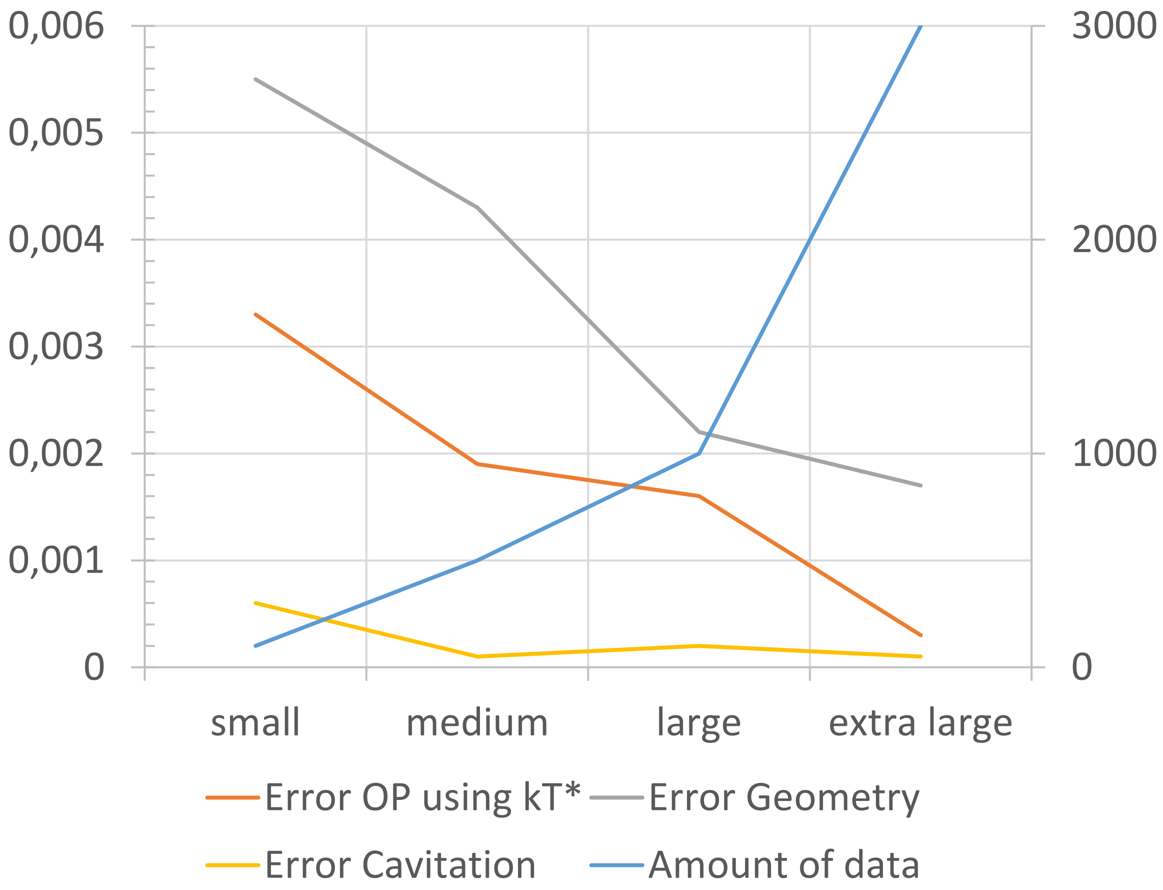
Neural network

Adjusted parameter

Parameter	Variations
Number of hidden layers	2
Neurons per layer	8, 16, 32
Activation function	ReLU, LeakyReLU, Softplus, Tanh
Optimizer	SGD, Adam, rmsprop
Learning rate	0.00001 to 0.1
Batch size	1, 2, 4, 8
Dropout probability	0, 0.1, 0.5

Neural network

Influence of training data amount on errors



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Autoencoder

Input and Output

Thrust

Input
- Z
- $k_T{}^*$
- k_Q (variiert)

Output
- J
- η
- k_T

Torque

Input
- Z
- $k_Q{}^*$
- k_T (variiert)

