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Design Optimization of a Synchronous Reluctance Electric Motor using Deep Learning Technology

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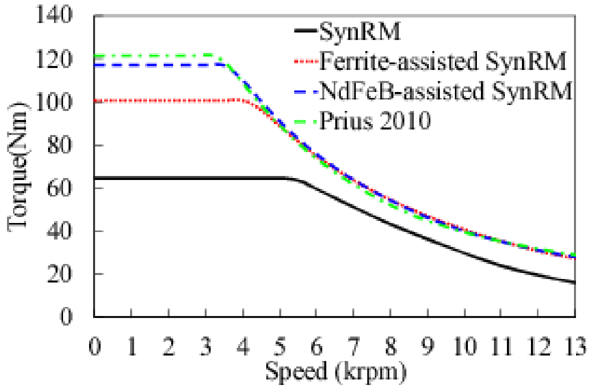
Content

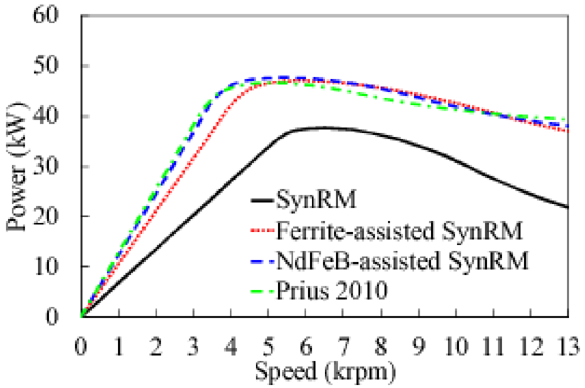
Background and motivations

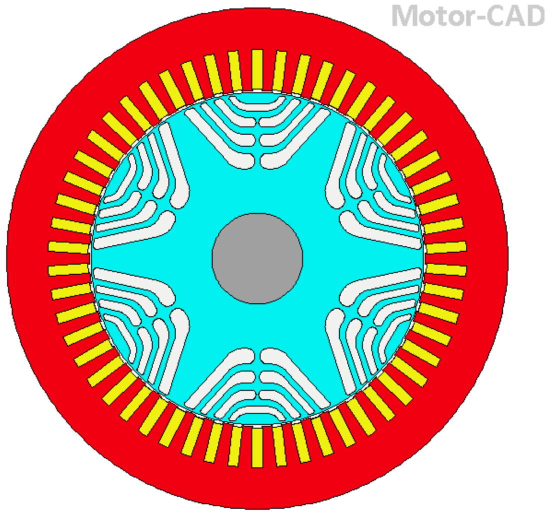
Synchronous reluctance (SyncRel) machine

- **Viable option for automotive applications:**
  - PM-free machine
  - overload and fault tolerant capabilities
  - reduced material cost, price and supply risks
- **SyncRel machines vs PM-based machines:**
  - lower torque/power density, cycle efficiency
  - limited performance at high speed operation
  - higher torque ripples across operating range
  - design optimization can be more challenging
- Rare-earth free / reduced rare-earth based PM used to boost performance (**PMaSyncRel**)
  - ferrite, dysprosium-free Neodymium magnets

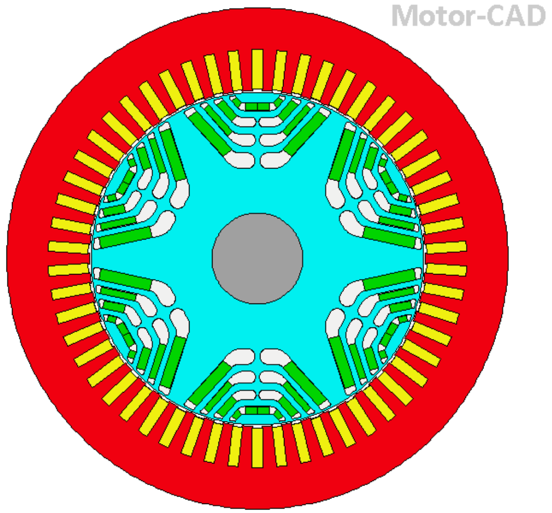
Design of synchronous reluctance and permanent magnet synchronous reluctance machines for electric vehicle application







SyncRel

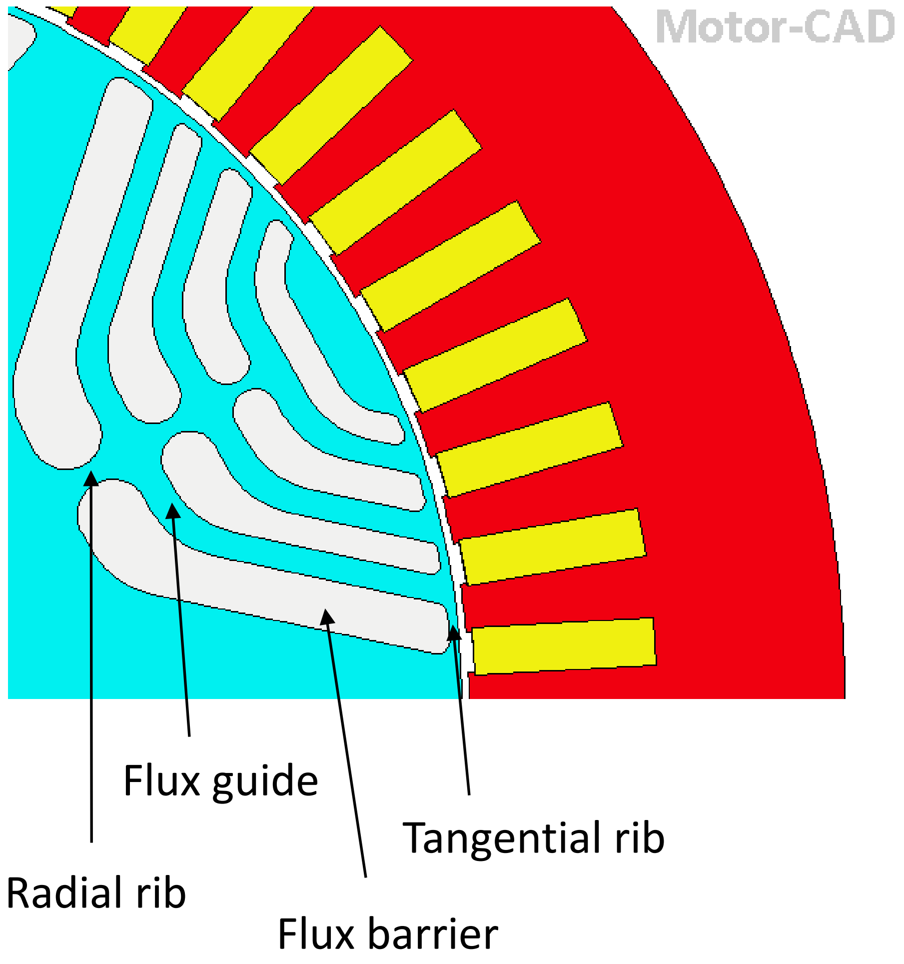


PMaSyncRel

SyncRel design optimization

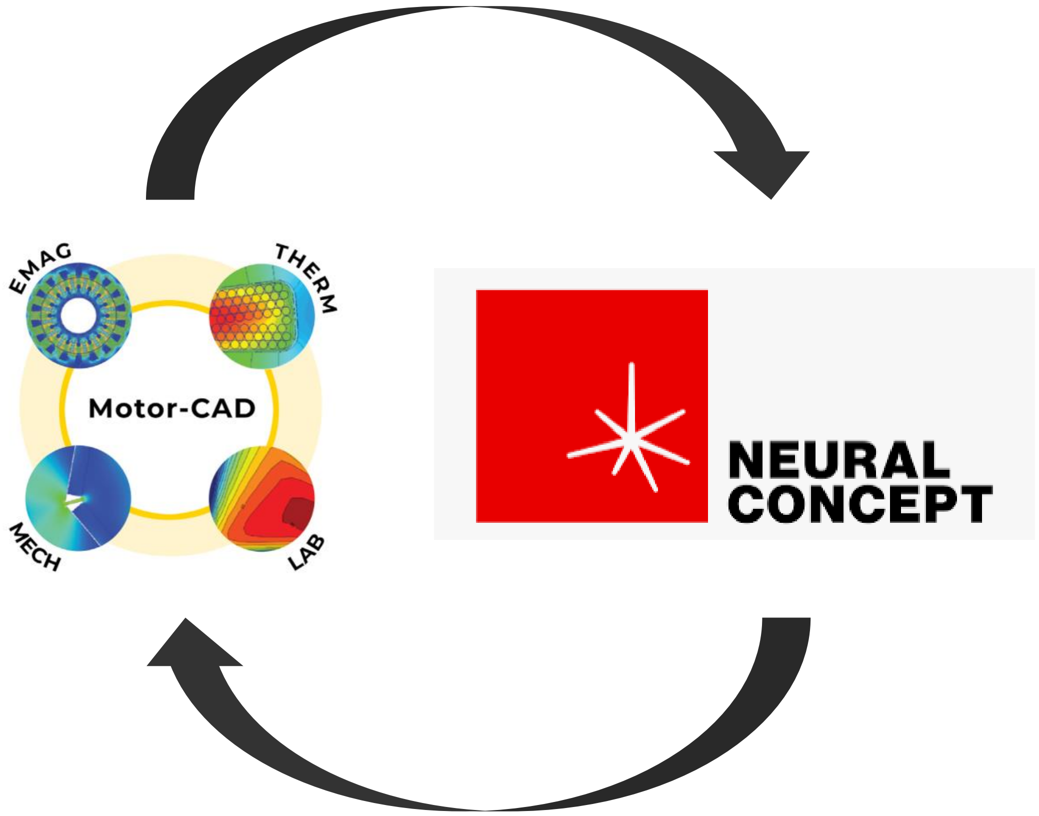
- **Challenges**:
  - Discrete number of flux barriers / flux guides
  - Variety of barriers' shape (fluid, circular, …)
  - Many parameters due to complex rotor geometry
  - Conflicting performance across the design space

- **Methods:**
  - as of today: parametric optimization using CAE data
  - avenue: shape optimization using CAE and CAD data



Proposed workflow

- Workflow that combines **Ansys Motor-CAD** (MCAD) **Neural Concept Shape** (NCS) tools:
  - MCAD is an integrated multi-physics design software mostly used for the concept design stage of electric motors.
  - NCS builds CAE and CAD-based predictive models from deep learning technology that can be used for design optimization.
- Input CAD and CAE data are generated by MCAD and used by NCS to build accurate **deep learning models.**

