

SIMULATION, HPC AND AI TO ACCELERATE THE ELECTRIFICATION OF POWERTRAINS



Vincent Leconte – Sr Dir. Business Development – Electromechanical solutions

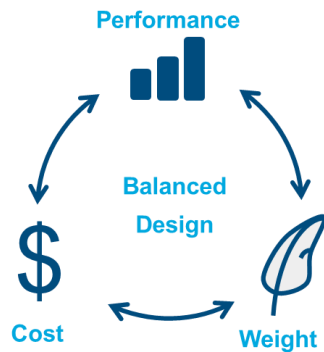
L. Fredriksson, M. Heroth, H. Husson, L. Mariano

To transform enterprise decision-making
by leveraging the *convergence*
of simulation, high-performance
computing, and artificial intelligence.

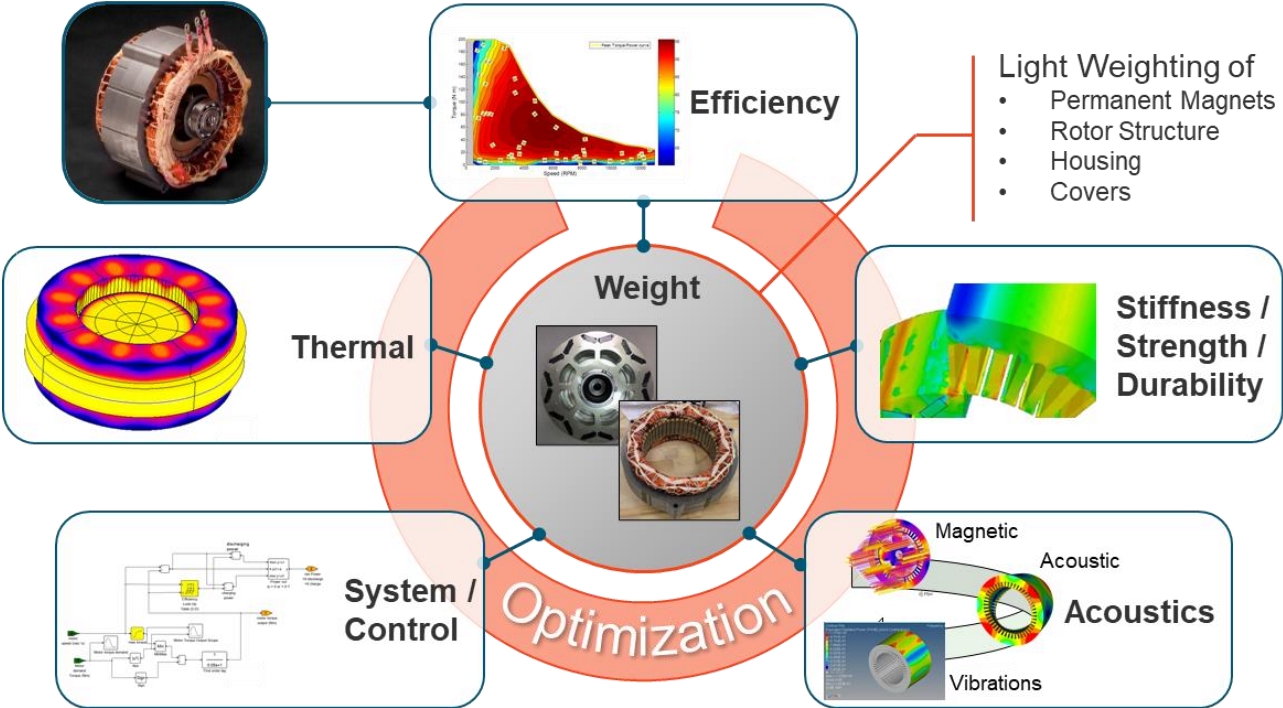


Building a More Sustainable Mobility

- Fierce competition to create electrified drivetrains
- Speed in Technology Development
- Stringent performance requirements
- Maximize efficiency throughout duty cycles
- Multiphysics design and constraints

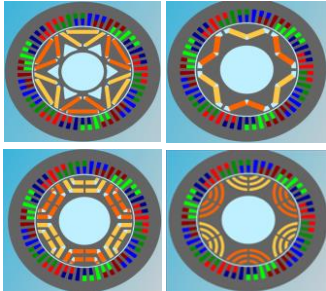


E-Motor Multiphysics Optimization



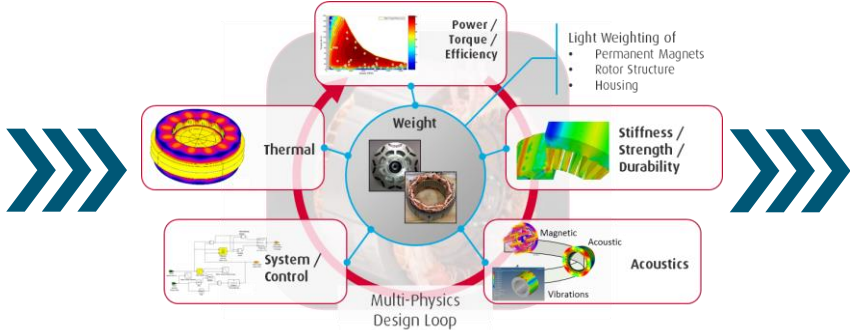
The e-Motor Design Process

Concept Design



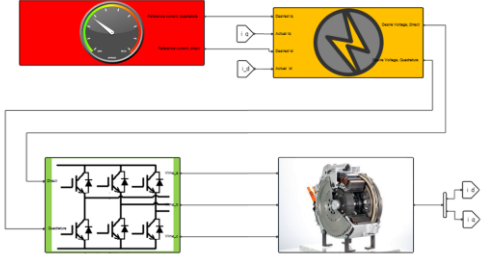
Rapid Design Exploration and Ranking

Detailed Design



Advanced multiphysics analysis

System Integration

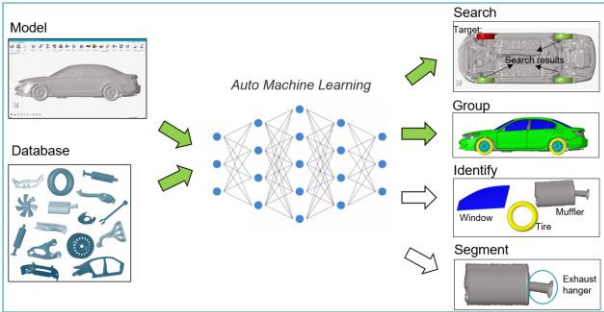


System Simulation – Control Design – Embedded software

Use of AI for Design

Shape

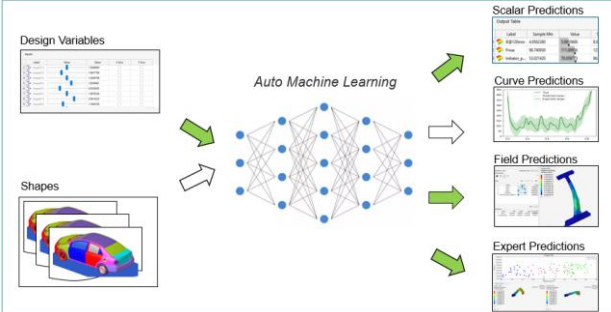
ML Augmented CAE



- Modelling
- Part search
- Part clustering
- Model segmentation
- Part and feature labelling
- Part and feature identification
- Model build automation