Output
- J
- η
- k_Q

Geometry

Input
- J
- η
- k_T
- k_Q
- Z

Output
- $A_e\ /A_o$
- P
- chord
- camber
- skew
- *cavitation*

Pressures

Input
- J
- P
- chord
- camber
- skew
- Z

Output
- shear and pressures:
- cp
- cavitation
- k_T
- k_Q
- η

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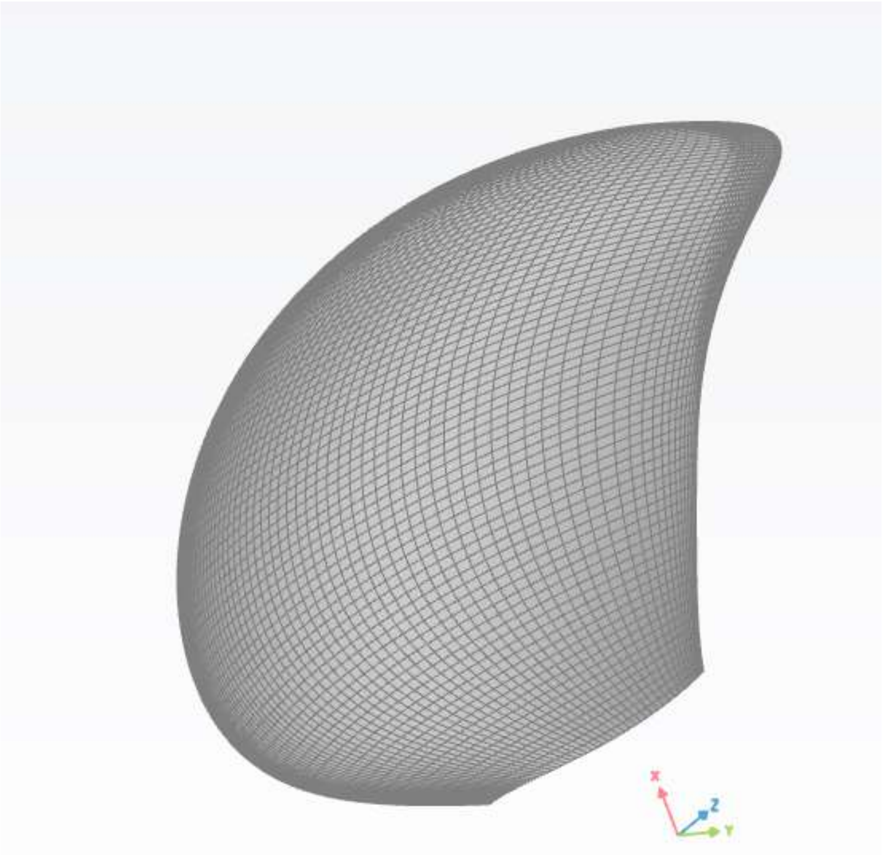
Autoencoder



- 80x80 grid
- Seperate for face and back
- Allows 2D Convolutional Neural Network (CNN) operations

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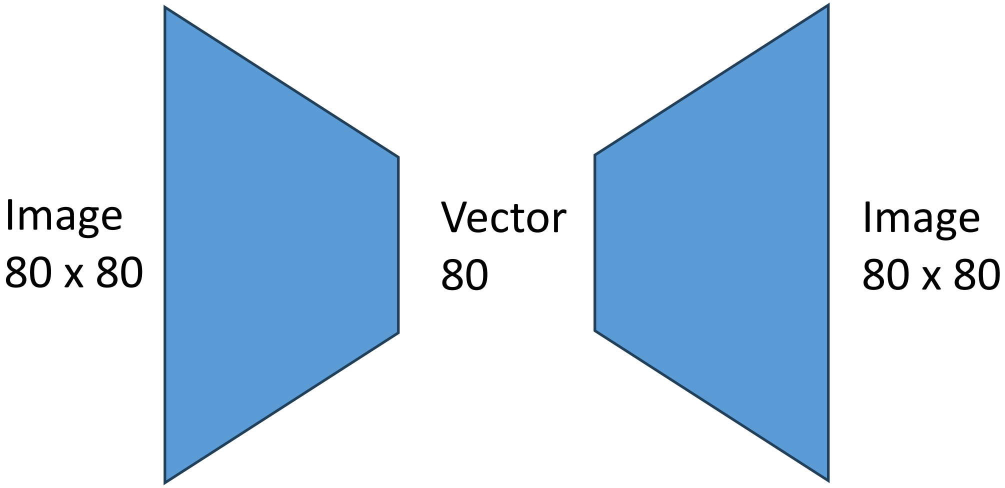
Autoencoder



- Convolutional Neural Network (CNN) in 2D – Autoencoder
- 80x80 grid input
- 4 Conv2D-Layer with activation function and pooling in between
- Kernel = 3
- Padding = 1
- Stride = 2