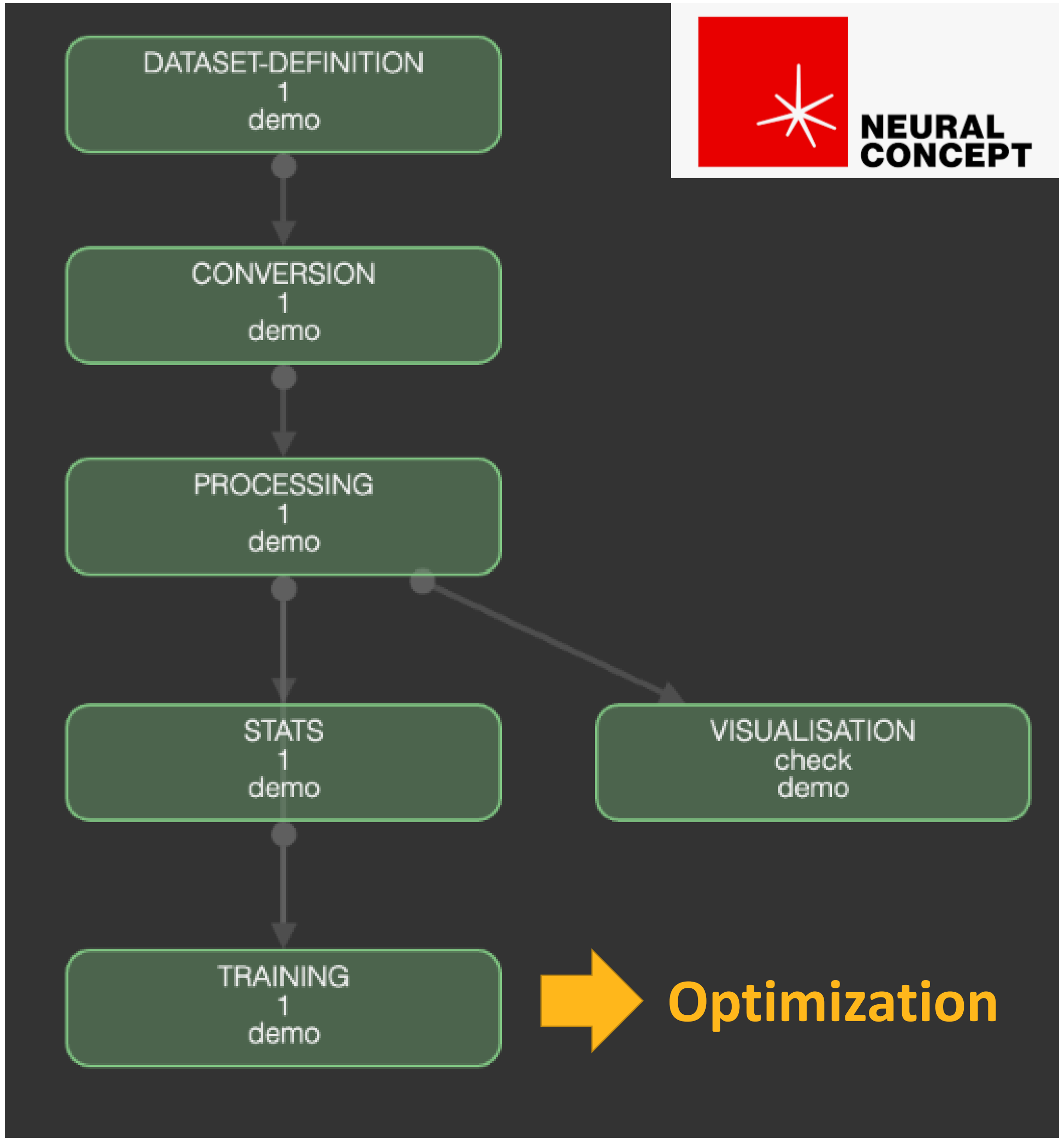


NCS pipeline overview

- NCS does not work from a parameter space but from the **design shape** directly.

- Potential **benefits** with respect to more conventional parametric optimization :
  - go beyond the initial parameter space and get out-of-the-box design geometries,
  - reduced computations times and increased accuracy from predictive models.

- NCS pipelines split into tasks from the dataset definition to design optimization.



SyncRel motor use case

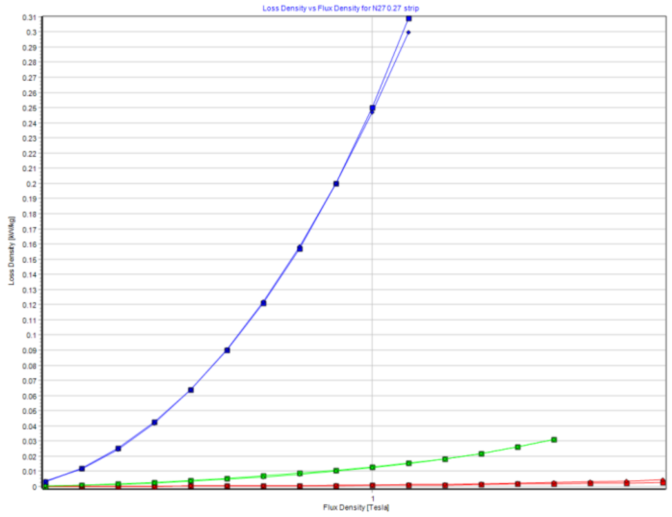
Specification

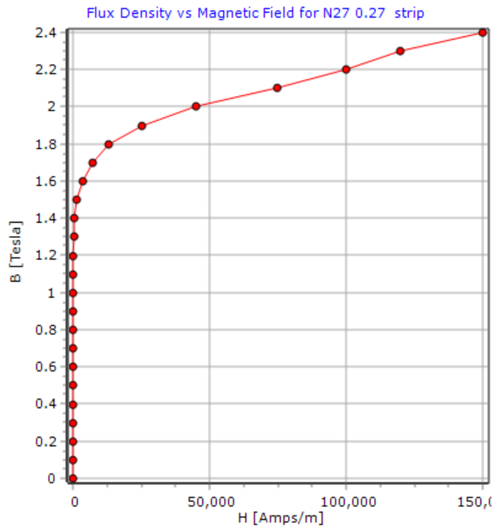
- **Requirements:**
  - Peak performance across speed range
  - Rotor mechanical stress at high speed
  - Thermal and electrical limits
  - Rotor and stator active space envelopes
- **Goals:**
  - Minimum torque ripples @ 5krpm
  - Maximum peak power @ 16krpm

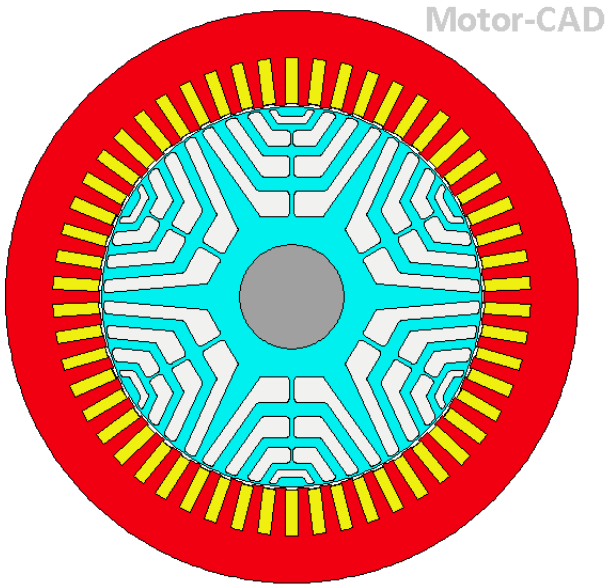
Parameter	Unit	Value
Maximum speed	rpm	16000
Operating temperature	°C	80
DC bus voltage	V	720
Peak phase current	Arms	460
Active length	mm	200
Stator diameter	mm	220
Split ratio	[–]	0.67
Airgap	mm	0.7
Peak torque	Nm	≥ 300
Peak power	kW	≥ 200
Peak stress @ 18krpm	MPa	≤ 450

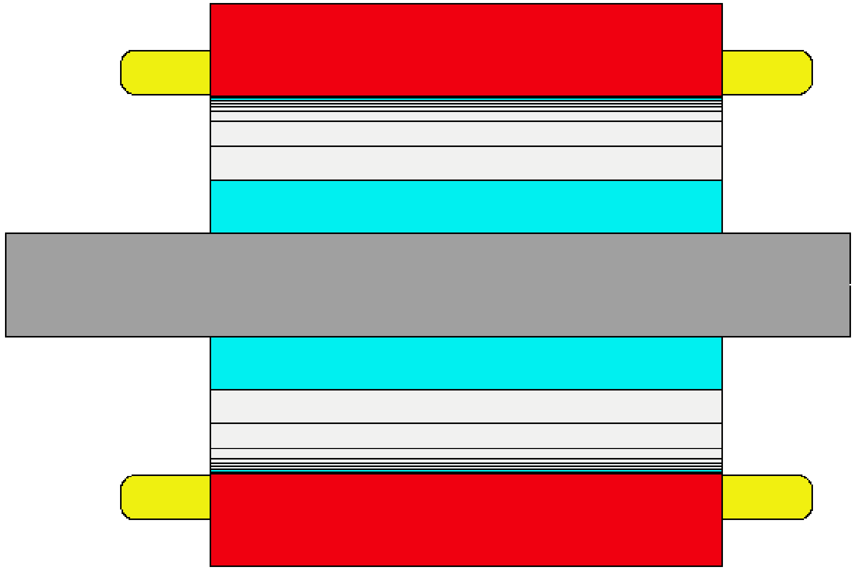
Design choices

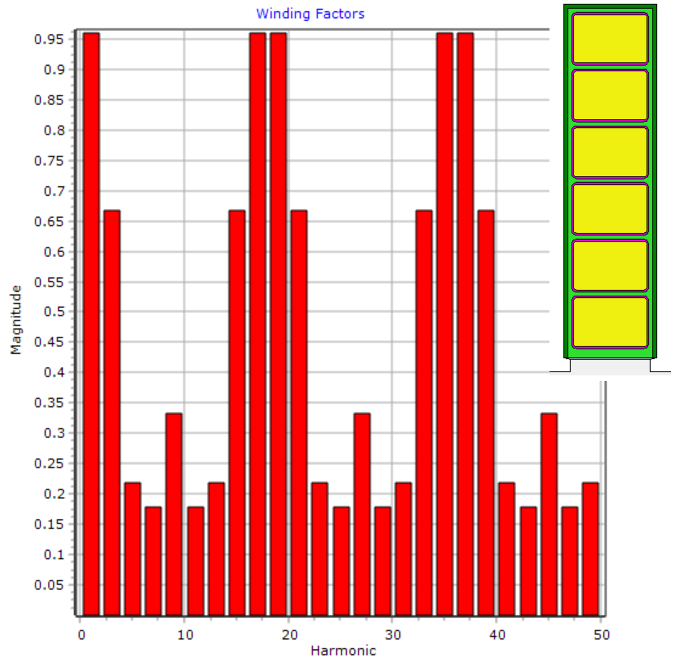
- 54-slot, 6-pole, 3 to 4-layer topology
- 3-ph, 6-layer hairpin winding (18 turns)
- N27 0.27 electrical steel, copper winding