Physics

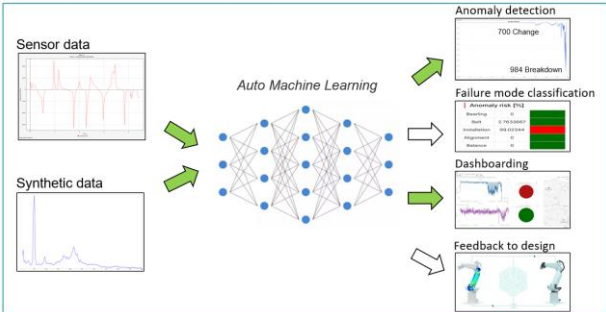
AI-Powered Design



- Real-time predictions
- Real-time KPI/curve/field predictions
- Expert emulation
- Clustering / Labelling / Classification
- Historical data
- Treating unstructured data

Signal

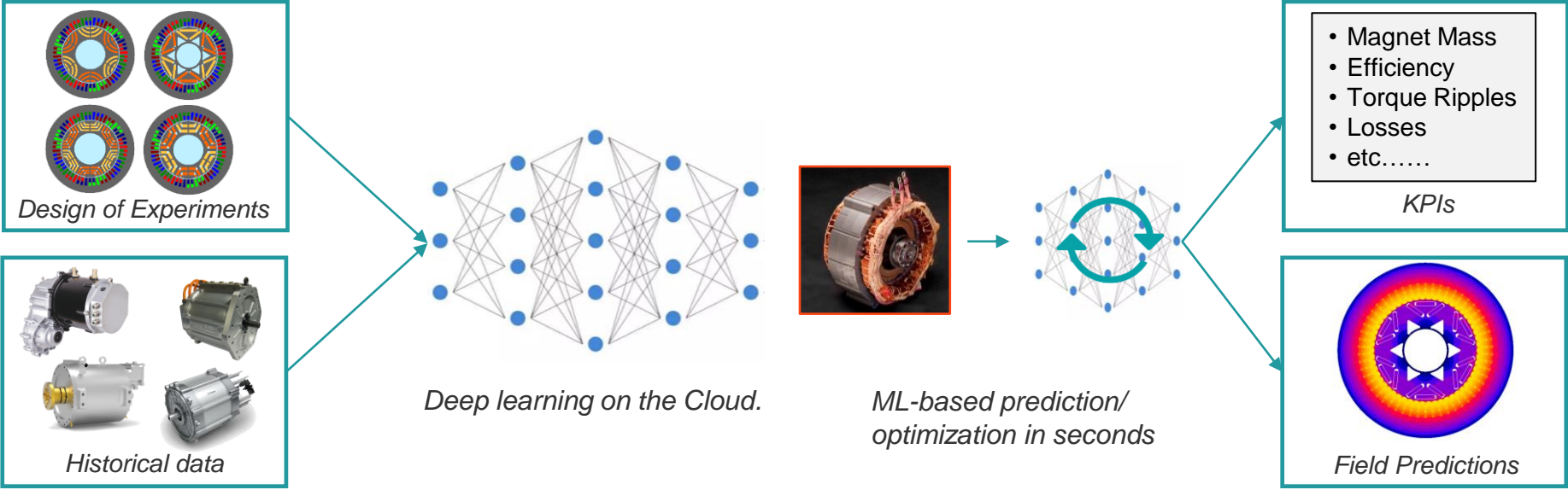
Predictive Analytics



- Test/Field data
- Synthetic anomalous data creation
- Anomaly detection
- Failure mode classification
- Data streaming
- Notifications
- Feedback to product designs

Machine Learning Models for Real-Time Predictions

Train a predictive model on CAE results **from any source**. Use the model for **real-time predictions** and optimizations. Update the model after each new solver run – **model improves over time**.



A SMALL EXERCISE

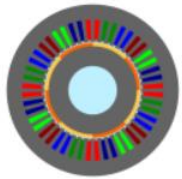
E-Motor Performance Prediction

Input Parameters

- Power supply
- Volume
- Poles
- Airgap
- Cooling system



Motor dimensions calculations
(Basic equations)

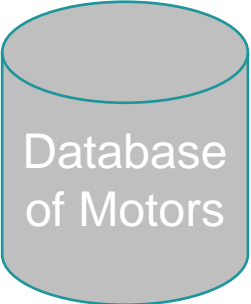


Finite Elements

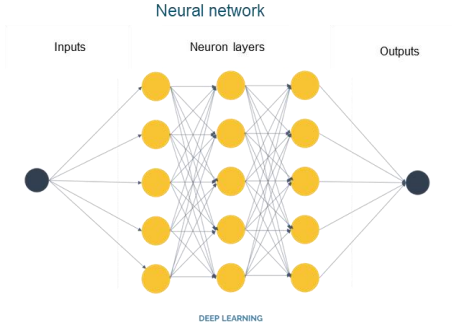
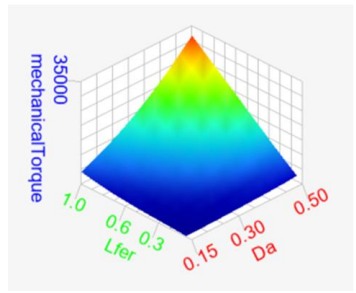


