MODELING OF A WINDOW LIFT DRIVE AND A CONTROL EDGE WITH NEURAL CONCEPT SHAPE

WOST 2021

ROBERT BOSCH GMBH
CR/AME3-SCHIRRMACHER

Neural Concept Shape: 1. Test Phase
Agenda

- Introduction
- IT-Infrastructure
- Examples
  - Window Lift Drive (structural mechanics)
  - Control Edge (computational fluid dynamics)
- Summary

Introduction
Current status of machine learning at Bosch

- Bosch uses a variety of machine learning tools like optiSLang, ASCMO (https://www.etas.com/de/) or Stochos (https://www.probaligence.de/) in order to get a relation between design parameters and key performance indicators. Additionally, Bosch has established an own center of artificial intelligence.
- Since more than 10 years Bosch uses multi-objective optimization and has collected millions of designs with different topologies and different designs spaces.
- Neural Concept advertises with the possibility to learn from all these designs and to predict/optimize geometry. In a first step, the functionality of NCS was tested at more simpler examples in the first half-year of 2020.

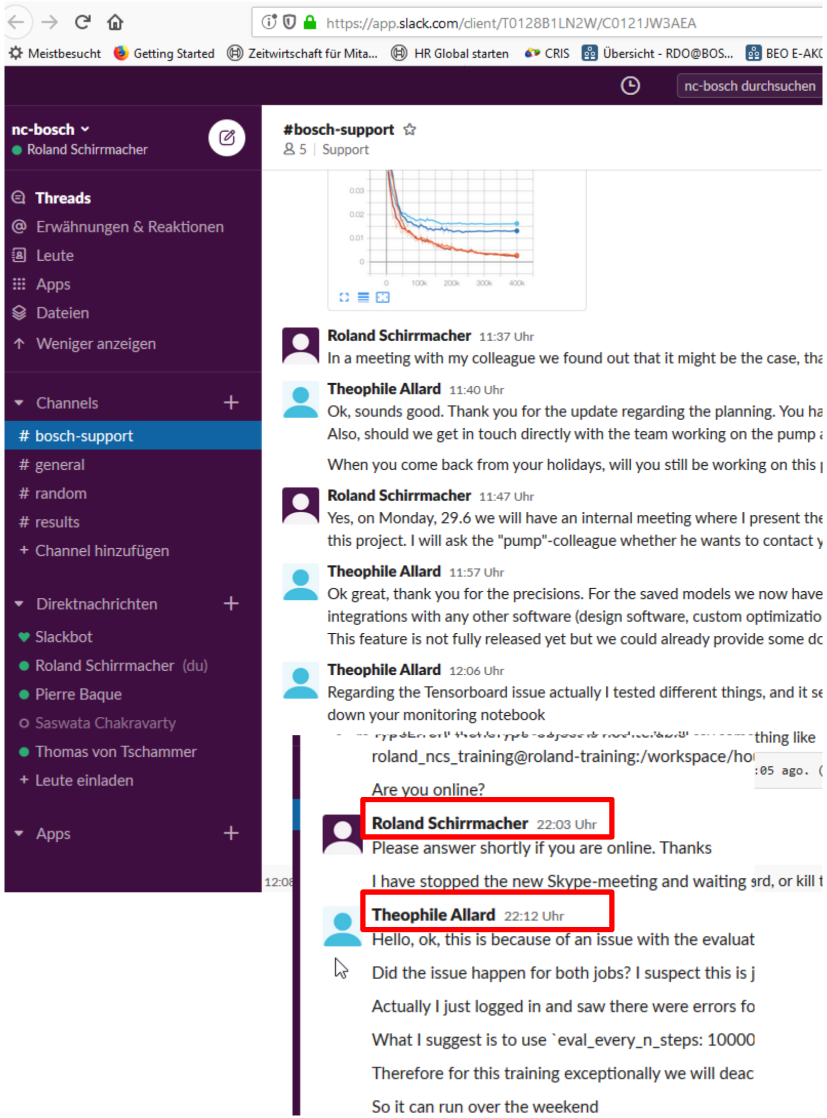
	Parametric models	**Different topologies**
Scalar outputs	optiSLang/MOP, Stochos, Ascmo	Neural Concept Shape
Signal outputs	optiSLang/signalMOP	Neural Concept Shape
Field outputs	SoS	Neural Concept Shape (static, harmonic, tran-sient)

IT-Infrastructure
Communication with NC

- The communication with NC took place with
  - Théophile Allard for technical aspects
  - Pierre Baqué for organisational aspects

- The technical support of Théophile Allard was excellent. He solved all problems and was available the whole day.

- The following communication channels were used
  - Slack for short questions, bug fixing information, new Python tools, status, results, etc.
  - Skype for discussion of model data and results

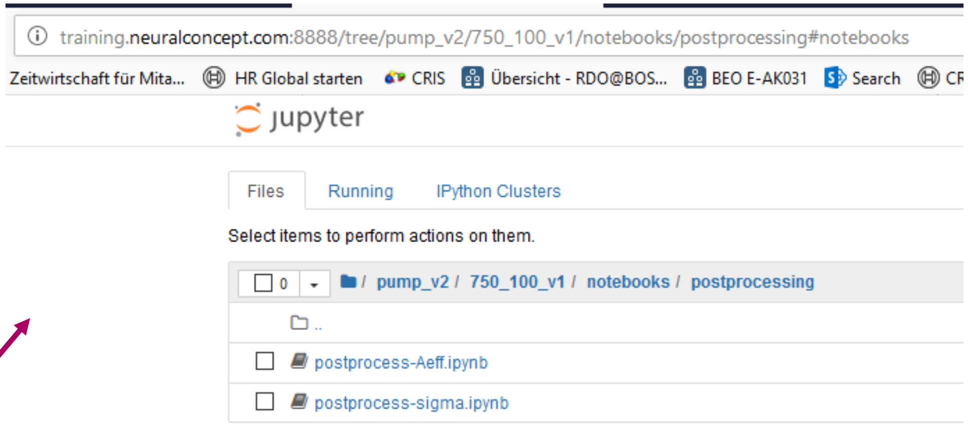


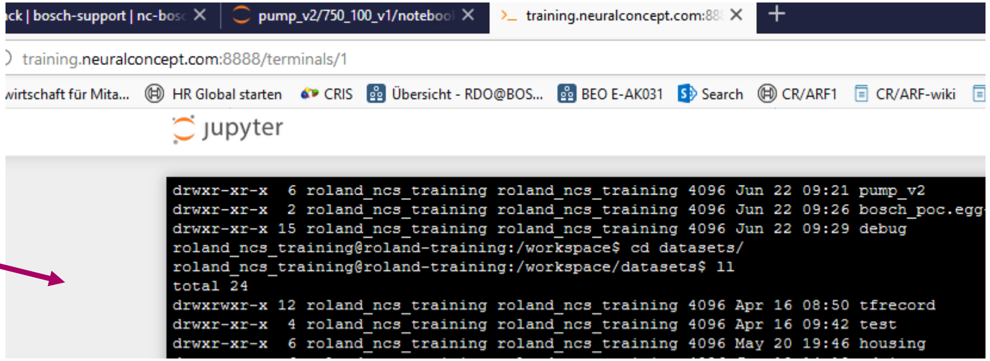
IT-Infrastructure
Hardware

- The software NCS could not be installed short-term and easily on a GPU cluster at Bosch.

- The GPU cluster of NC was used which allowed three parallel NCS runs
  http://training.neuralconcept.com:8888

- For the usage of NCS two different frontends were offered
  - Jupyter notebooks for monitoring, postprocessing and editing of configuration files
  - Linux for running pre-processing, training and prediction

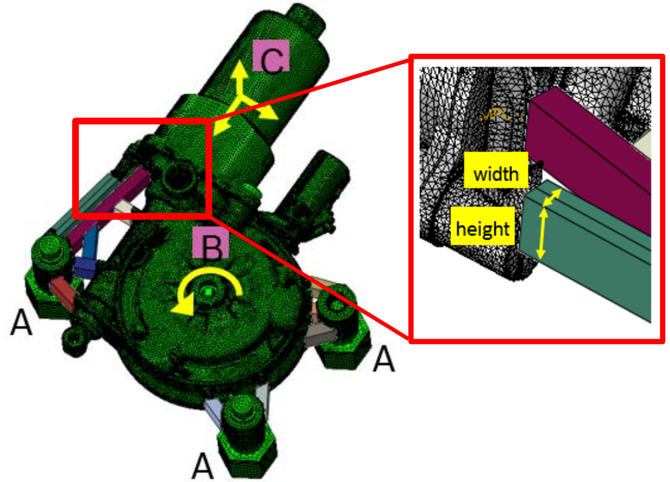




Examples
Window lift drive

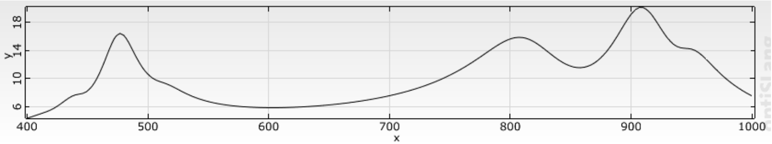
- Parametric
  - Height and width of 12 ribs at 3 mounting points A
  - Switch for activation/deactivation of the rib