Ansys

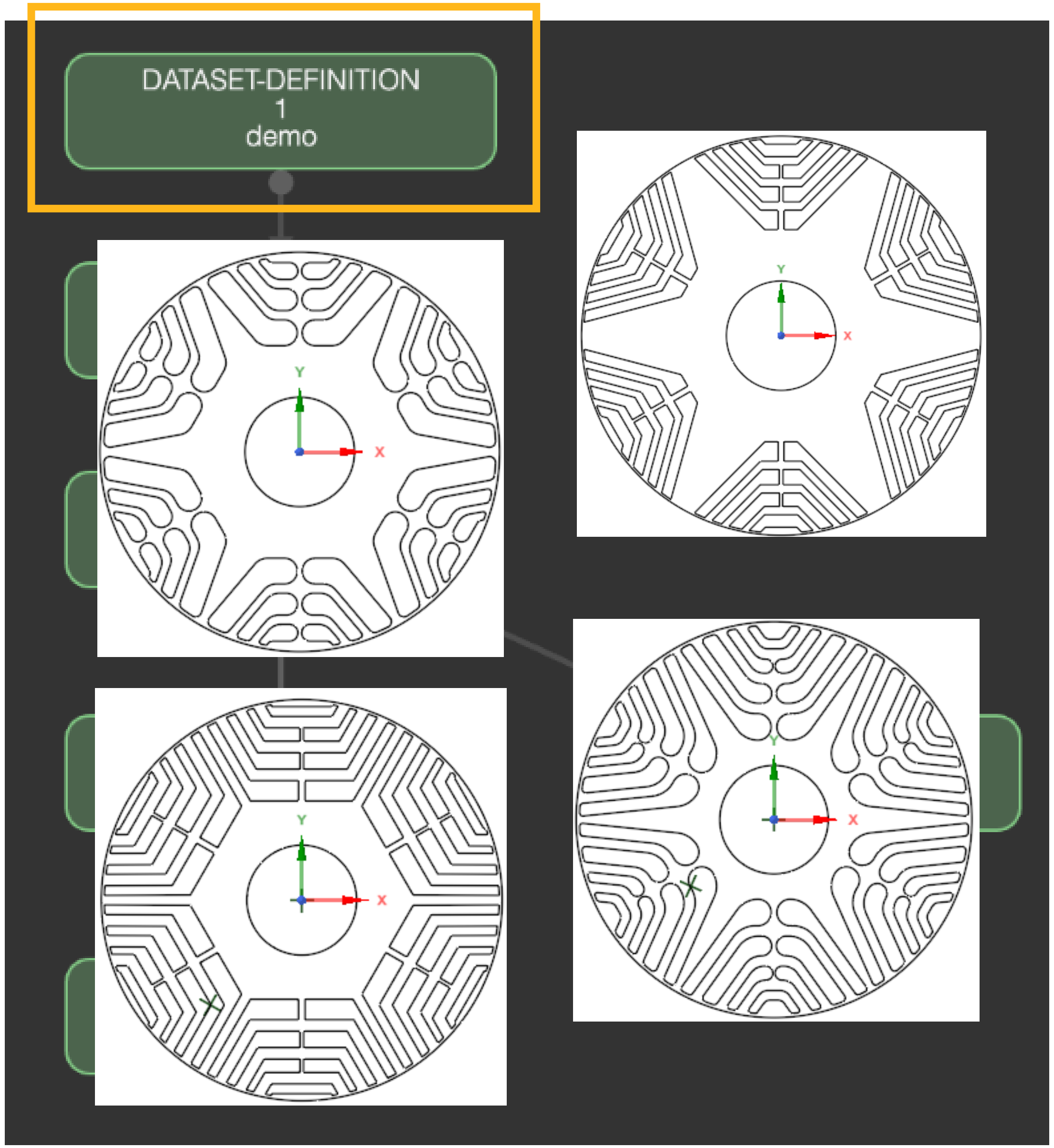
Design optimization walk through

Dataset definition

- CAE (*json) and CAD (*dxf) data are created from MCAD and imported into NCS.

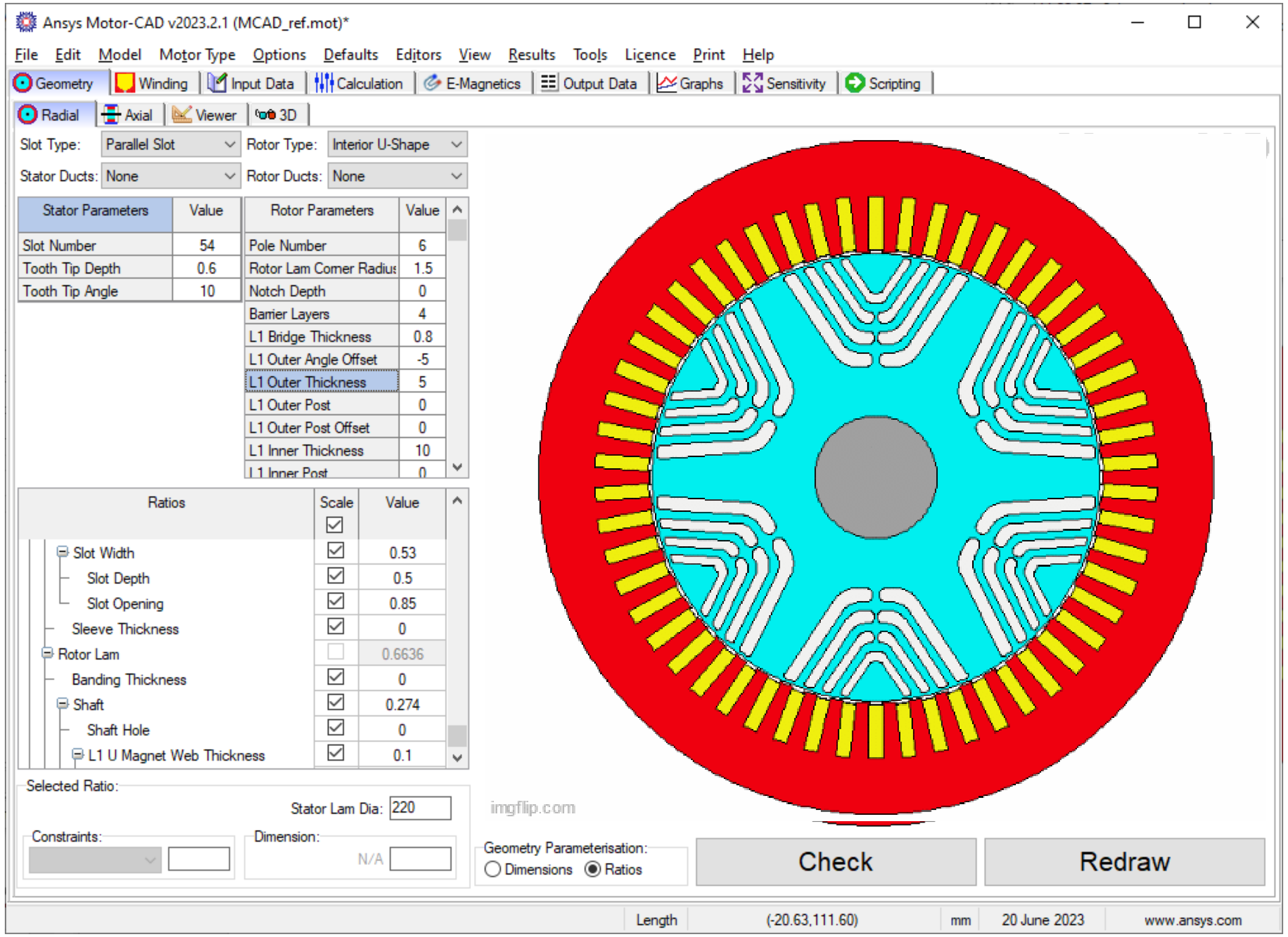
Outputs_Design0003.json


```
{
    "peak_Shaft_Torque_MaxValue": 280.66037272517065,
    "peak_Shaft_Power_MaxValue": 211149.01667721182,
    "peak_Shaft_Power_16000rpm": 80571.7892771748,
    "Rotor_Lamination_Stress_max_18000rpm": 497.766163230059,
    "L1_Average_Magnet_Bridge_Stress_18000rpm": 248.626666666667,
    "L2_Average_Magnet_Bridge_Stress_18000rpm": 105.938666666667,
    "L3_Average_Magnet_Bridge_Stress_18000rpm": 43.366,
    "L4_Average_Magnet_Bridge_Stress_18000rpm": 0,
    "Torque_Ripple_MsVw_percent_16000rpm": 35.7521567394084,
    "Torque_Ripple_MsVw_percent_5000rpm": 37.9687061909912,
    "L1_Centre_Post_Avg_Stress": 416.24666666666656,
    "L2_Centre_Post_Avg_Stress": 225.80666666666664,
    "L3_Centre_Post_Avg_Stress": 74.69000000000003,
    "Barriers_Nb": 3,
    "Stress_Av_Max": 416.24666666666656,
    "Saturation_Ratio": 0.3802402053545106
}
```

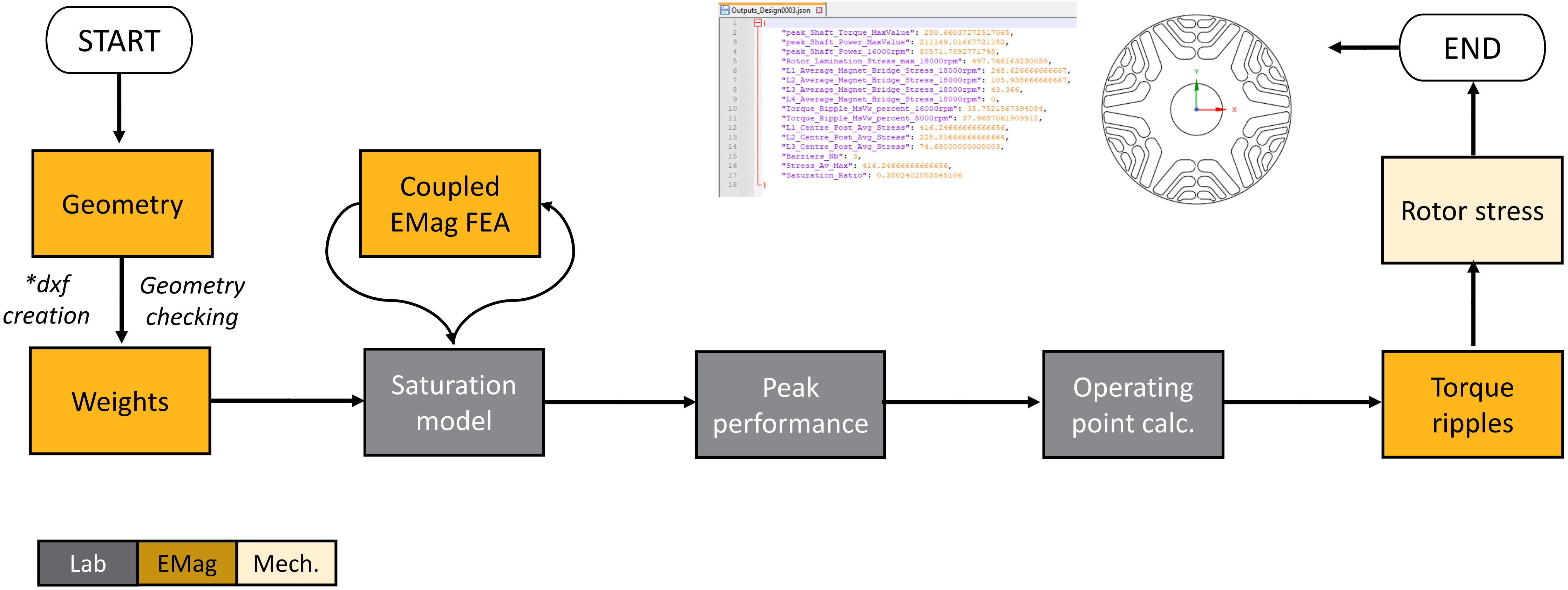
MCAD parameterization

- **Rotor parameterization:**
  - ratio-based parameterization to leverage a large initial design space,
  - custom parameterization through customized python scripting.
- **Rotor parameters varied**:
  - flux barriers' shape / dimensions,
  - ribs' dimensions (radial / tangential),
  - lamination corner rounding.