Outputs

- Torque
- Power
- Speed
- Losses
- Efficiency



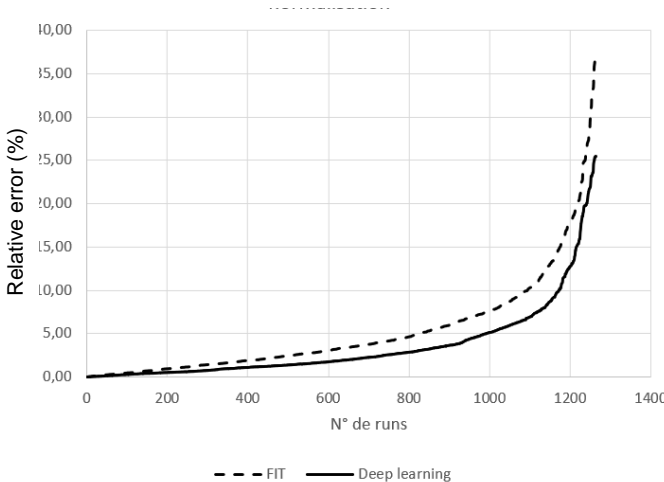
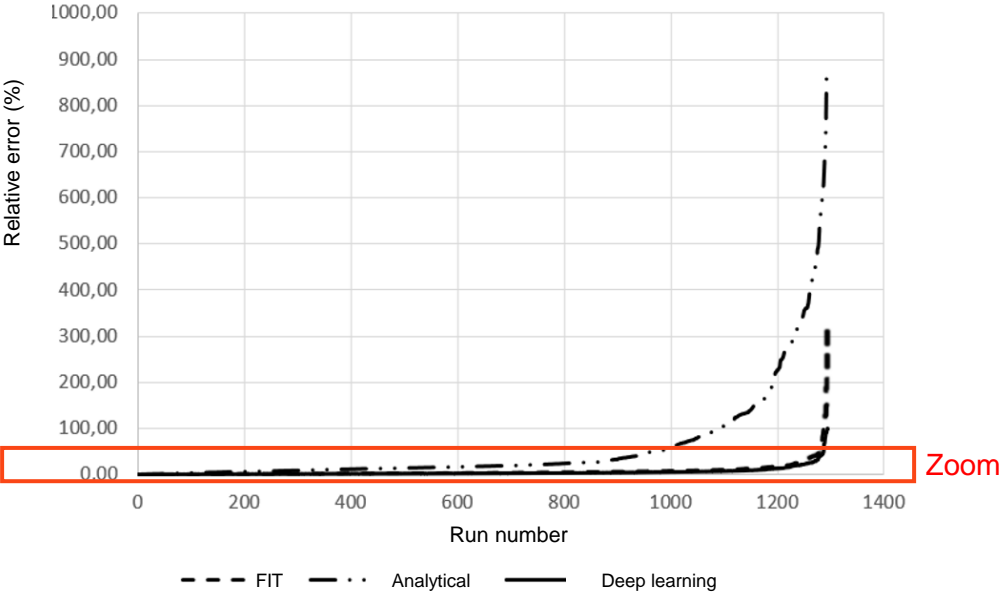
Response surfaces



DEEP LEARNING

Comparison of Predictive Algorithms Performances

Relative error on the torque for different predictive methods with normalized torque

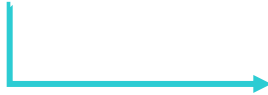


Find the Best Motor for Given Requirements

Required torque: 5000 Nm

Required power: 200 kW

Efficiency : > 92 %



	<i>Torque</i>	<i>Speed</i>	<i>Electromagnetic power</i>	<i>Efficiency</i>	<i>Torque relative error</i>	<i>Power relative error</i>
N°1	4822 Nm	372 RPM	188 kW	94.5 %	3.56 %	6 %
N°2	4851 Nm	351 RPM	180 kW	94.2 %	2.98 %	10 %

Required torque : 300 Nm

Required power : 130 kW

Efficiency : > 92 %

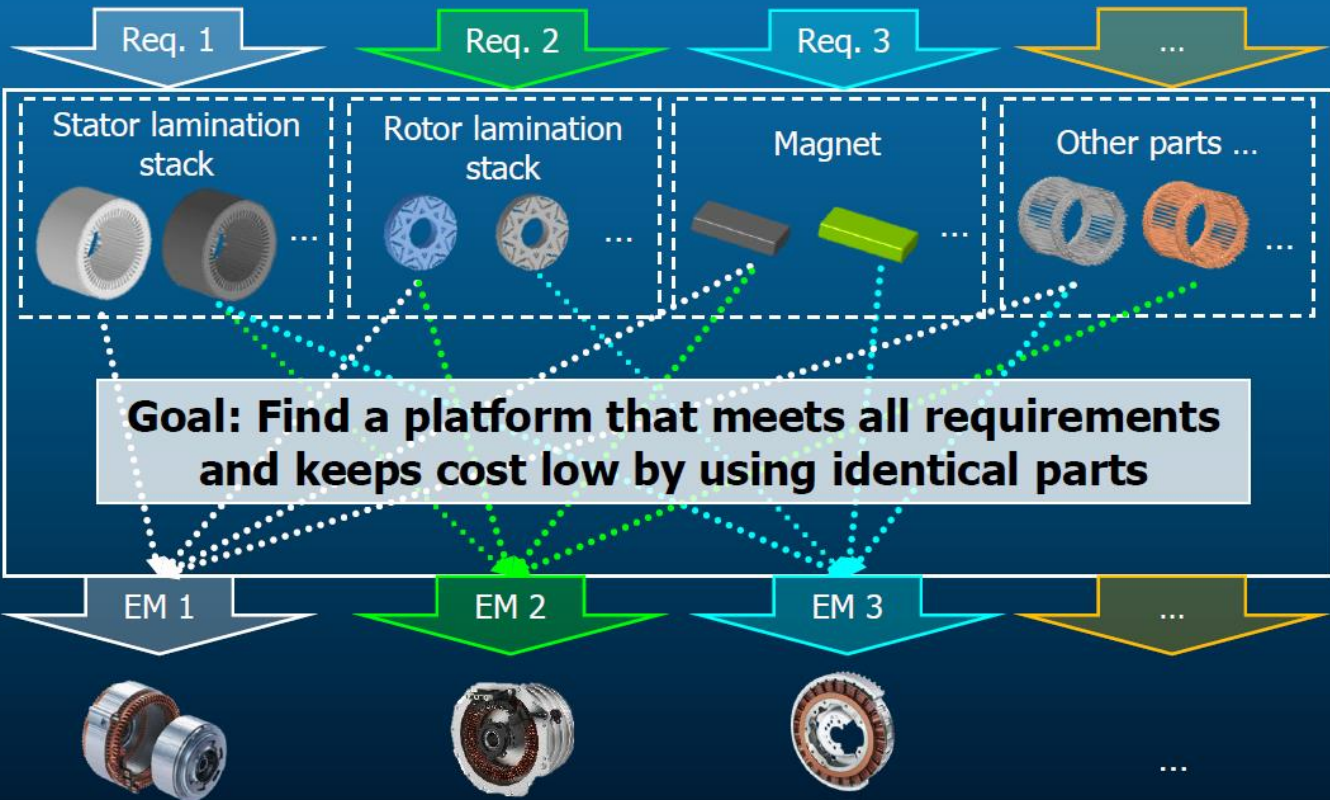


	<i>Torque</i>	<i>Speed</i>	<i>Electromagnetic power</i>	<i>Efficiency</i>	<i>Torque relative error</i>	<i>Power relative error</i>
N°1	277 Nm	2685 RPM	78 kW	92.5 %	7.6 %	40 %
N°2	283 Nm	4441 RPM	132 kW	95 %	5.7 %	1.5 %