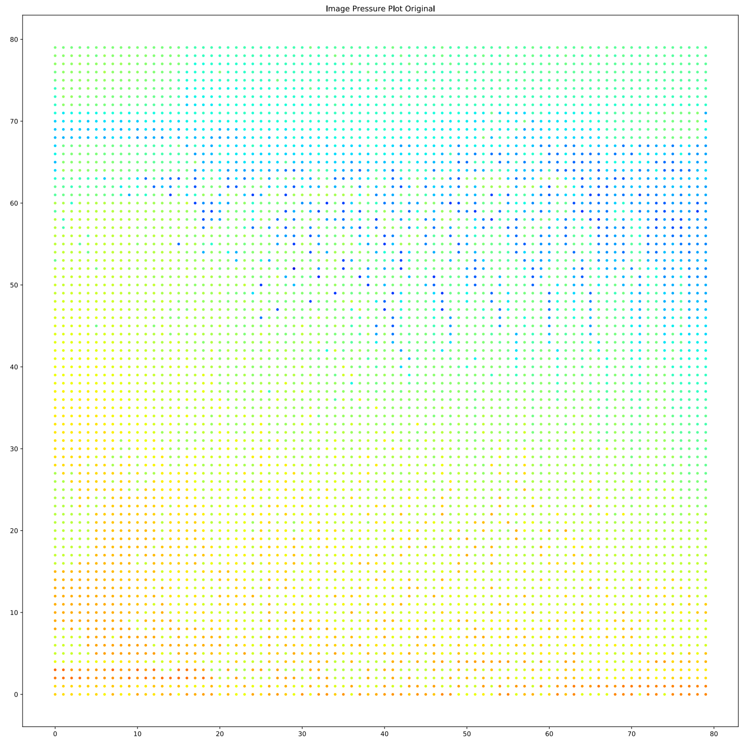
Autoencoder

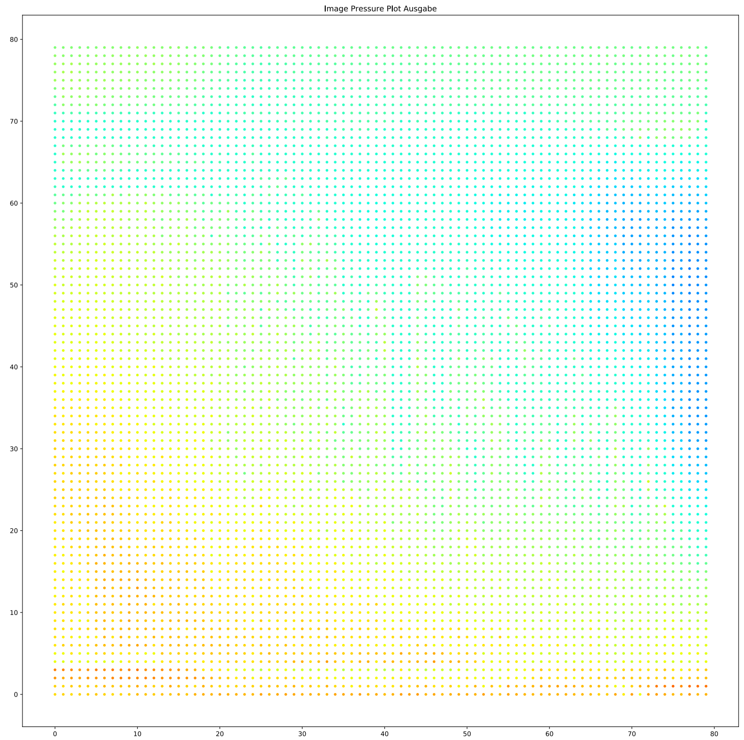
Adjusted parameter

Parameter	Variations
Activation function	ReLU, LeakyReLU, Softplus, Mish, ELU
Optimizer	SGD, Adam, rmsprop
Learning rate	0.00001 to 0.1
Batch size	1, 2, 4, 8
Latent dimension	80, 128