MCAD simulation

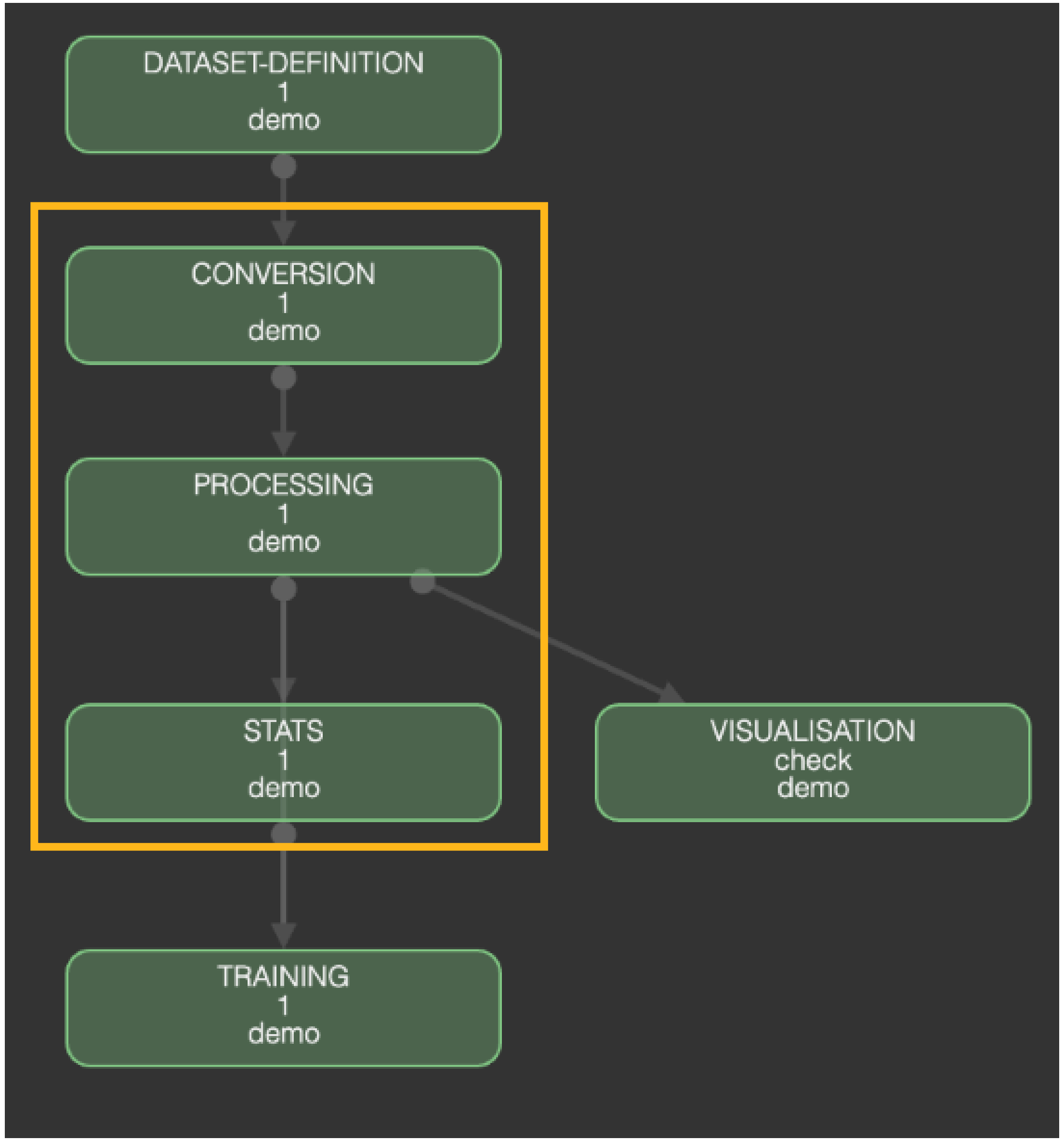
- A python script automatically runs a sequence of analysis within Motor-CAD modules.



Conversion, Processing & Stats

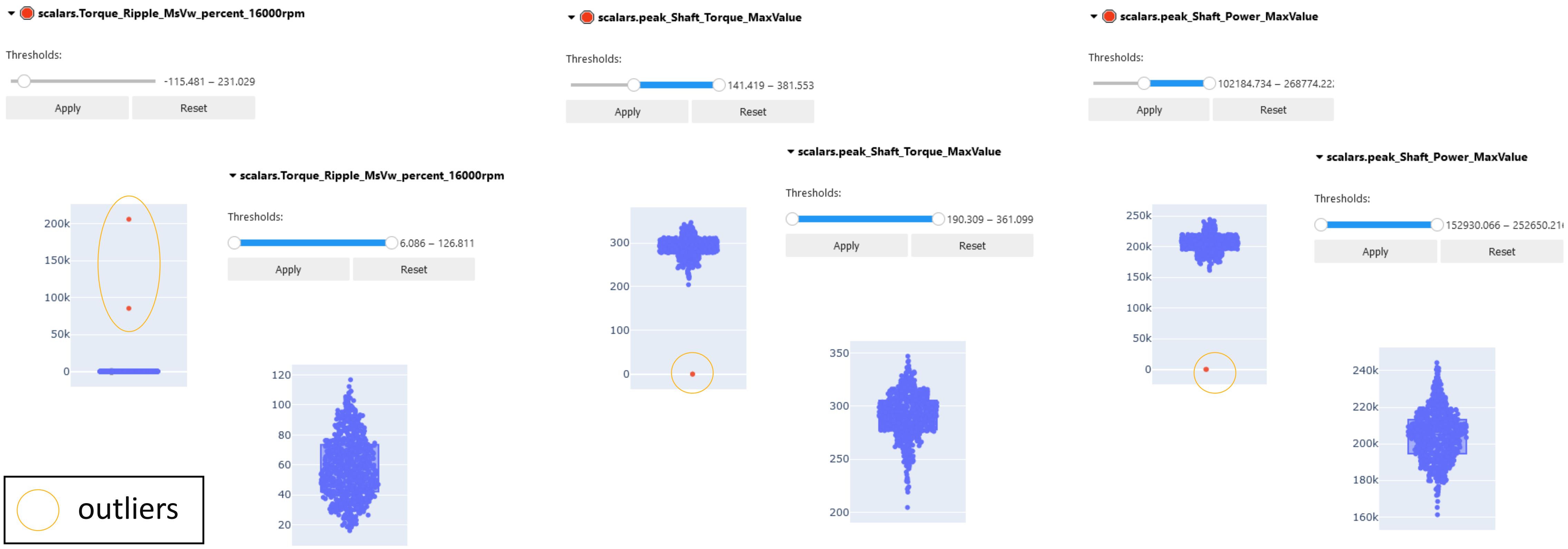
- **Conversion**: converts the dataset into a format that can be consumed by the predictive models.

- **Processing & Stats**: prepare the data for the training task and allow to remove outliers, if any:
  - **physics outliers**: inconsistent and or out-of-distribution CAE data.
  - **geometric outliers:** broken or invalid design geometry.



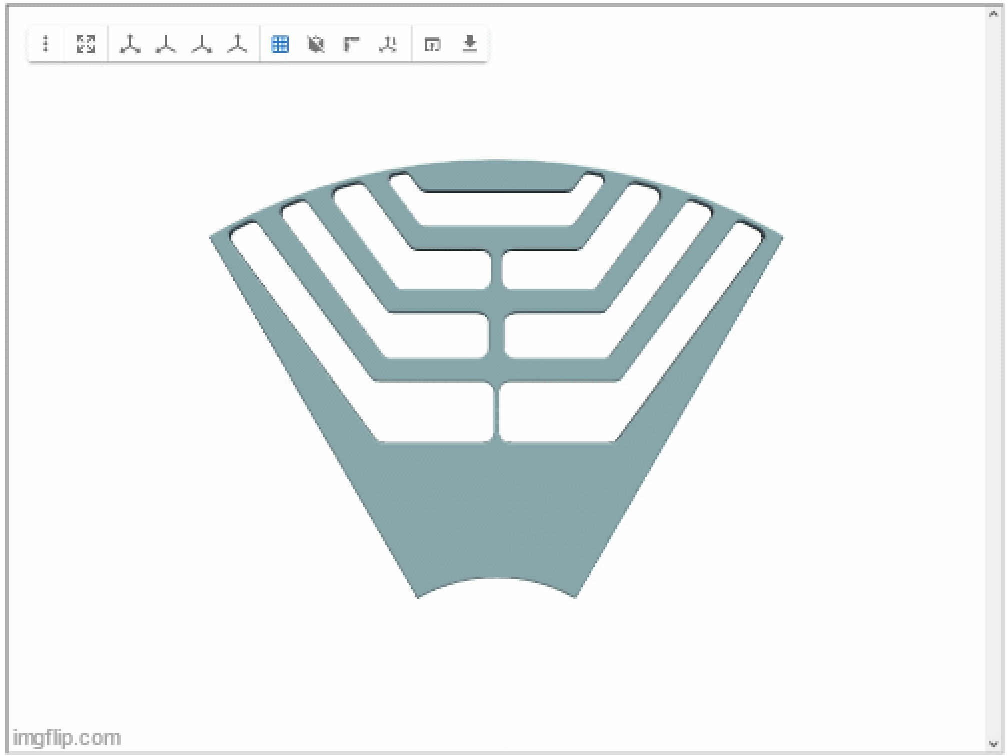
Physics outliers

- Outliers can be detected to get consistent distributions of data
- In this workflow, only few sample were removed from the dataset.