THE ZF USECASE



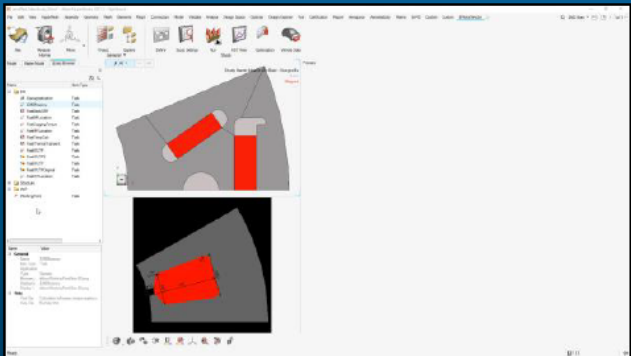
Modular EMotor Platform Development


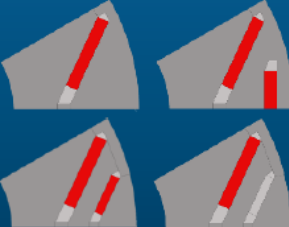
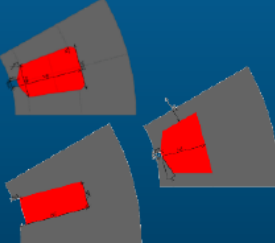
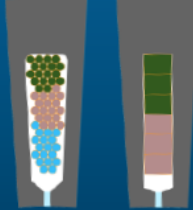


Design Information Storage



EMotor Database Creation



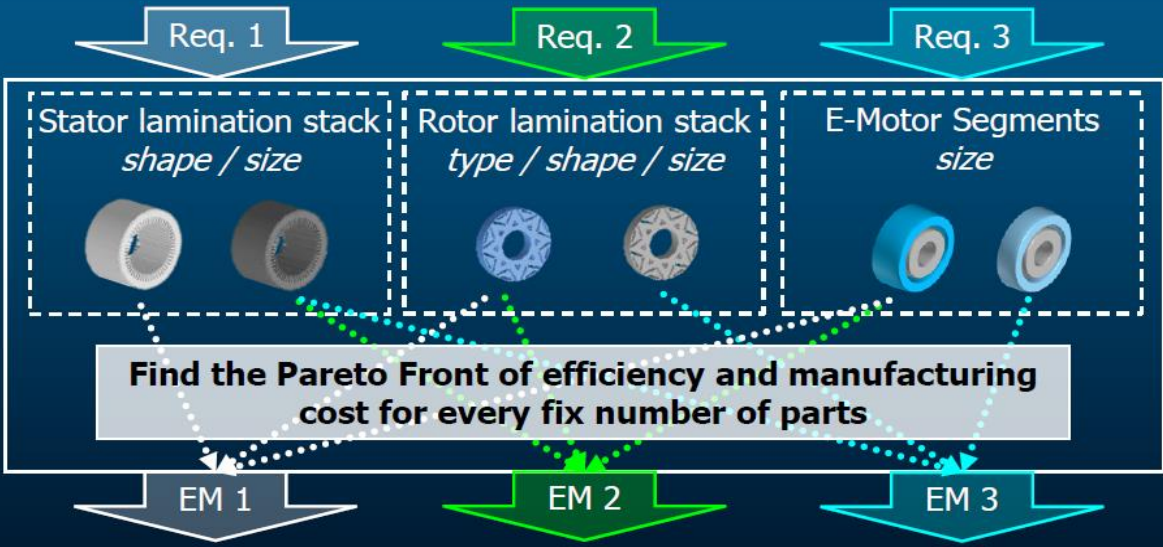
	E-Motor	Rotor	Stator	Winding
Coverage through different DoEs				
	E-Motor types	Rotor configurations	Slot configurations	Winding configurations
In DoE design variables	Voltage level Max current Length	Magnet sizes Magnet positions Magnet orientations	Slot length Slot width	No wires in hand No turns Fill factor Wire diameter/size



Example Usecase

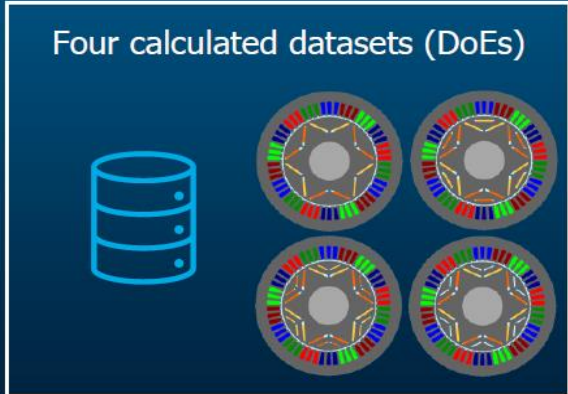
Parameter	Req.1*	Req.2*	Req.3*	Unit
Max E-Motor Torque	160	220	280	[Nm]
Efficiency Measure	Maximize	Maximize	Maximize	[%]
Manufacturing Costs	Minimize	Minimize	Minimize	[]

(*) Additional Constraints to further constrain solution space



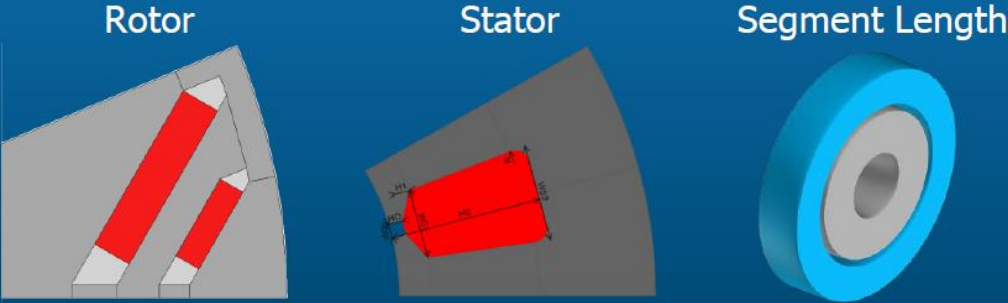
Design / Optimization Task

- 3 e-motors to be found using a set of 4 DoEs representing different rotor lamination sheet configurations
- 3 possible common parts defined





Considering Multiple Scenarios



Maximum Common Parts
(Maximum linking)