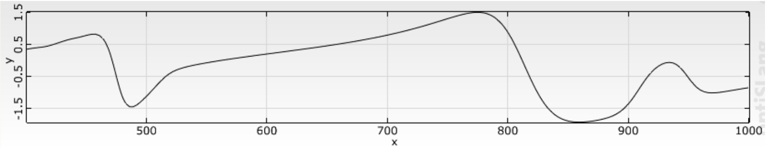
- Results
  - Stress distribution on the outer surface of the ribs generated by a torque load at B (field, static)
  - Reaction forces at the three mounting points A in all directions and for all data types “Real/Imag” (signal, harmonic) generated by a harmonic force at the pole housing.
  - Velocity of the load point C (signal, harmonic)

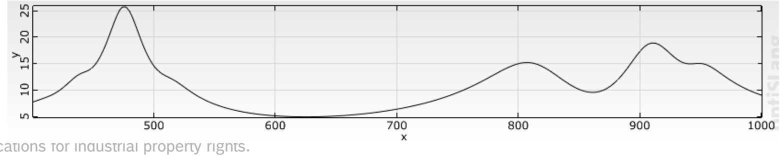



```
R1_H = 8.0
R1_W = 4.0
R2_H = 8.0
R2_W = 4.0
R3_H = 8.0
R3_W = 4.0
R4_H = 8.0
R4_W = 4.0
R5_H = 8.0
```

```
# Deaktivi
SW_R1  = 1
SW_R2  = 1
SW_R3  = 1
SW_R4  = 1
SW_R5  = 1
SW_R6  = 1
SW_R7  = 1
```







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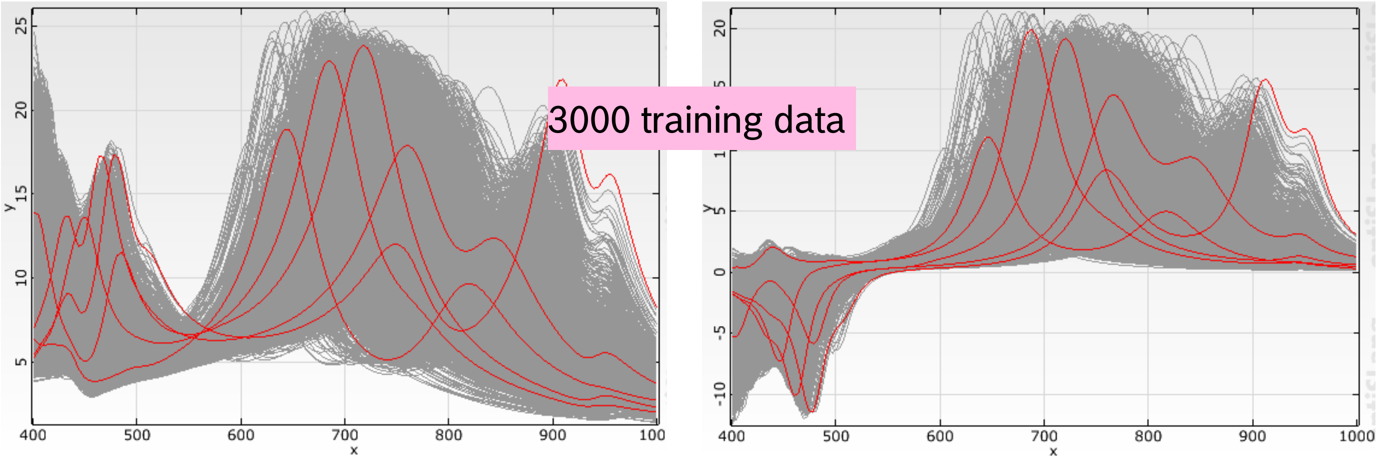
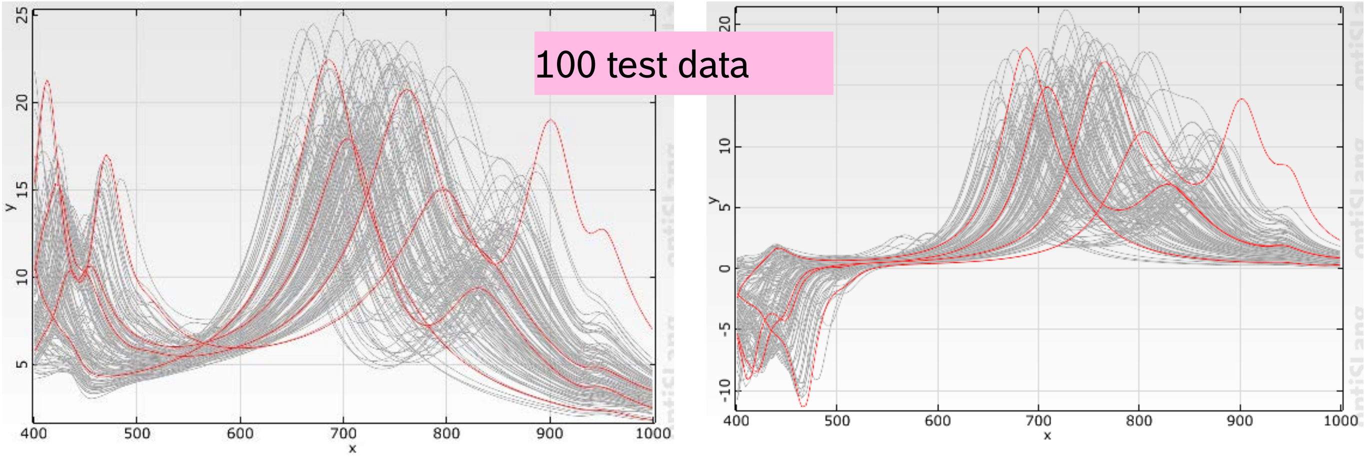
Window lift drive
Training and test setup

- Training data
  - 3000 designs using Latin-Hypercube-Sampling
- Test data
  - 100 designs using Latin-Hypercube-Sampling
- Signal types
  - Total reaction force “RFO_ampl”
  - Reaction force at each mounting point
  - Reaction force for each mounting point, direction and data type (real,imag) “RFO_1_3_imag”
- Outliers and incomplete designs were deactivated





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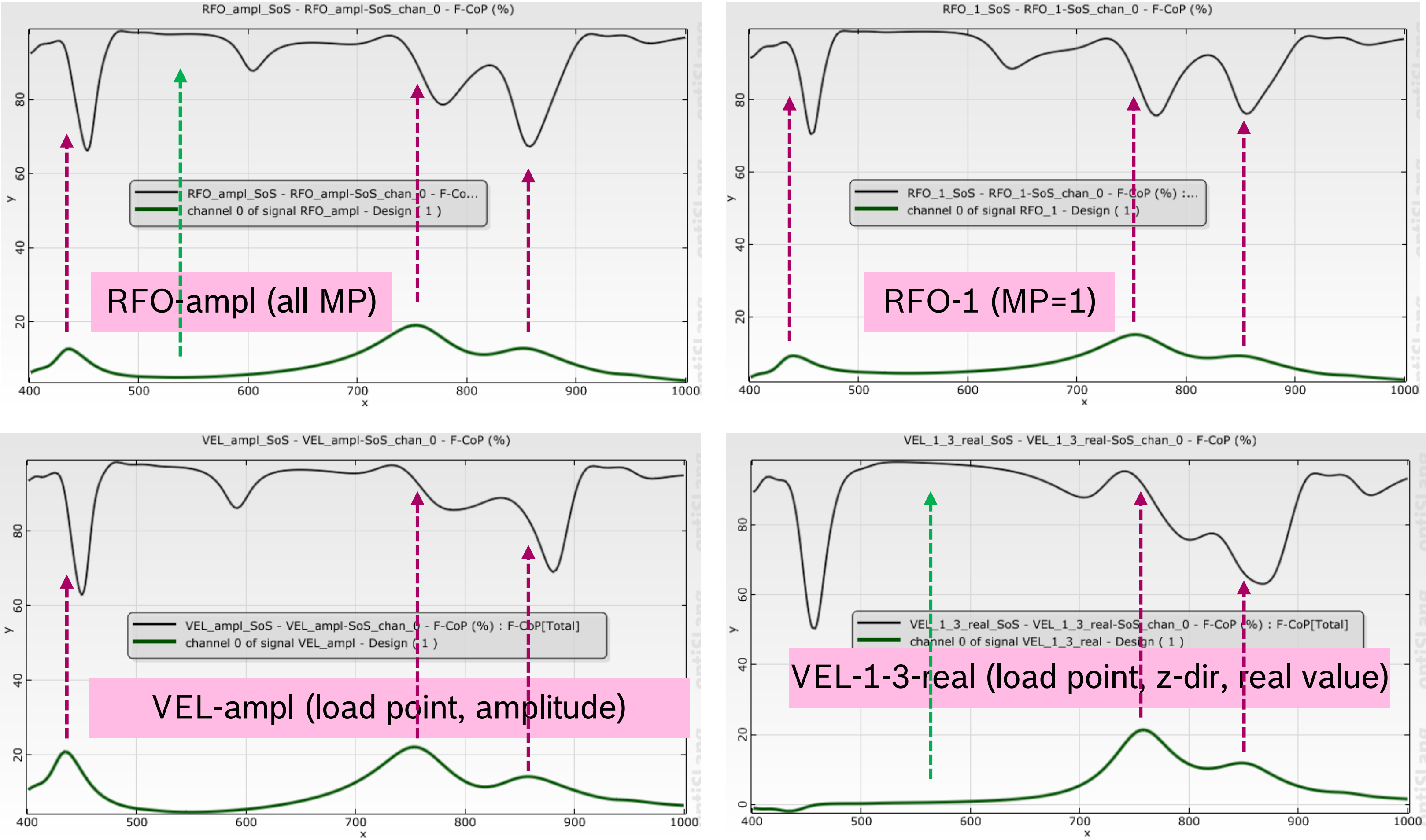
Window lift drive

