IDAJ CAE Solution Conference 2019

20th >> 21th NOV 2019
>> **Shanghai, China**

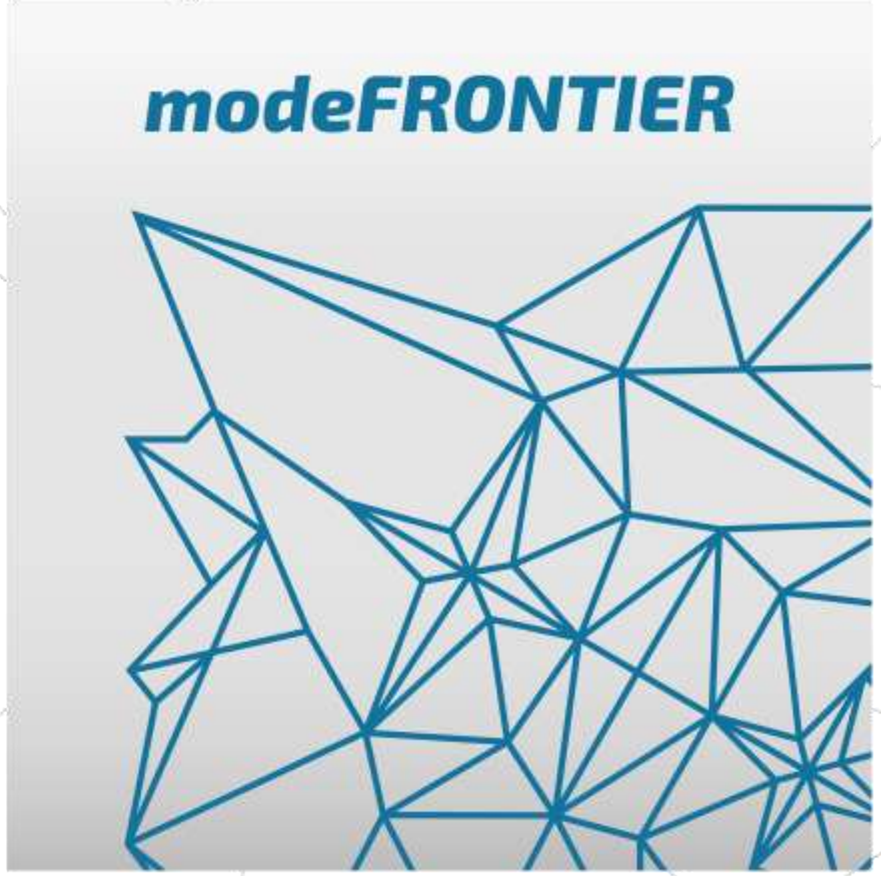
Successful stories with ESTECO Technologies

31楼景观宴会厅 C5 16:10 – 16:40

Zhongli Wen

Our Products

DESKTOP PLATFORM



Process automation and optimization of the engineering design process

WEB PLATFORM

Multidisciplinary business process optimization and enterprise simulation data management

modeFRONTIER

Automate simulations within a single workflow

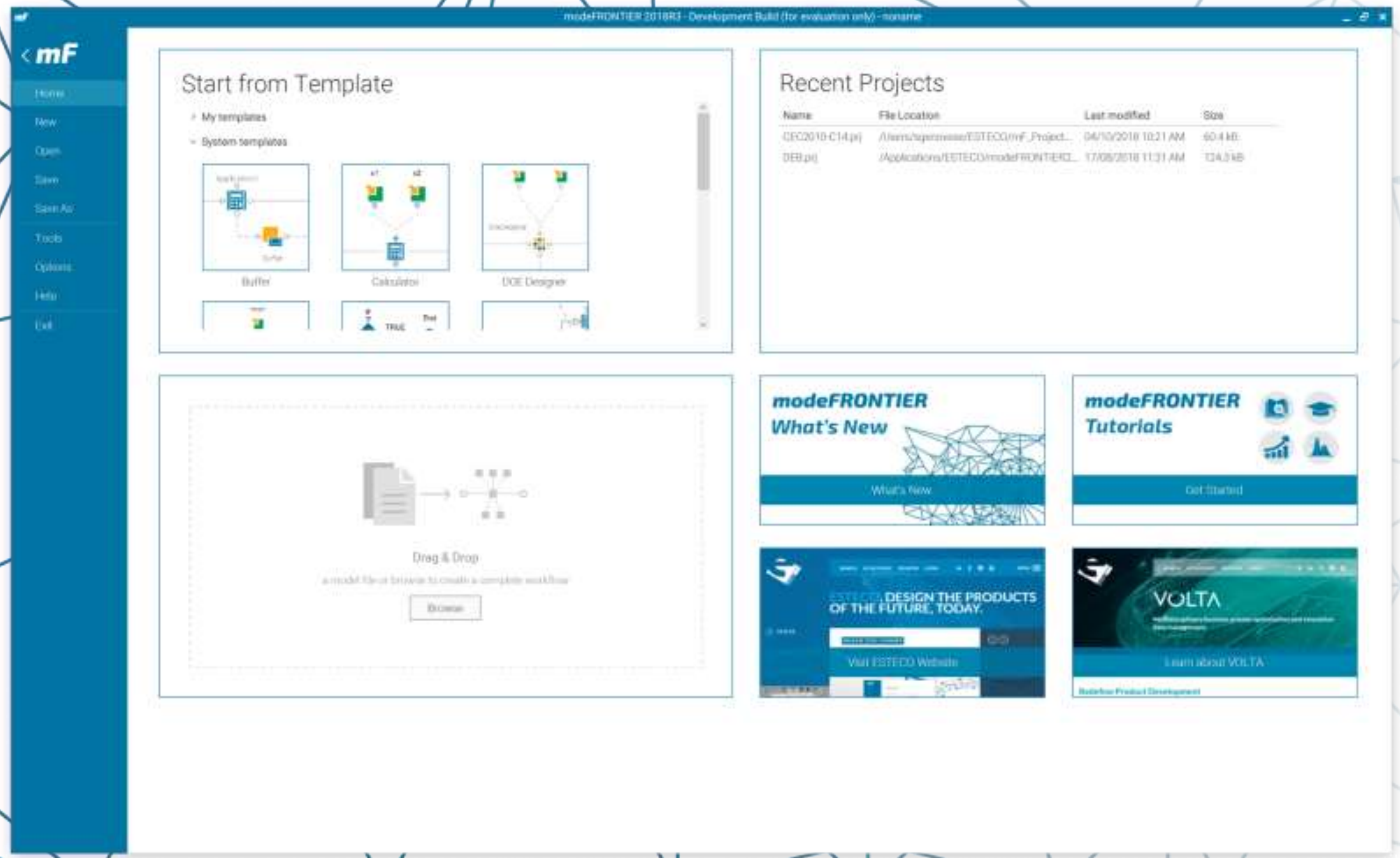
Embrace optimization-driven design

Seamless integration with engineering solvers

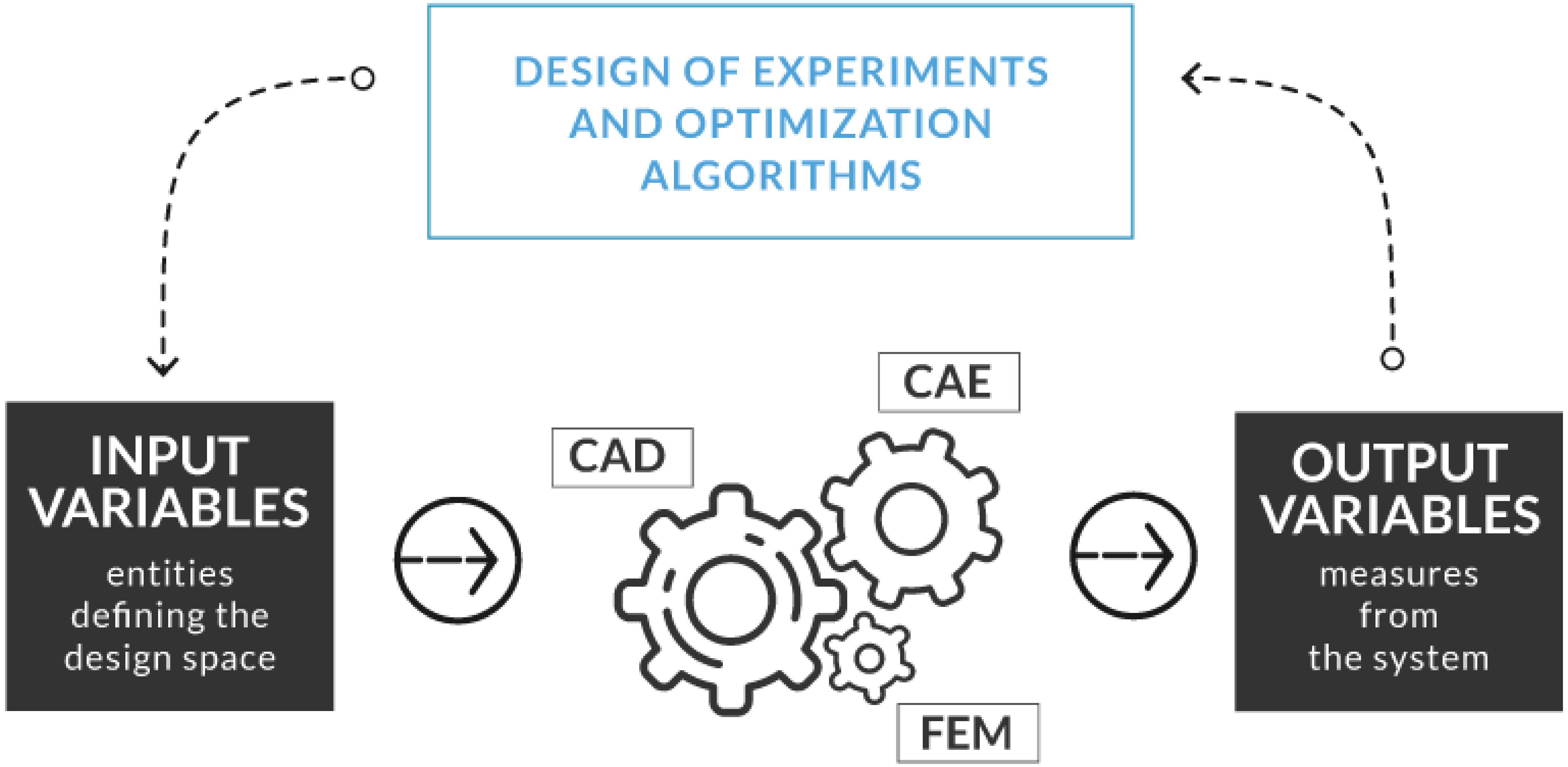
Turn uncertainties into well-performing products

Gain better understanding of the design space

Make better decisions with data analysis and visualization tools



Optimization-Driven Design



Input Variables
Define design domain

Black Box
Computes outputs based on inputs

Output Variables
Measure the system response

Types of Parametric Input Variables

Continuous variables:

- Point coordinates
- Process variables
- Dimensions or shape variables

Discrete variables:

- Components from a catalog
- Material selection

Our Technical Partners

Seamless integration at hand

Our solutions are fully integrated with the most commonly used engineering tools

MADYMO

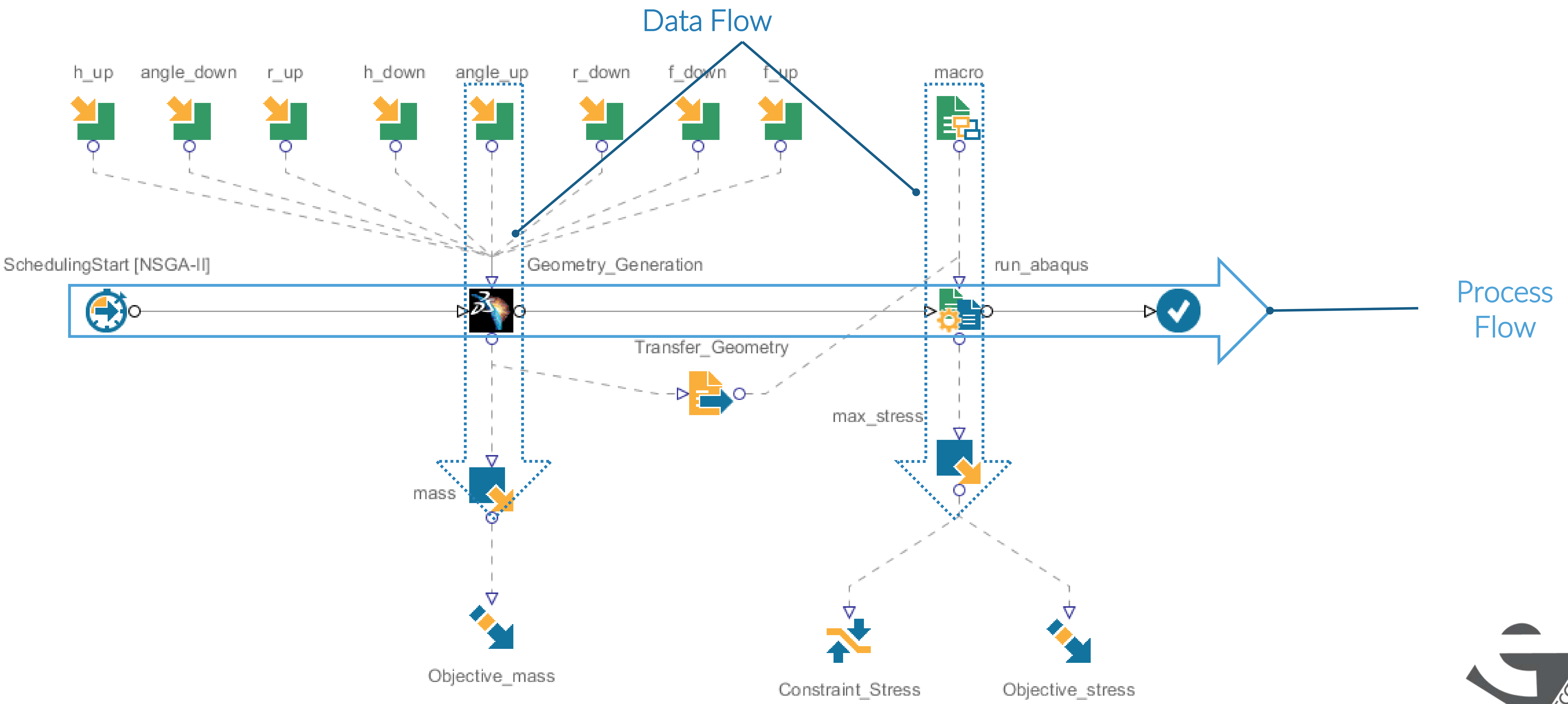
OS

X

CATIA

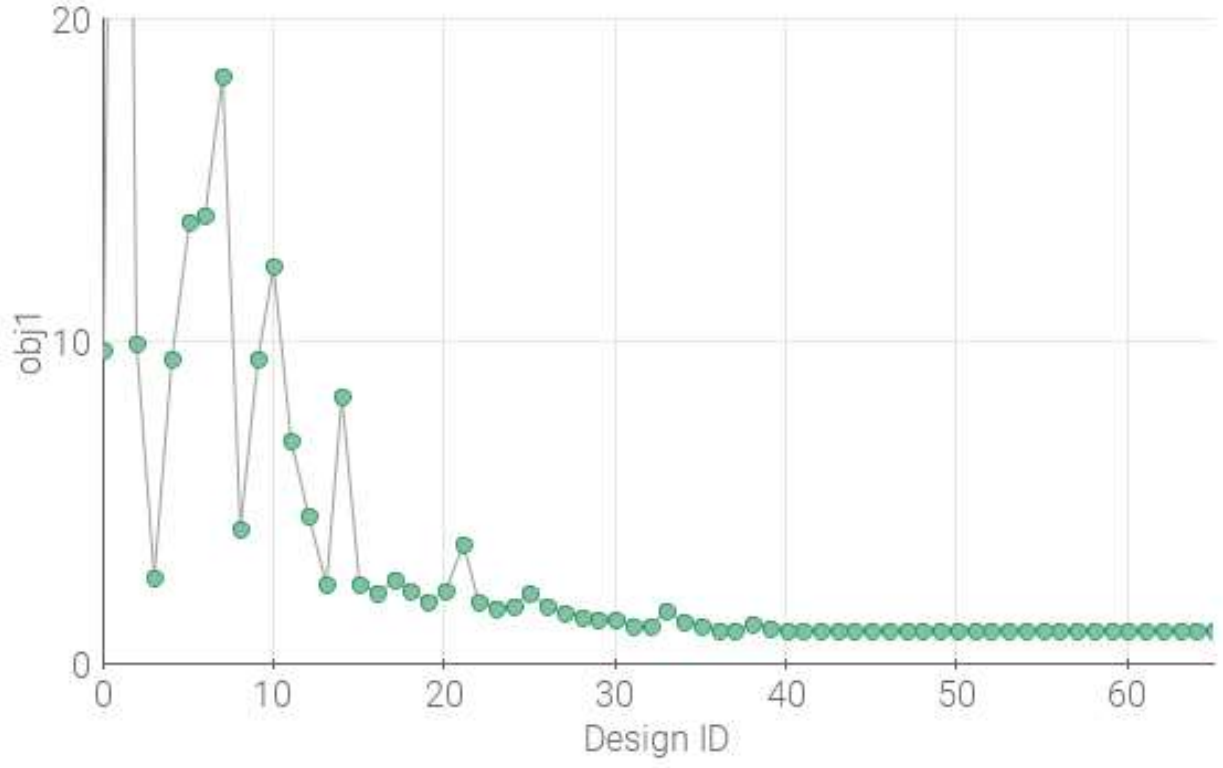
Workflow: Process Automation

Combines Process Flow and Data Flow



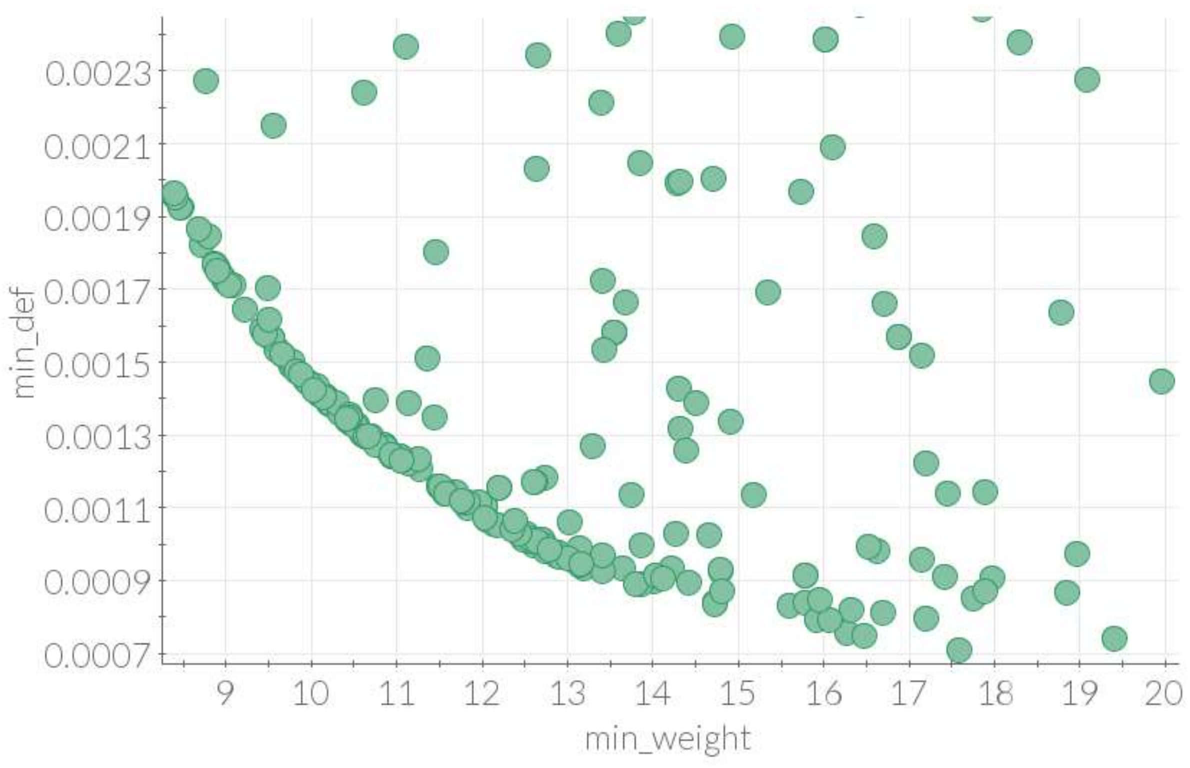
Single vs. Multi-Objective

Single-objective



Converge to only **one** optimal solution

Multi-objective



There is a set of equivalent optimal solutions called the Pareto frontier

Aerodynamic Optimization of a Wide Body Train Front

Bombardier Transportation

BOMBARDIER

Reduced 20% aerodynamic drag and energy consumption by 10%

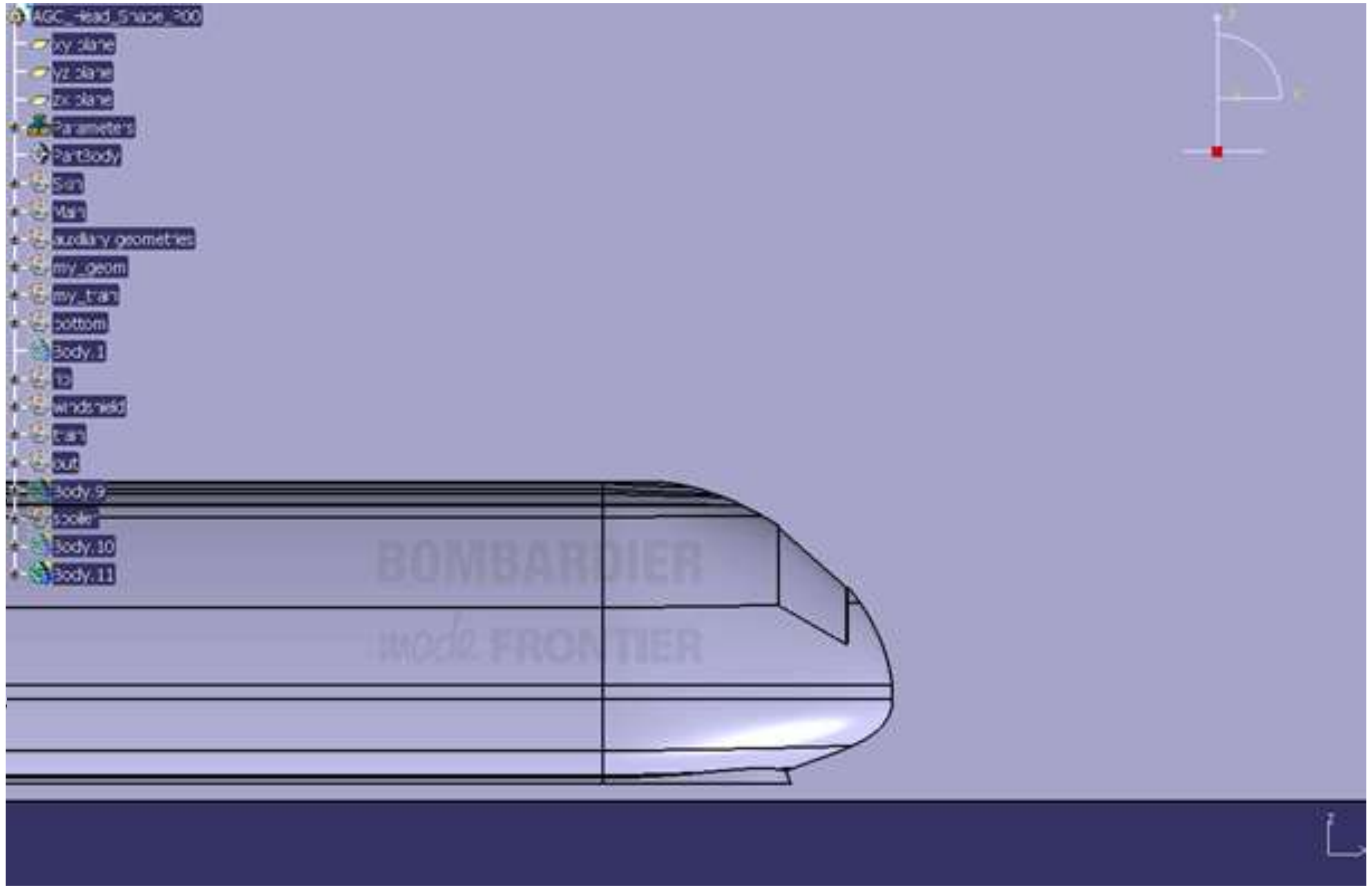
“ Wind tunnel tests of the shape produced by the modeFRONTIER optimization confirmed that it was one of the best we had seen. Based on this result, Bombardier Transportation now uses modeFRONTIER to drive the analysis tools for all our aerodynamics projects ”

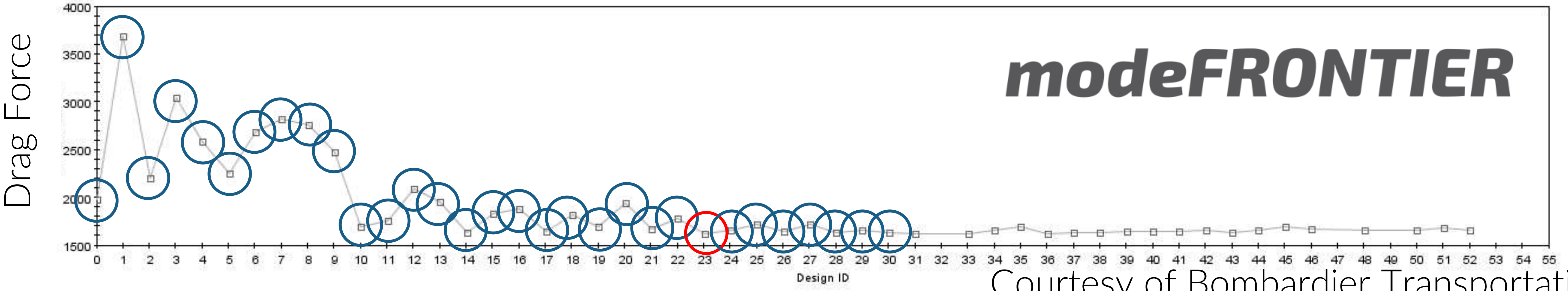
DR ALEXANDER ORELLANO
Head of Aerodynamics

Reducing Energy Consumption of Bombardier Trains

1. Create a parametric train model with CATIA V5 - 10 geometric parameters
2. CFD simulation (STAR CCM+)
3. Incorporate model in automatic optimization loop
4. Minimize drag

Reducing Energy Consumption of Bombardier Trains



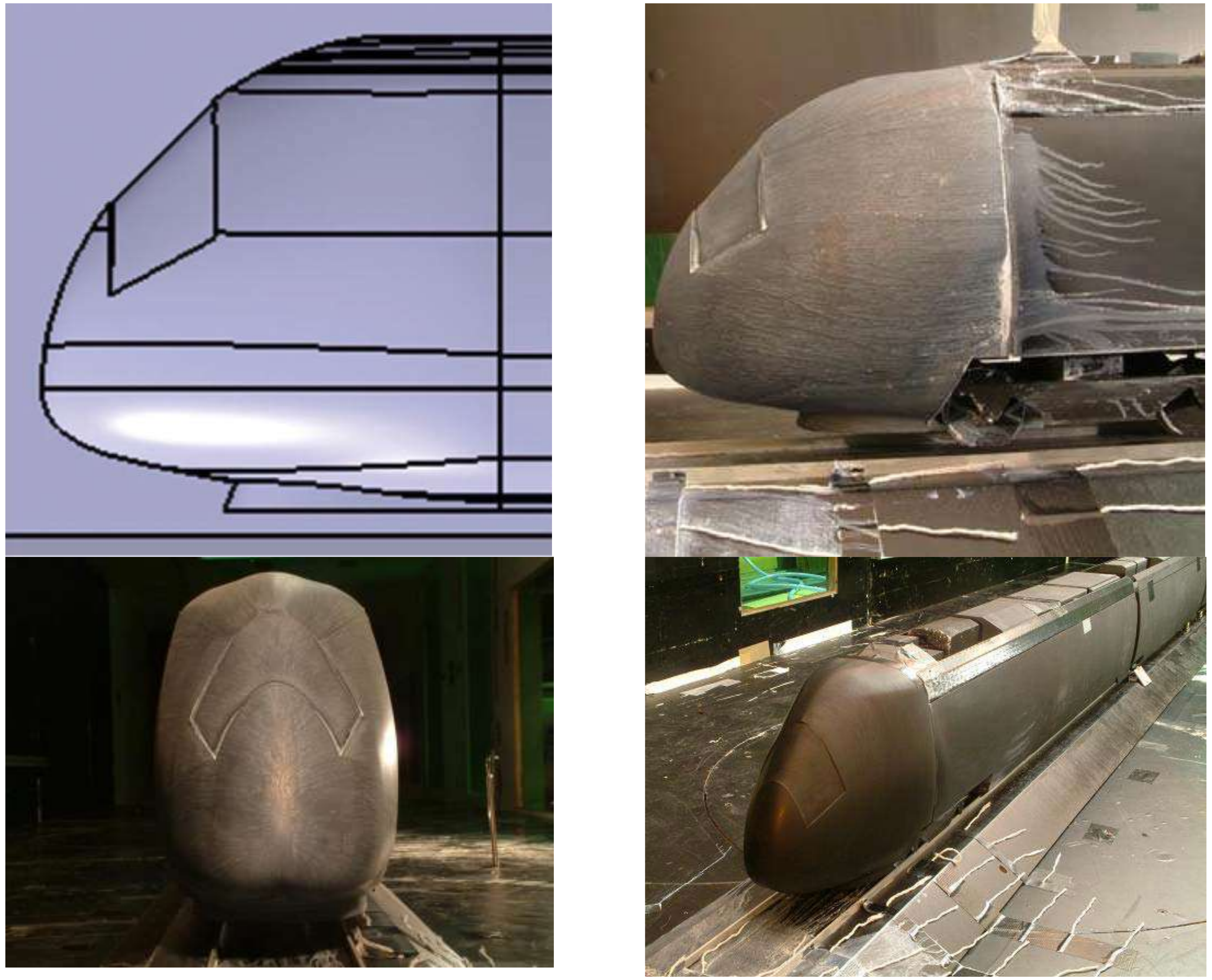


Courtesy of Bombardier Transportation

Reducing Energy Consumption of Bombardier Trains

Wind tunnel tests confirmed optimization results

Benefit: optimization resulted in faster design process along with significant reduction in the use of expensive wind tunnel testing



Courtesy of Bombardier Transportation

Introduction

Understand **global correlations** between geometric parameters and **CFD performances.** Give inputs to future train design to **reduce energy consumption** and **maximize safety**.

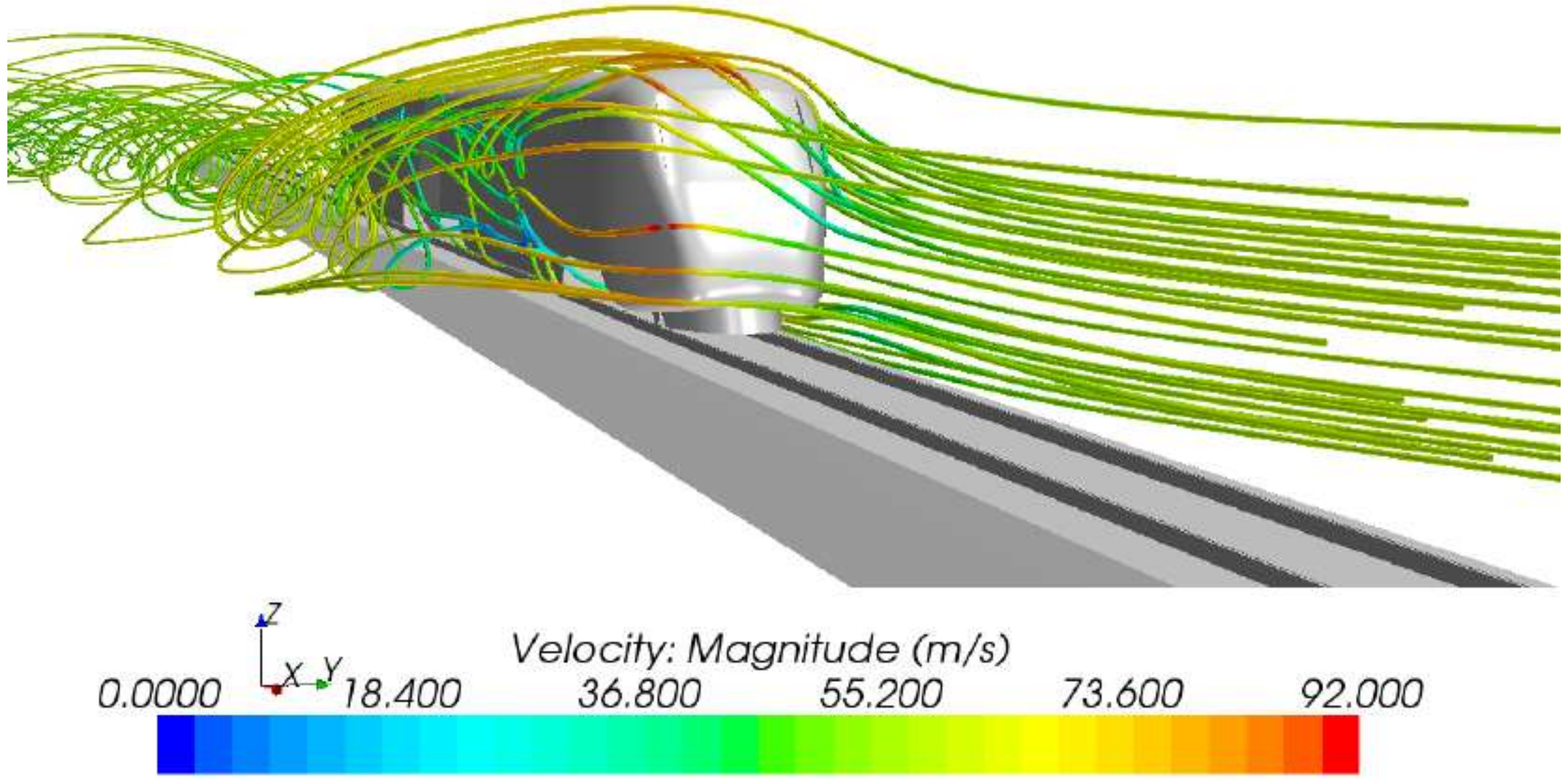
Regulations and Fluidynamics

Regulation constraints:

- Head Pressure Pulse (HPP) less than 800Pa
- Crosswind Stability (CWS)

Fluidynamics performances:

- Drag

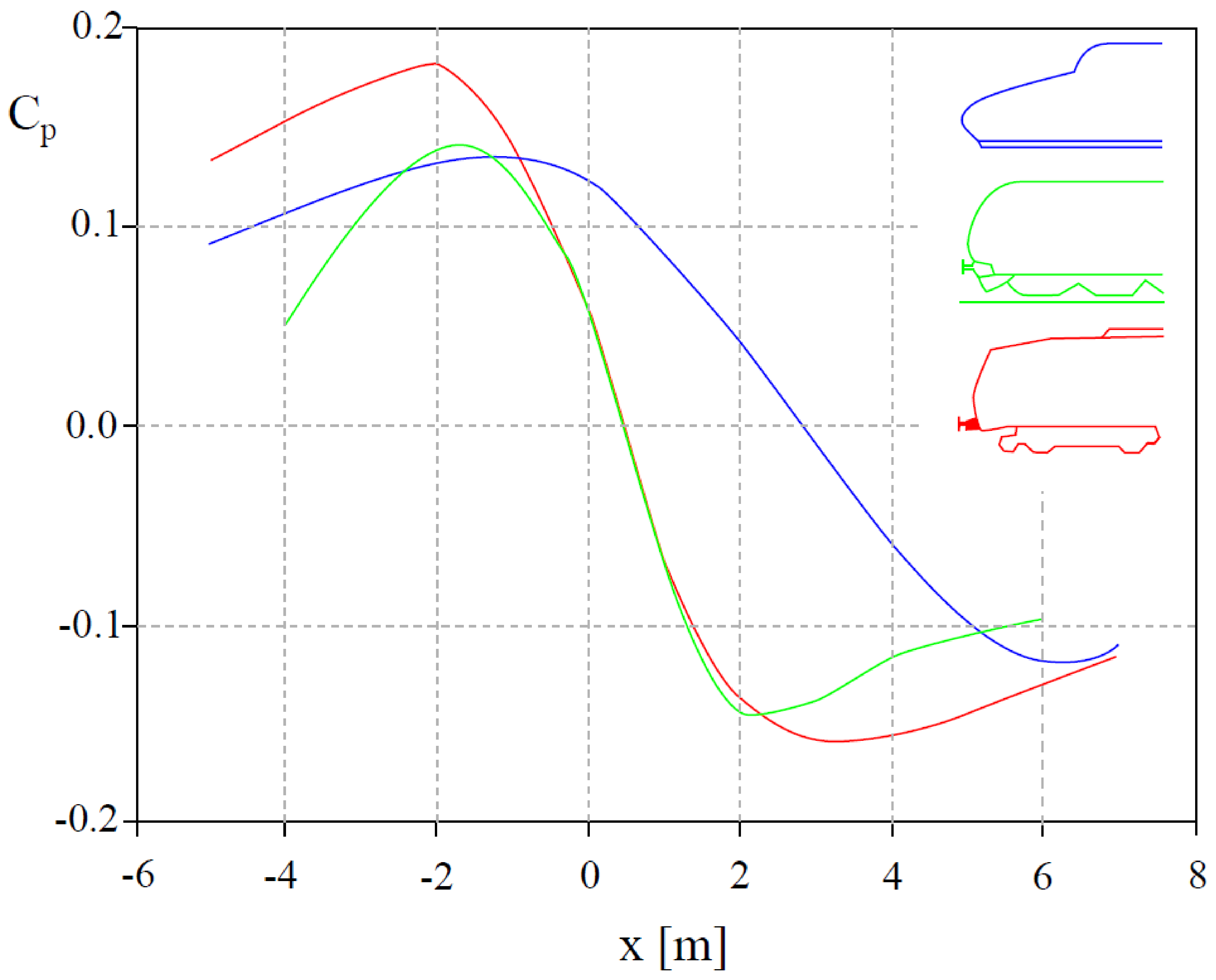


Streamline visualization of velocity field around the train in crosswind

Head Pressure Pulse

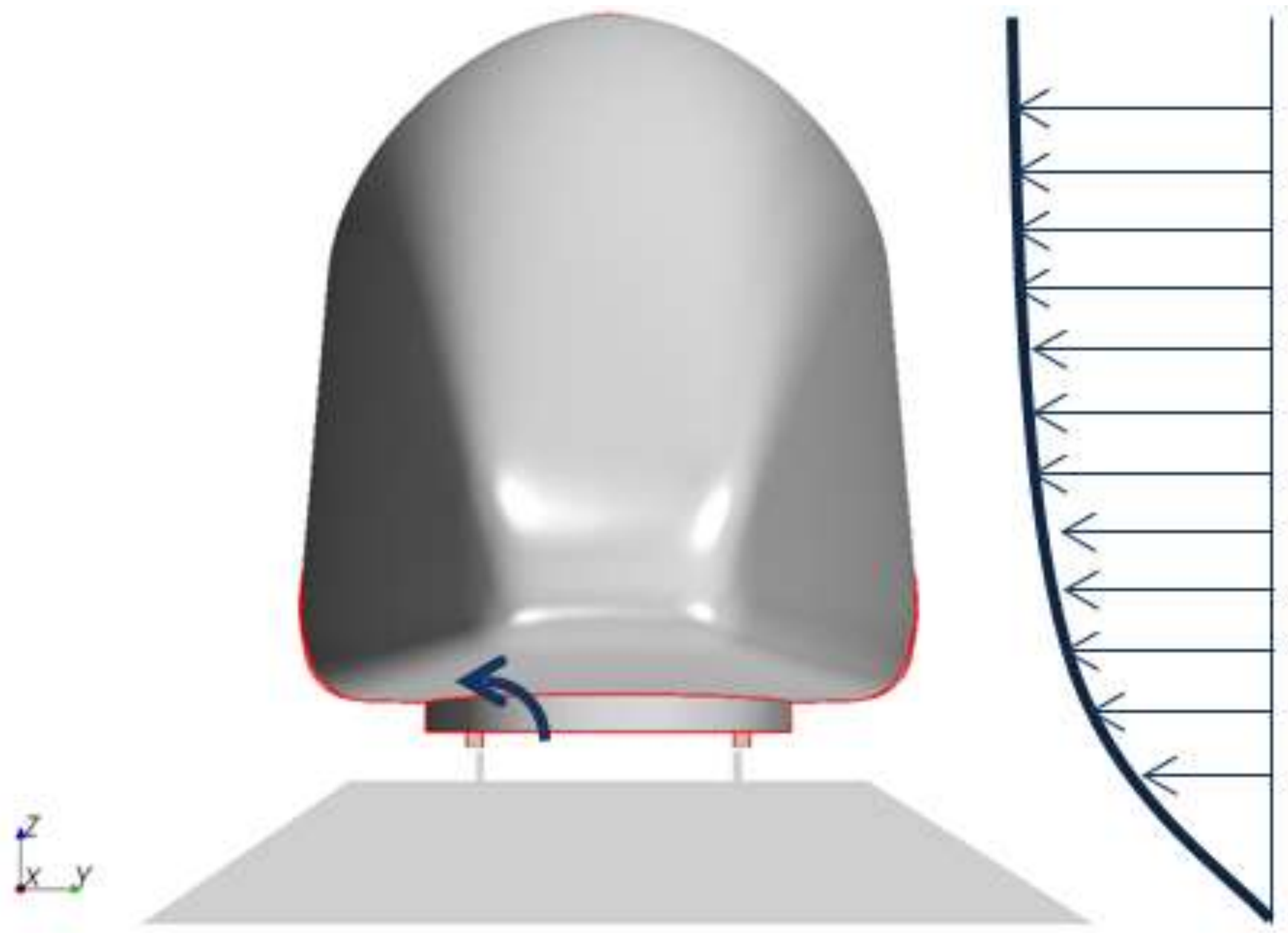
It is the Pressure Pulse caused by a moving train.

- Different nose shapes have different HPP values
- For a given shape limit the HPP means speed limit



Crosswind Stability

Stability is fundamental for safety: lateral winds can cause the train to roll over leeward rail.

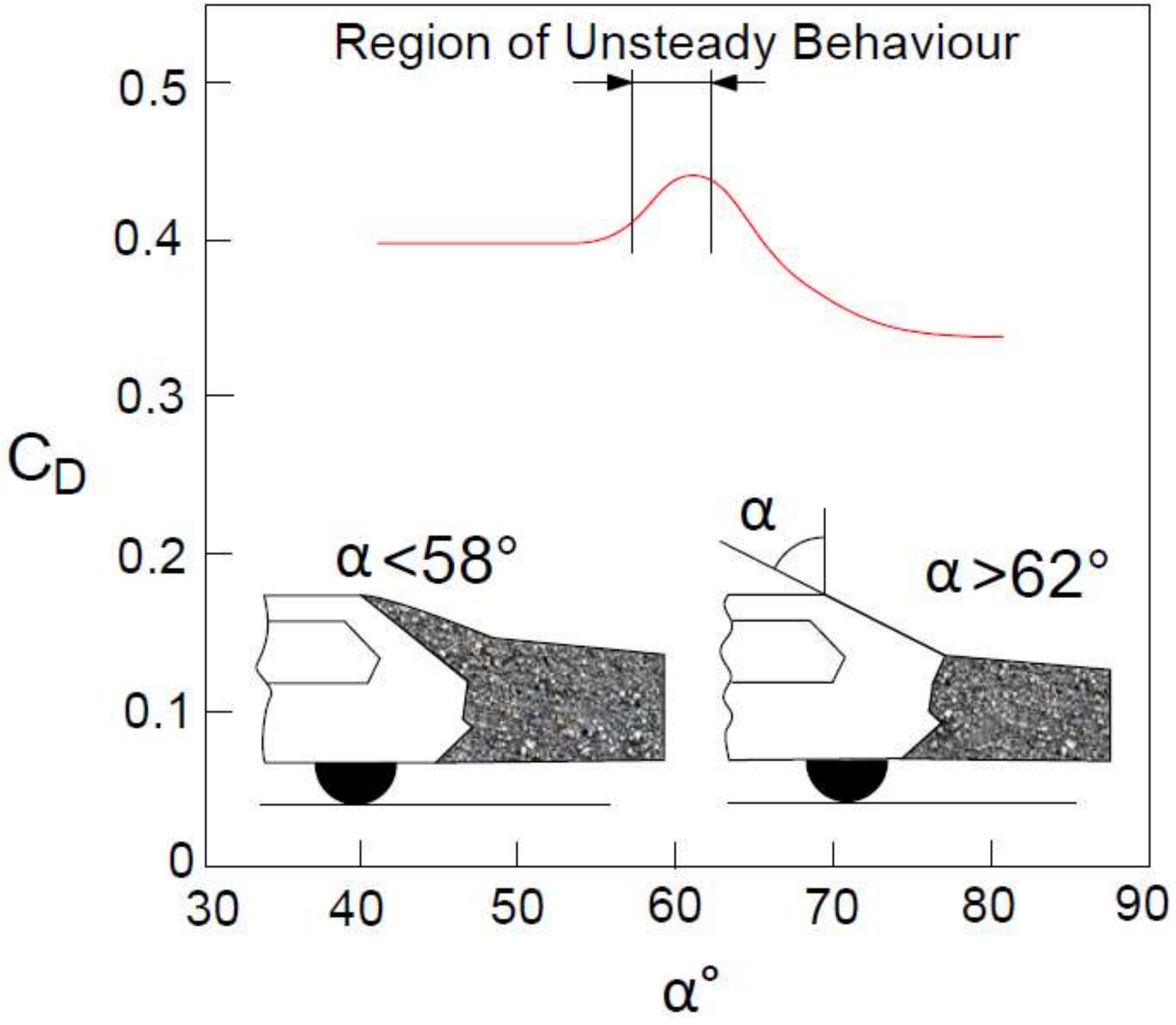


Drag

Reduce drag to reduce energy consumption.

Two different behaviors at tail:

- flow stays attached for α>62°
- flow detaches for α<58°
- Unsteady behavior for 58°< α<62°

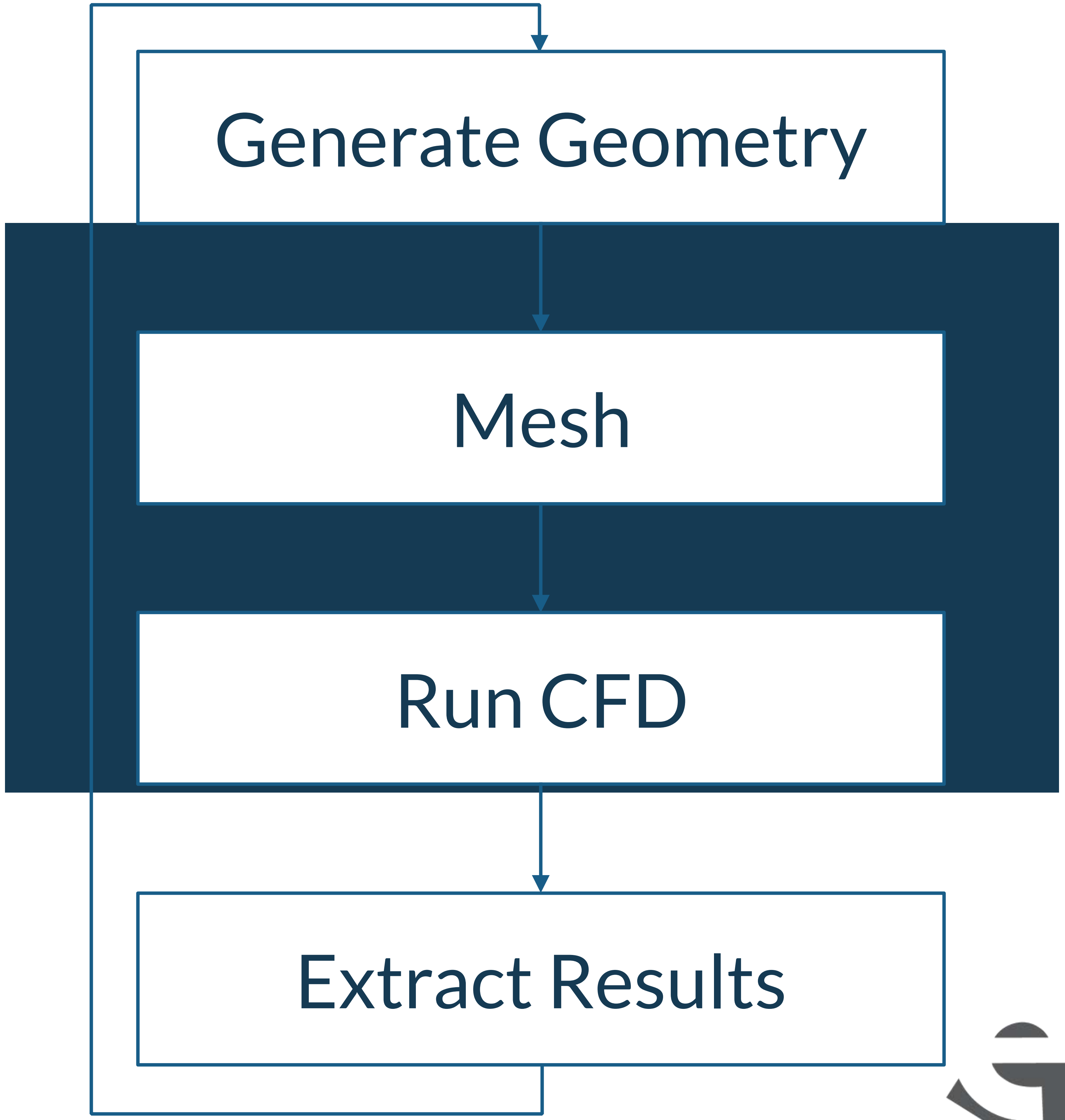


modeFRONTIER Workflow

modeFRONTIER allows the coupling with:

- CAD software for geometry generation
- CFD software for Mesh generation and CFD solution

It automates the run process and optimization run.