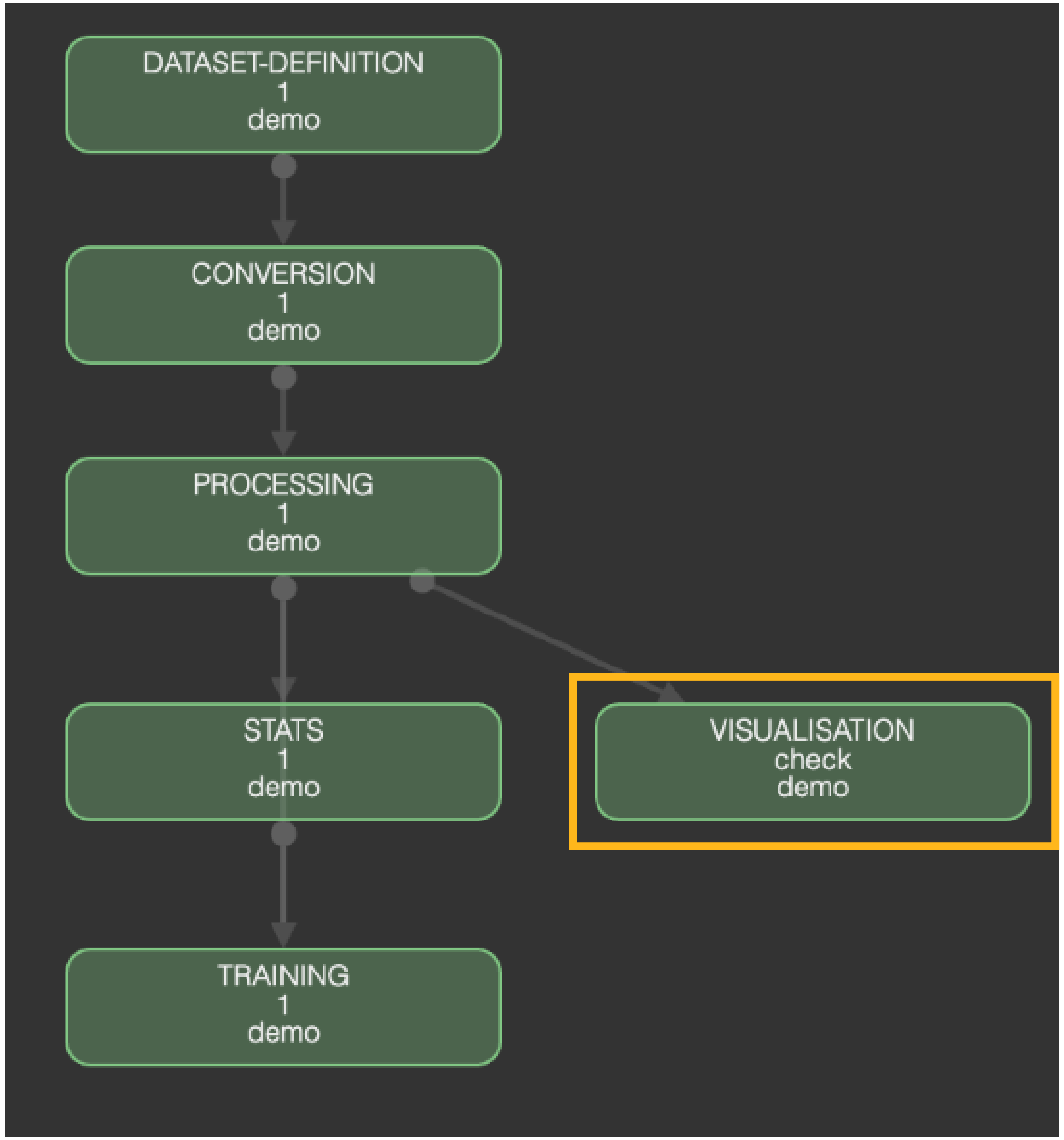


Visualization

- Shows the data processed for the training.



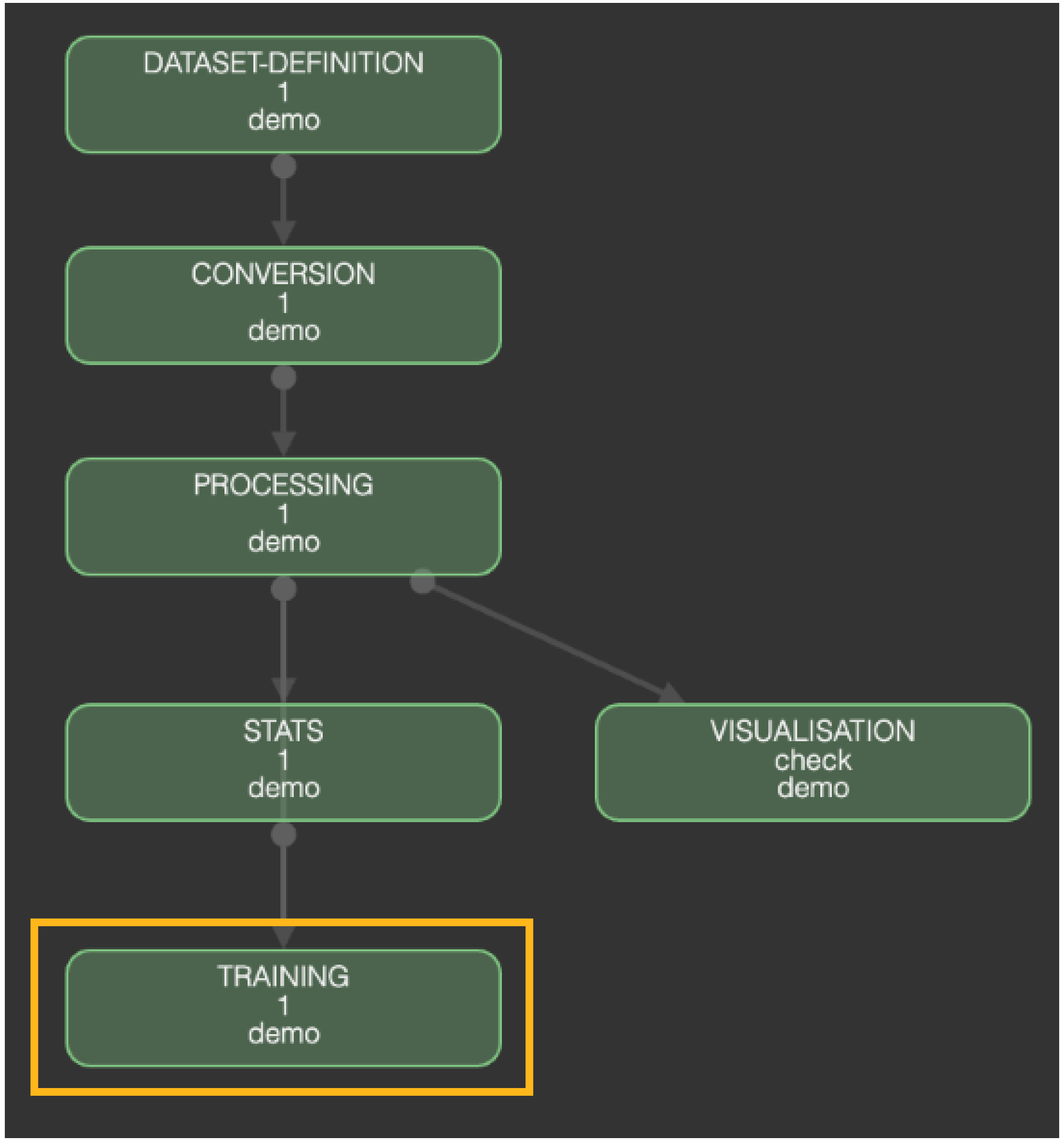
Visualization of 10 samples in NCS



Training

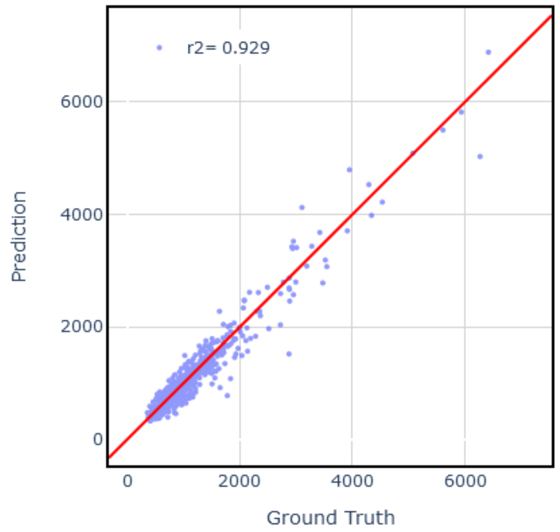
- **Predictive models** are produced using machine learning algorithms:
  - one deep learning model is trained to predict performance from an input shape,
  - another one learn the geometric features to create new shapes.

- **Confidence indicators** can be used as forecast quality measures.