Status for harmonic signals using signalMOP (all ribs active)

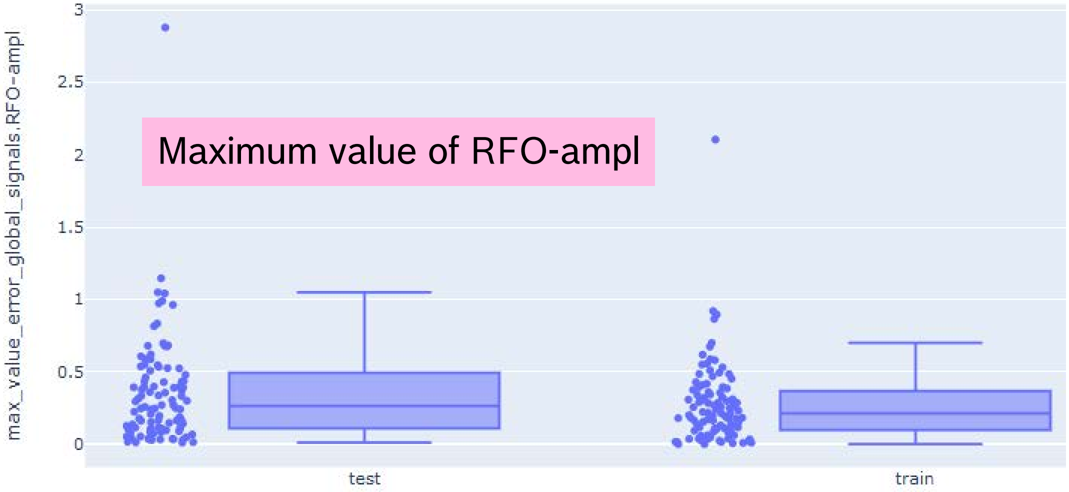
- 3000 Designs using Latin-Hypercube-Sampling
- The accuracy (F-CoP) for the reaction forces has a range between about 0.65 and about 0.85 at the peak values.
- The accuracy (F-CoP) for the velocity at the load point has a range between about 0.65 and about 0.90 at the peak values.



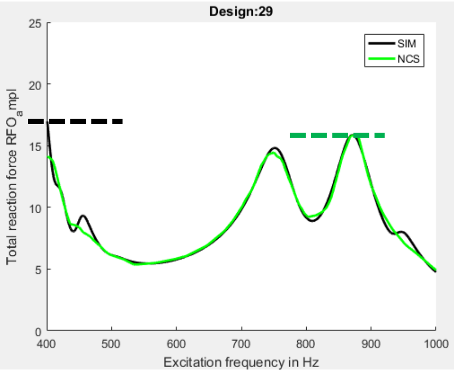
Window lift drive

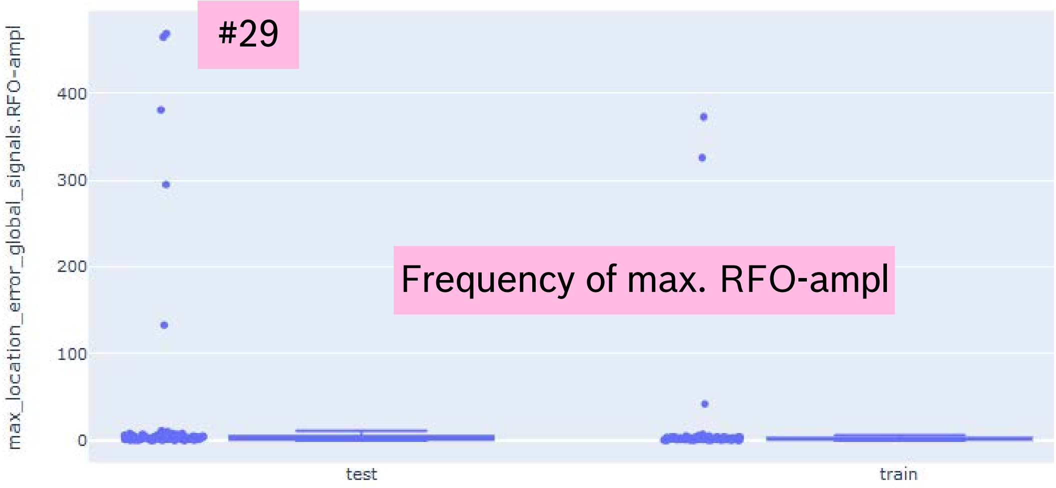
Results for RFO-ampl /1/

- The training lasted 148 hours for 400000 iterations.
- The error of the maximum value of the sum of all reaction forces is predicted very well. The medium error is less than 0.25 N



- The frequency of the maximum sum value is predicted very well, only 5 designs have a quite different frequency.
- These "outliers" have the peak value at the lower frequency limit and the prediction at the limits is not so good.





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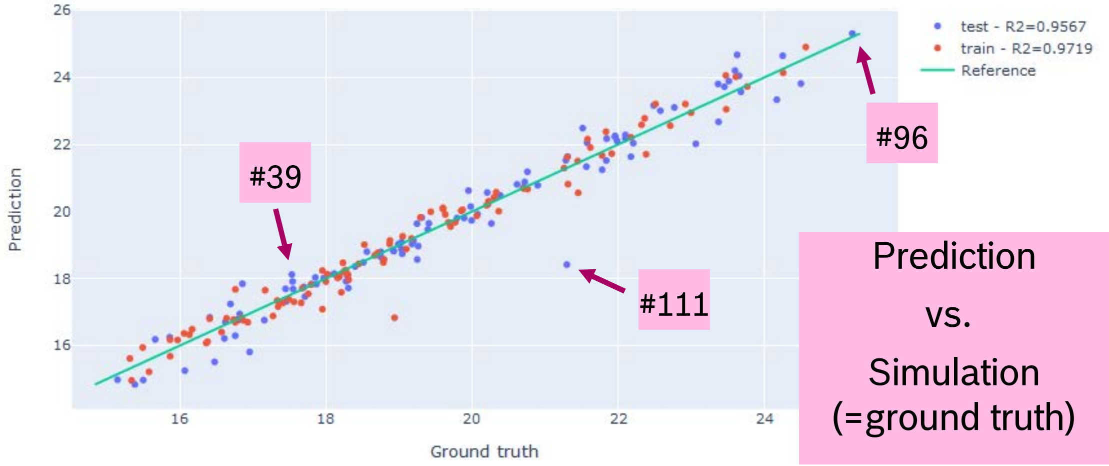
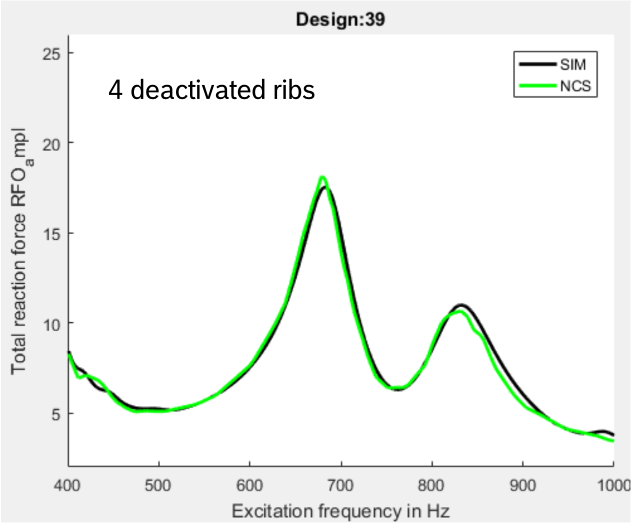
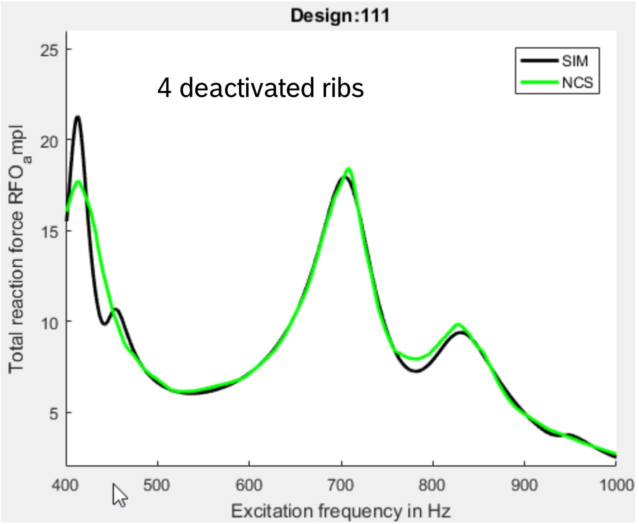
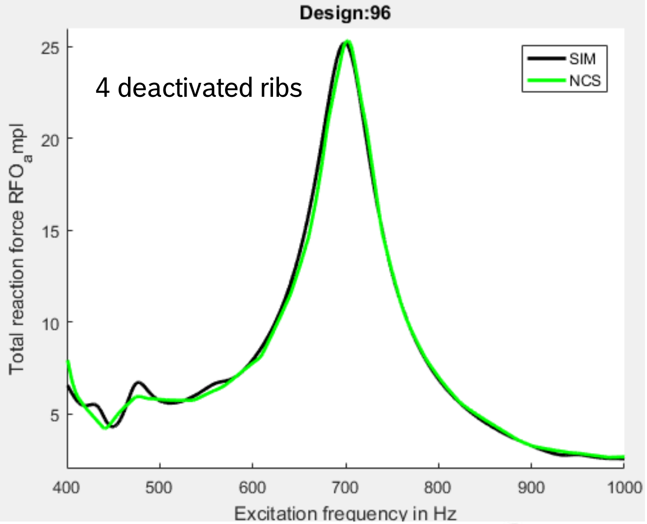
Window lift drive
Results for RFO-ampl /2/