Part Count

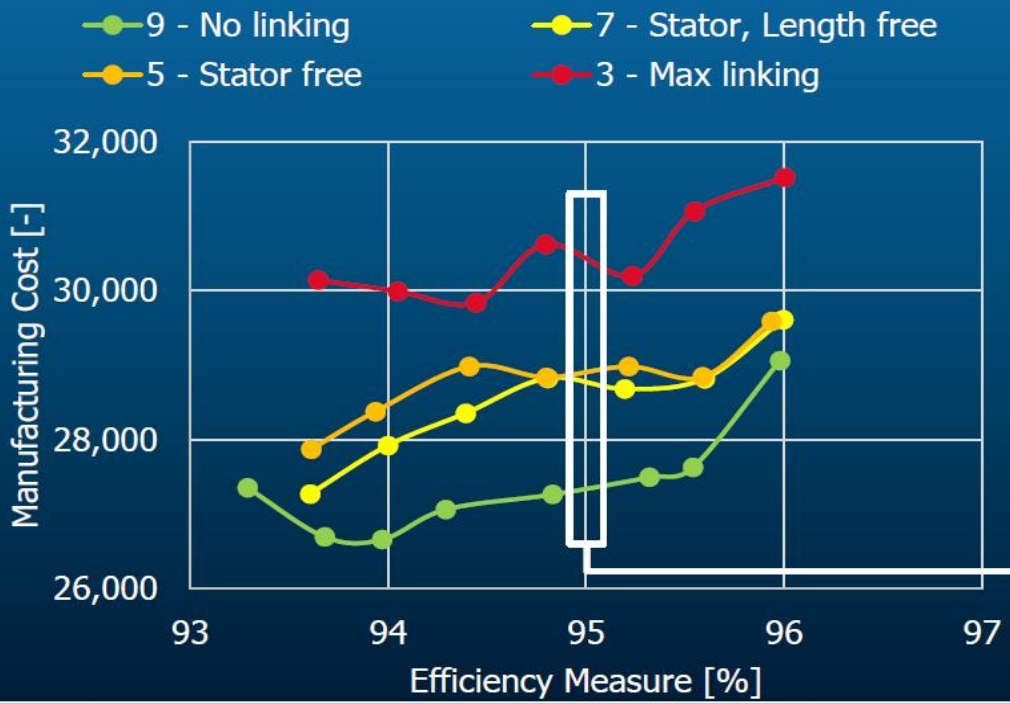
- 3
- ⋮
- 5
- ⋮
- 7
- ⋮
- 9

No Common Parts
(No linking)



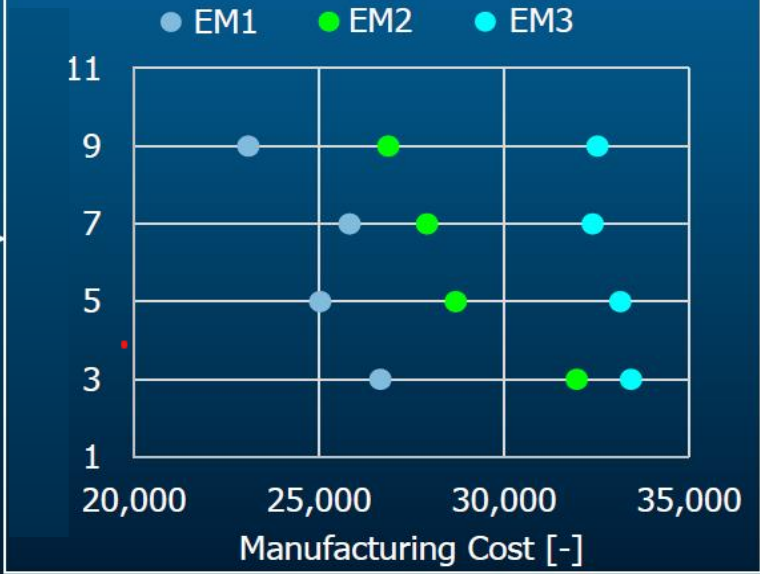
Optimization Results

Average Manufacturing Costs vs Efficiency



Trade Cost and Part Count to reach Efficiency Target

Part Count at 95% Efficiency





ZF Usecase Summary

The benefit of synergies between individual projects can be directly identified



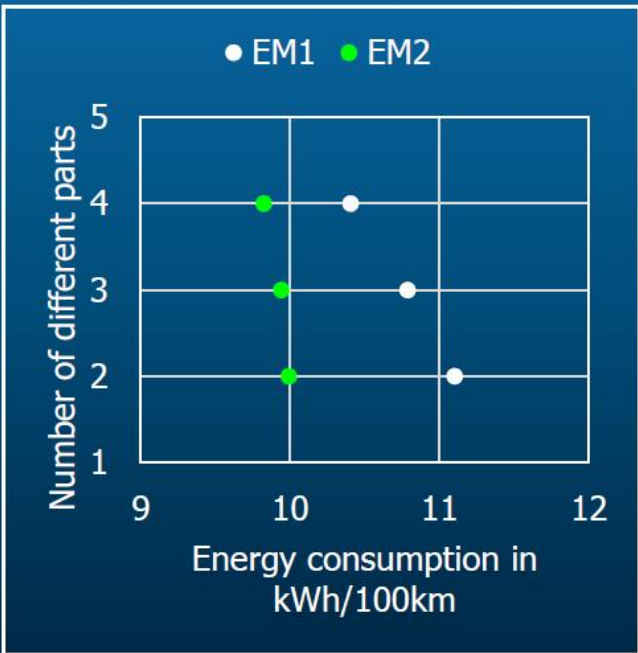
Identical parts reduce development cost



Identical parts reduce development time



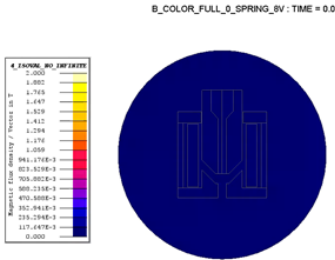
Helps ZF as a basis for decision making process in the projects



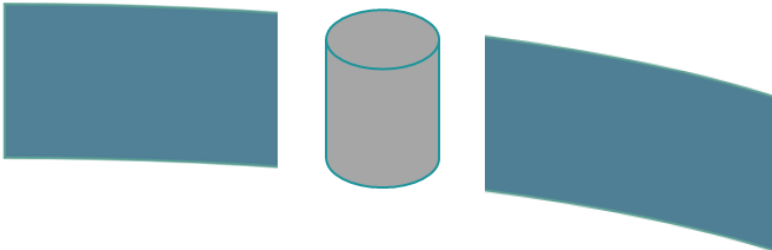
USING AI FOR REDUCED ORDER MODELLING

Reduced Order Modeling Based on AI

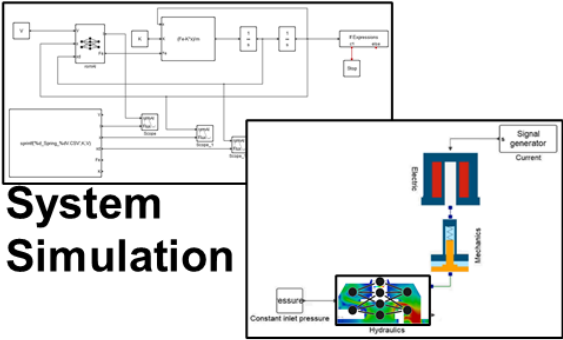
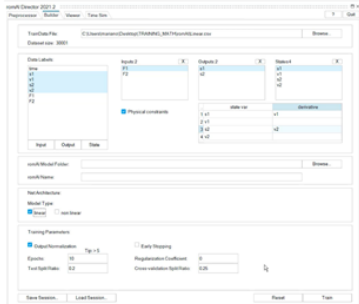
Simulations or Tests