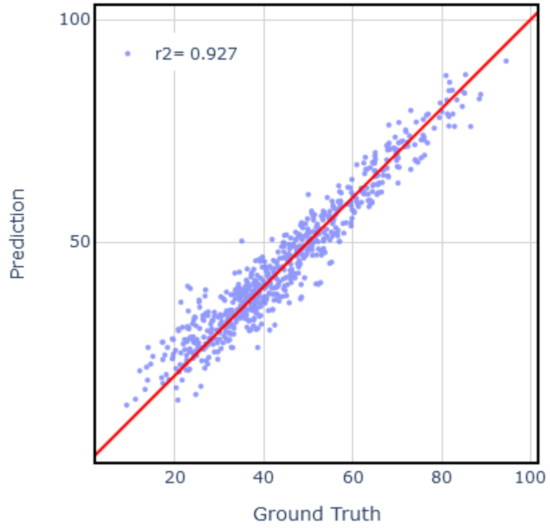


Performance predictions

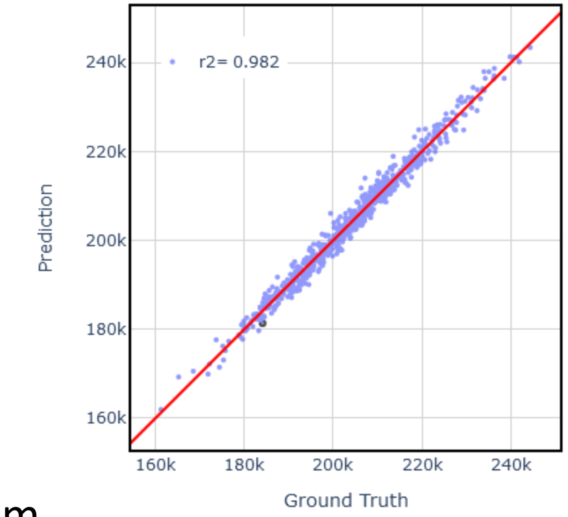
Max stress



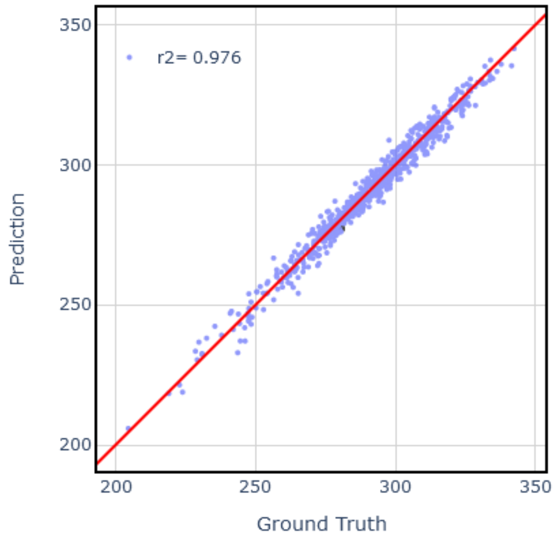
Torque ripples



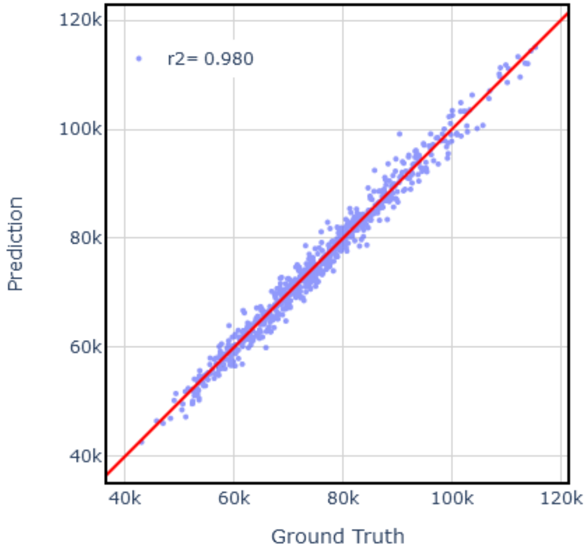
Max power



Max torque

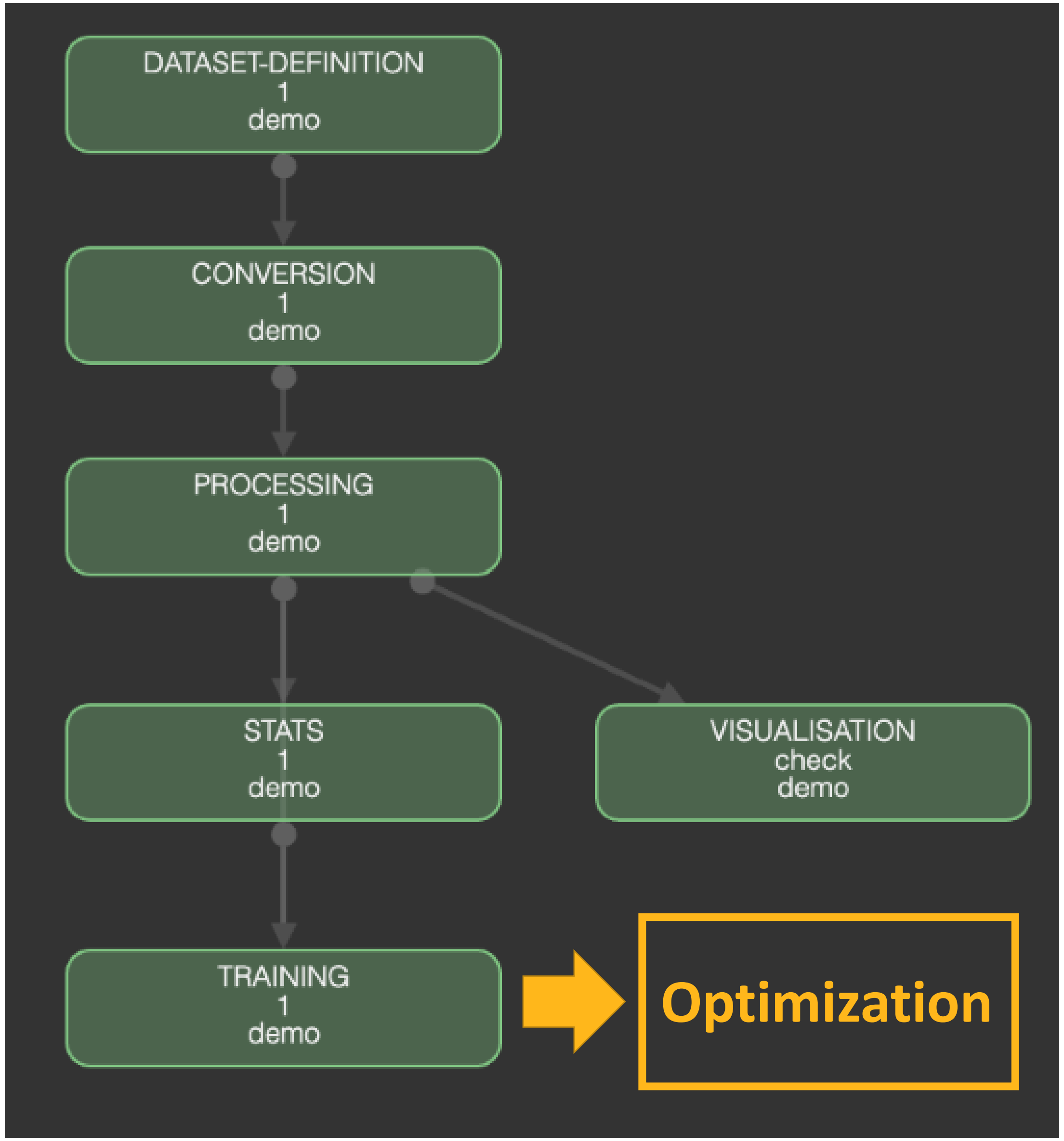


Power @ 16krpm

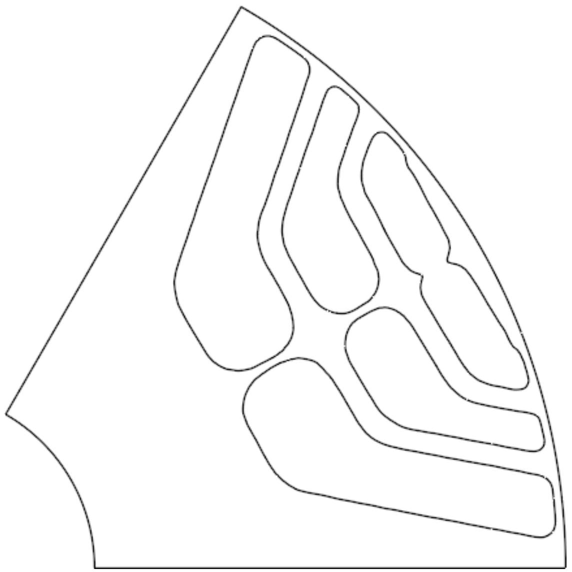


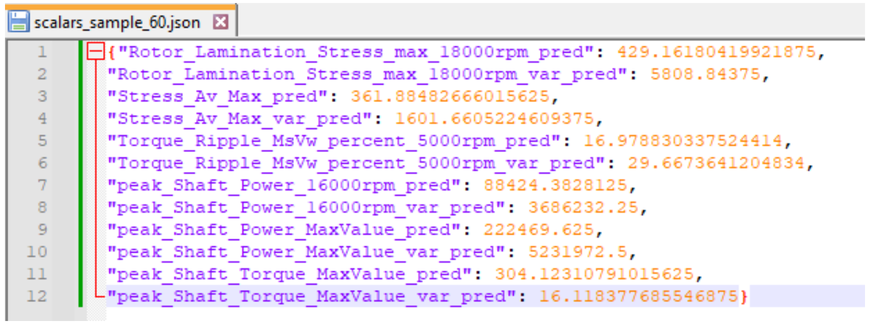
Optimization

- The predictive models for the motor rotor geometry and performance are combined to perform a multi-objective optimization:
  - **optimization algorithm:** genetic
  - **population size**: 500
  - **evolution steps**: 50