- The R^2 value is very high (>0.95) for an accumulated signal. Only few designs with a bigger error exist.
- The simulated and predicted (NCS) test design match very well. The peak values are found.







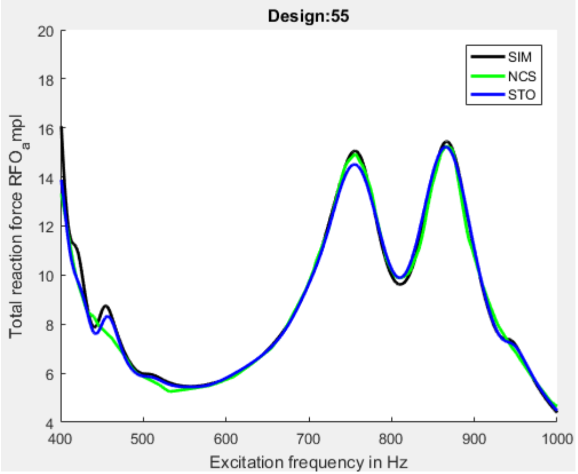


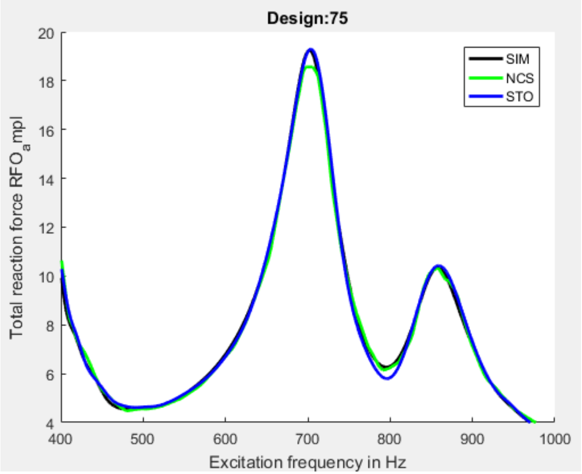
Window lift drive
Comparison of RFO-ampl with existing ML-tools

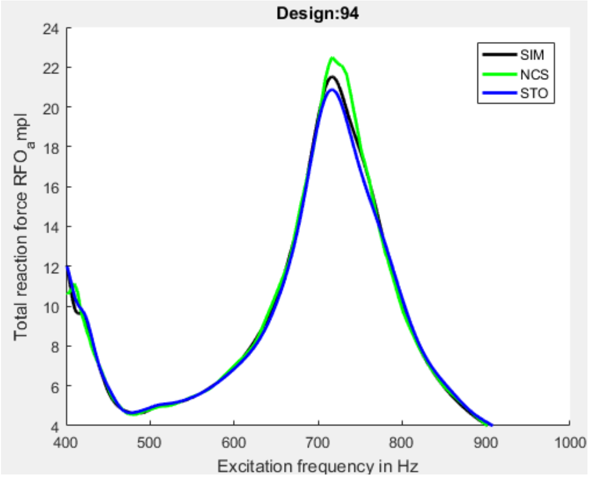
- Comparison between
  - Simulation (Abaqus)
  - NCS (Neural Concept Shape)
  - STO (Stochos)

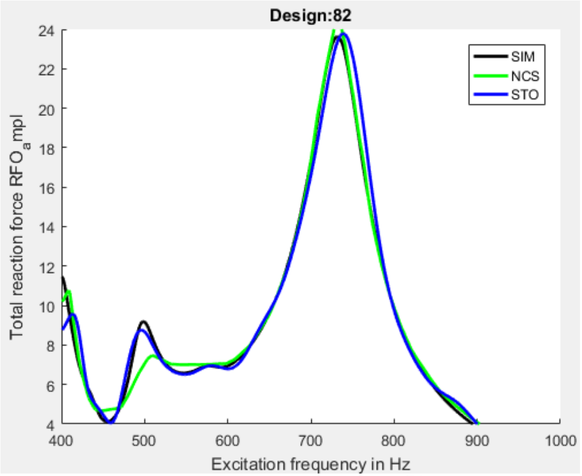
- Signal RFO-ampl for designs with a **high error** of the maximum value of RFO-ampl based **on NCS error calculation.**

- Stochos shows a similar accuracy as NCS.









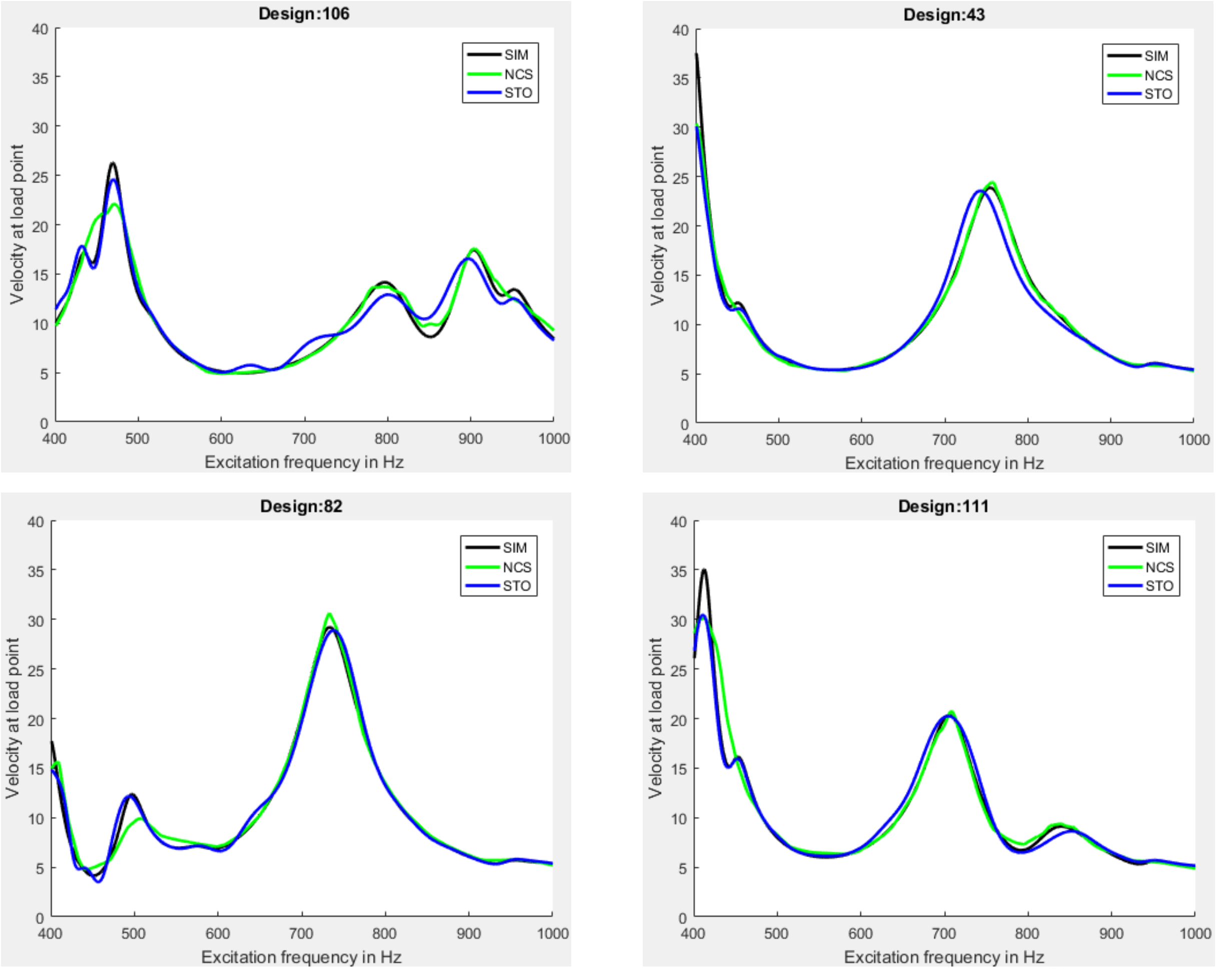
Window lift drive

Comparison of VEL-1 with existing ML-tools

- Comparison between
  - Simulation (Abaqus)
  - NCS (Neural Concept Shape)
  - STO (Stochos)