Autoencoder

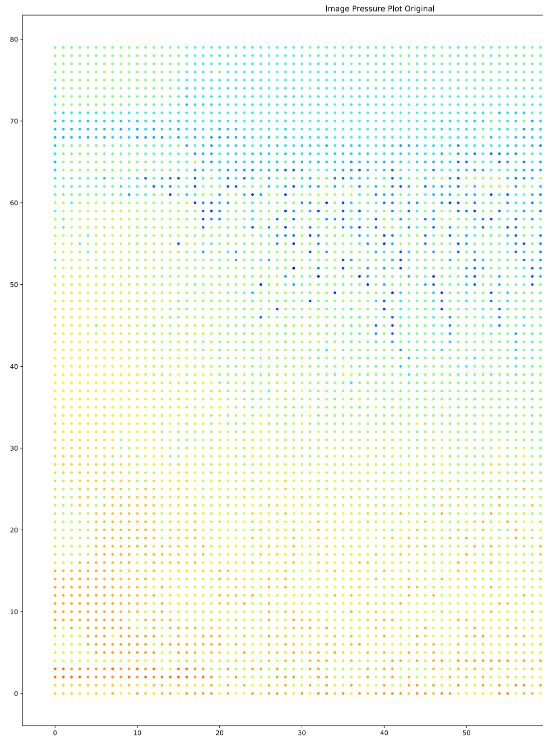
Num = 200

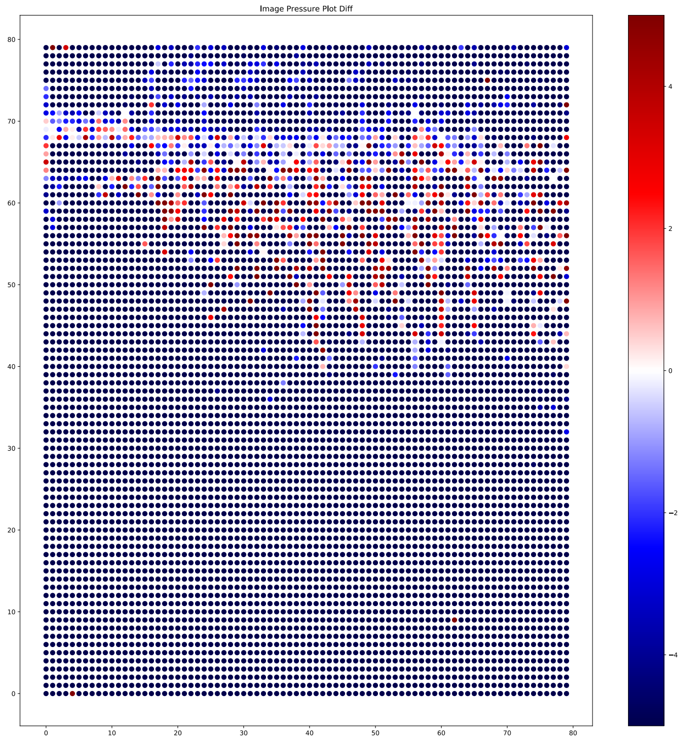


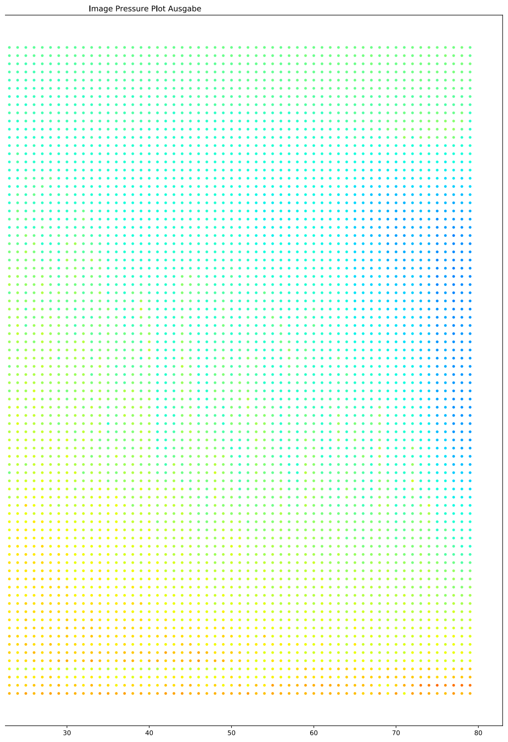


Autoencoder

Num = 200







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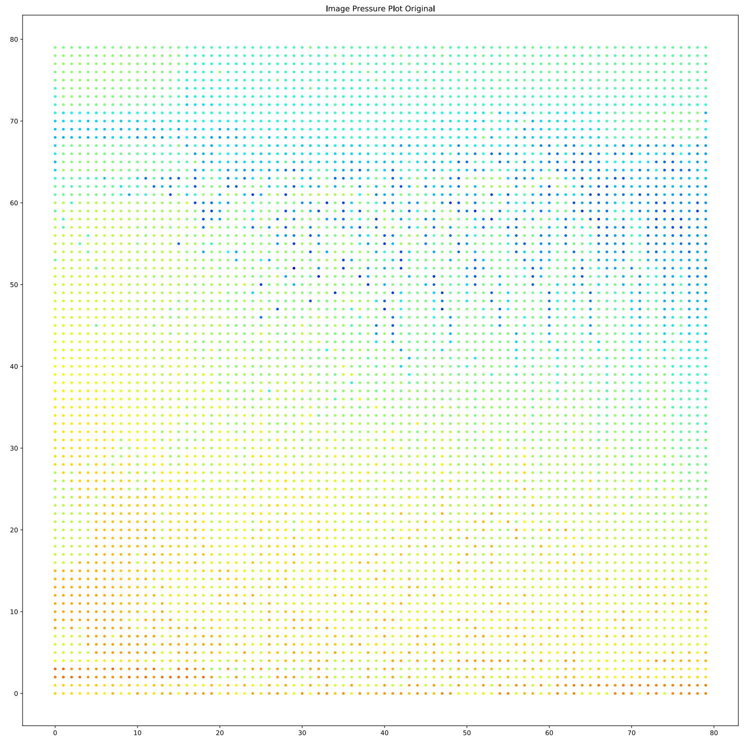
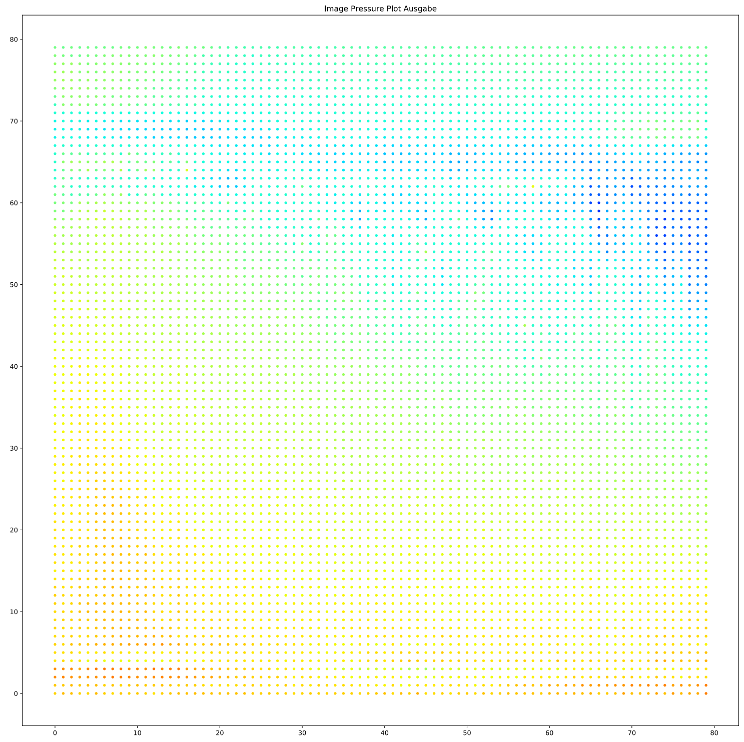
Autoencoder