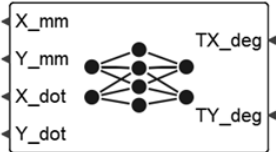
Training Data



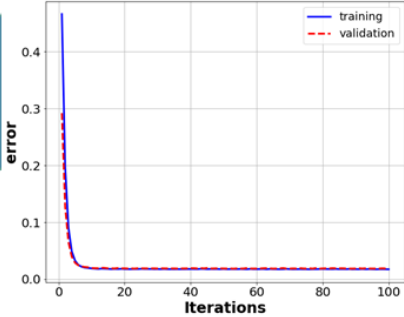
Machine Learning



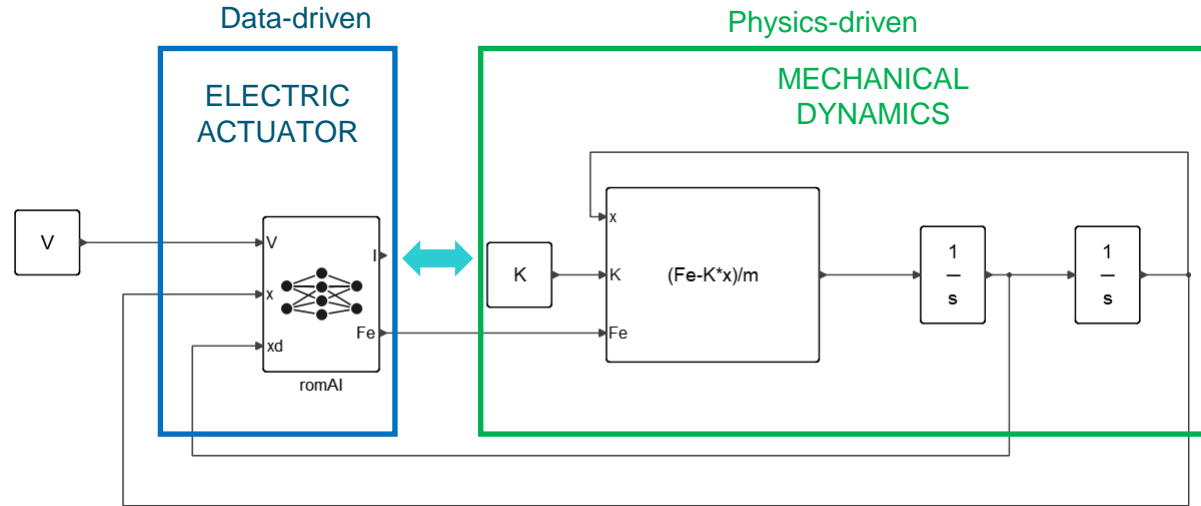
System Simulation



romAI

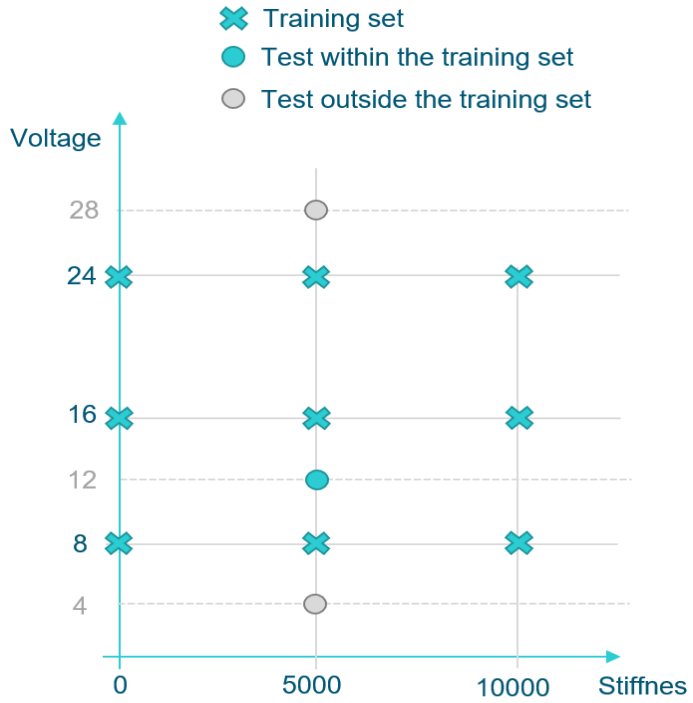


Electromechanical Actuator Example

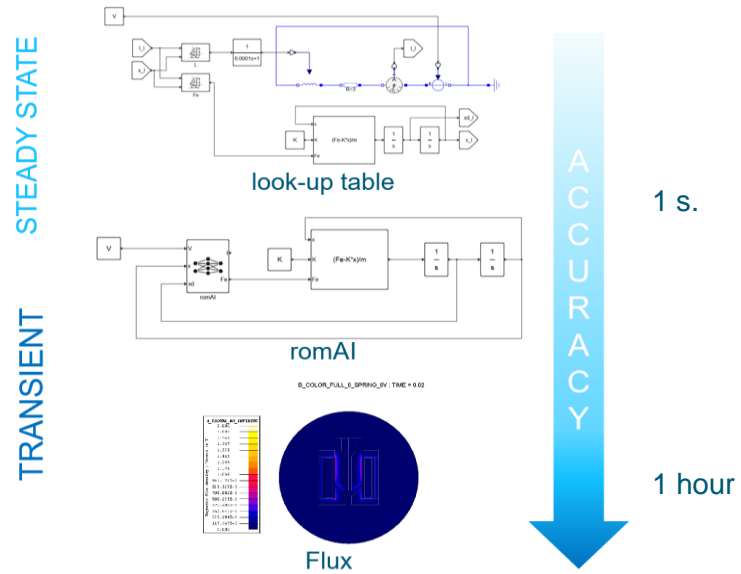


- Data created based on transient finite element electromagnetic computations
- All dynamics effects captured (non-linearities, eddy currents)