- Signal VEL-1 for designs with a **high error** of the maximum value of VEL-1

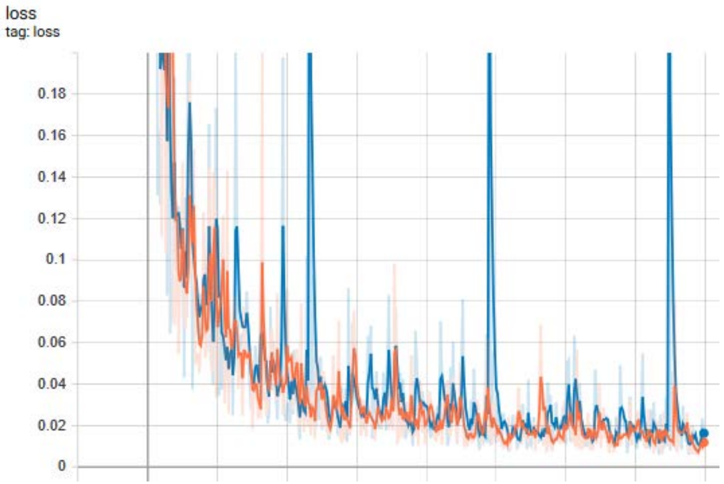
- Stochos shows a similar accuracy as NCS. The approximation at the limits of the excitation frequency range is also similar to NCS.

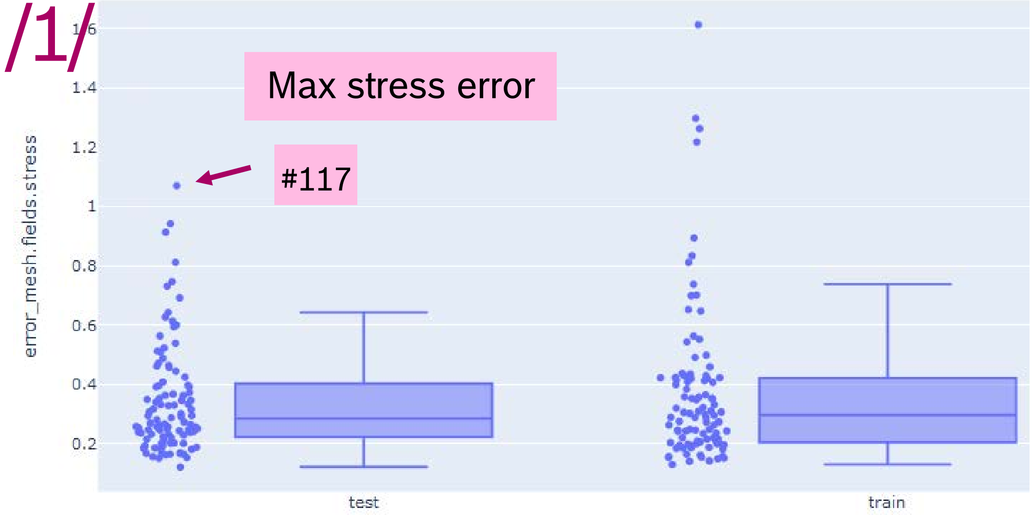


Window lift drive
Results for static stress distribution /1/

- The training ran predefined 400000 iterations. The training lasted about 72 hours on the GPU cloud of the company Neural Concept.

- The loss error (l2 error) shows no overfitting of the training. The convergence is not completely. reached.



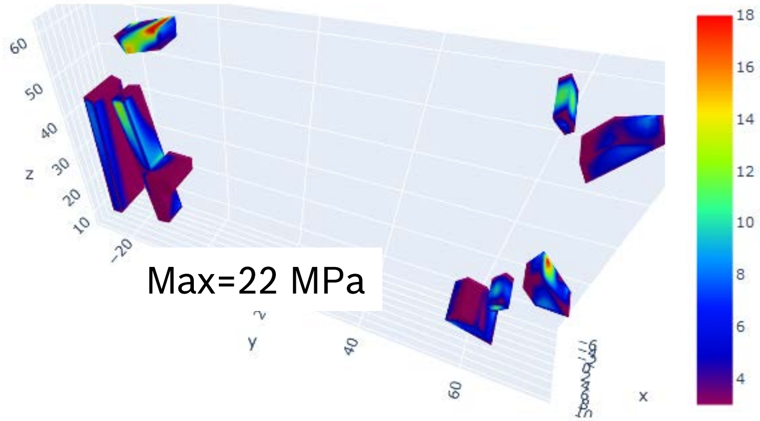


Window lift drive

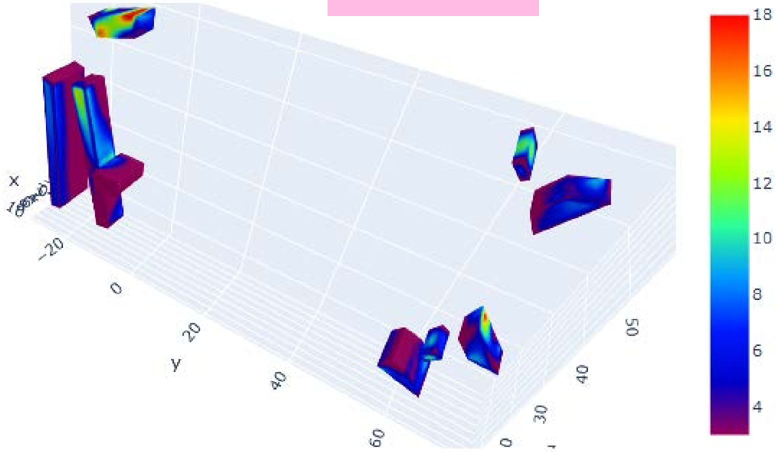
Results for static stress distribution /2/

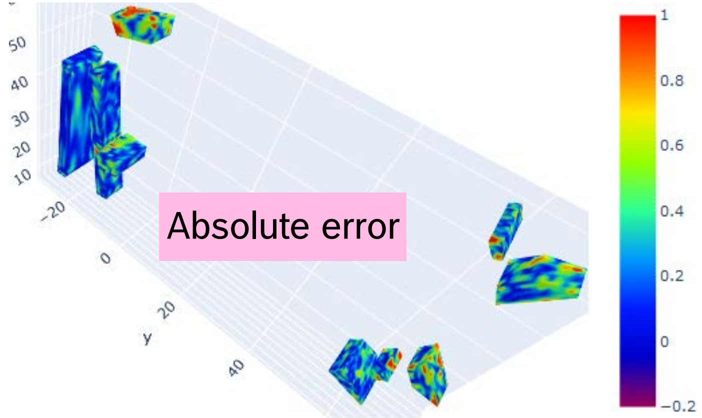
- The design #42 (2 deactivated ribs) shows the lowest error for the maximum stress.
- The stress distribution of simulation and prediction is very similar and mostly the absolute error is less than 0.5 MPa. The maximum error is about 1 MPa (about 3% error).
- The error is continuously distributed over the mesh.