Solution space




scalars_sample_60.json

{"Rotor_Lamination_Stress_max_18000rpm_pred": 429.16180419921875,
"Rotor_Lamination_Stress_max_18000rpm_var_pred": 5808.84375,
"Stress_Av_Max_pred": 361.88482666015625,
"Stress_Av_Max_var_pred": 1601.6605224609375,
"Torque_Ripple_MsVw_percent_5000rpm_pred": 16.978830337524414,
"Torque_Ripple_MsVw_percent_5000rpm_var_pred": 29.6673641204834,
"peak_Shaft_Power_16000rpm_pred": 88424.3828125,
"peak_Shaft_Power_16000rpm_var_pred": 3686232.25,
"peak_Shaft_Power_MaxValue_pred": 222469.625,
"peak_Shaft_Power_MaxValue_var_pred": 5231972.5,
"peak_Shaft_Torque_MaxValue_pred": 304.12310791015625,
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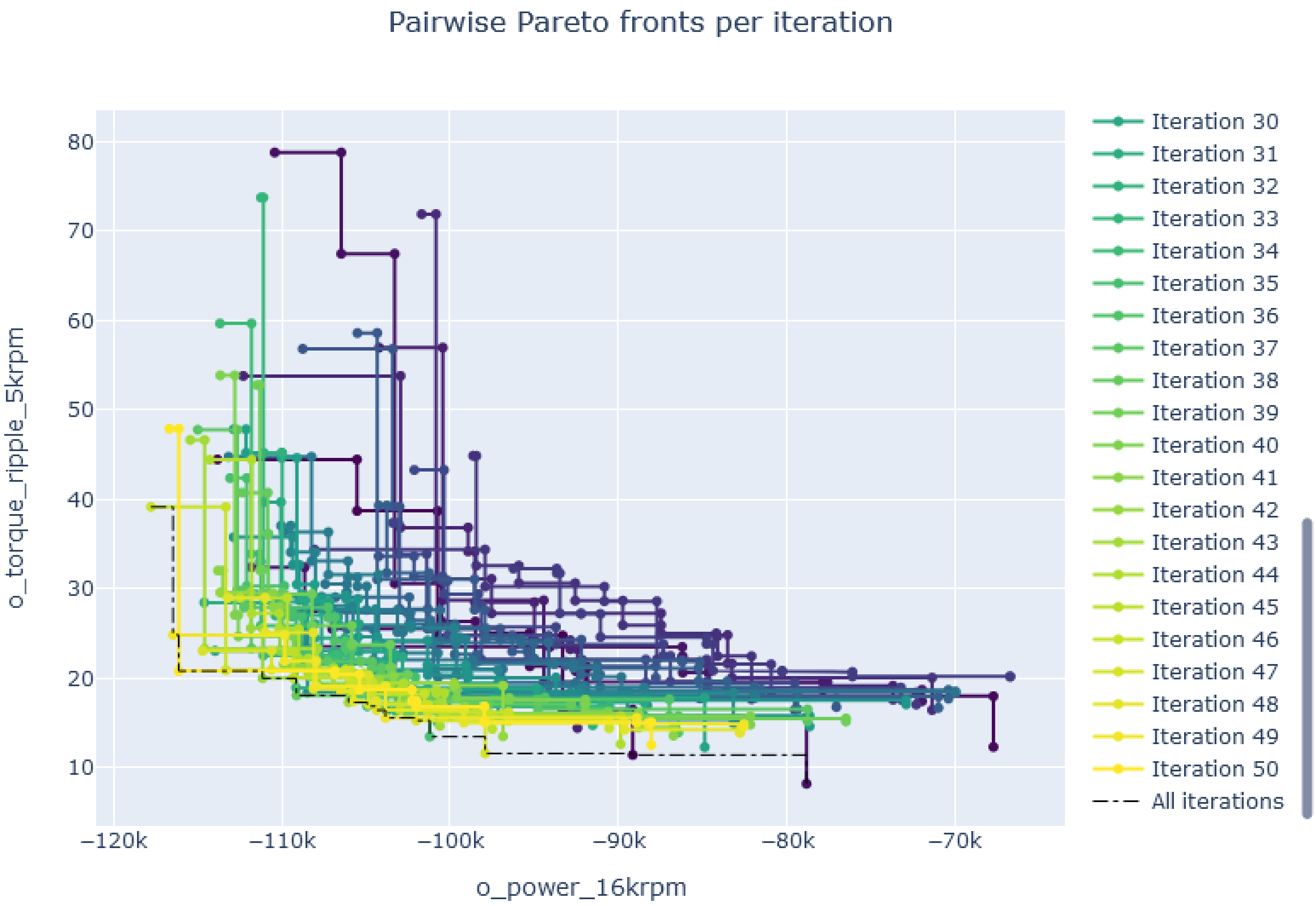
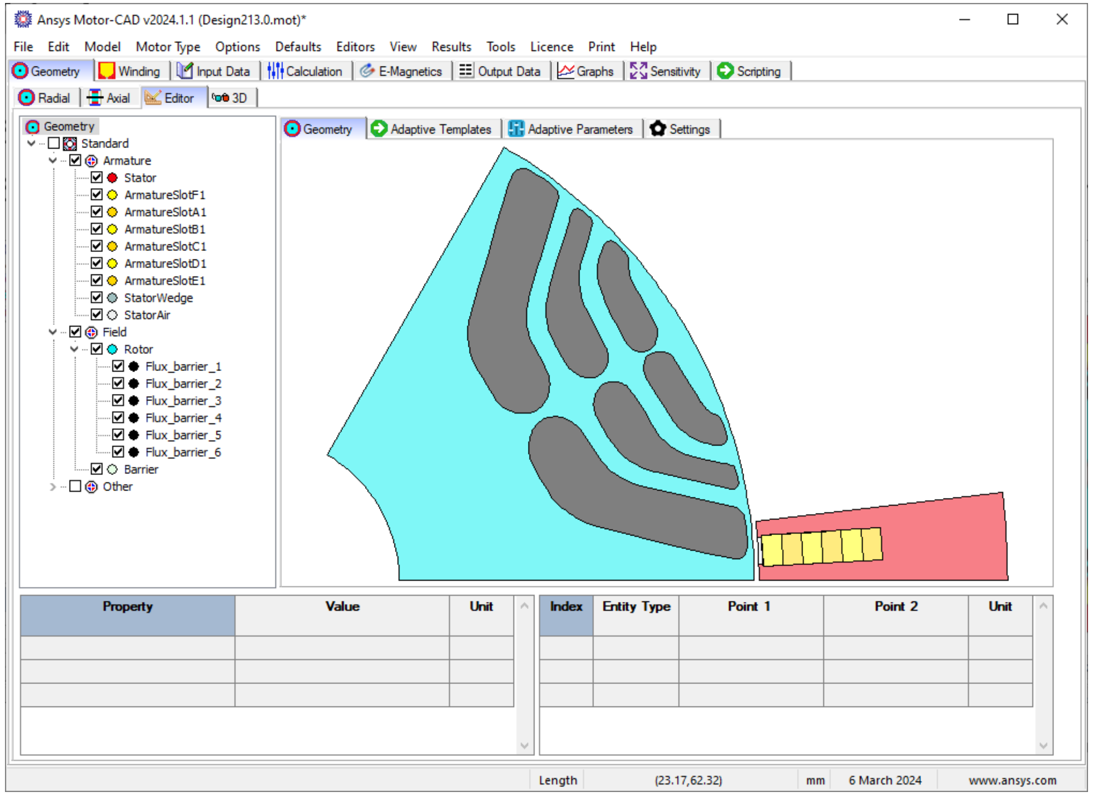
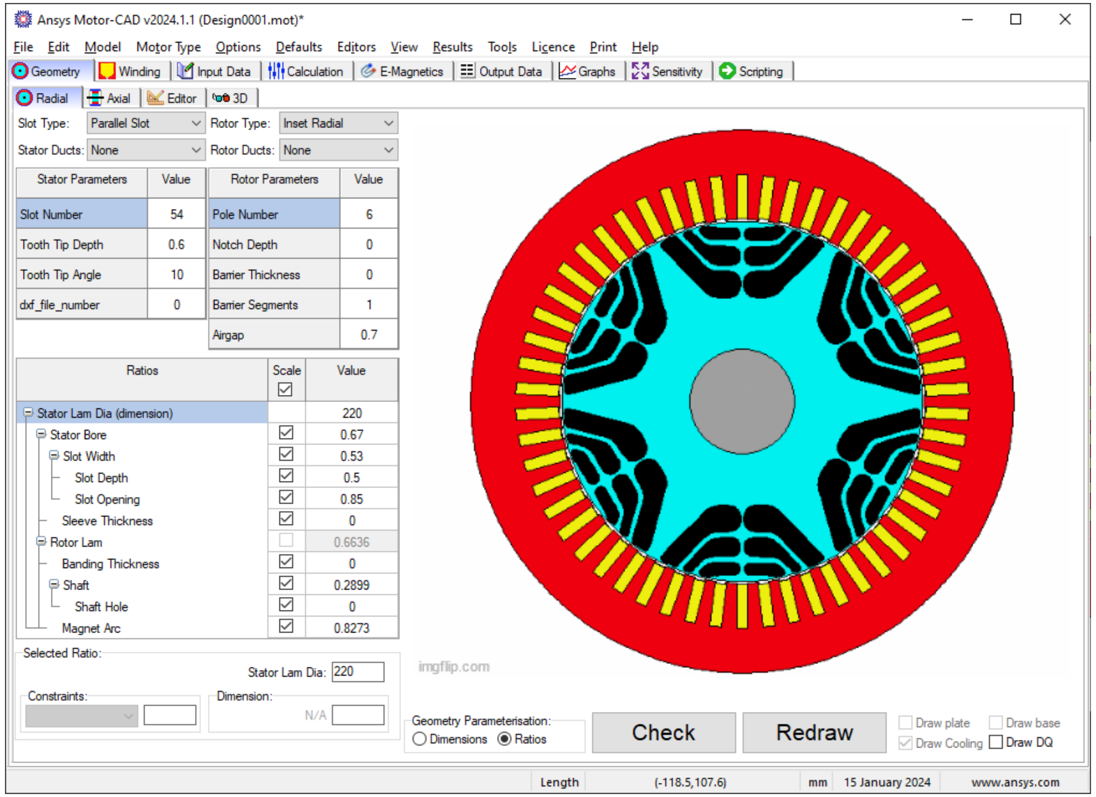
Example of result files from NCS



Validation

- Shapes from the deep learning-based optimization are sent to MCAD for validation.
- Samples are loaded and simulated using the **adaptive template** functionality (2024 R1).



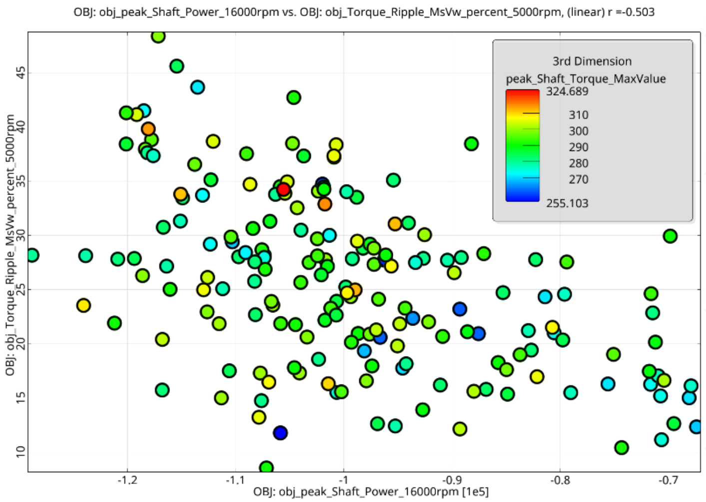


MCAD predictions

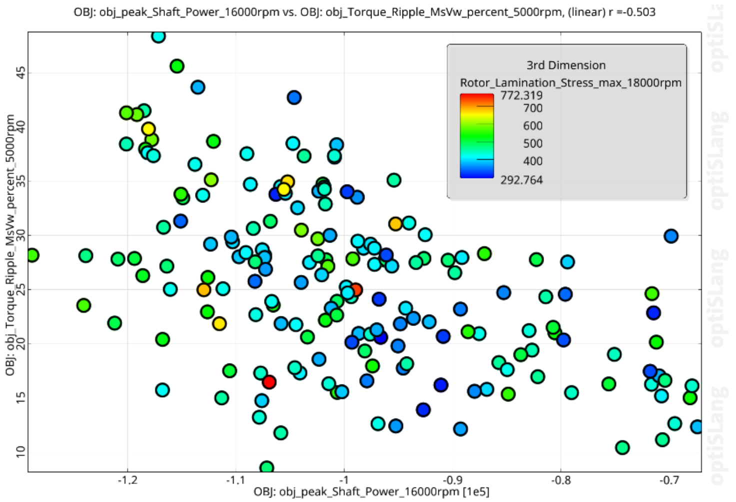
- Performance data are shown across the Torque ripples vs Peak power @ 16krpm plane.
- MCAD and NCS data match quite well with each other in terms of objectives.
- Designs highlighted in red in the bottom left are validated within 2% of the constraints.