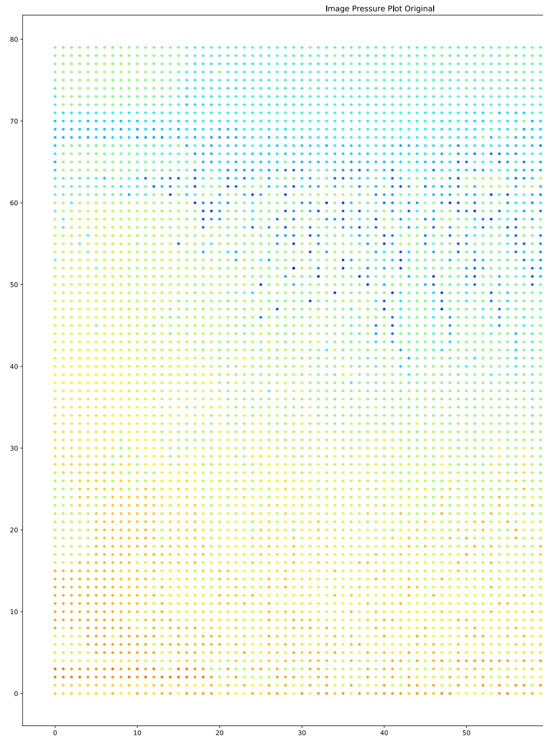
Num = 500

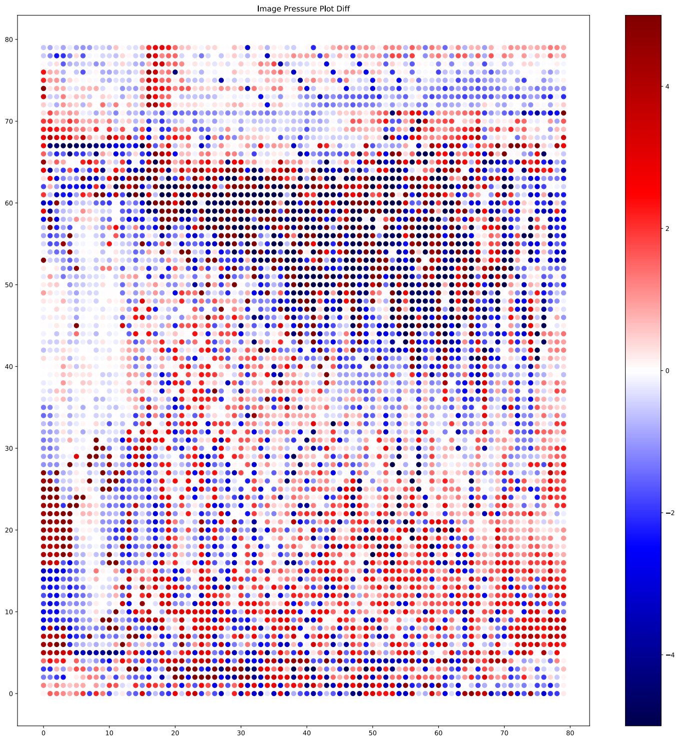


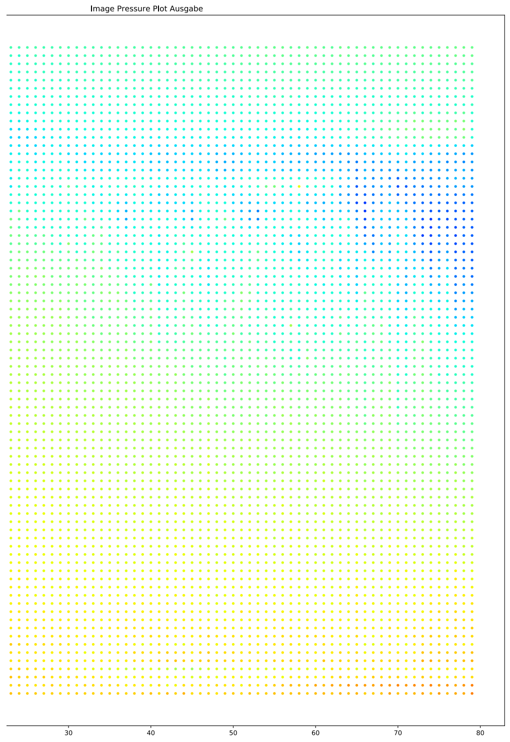


Autoencoder

Num = 500

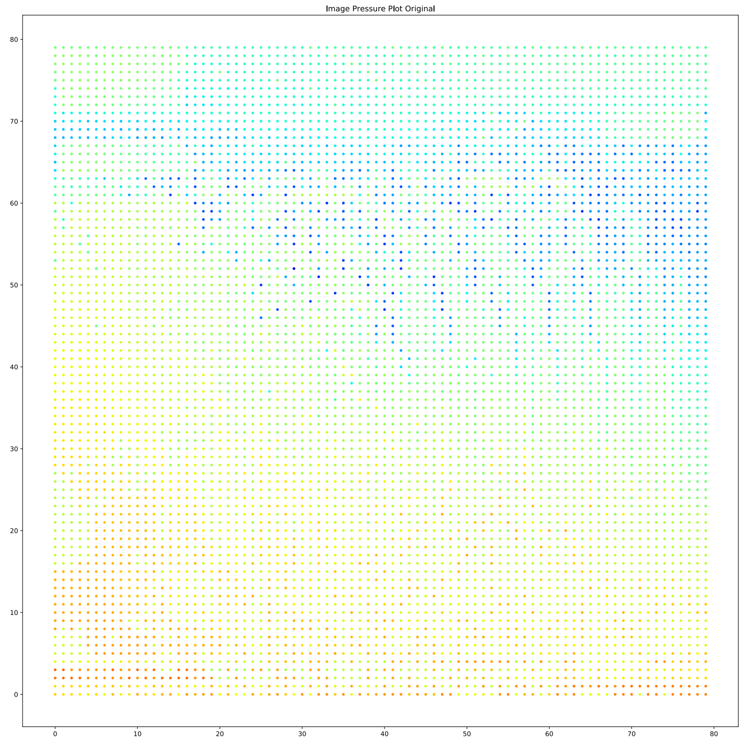