Simulation



Prediction

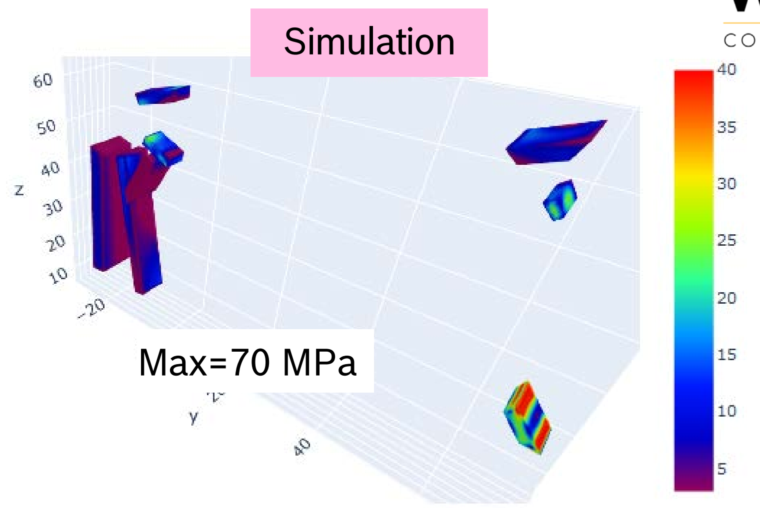


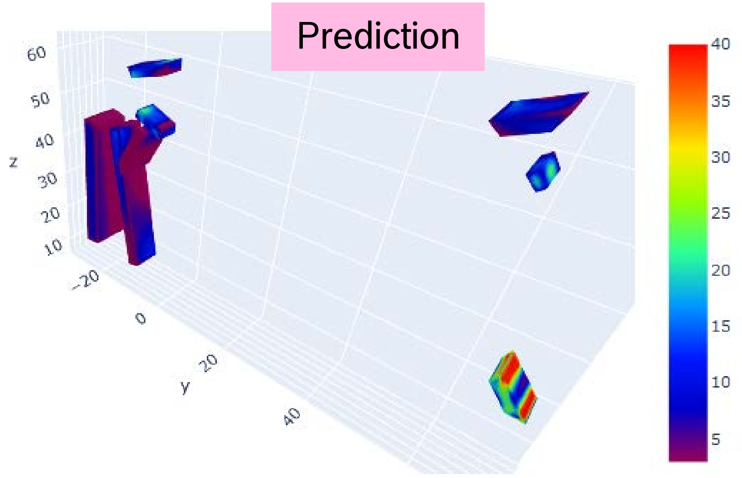


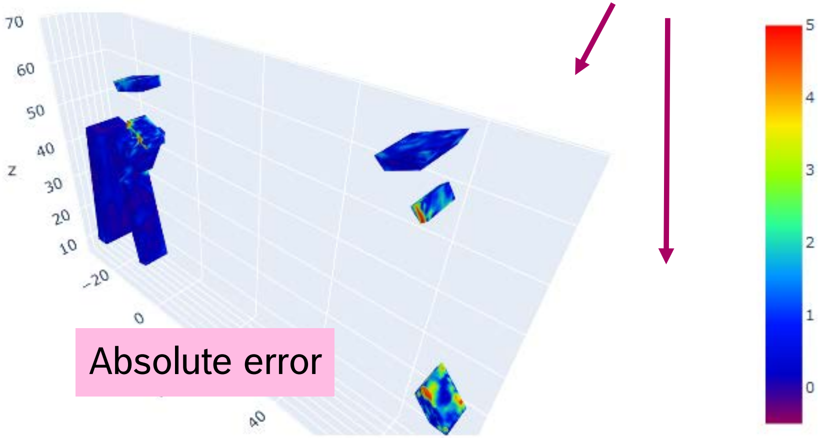
Window lift drive

Results for static stress distribution /3/

- The design #117 (4 deactivated ribs) shows the highest error for the maximum stress.
- The stress distribution of simulation and prediction is very similar and mostly the absolute error is less than 1.0 MPa.
- At mounting points with deactivated ribs the error increases up to 5 MPa (about 7% error).



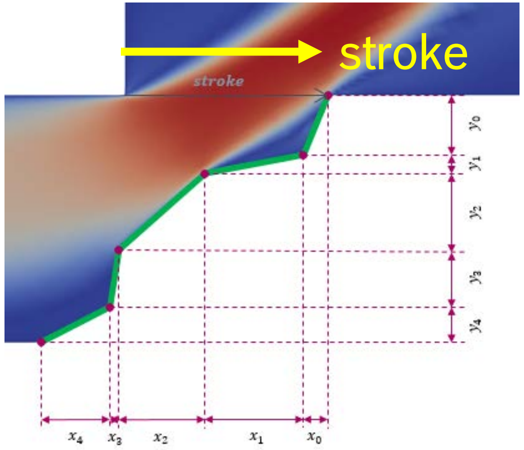




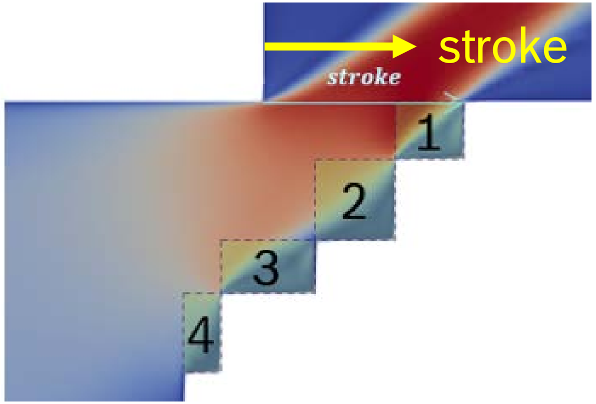
Examples
Control edge

- Parametric
  - Setup 1 : 1 topology, 10 parameters x_i, y_i
    5 stroke positions
  - Setup 2 : 3 topologies, 0 parameters, only geometry in STL format
    20 stroke positions

Setup 1

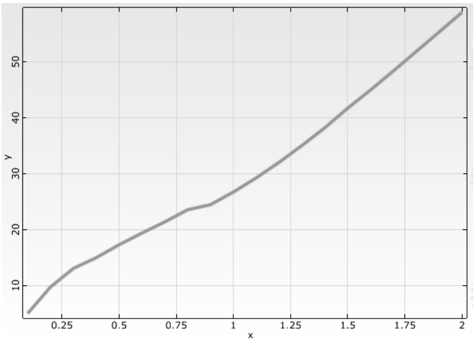


Setup 2

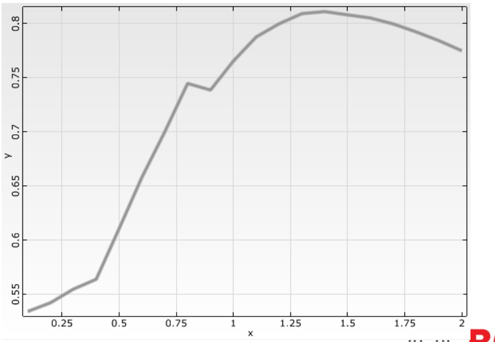


- Results
  - Aeff = stroke-dependent effective flow area (signal, nonlinear)
  - Sigma = stroke-dependent flow force factor (signal, nonlinear)

Aeff: Effective flow area

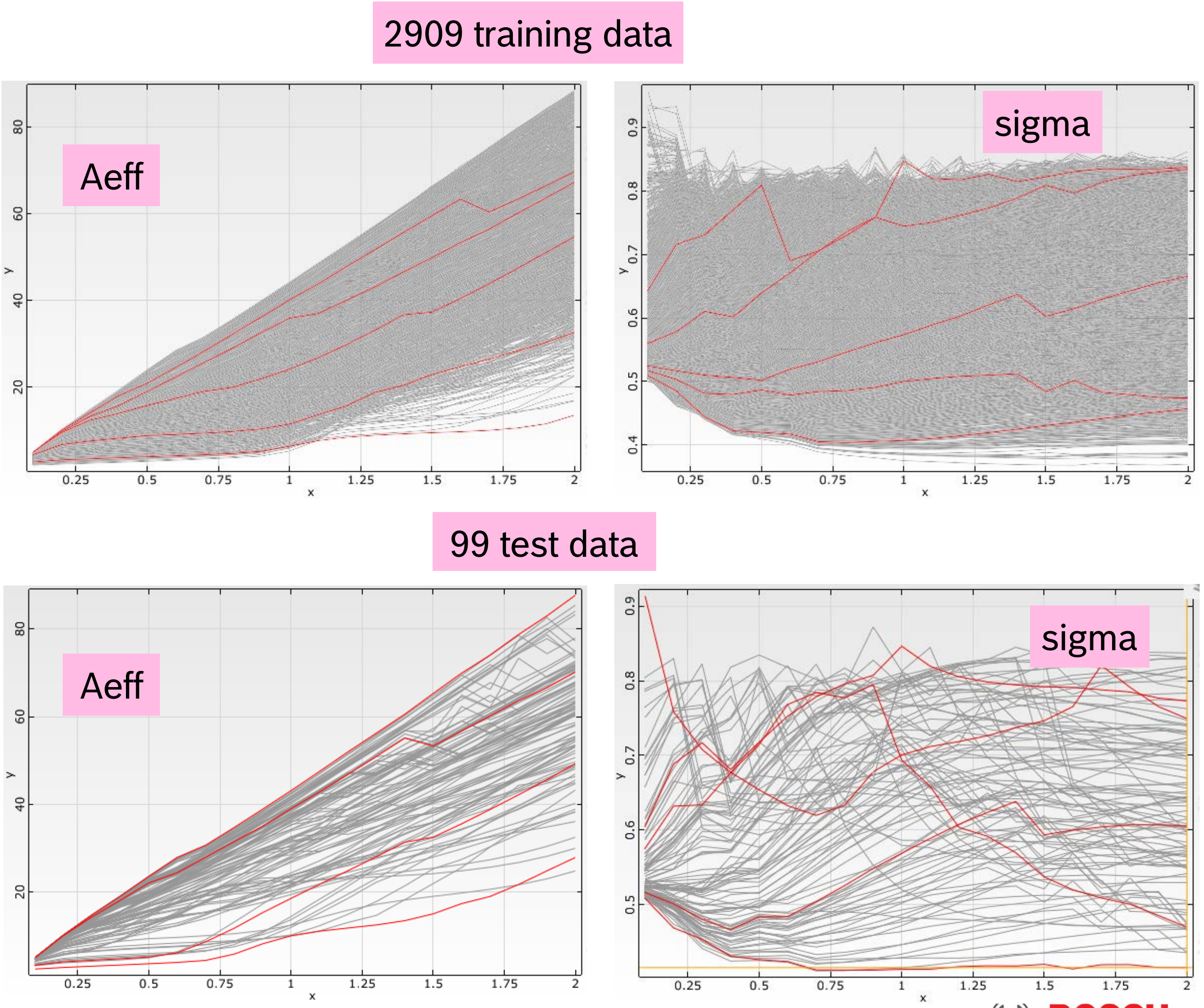


Sigma: Flow force factor



Control edge
Training and test setup

- Training data
  - 2909 Designs using Latin-Hypercube-Sampling
- Test data
  - 99 Designs using Latin-Hypercube-Sampling
- Signal types
  - Effective flow area „Aeff“
  - Flow force factor „sigma“
- Outliers and incomplete designs were deactivated