Electromechanical Actuator Example

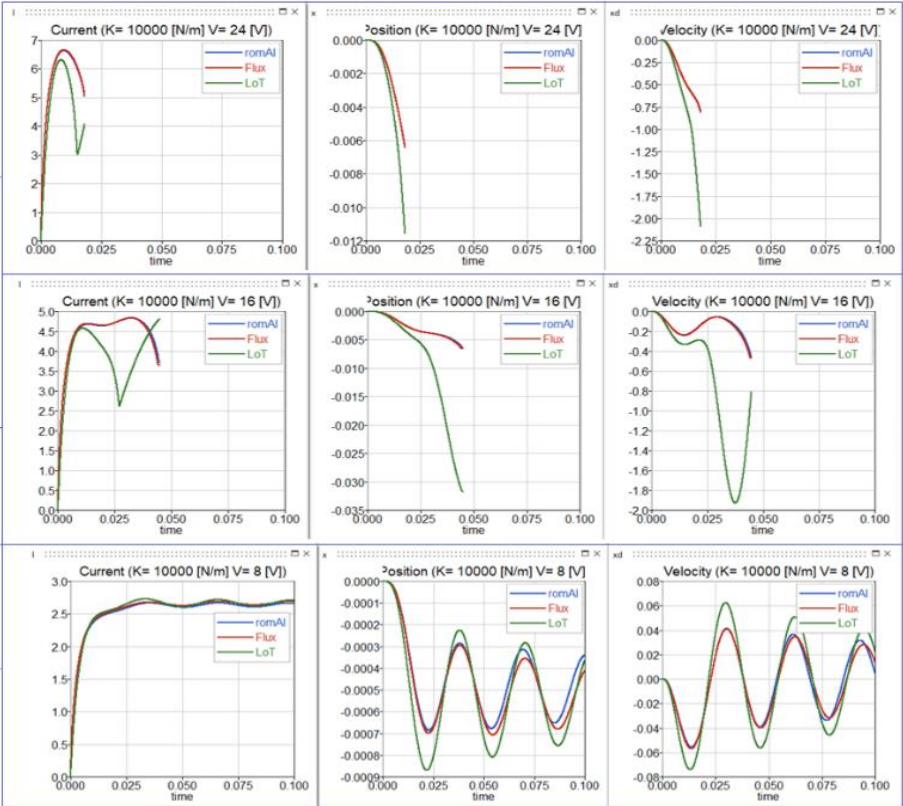
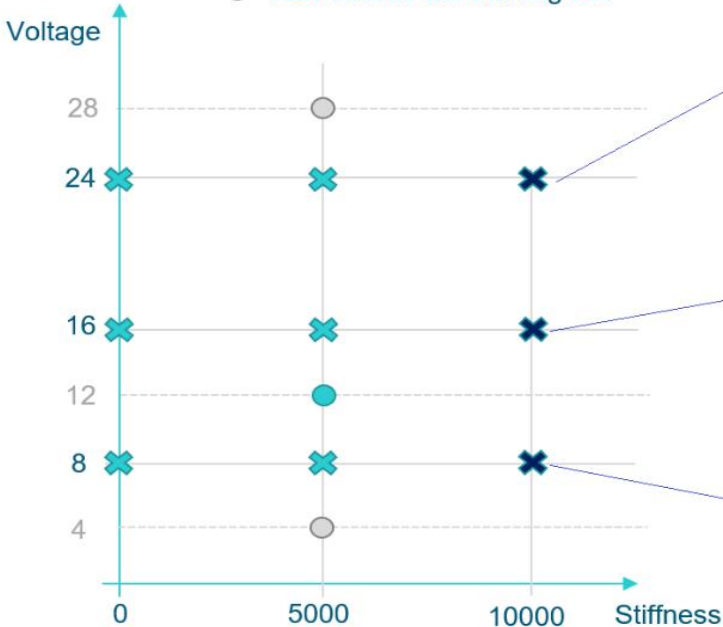


Modeling options



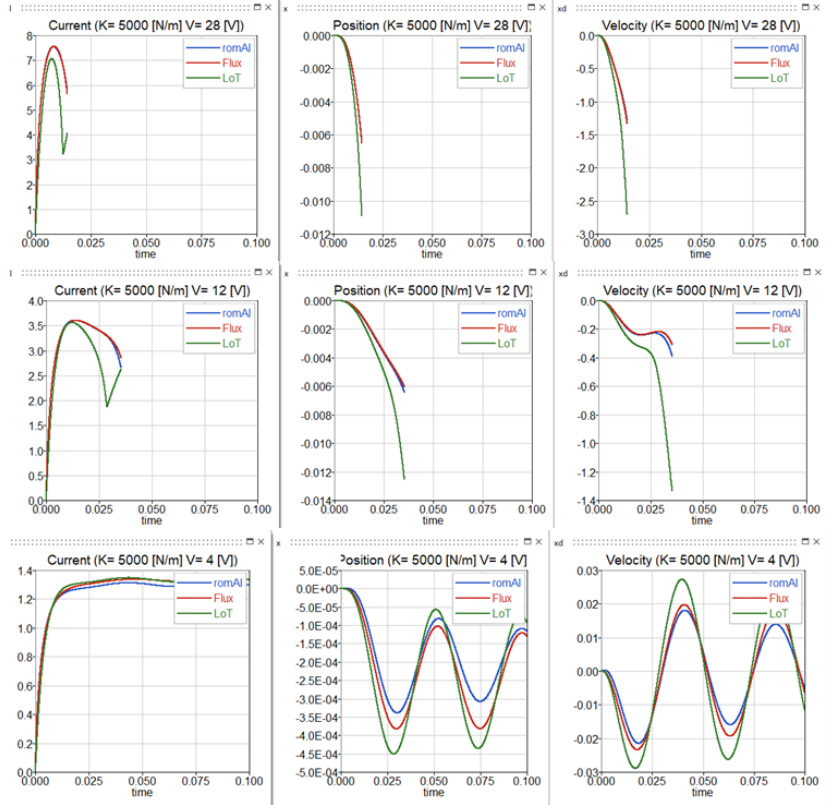
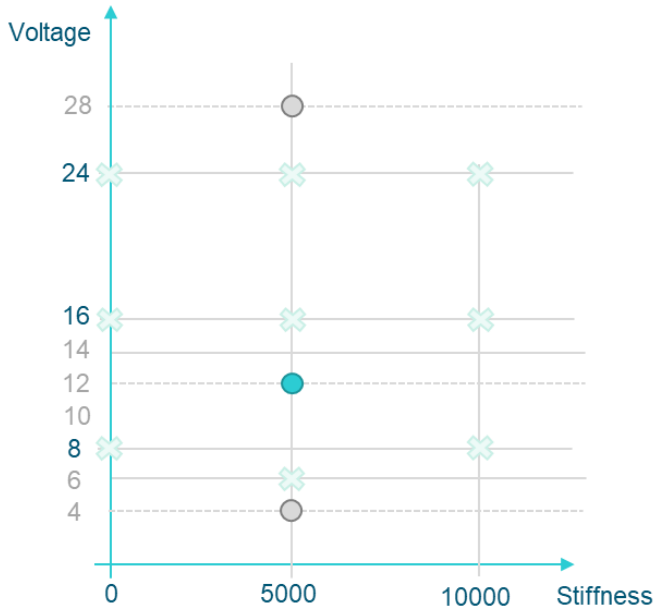
Electromechanical Actuator Results