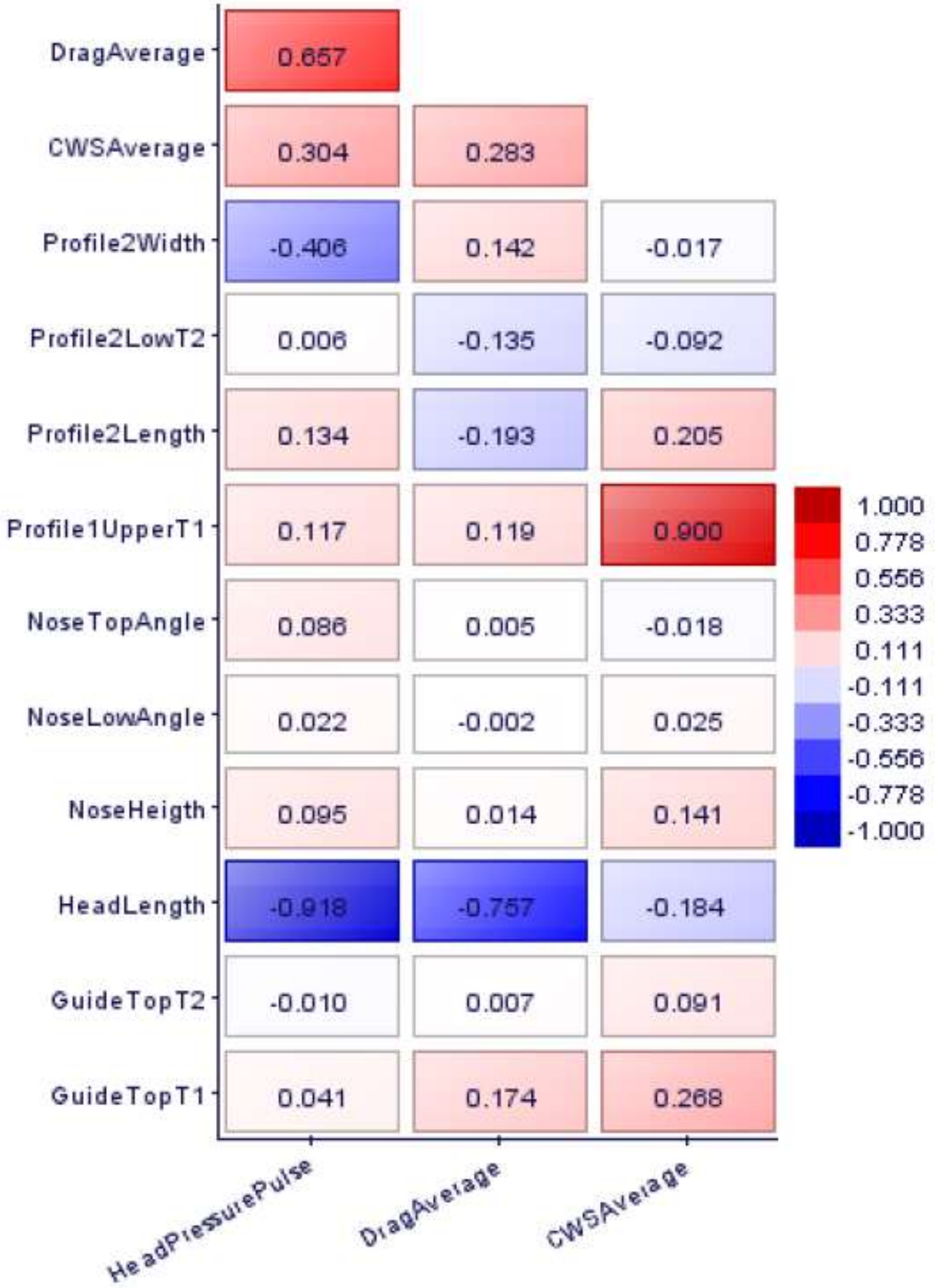


Optimization Results

First Uniform Latin Hypercube DOE is run to spot **correlation between inputs and outputs**.

Most important correlations:

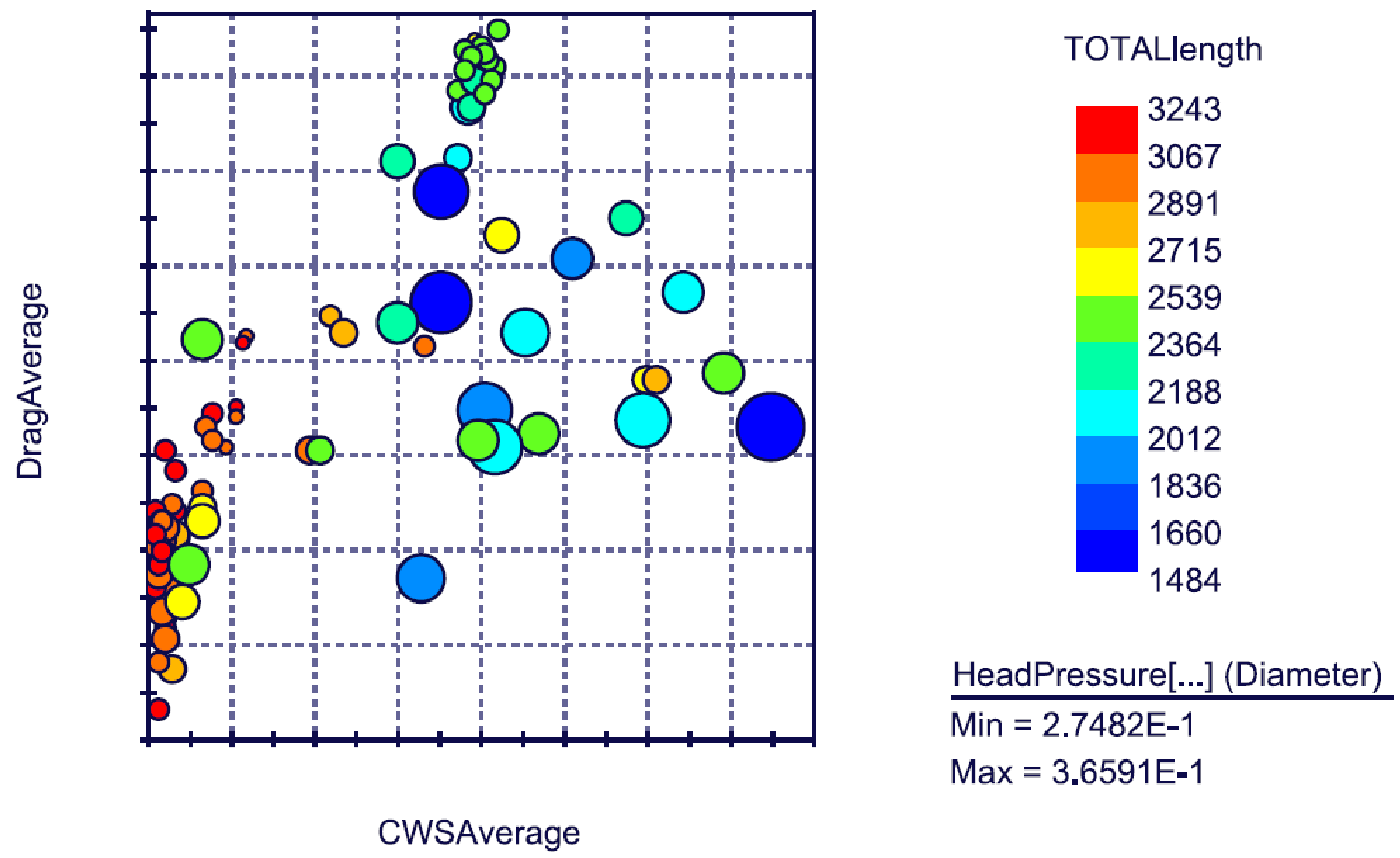
- The **rounder the roof** the higher the CWS
- The **longer the nose** the lower the HPP and Drag



Optimization Results

FAST multi strategy: 200 designs evaluation.

Algorithm finds the Pareto frontier.



Best Train Shapes

Comparison with Bombardier regional train

Best Crosswind Stability. 20% less than production train

Best Drag: 7% less than production train

Best Head Pressure Pulse behavior.

Summary

Best drag:
- Higher nose for less turbulent wake
- Drag reduction of 7% with respect to production train

Best HPP:
- Longer noses

Best CrossWind Stability:
- Sharp angles on the nose upper part
- Sloping and flat noses
- 20% better stability with respect to production train

Using Deep Learning in electric motor optimization

Esteco & University of Trieste

UNIVERSITÀ
DEGLI STUDI DI TRIESTE
Dipartimento di Ingegneria e Architettura

Corso di laurea in Ingegneria Elettronica e Informatica

Applicazione di reti neurali nella progettazione di componenti per l'industria automobilistica

Tesi di laurea magistrale

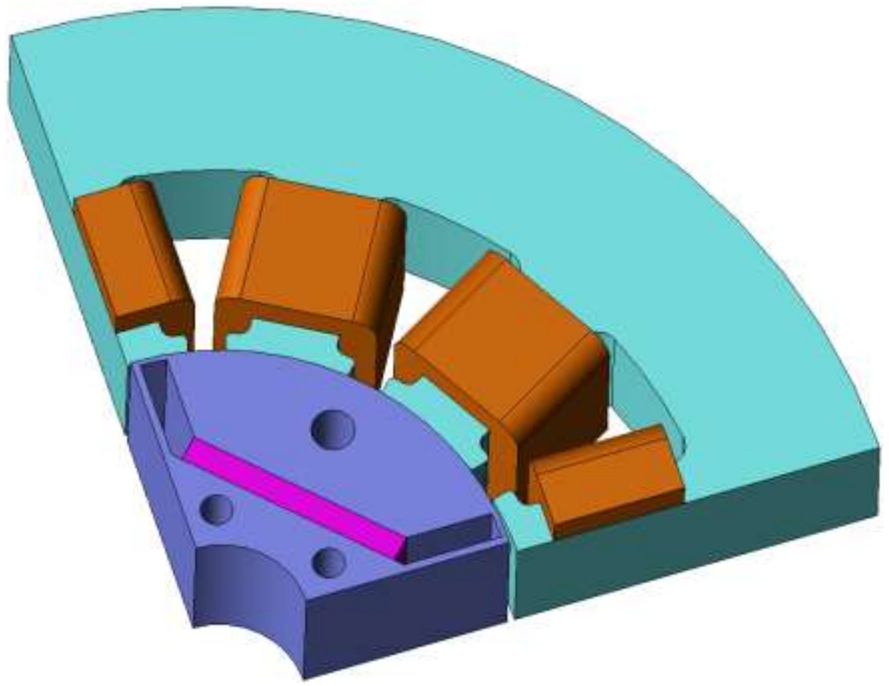
Laureando:
Mattia De Bernardi

Relatore:
Prof. Gianni Ramponi

Correlatore:
Ing. Livio Tenze

Electric motor optimization for NEVs development

Interior Permanent Magnet (IPM) Motor



Electric motor optimization for NEVs development

Optimization of an **Interior Permanent Magnet** (IPM) Motor

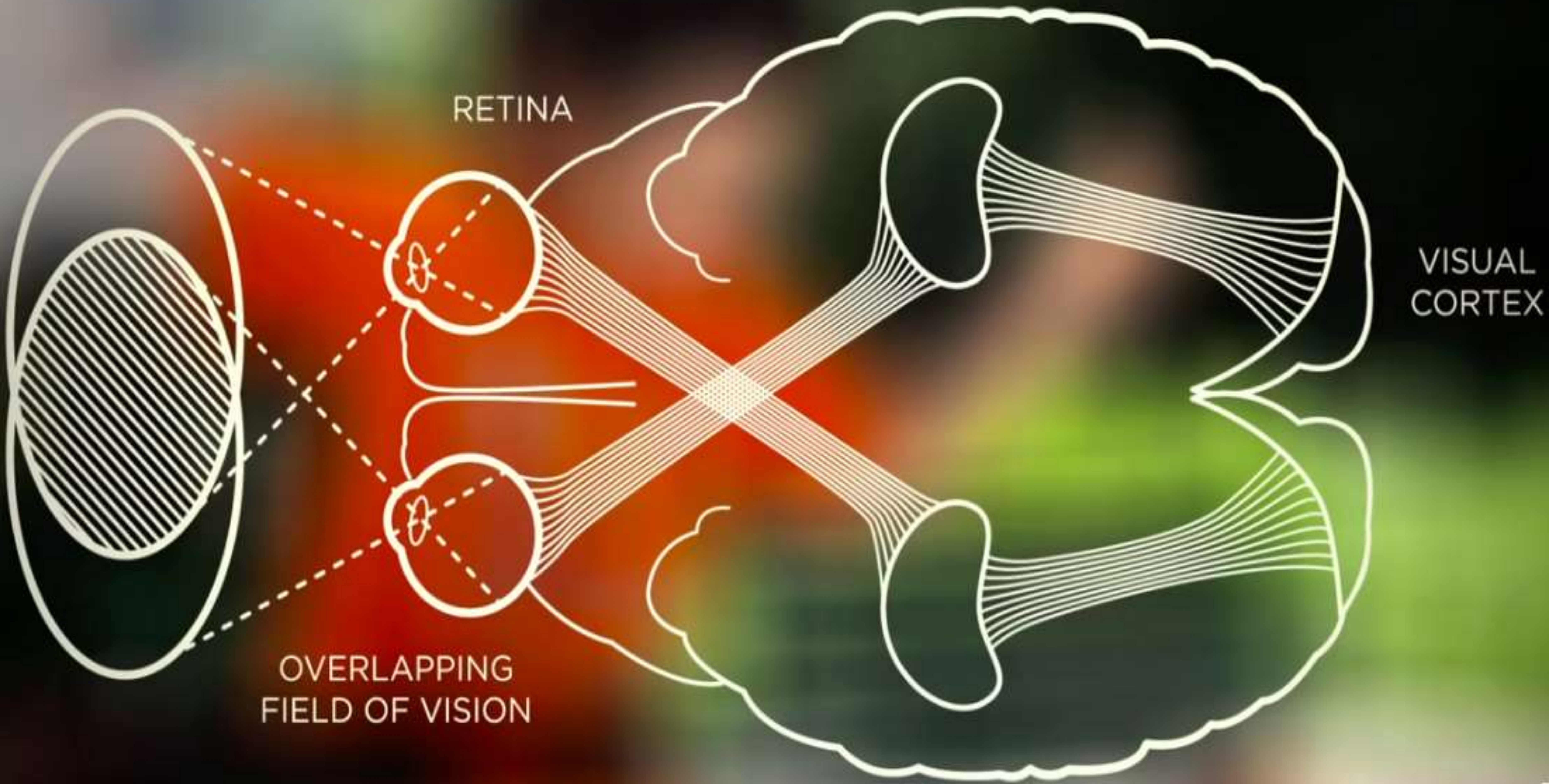
Challenge:

- Huge number of geometry configurations to explore
- Heavy computational simulations

Solutions:

- Deep Learning approach using convolutional neural network (CNN) to analyze image and reduce simulations
- modeFRONTIER optimization platform to reach the optimal

How Does The Human Eye Work?



Vision begins with the eyes, but truly takes place in the brain.

Problem descriptions

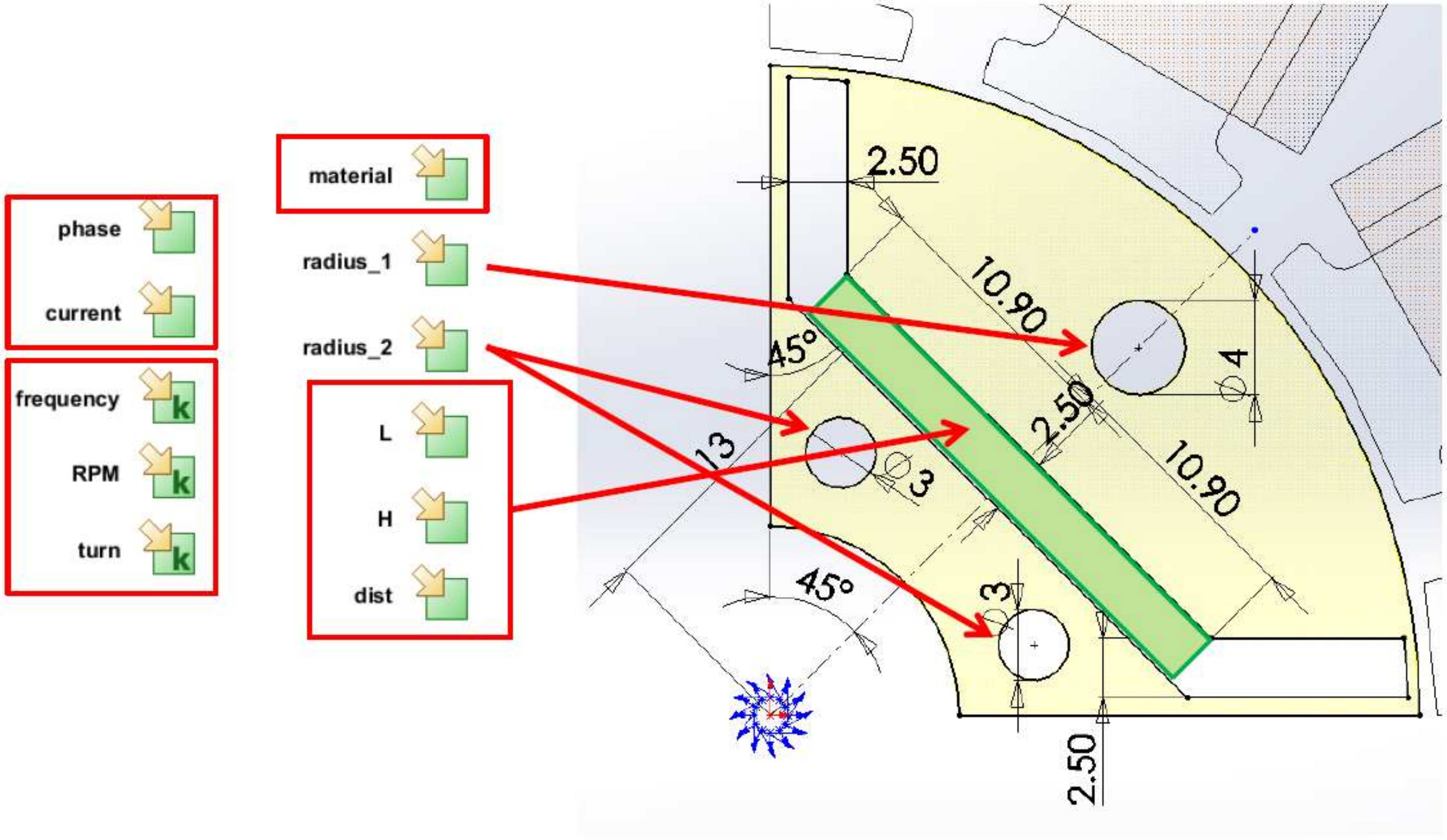
The steps are:

1. Select a geometry
2. Simulation using JMAG
3. Electromagnetic field
4. Power band
5. Average torque

The objectives are:

- Maximize the torque
- Minimize the geometry

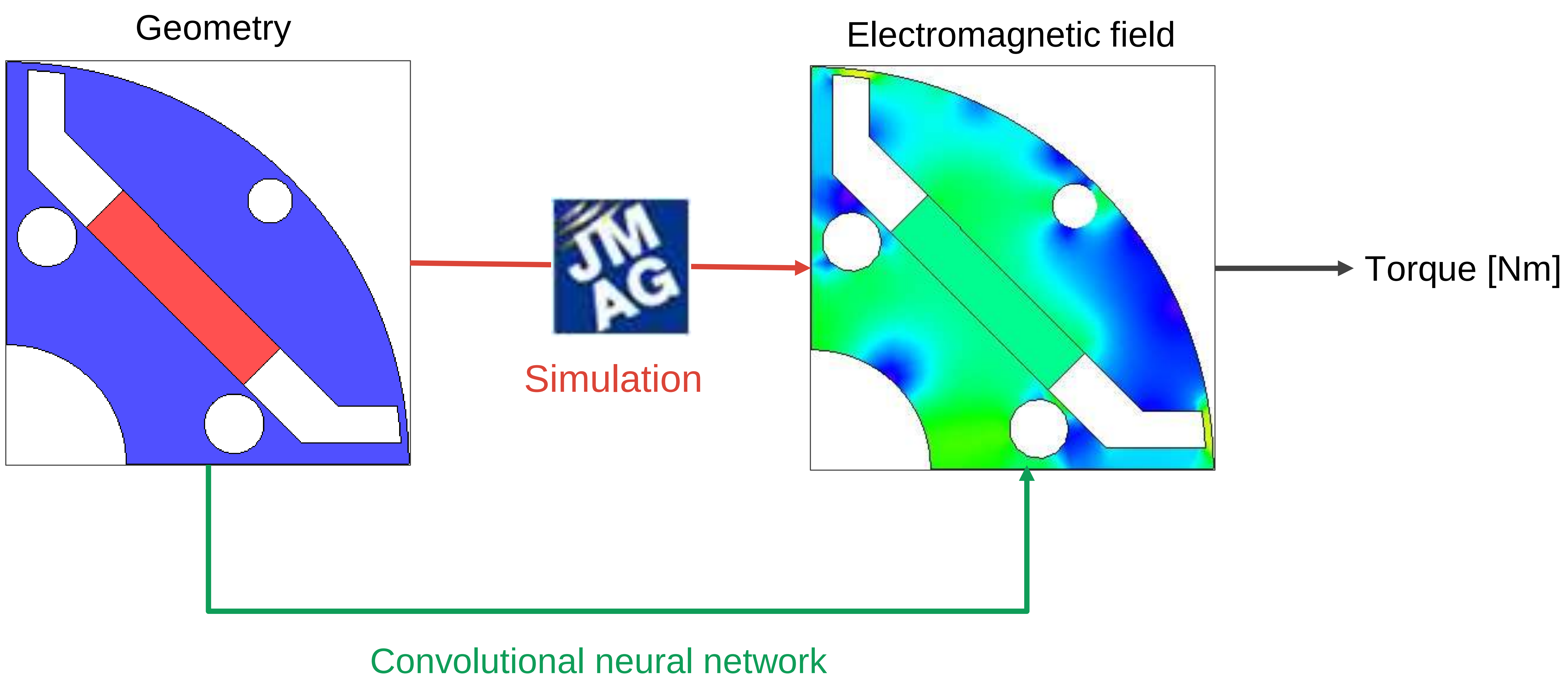
Rotor parametrization



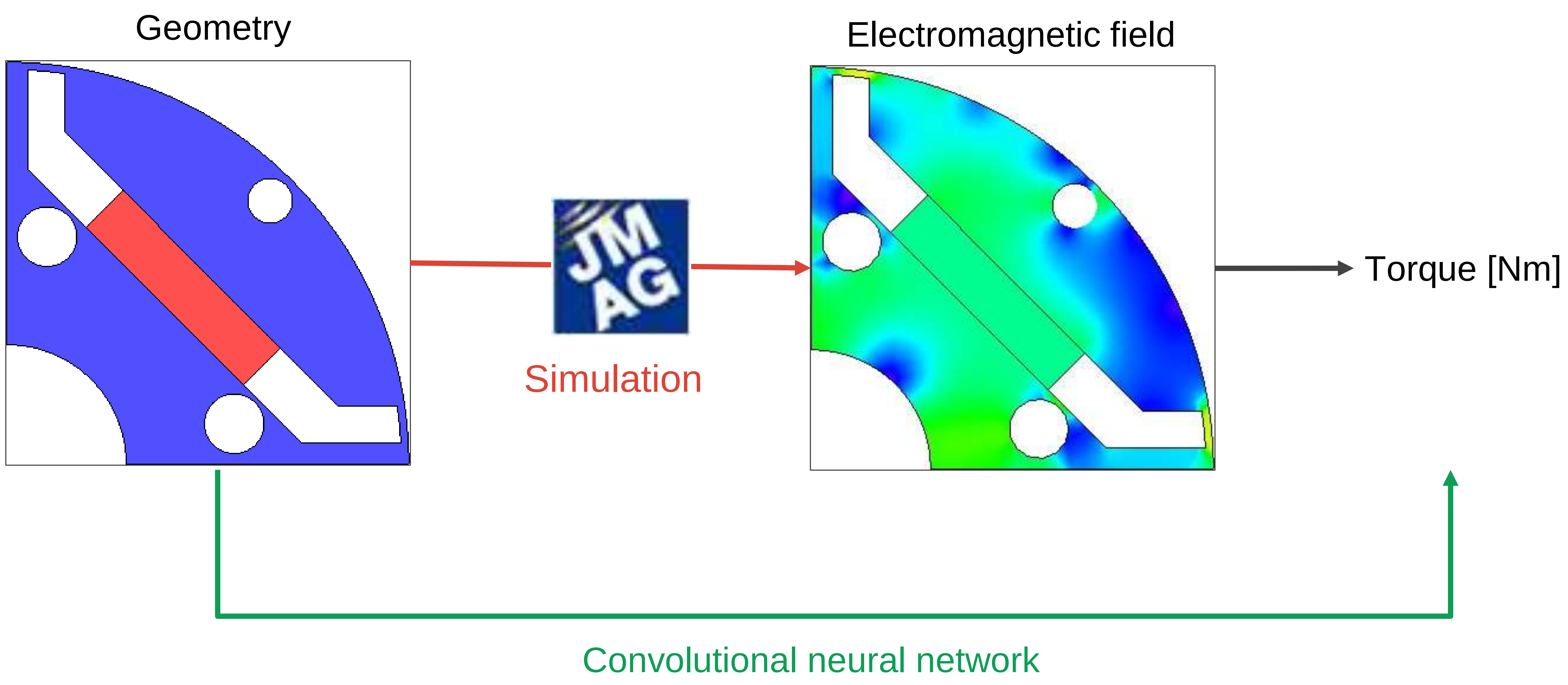
Classification based on Torque value

Coppia [N m]	Classe
<0.02	0
0.02 – 0.04	1
0.04 – 0.06	2
0.06 – 0.08	3
0.08 – 0.10	4
0.10 – 0.12	5
0.12 – 0.14	6
>0.14	7

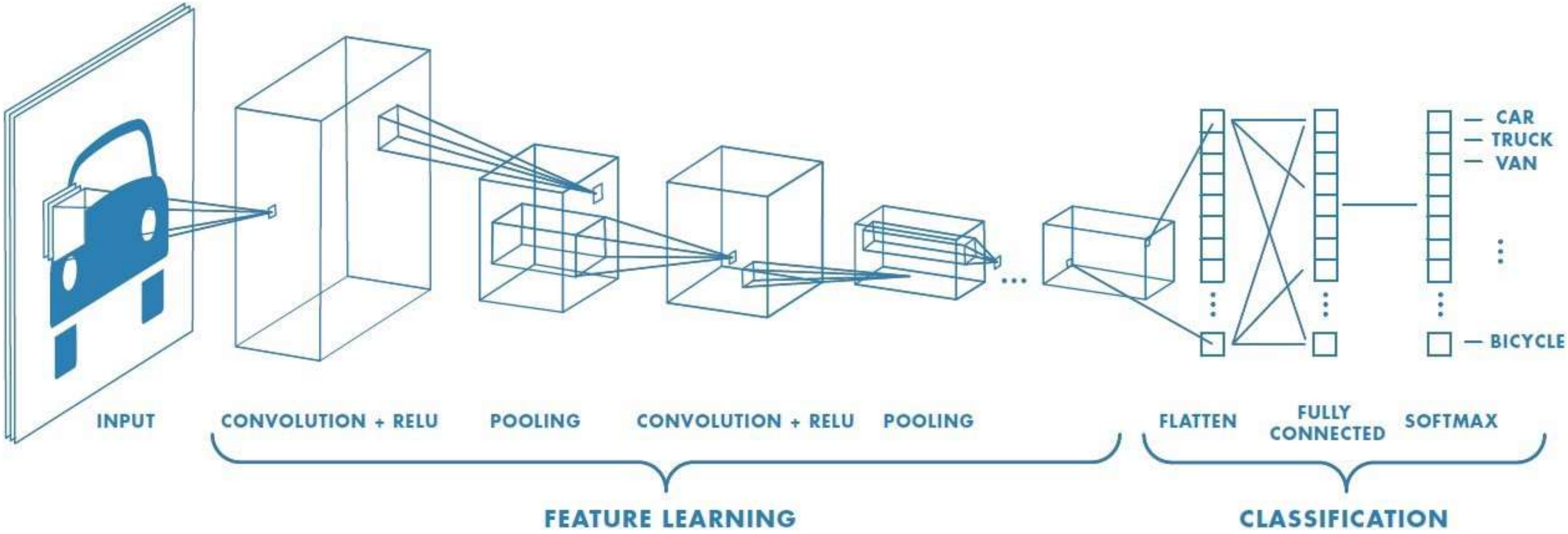
Deep Learning approach



Deep Learning approach



Convolutional Neural Network



A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other.

How Does The CNN works

CNN goal is approximate an unknown function **f*** with another function

$$y=f(\mathbf{x};\mathbf{W})$$

Neural Network optimize the weight **W** to minimize the loss function **L** and obtain the best approximation of the function **f***

$$\mathbf{W} = \mathbf{W} - \boldsymbol{\epsilon}\,\mathbf{g}$$

$\boldsymbol{\epsilon}$ is the learning rate

$\mathbf{g}$ loss function gradient respect to **W**

CNN general architecture

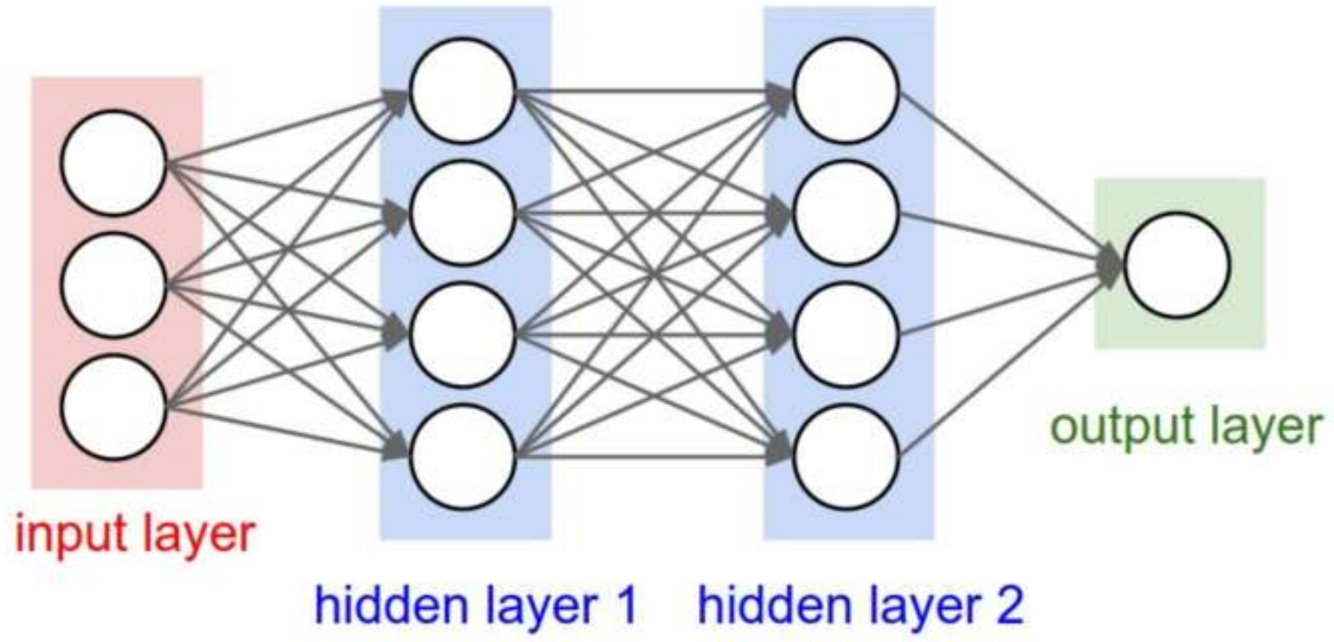
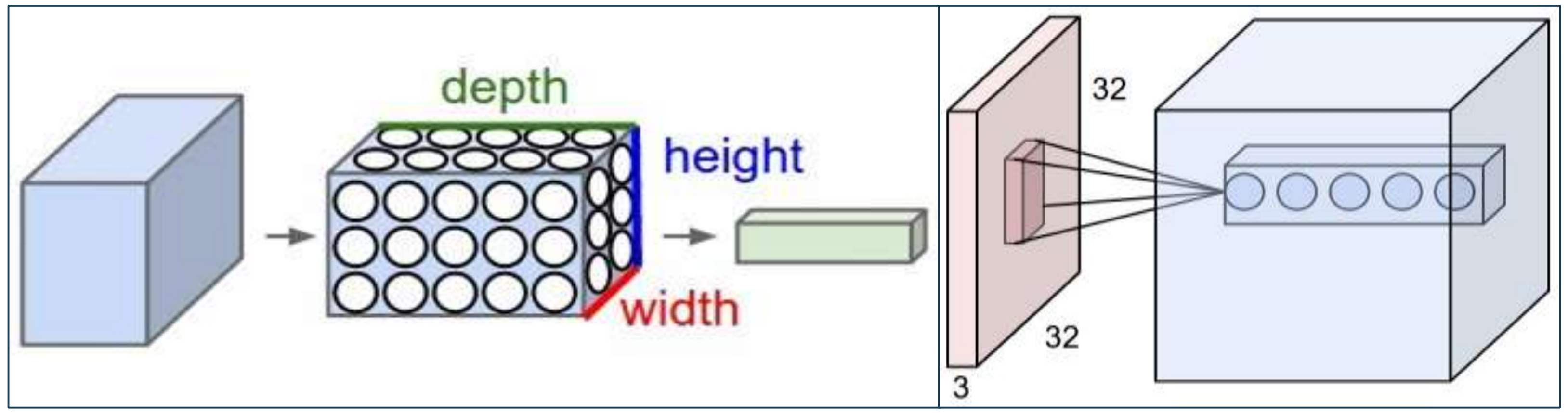


Figura 8: Una rete neurale a tre strati (lo strato di ingresso non si conta)



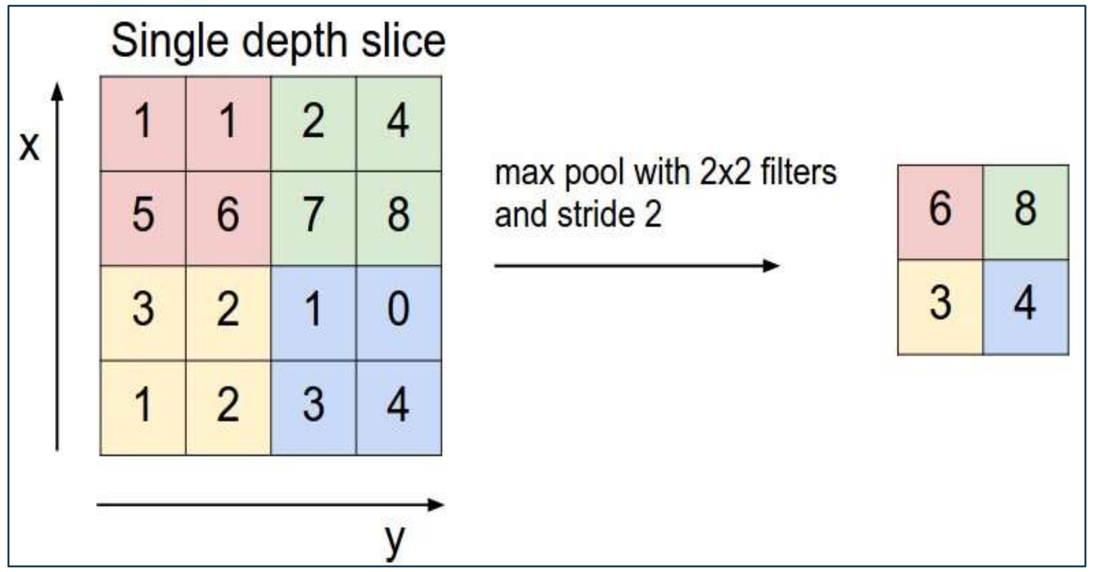
Fully connected layer

Convolutional layer

CNN general architecture

Convolutional neural network has different type of layer:

- Convolutional
- Fully connected
- Pooling
- Normalization



Different architecture and techniques

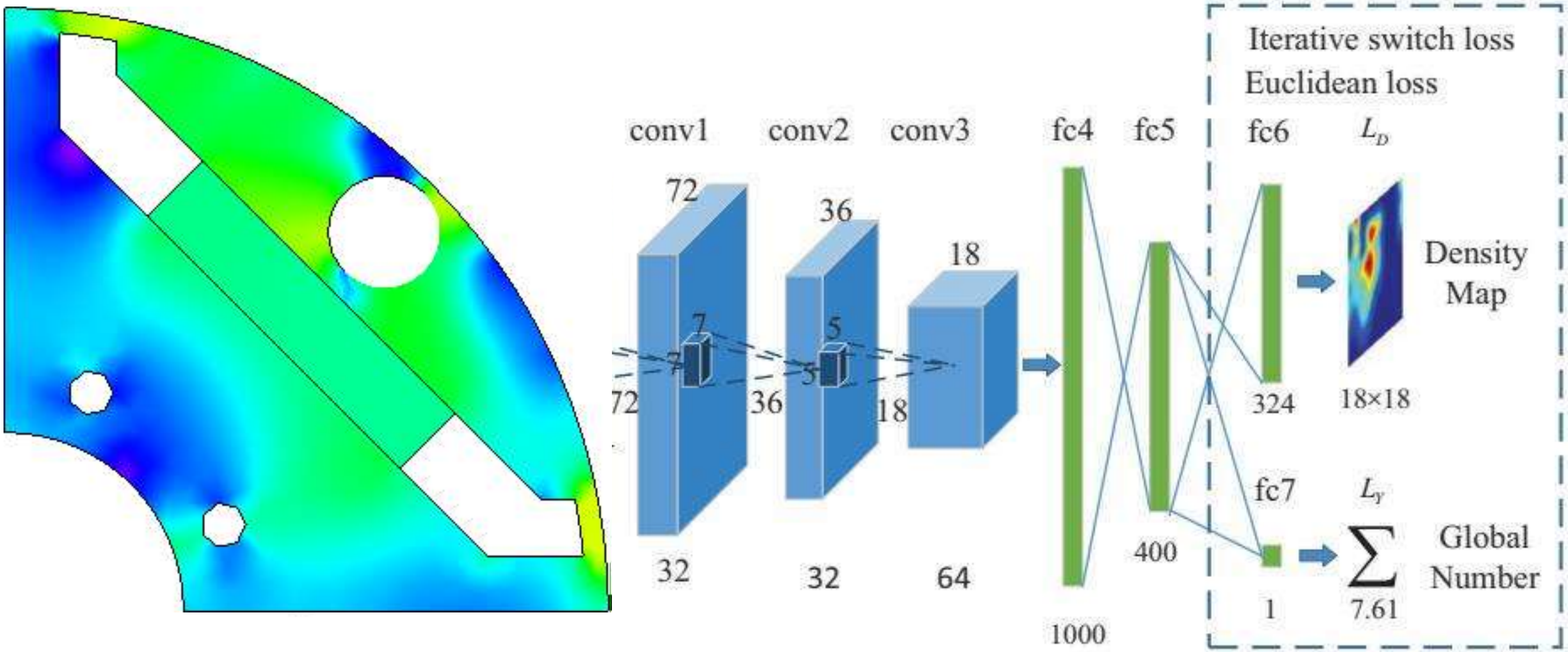
Various architectures of CNNs available:

1. **LeNet**
2. AlexNet
3. VGGNet
4. GoogLeNet
5. ResNet
6. **ZFNet**

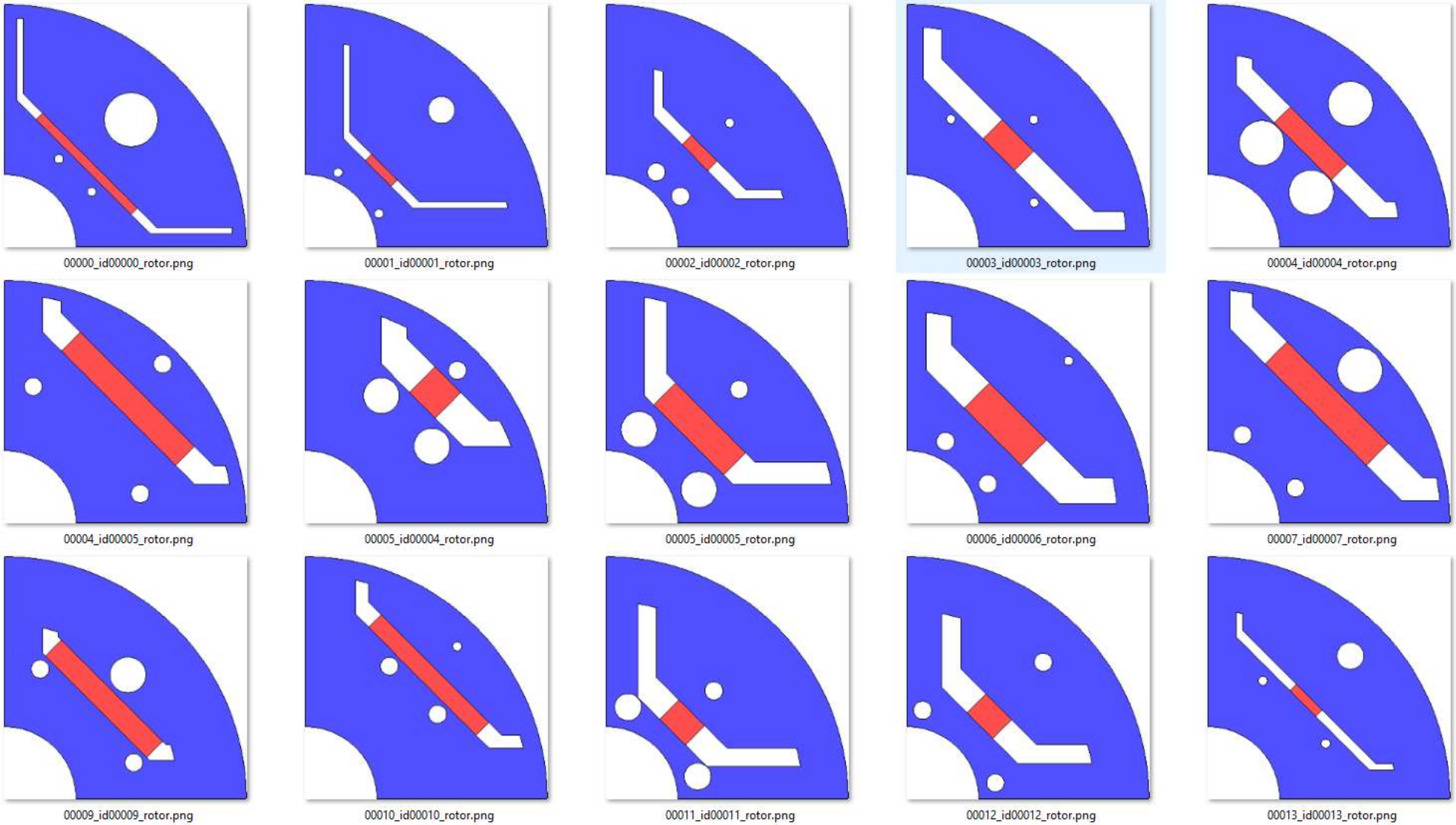
Learning techniques to improve performance:

1. Decay learning rate
2. Early stopping
3. Data augmentation

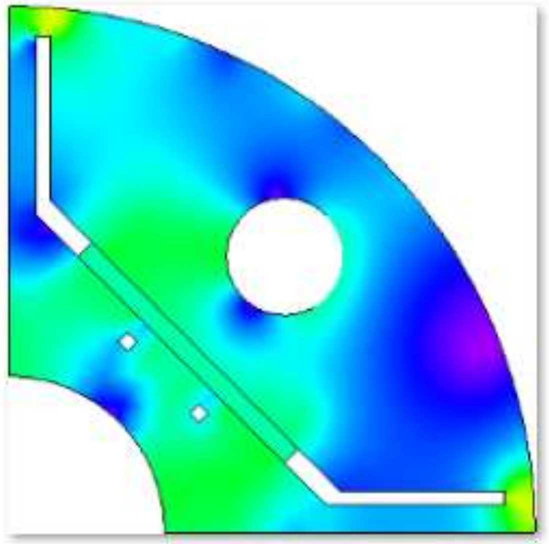
Learning Process



Learning Dataset



Learning Dataset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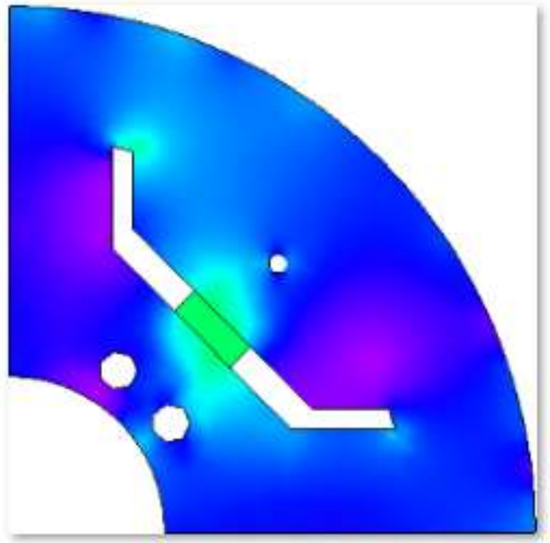
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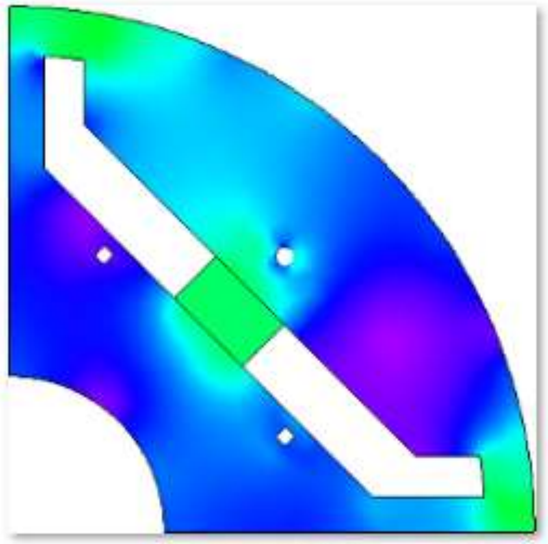
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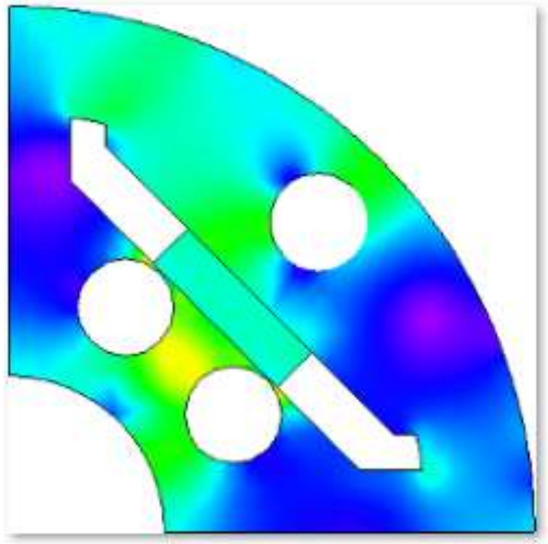
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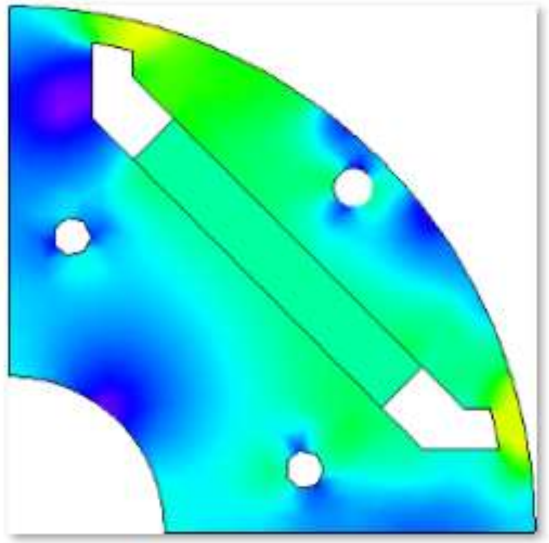
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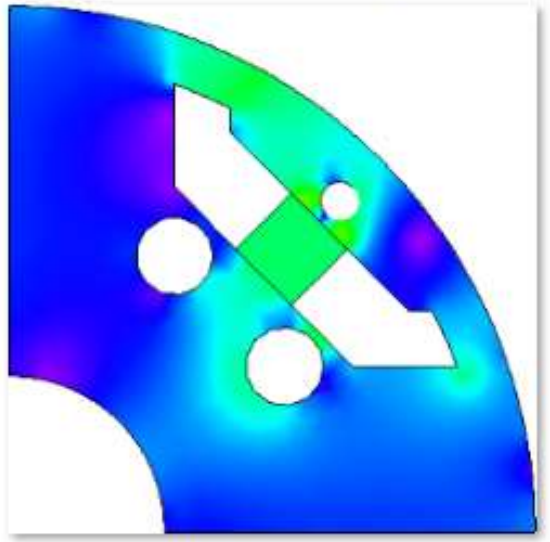
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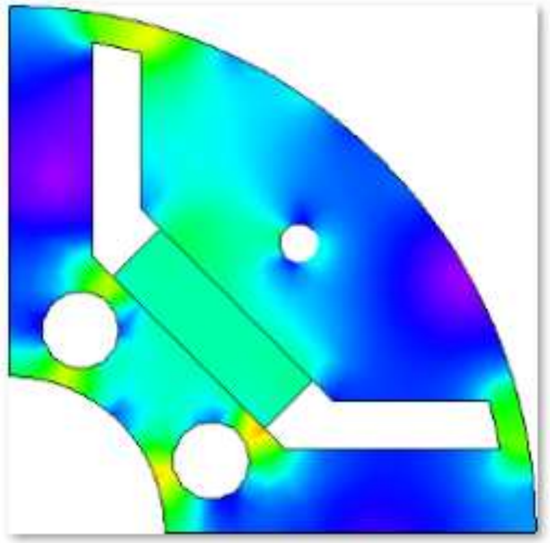
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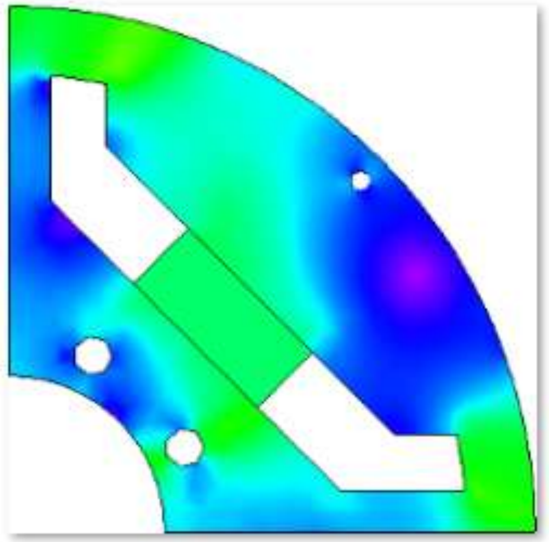
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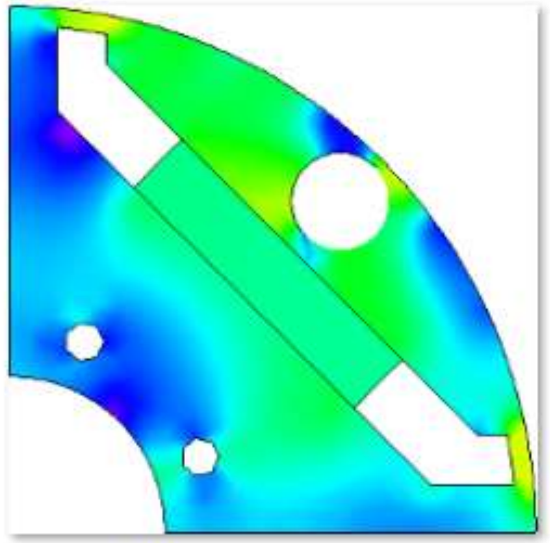
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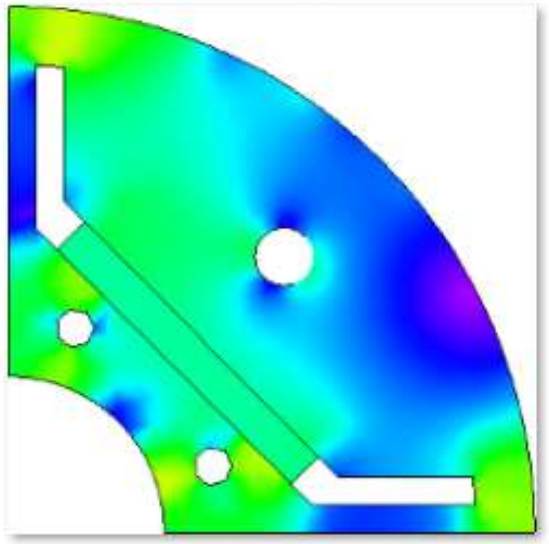
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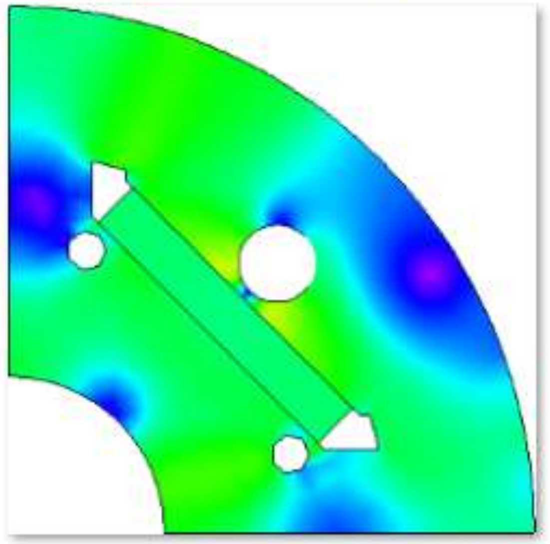
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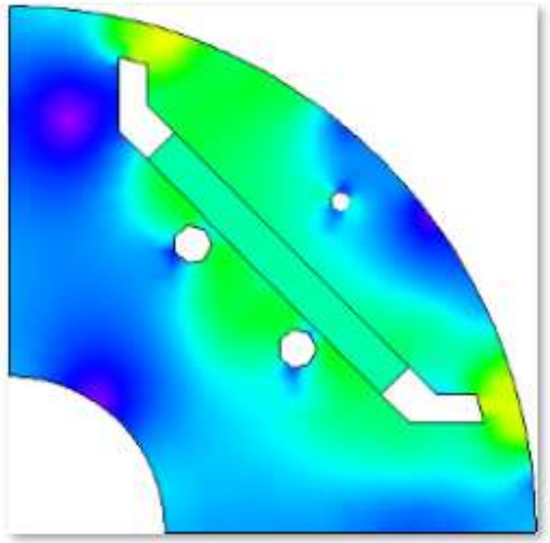
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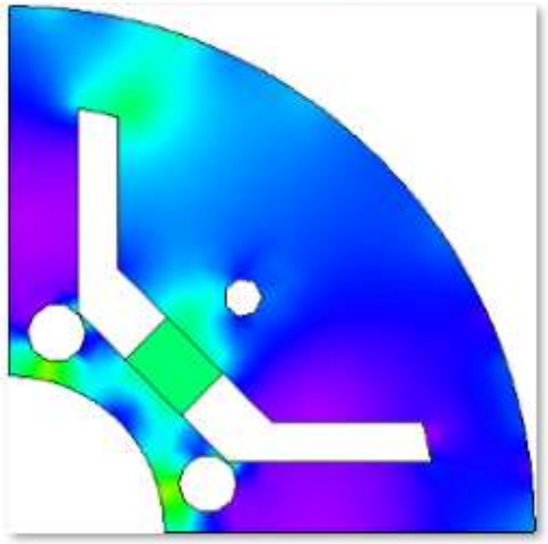
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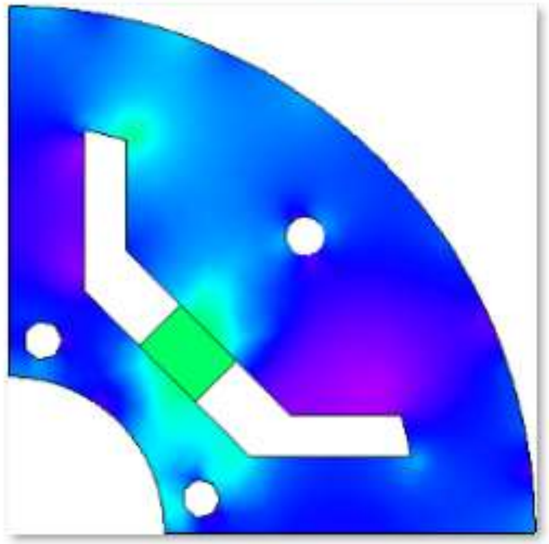
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Image preprocessing