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Control edge

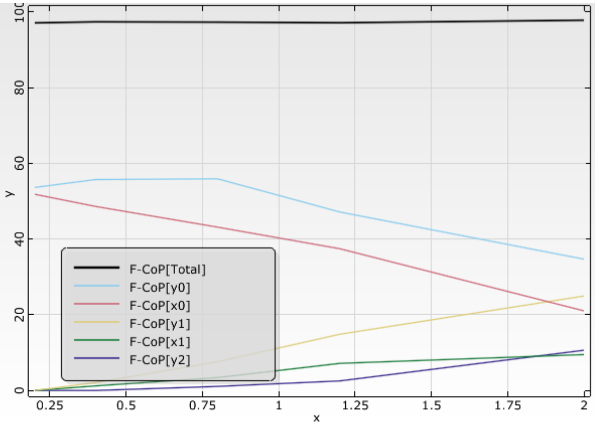
Setup 1: Results from optiSLang, Stochos and SoS (signalMOP)

- The CoP shows mostly good results for all 5 stroke positions.
- Stochos has always a higher CoP value than optiSLang.

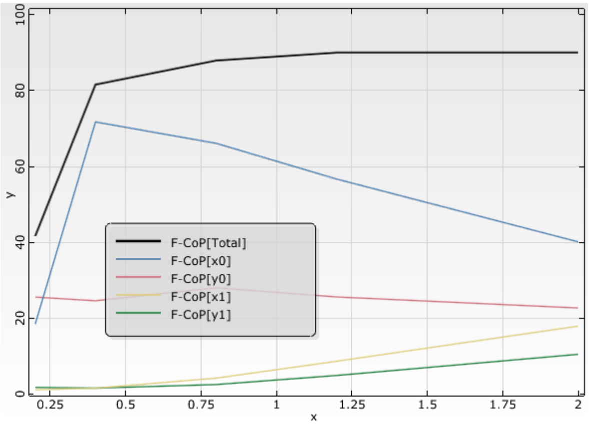
- signalMOP shows a good approximation for the effective flow area, but not for the flow force factor.
- The signal COPs are lower than the scalar COPs.

Response variable	optiSLang	Stochos	optiSLang algo
Aeff stroke pos. 1	0.999	1.000	Kriging
Aeff stroke pos. 2	0.997	0.999	Kriging
Aeff stroke pos. 3	0.995	0.999	Kriging
Aeff stroke pos. 4	0.987	0.997	Kriging
Aeff stroke pos. 5	0.988	0.993	Kriging
Sigma stroke pos. 1	0.905	0.925	Moving Least Square
Sigma stroke pos. 2	0.948	0.978	Kriging
Sigma stroke pos. 3	0.974	0.993	Kriging
Sigma stroke pos. 4	0.966	0.989	Kriging
Sigma stroke pos. 5	0.962	0.990	Kriging

Aeff: Effective flow area



Sigma: Flow force factor

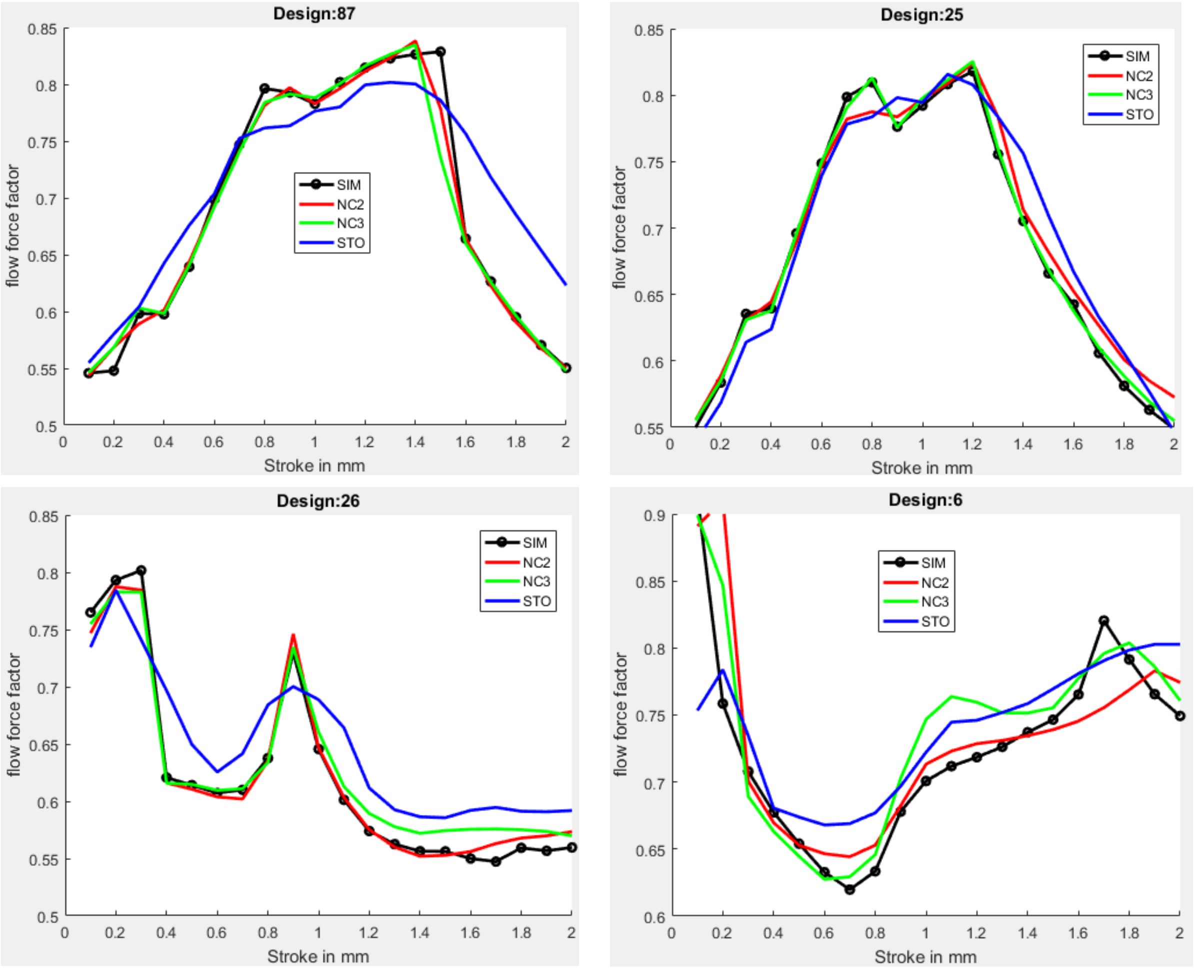


Control edge
Setup 1: Comparison of sigma with existing ML-tools

- Comparison between
  - Simulation (CFD)
  - NC2 (Neural Concept Shape – variant v2)
  - NC3 (Neural Concept Shape – variant v3)
  - STO (Stochos)

- Signal sigma for four designs with a medium error for the maximal value.

- NCS and Stochos can approximate the signal quite well, but NCS is clearly better.