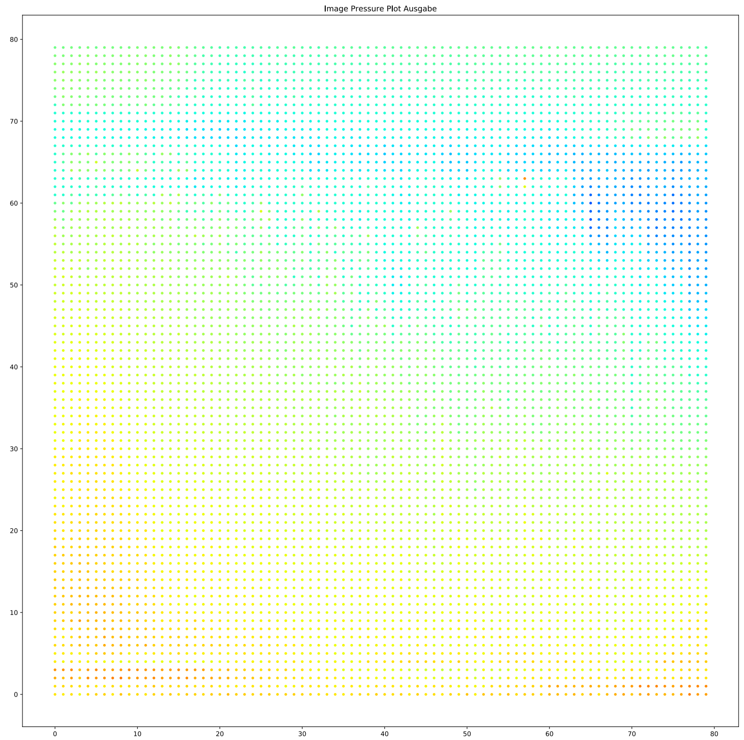




Autoencoder

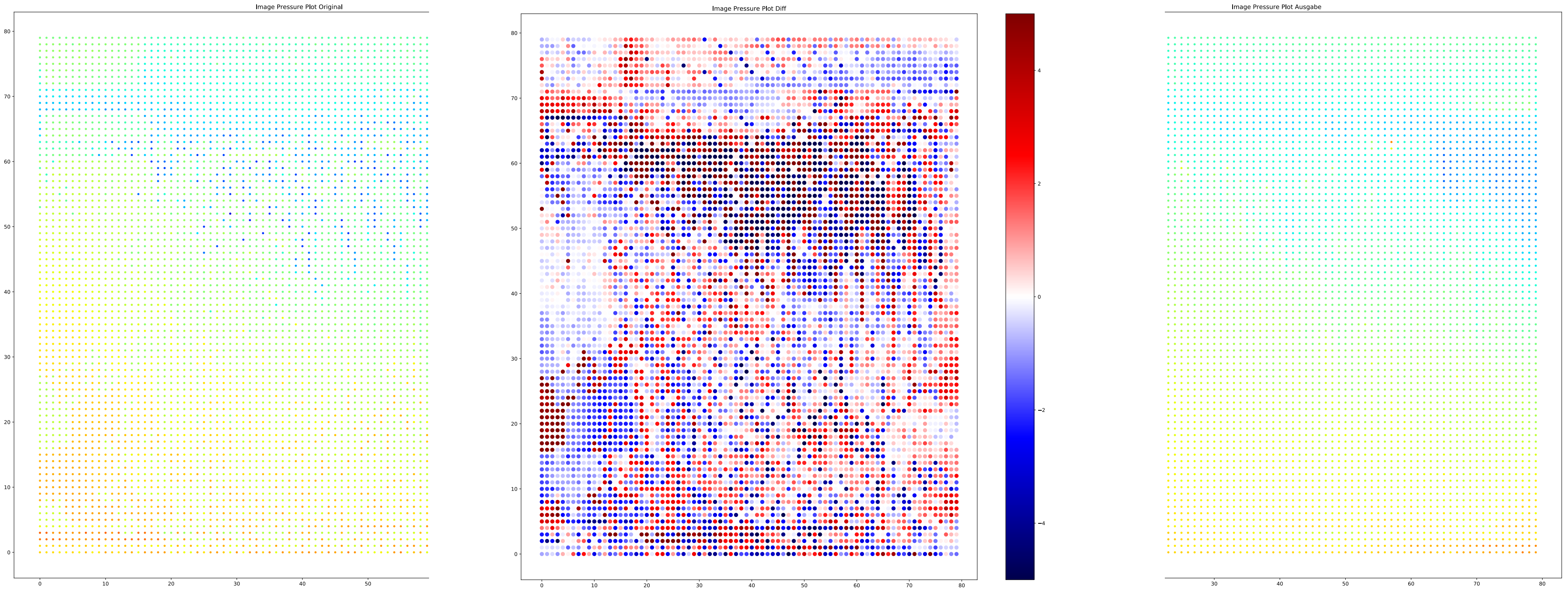
Num = 1000





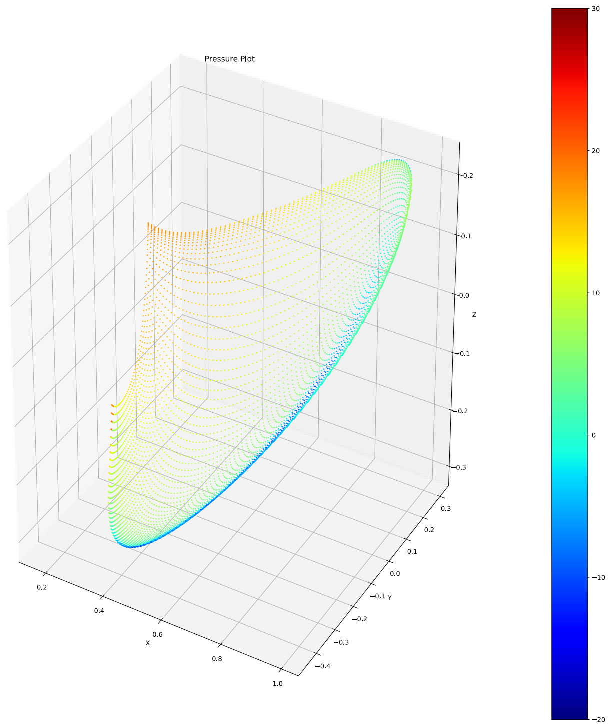
Autoencoder

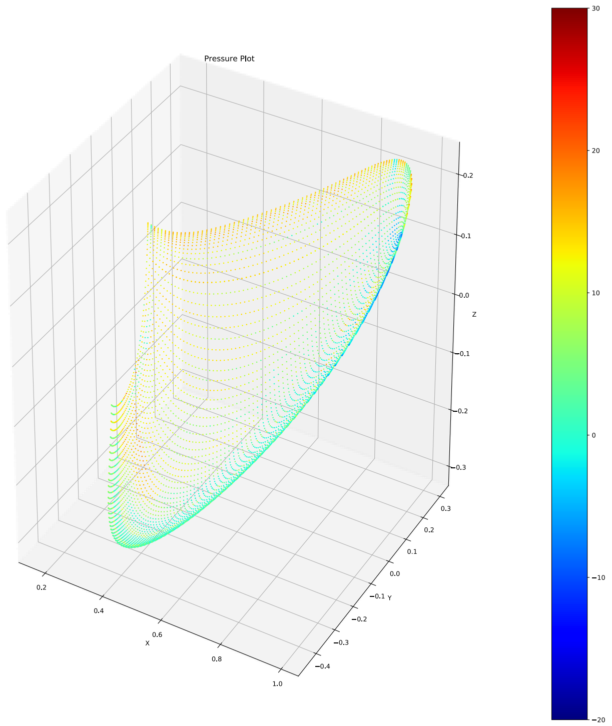