Image preprocessing improve CNN accuracy and speed up loss function convergence

Different image preprocessing are used:

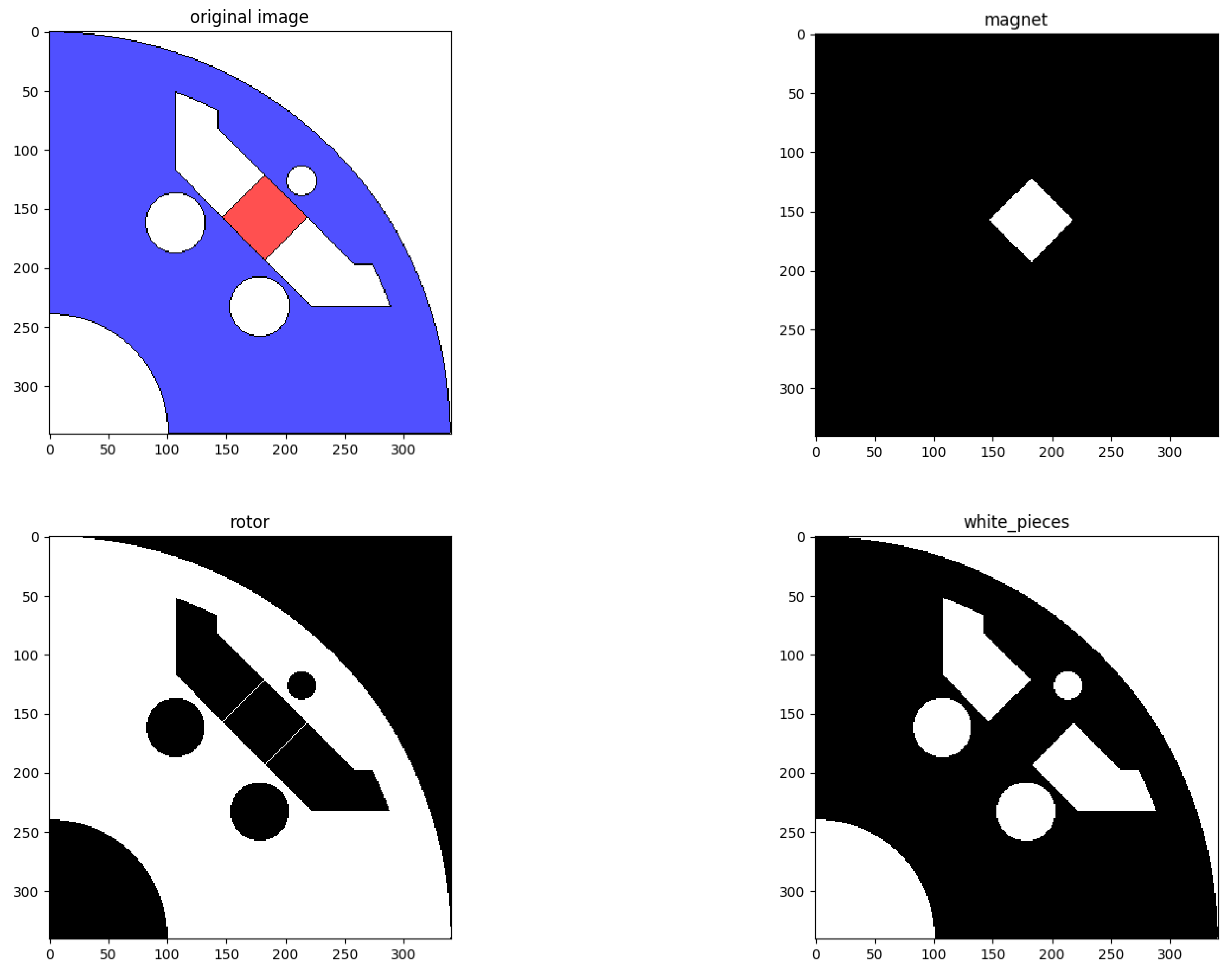
1. Image centering e normalization

2. Color segmentation

3. Part segmentation

The 1st is a general technique for image processing while the other two are specific techniques for electric motor

Color Segmentation



Part Segmentation

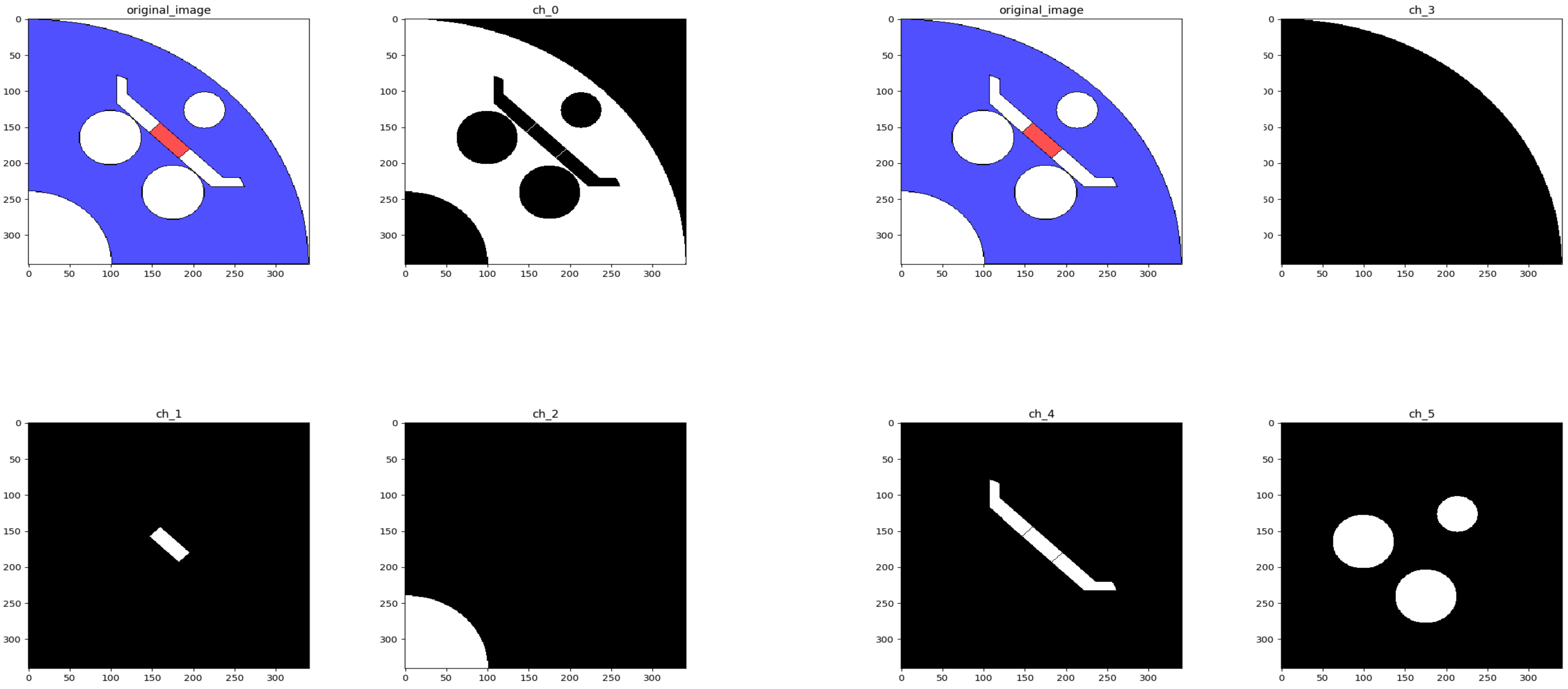
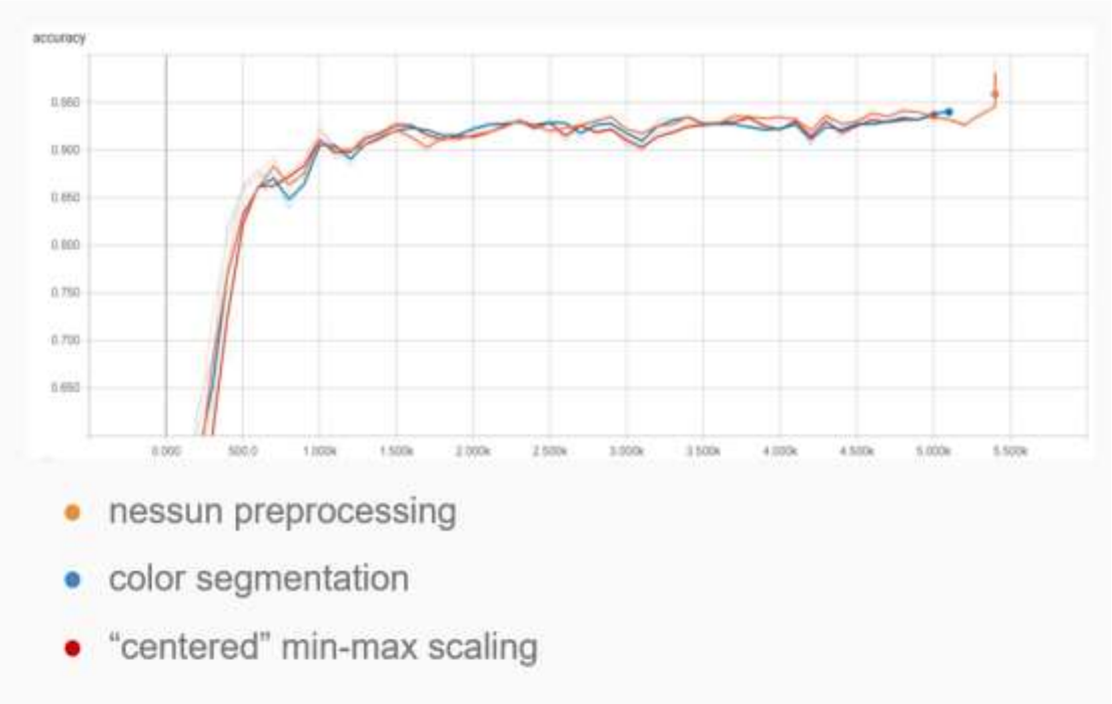
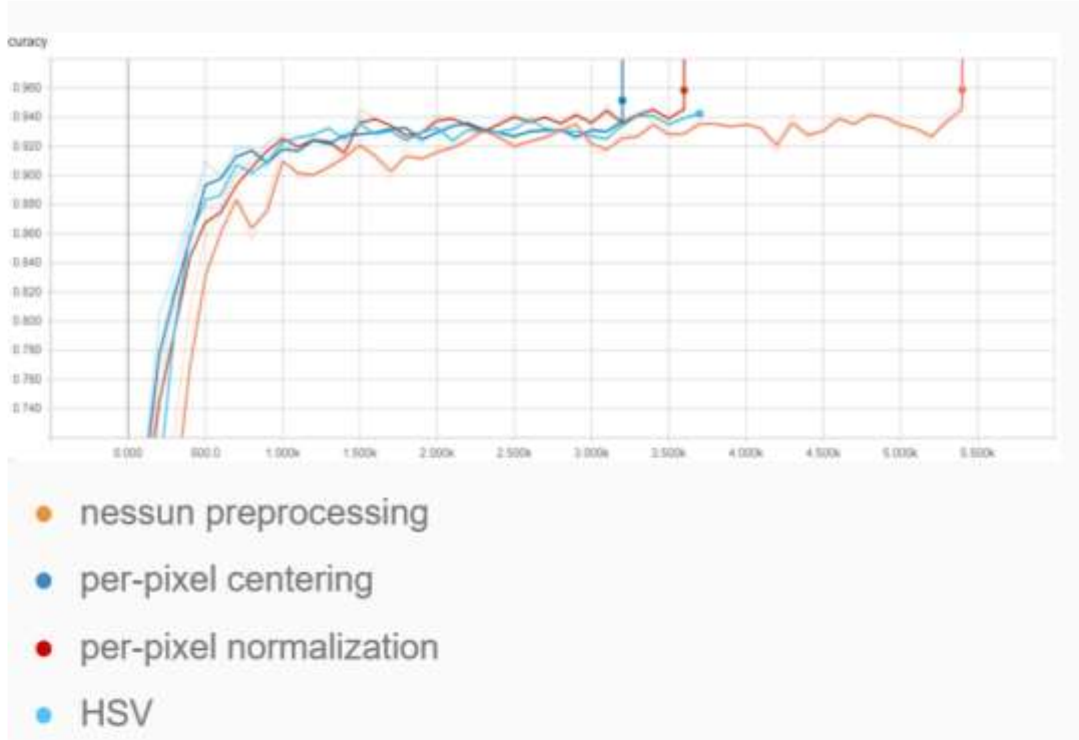
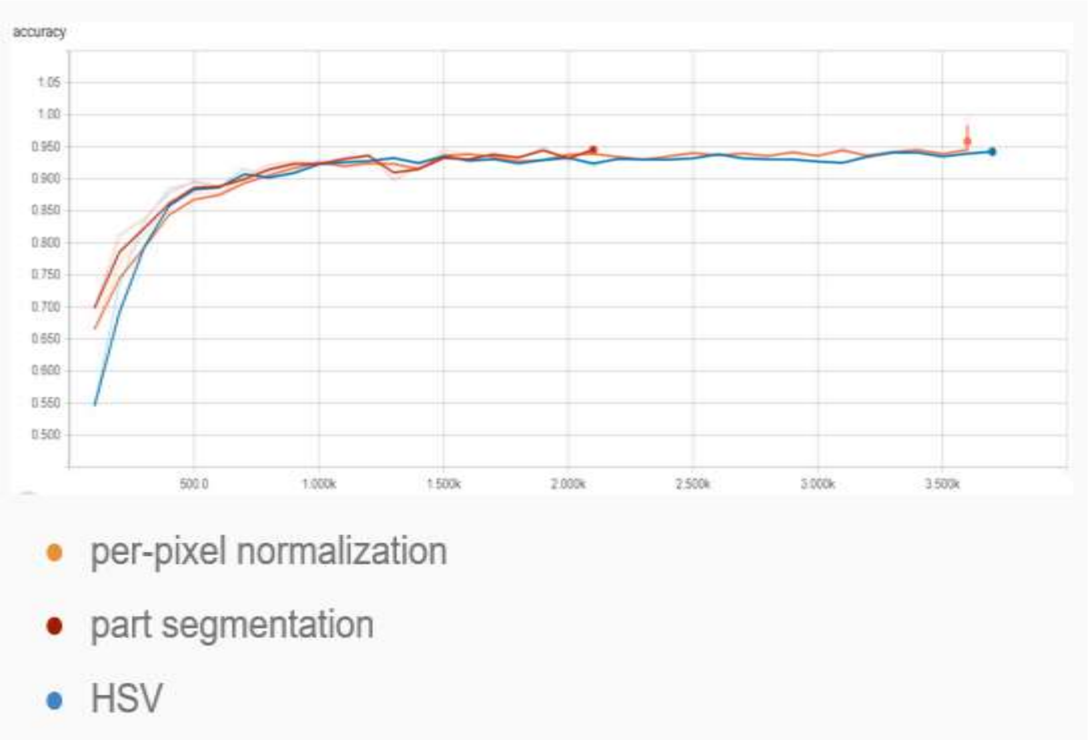