- ✕ Training set
- Test within the training set
- Test outside the training set

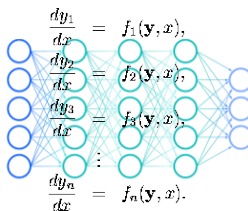


Electromechanical Actuator Results

- ✕ Training set
- Test within the training set
- Test outside the training set



romAI benefits



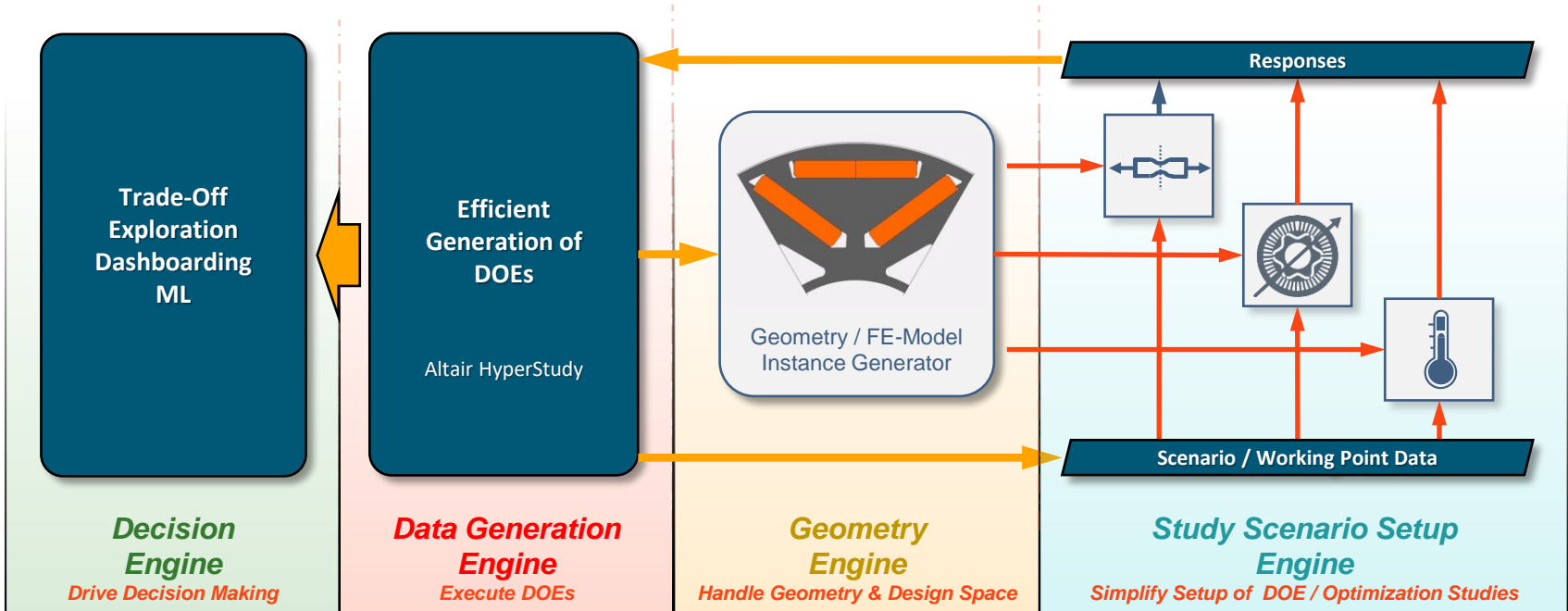
Unique combination of machine learning and system modeling techniques:

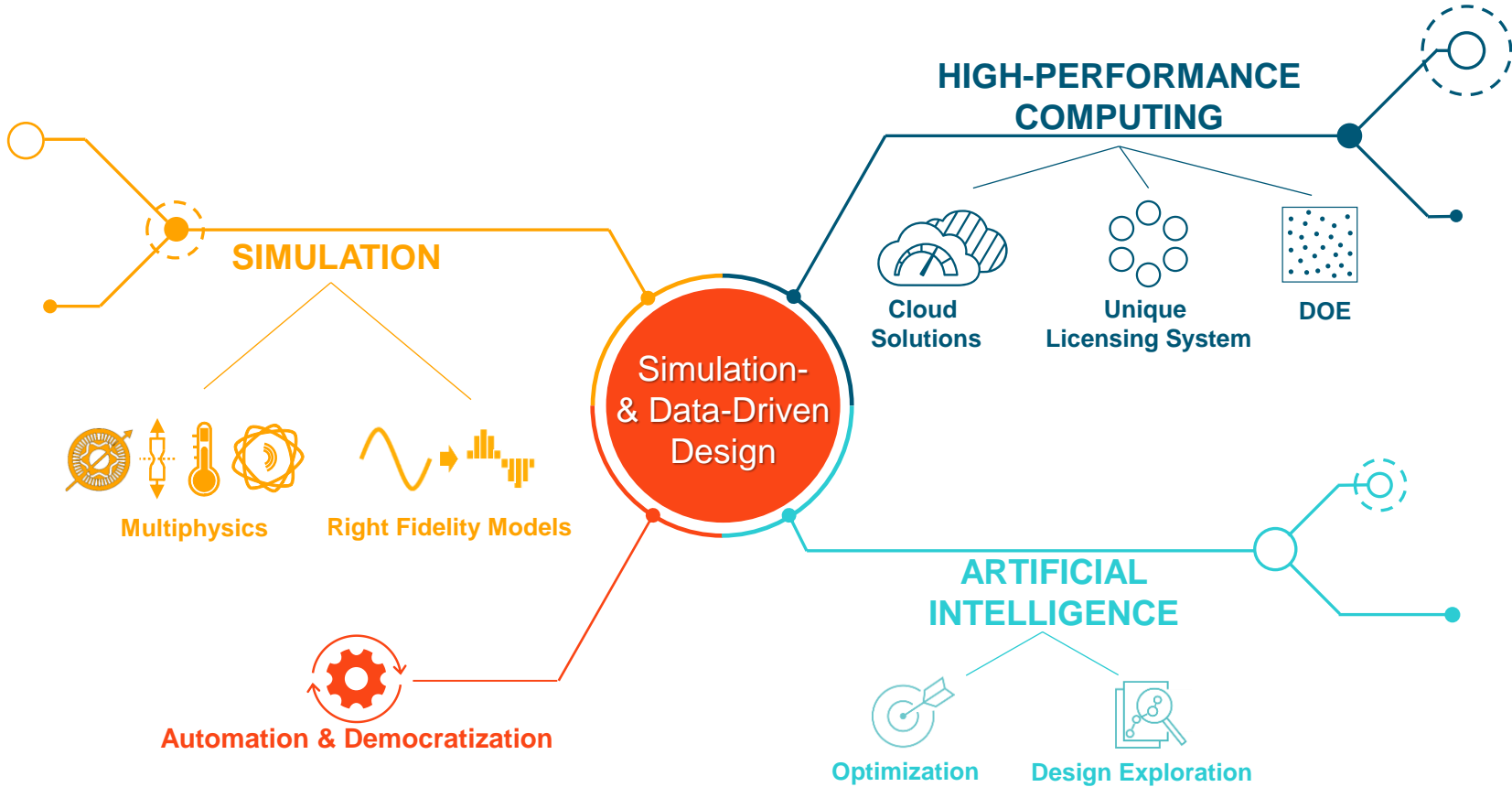
- **Less training data** with respect to pure data-driven approaches → Fewer 3D simulations run or tests
- **No influence of time discretization** → Very robust; works with any solver
- Possibility to **set the state variables** and consider **physical dependencies** → Allow to leverage the knowledge on the underlying physics involved
- **Satisfactory generalization properties** → Great accuracy when interpolating;
Adequate accuracy when extrapolating

SUMMARY & OUTLOOK

A Tool to Automate EMotor Design Explorations

- Define designable Geometry – Create Test Scenario – Run DOE – Explore and create Decision Material





The Future of Data-Driven Design

- Massive design exploration and optimization in **real-time to drive decision making**
- Synthesize engineering data to enrich the historical simulation & in-service data
- Automation to **democratize AI** in product design & engineering