Num = 1000



Autoencoder

Num = 200





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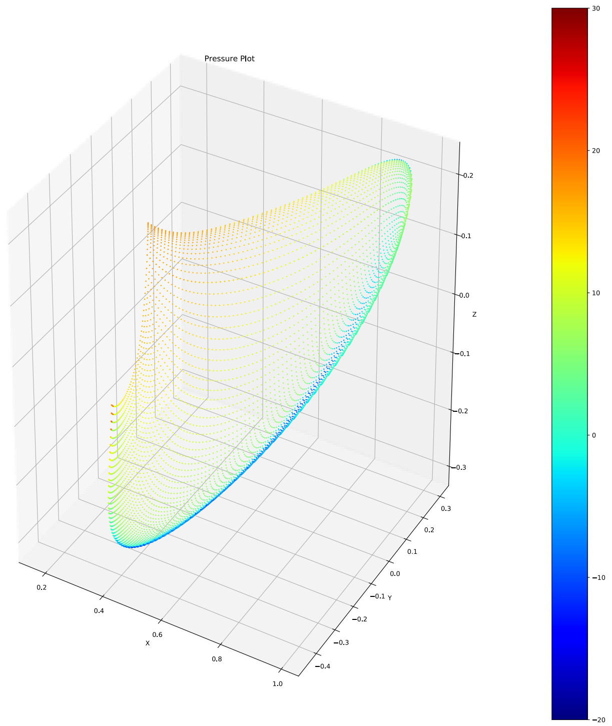
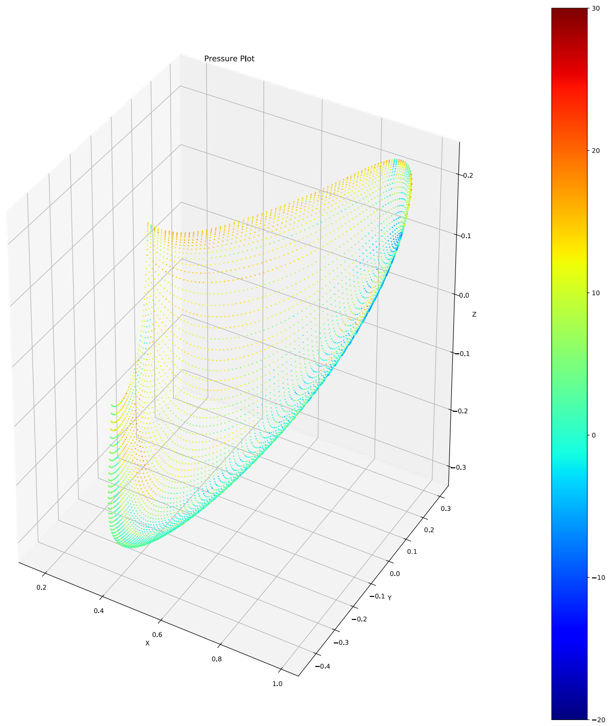
Autoencoder