**Results visualized in the Ansys optiSLang postprocessing tool*

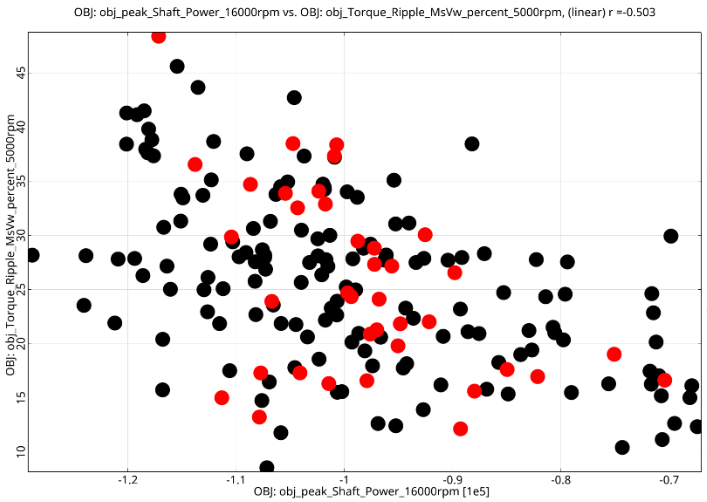
Performance across the Torque ripples @ 5krpm vs Peak power @ 16krpm*



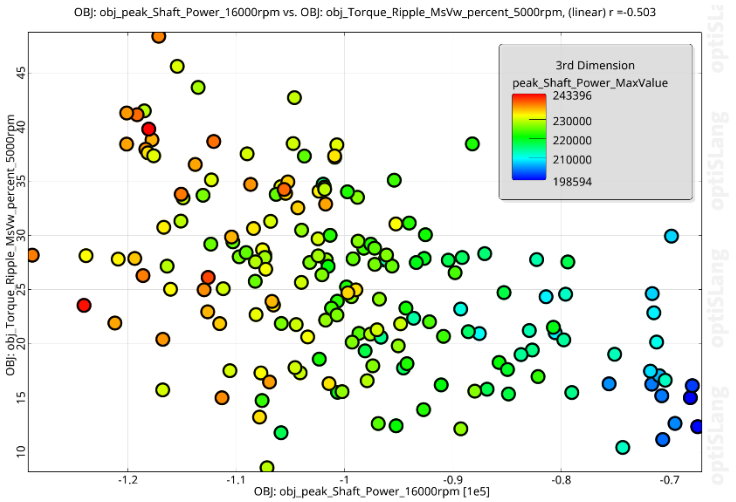
Peak torque



Peak stress

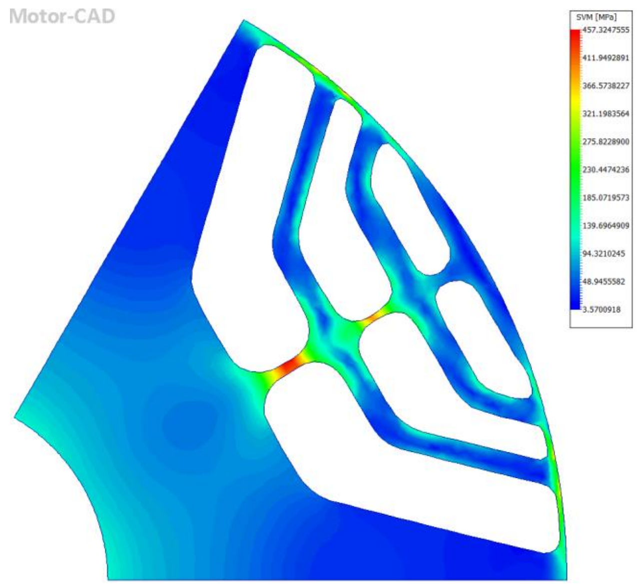


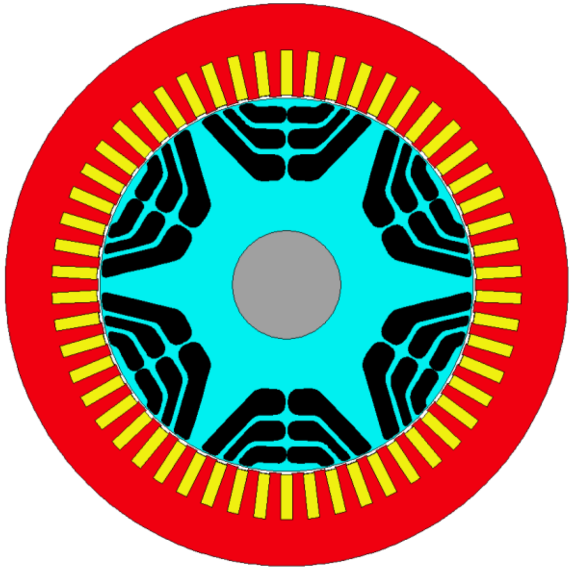
Feasible designs within 2% (red)

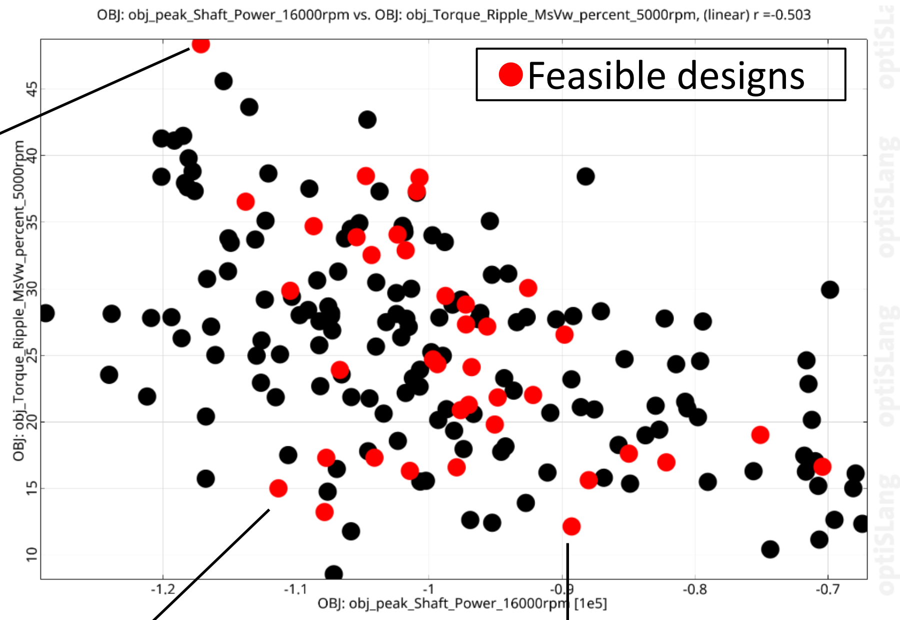


Max peak power

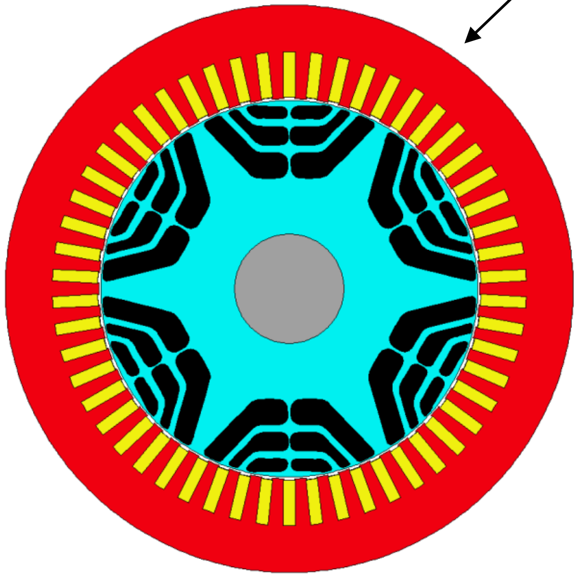
MCAD predictions

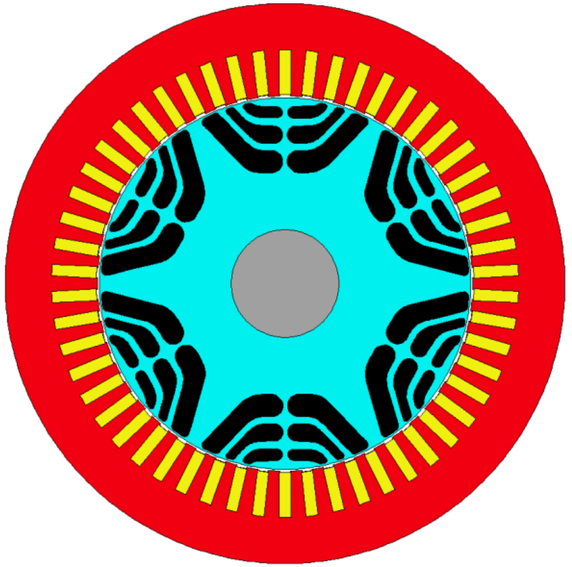


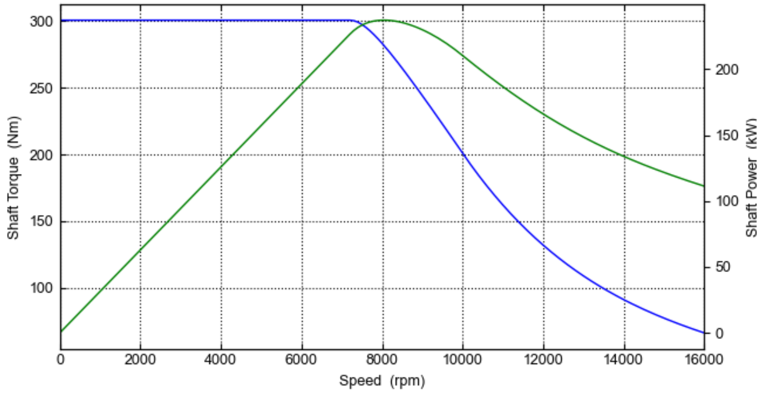




Peak performance







Mechanical stress

Conclusion and next steps

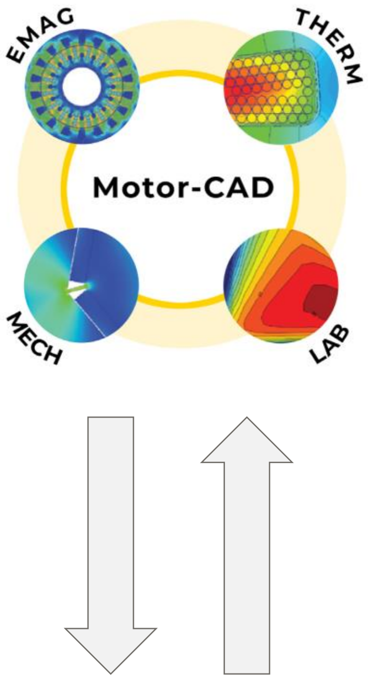
Conclusion

- The rotor of a **SyncRel motor** was optimized for minimum torque ripples and maximum power within strong electromechanical requirements.

- The **design optimization** workflow combines the **deep learning technology** of Neural Concept with the multi-physics simulations of Ansys Motor-CAD.

- The predictive models trained on Motor-CAD CAE and CAD data were used by a **genetic algorithm** to find optimal shapes for the desired requirements.

- **Pareto design solutions** were sent to Motor-CAD for validation and results showed a good agreement with Neural Concept Shape predictions.



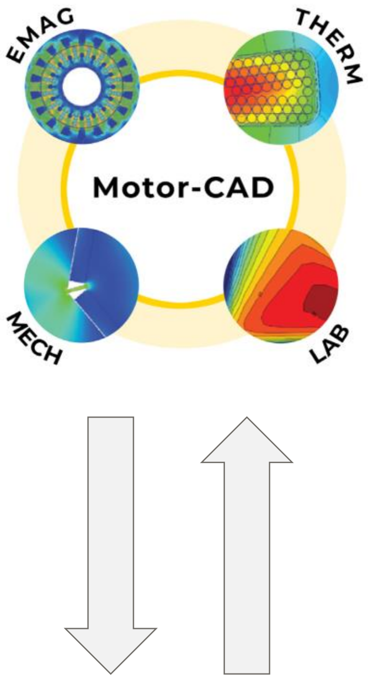
NEURAL CONCEPT

Next steps

- Import the MCAD validated CAE and CAD data into NCS for **improving deep learning models** along with optimization results.

- **Automate the workflow** as much as possible, especially the MCAD-NCS coupling at the data definition and validation stages.

- Apply this innovative motor design optimization workflow to:
  - other machines types, e.g **PM-based motor topologies**,
  - the **detailed design stage**, e.g fine-tune air pocket for reduced NVH.



NEURAL CONCEPT

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