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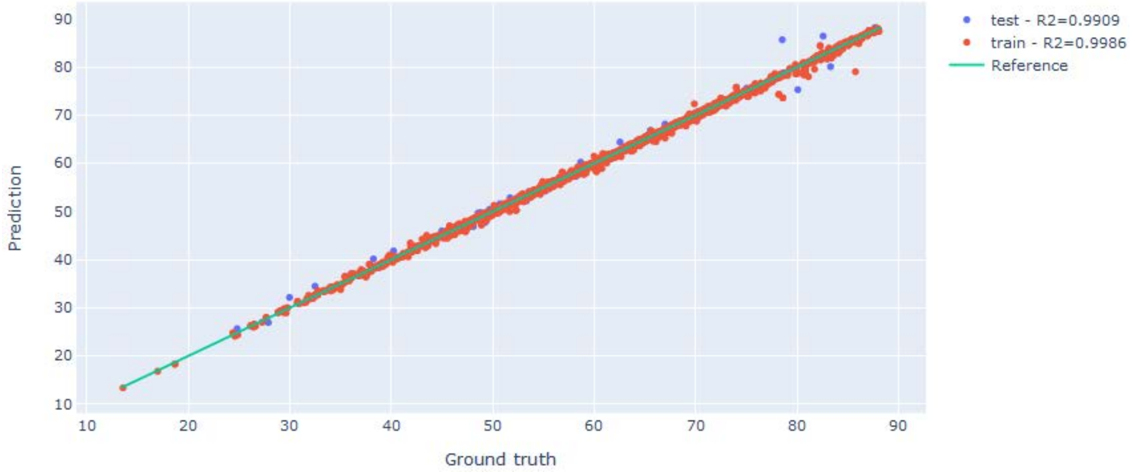
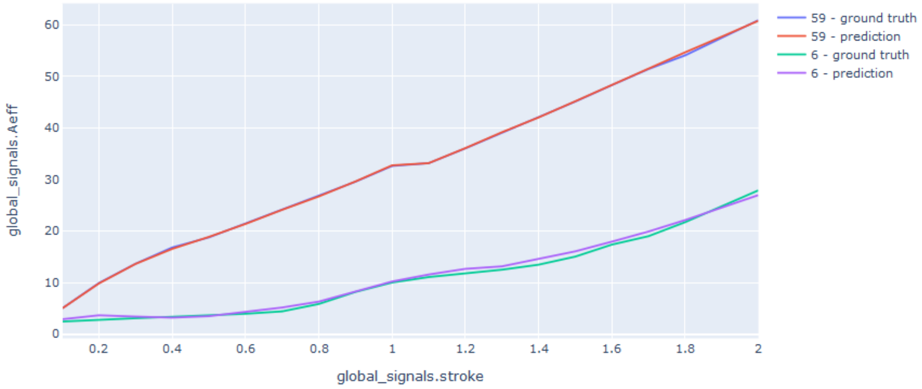
Control edge

Setup 2: Results for effective flow area /2/

- The training was saved after 38 hours for 705000 iterations.
- The R^2 value of 0.998 for the effective flow area (Aeff) is very high.
- The simulated and predicted Aeff curves are plotted for
  - The lowest (#59) and highest (#6) loss error
  - The lowest (#5) and highest (#39) error of the

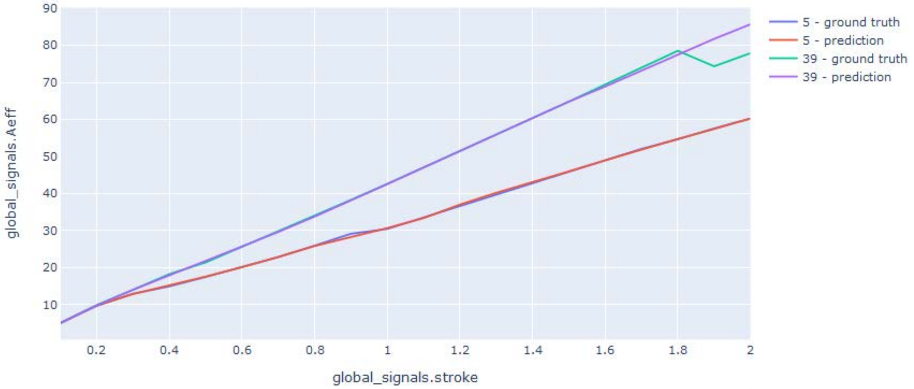




Prediction

vs.

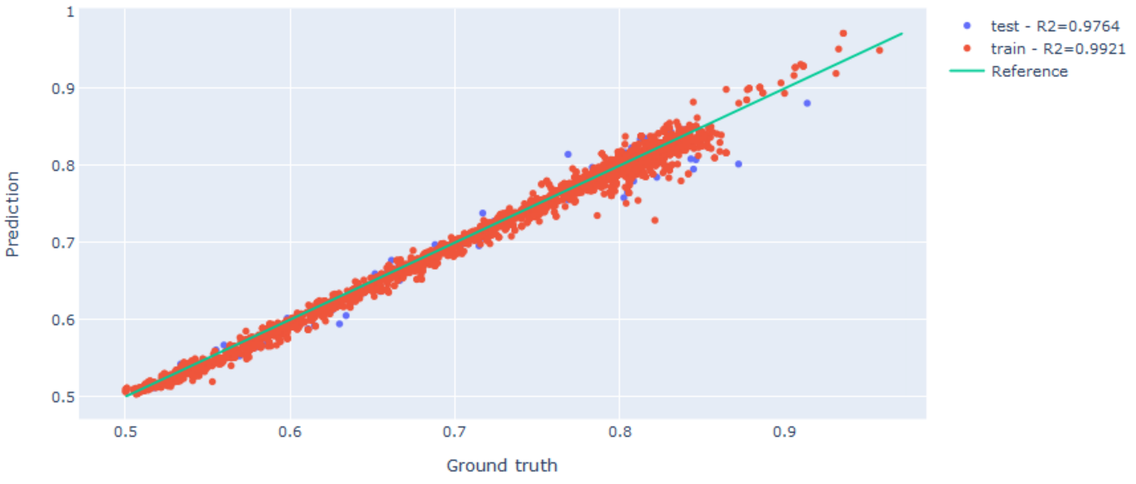
Simulation (=ground truth)

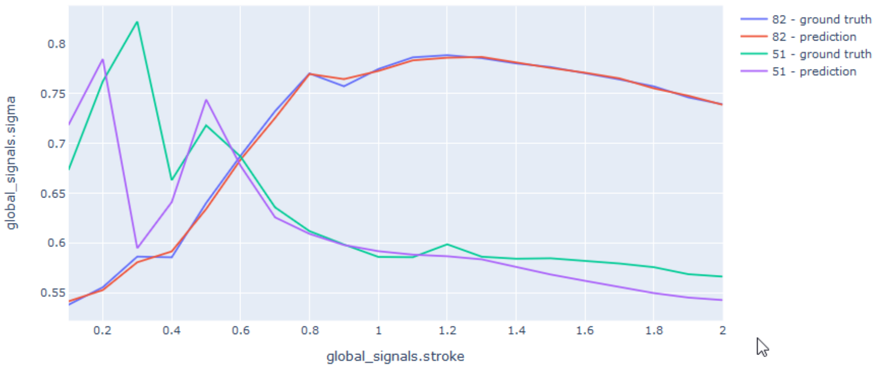


Control edge
Setup 2: Results for flow force factor

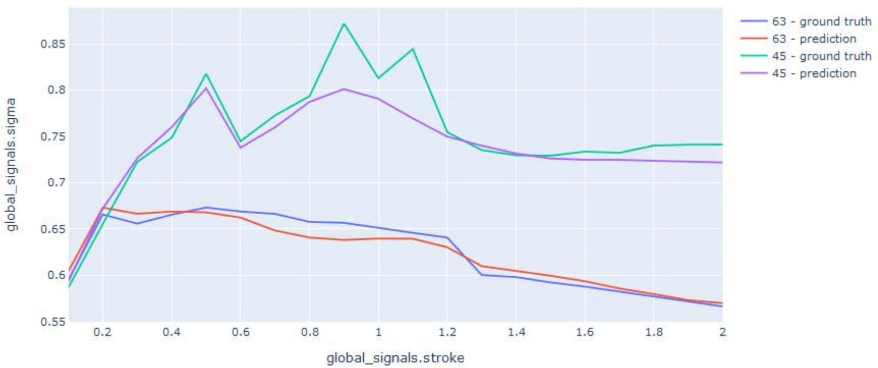
- The R^2 value of 0.976 for the flow force factor is high, but lower than for the train data.

- The simulated and predicted sigma curves are plotted for
  - The lowest (#82) and highest (#51) loss error
  - The lowest (#63) and highest (#45) error of the maximum value.





Prediction vs. Simulation (=ground truth)



Summary

- NCS could be applied successfully to all examples.
- In comparison to existing solutions at Bosch, the results of NCS are
  - clearly better than optiSLang
  - similar to Stochos from Probaligence for long, smooth signals (Window Lift Drive), but better for short, discrete signals (Control Edge).
  - new and accurate for the training of signal and field outputs of different topologies.
- NCS requires a GPU-cluster in comparison to optiSLang and Stochos. The computing time for training is significantly longer than for optiSLang and Stochos.
- The usage of NCS needs highly skilled users in setting up parametric models, setting up workflows, scripting, knowledge of 3D deep learning, etc. There are a lot of tasks to do until an optimization/sampling can run.

- Bosch is currently applying NCS for another application for shape optimization of different topologies.

	Task	VC	V	VV
Preprocessing	STL data for Runs directories	1	1	
	Matlab script run2mat.m	1	1	
	Matlab file with outliers	1	1	
	Matlab script mat2ncs.m	1	1	
	optiSLang reevaluation	1	1	
	optiSLang outliers	1	1	
	Matlab script copySTL_run2ncs	1	1	
	Data transfer to GPU-Cluster	1	1	
Training	Converting the data for deep-sdf; Running stats	1	0	
	Converting the data for surr-model; Running stats	1	0	
	Training of deep-sdf	1	0	
	Training of surr-model on original mesh	1	0	
	Remeshing the mesh from .stl in .h5 format	1	0	
	Running stats on remeshed designs	1	0	
	Training of surr-model on the remeshed designs	2	0	
Prediction	Predition of training and test designs on original mesh	1		
	Predition of training and test designs on remeshed mesh	0		
	Creating deep-sdf meshes	0		
	Sampling	0		