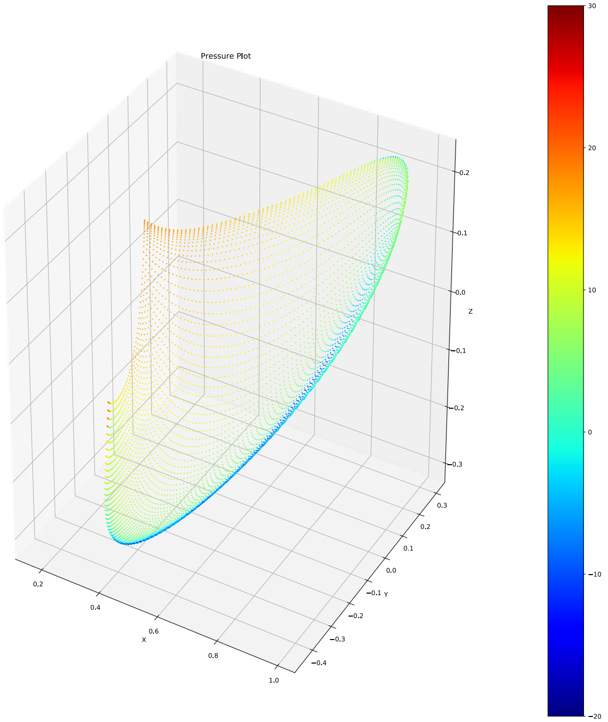
Num = 500

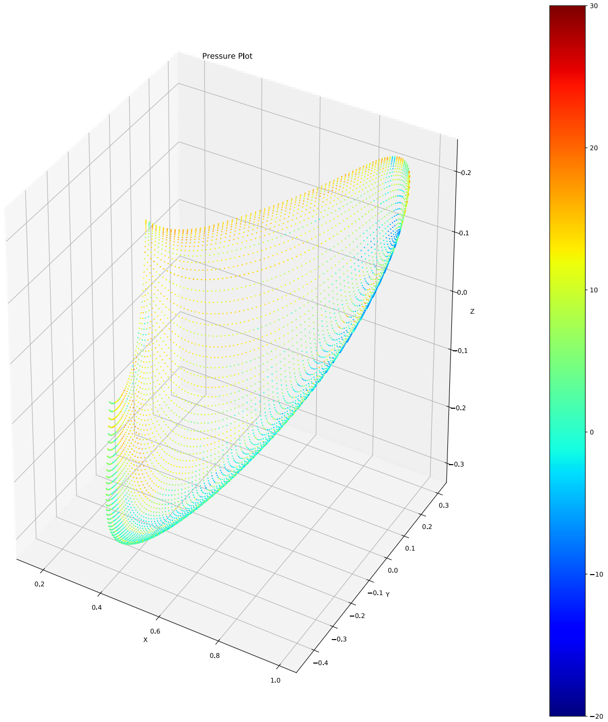




Autoencoder

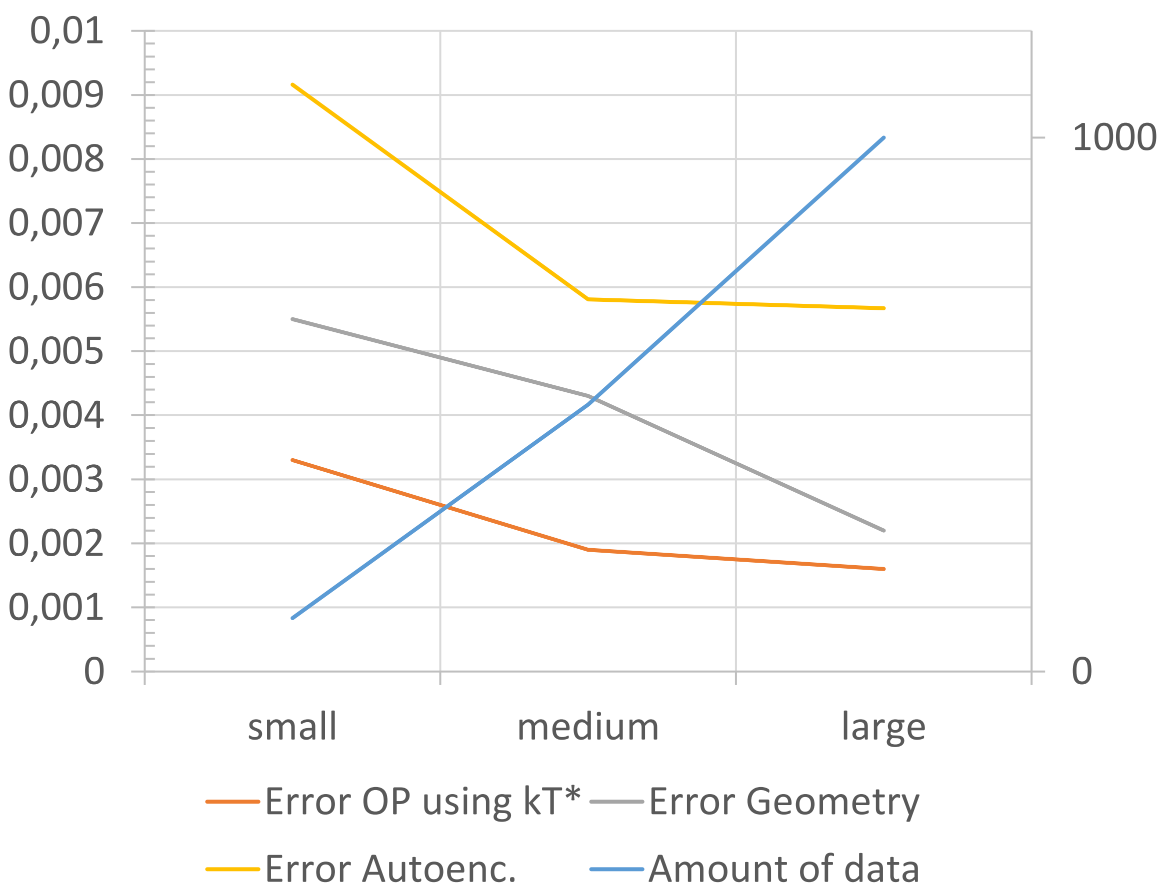
Num = 1000





Autoencoder

Influence of training data amount on errors



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Conclusion and Outlook

- Neural networks are easily usable and show reasonable quality
  - Fast results compared to CFD calculation
- Similar datasets can be trained with pre-set parameters
- Necessary amount of data 500 points or more
  - Depending on the output
- Known physical equations have partly been used
  - More equation usage
- Pressure data as 3D data
  - Data amount study
  - Combine with other networks

Thank you
for your attention!