Image preprocessing result comparison







The best technique is Part Segmentation in term of:

- Accuracy = 0.9505
- Convergence = 2.1k step

Best CNN trained

ZFNet architecture

- Early stopping
- Decay learning rate (parameter refinement)
- Part segmentation

Performance:

- Accuracy 0.9560
- Convergence 3.2k step

Performance on validation set:

- Accuracy 0.9451

Less than 1% error

Conclusions

- Successfully apply CNN deep learning approach on automotive industry

- Not easy to find the best model considering:
  - CNN architectures
  - learning techniques
  - Image preprocess
  - Optimization algorithms
  - Etc.

- Simulazion

  Rotor → Electromagnetic field
  - 2 - 3 minutes
- CNN

  Rotor → Torque
  - 20 - 30 ms

on CPU Intel Core i7 4770

Future improvements

- Tensorflow library to decide whether using CPU machine o GPU for the training

- Transfer Learning
  - 2 CNN with the same configuration transferring W (weight) to each other to reduce Training Dataset

- Generative Adversarial Networks
  - Rotor → Electromagnetic field

Scale up

modeFRONTIER

across the enterprise with the collaborative web platform

VOLTA

VOLTA

Orchestrate engineering data and run simulation projects across teams

Aggregate product and process data into a single, shared repository

Quickly set-up and maintain a safe enterprise system

Connect from any location, anytime, from computer and mobile devices

modeFRONTIER

Solid Foundation

Workflow Authoring
Optimization and Robust Design
Advanced Data Analytics
Response Surfaces Modeling

VOLTA

Web Native

Collaboration
Simulation Data Management
Generative knowledge
Process Execution
DOE / OPT

VOLTA

Distributed Execution

Scalable Execution

Concurrent Execution
Remote Job Management
Batch Engines Balance

Success Story – MDO at Ford Motor Company

white paper

COLLABORATIVE MULTIDISCIPLINARY DESIGN OPTIMIZATION IN THE AUTOMOTIVE INDUSTRY

Ford attains streamlined, multi-user design process management by expanding its MDO approach at enterprise level with ESTECO's collaborative web-based environment.

MAY 2016

CONTENTS

Taking on the multifaceted challenge of vehicle engineering in a rapidly changing, globalized market, the automotive OEM adopts an innovative design strategy enabled by the new collaborative design optimization technology and turns engineering knowledge into a corporate asset.

01
Introduction.

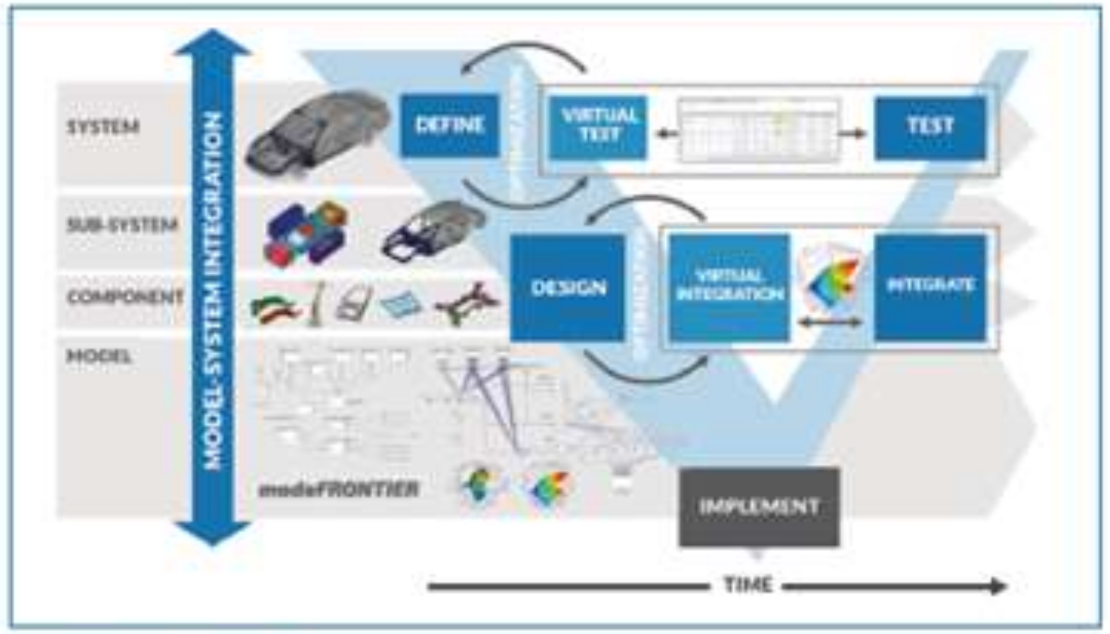
The automotive industry is facing new and pressing challenges from all sides. As the broader economy slowly recovers, automotive players are starting to see their revenues increase again and are expected to add headcount in the next years. Nevertheless, being able to maintain profit margins is bound to become more difficult as public policies focus more and more on meeting environmental and safety standards, adding further pressure on cost structures. In recent years, the role of innovation in the automotive industry has emerged as a key factor, with companies shifting their revenues from well-established models to new ones: Original Equipment Manufacturers (OEMs) are seeking to develop alternative powertrain technologies for digital-intensive and lower-emission vehicles to counterbalance the uncertainty related to future prevailing technologies; at the same time they are aiming to adapt to changing regional and segment patterns of consumer preferences. This has resulted in a trend towards shared production platforms and more modular systems. The growing number of tiers serving different vehicle segments and markets based on a single platform unprecedentedly raises the complexity of both design and production processes. Rethinking design strategies and approaches in order to anticipate manufacturing and market requirements in the earliest phases becomes crucial for OEMs to differentiate themselves with new features while extracting economic value. Leading Computer-Aided Engineering (CAE) software companies such as ESTECO have been keeping pace with changes in industry and working together with companies to create technologies and solutions that not only can handle current challenges, but can also steer the industry toward more innovative product design and processes.

02
The Case for Collaborative Multidisciplinary Design Optimization (MDO) in the Automotive Industry.

With car buyers worldwide becoming more and more demanding - asking for highly customized features, increased performance, and diversified styling despite the mass market nature of the product - the response of automotive manufacturers has been to raise the number of body styles derived from the same engineering frame. These "derivatives" have numerous common product elements not visible to the consumer (e.g., common chassis, body structures, core components) in order to make differentiation of consumer-facing features valuable. Developing an increasing number of derivatives per shared platform increases the complexity of managing the product development processes, given the explosion in the number of design models generated using different simulation tools and containing large numbers of design variables, responses, objectives and constraints.

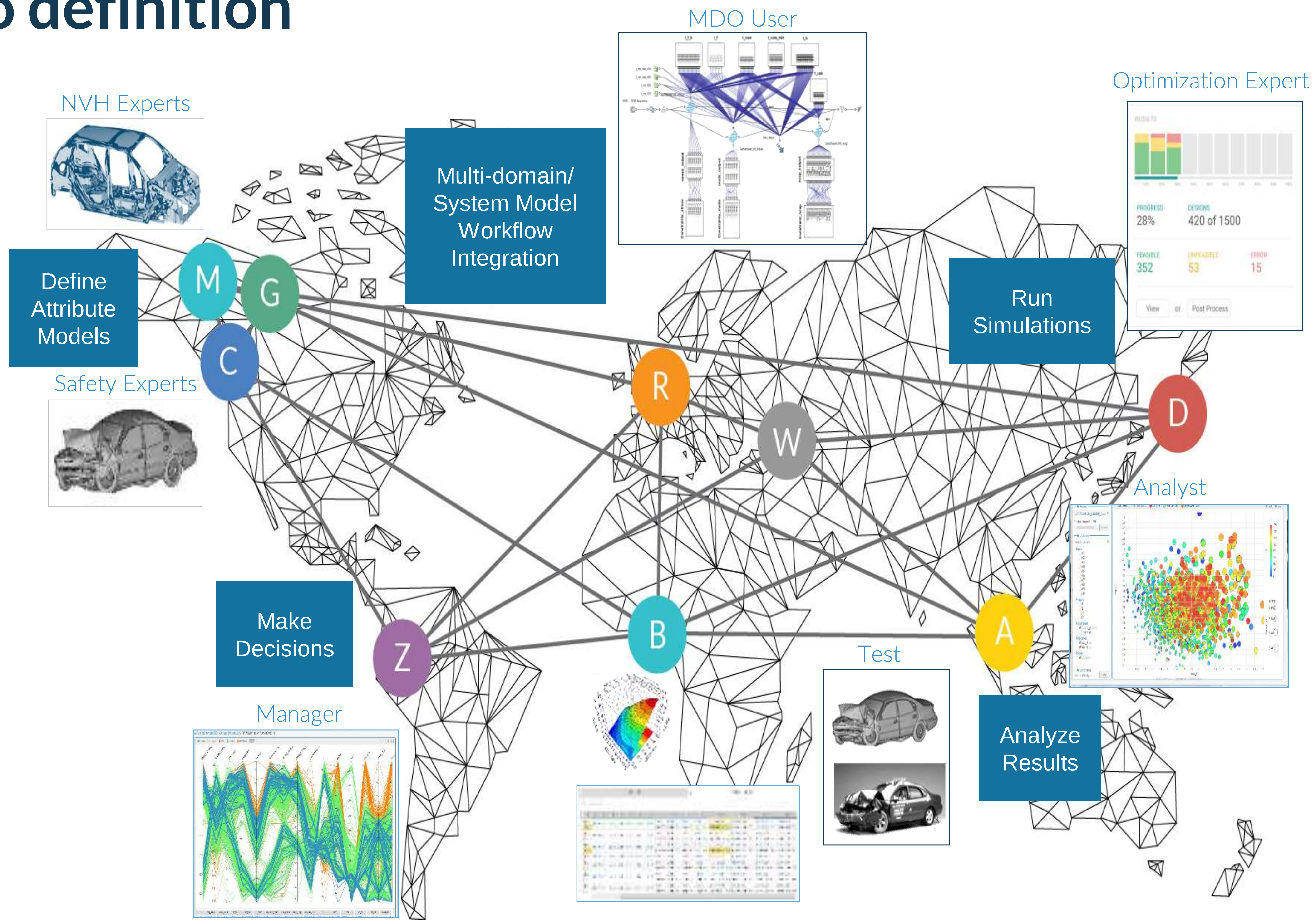
> Enterprise-wide Multidisciplinary Design Optimization (EMDO) will be one of the key enablers for us to make an impact on the company's global community.
>
> **Yan Fu**, Technical Leader of Business Strategy and Engineering Optimization at FORD

Take for example the structure of a car frame; engineers must take into account multidisciplinary load cases such as safety, NVH (noise, vibration and harshness), stiffness, durability and aerodynamics, to name a few. Given that structural requirements to meet loads in one discipline are often impacting the requirements for others, structural performance of all disciplines should be considered simultaneously. On top of the sheer complexity of design, teams are getting bigger and more often than not working in dif-



01 The simulation process complexity

Scenario definition



EXPEDITE

ESTECO TECHNOLOGY AND THE EXPEDITE MADO CHALLENGE

07/31/2018

Clifton Davies

EXPEDITE PM

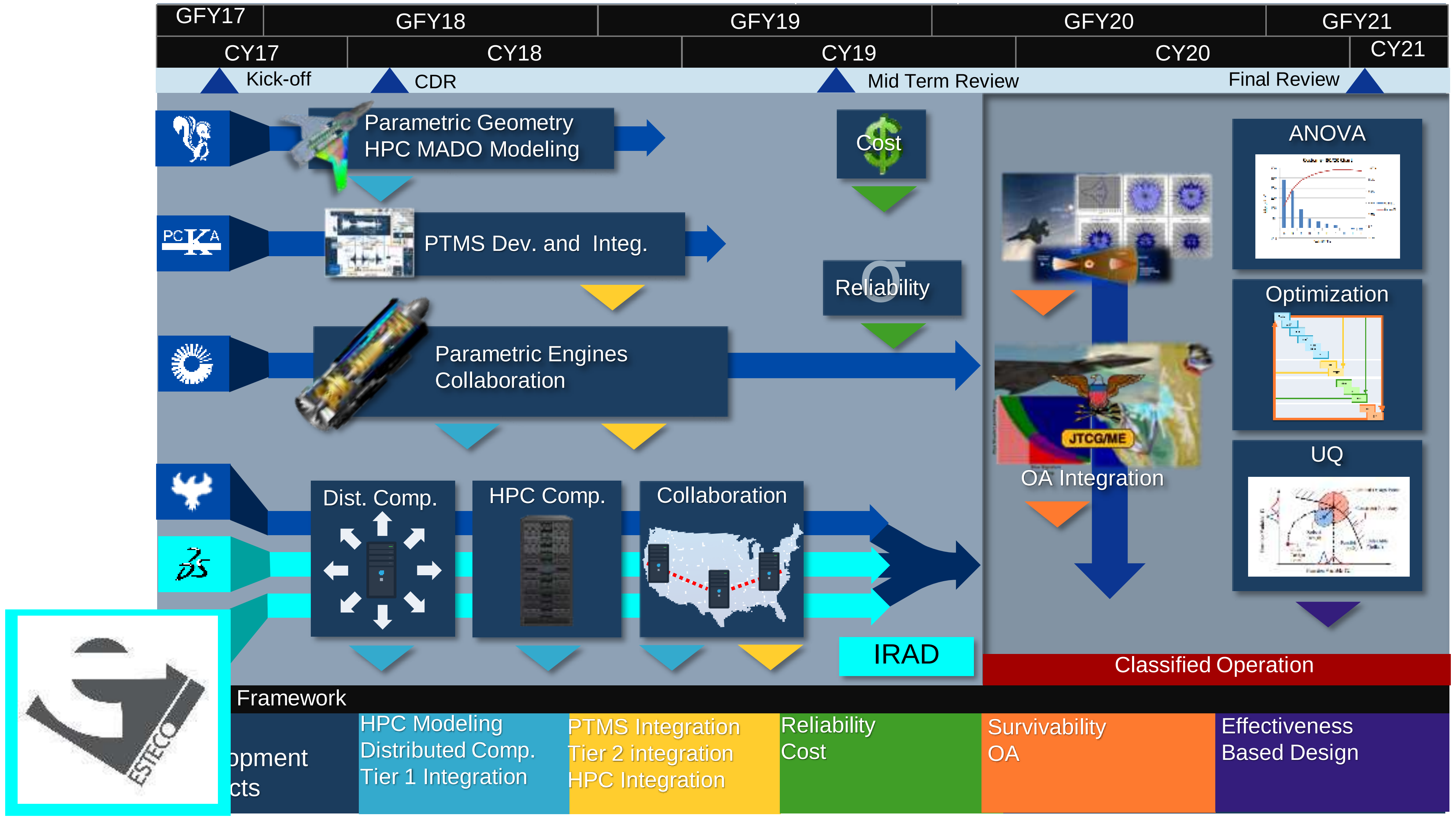
Michael Mull

Conceptual Design Engineer

LOCKHEED MARTIN

APPROACH TO EXPEDITE

- Open, non-proprietary approach to program
- Propulsion/PTMS disciplines as target for geographically distributed MADO
  - P&W for propulsion partner
  - PCKA for subsystem modeling
- Two phases to support EBD
  - Large open phase for model/tool development
  - Classified end phase to enable realistic OA operation
- Multi-vendor approach to computing challenges
  - Distributed computing
  - HPC
  - Collaboration (Geographically Distributed)
  - Uncertainty Quantification



modeFRONTIER

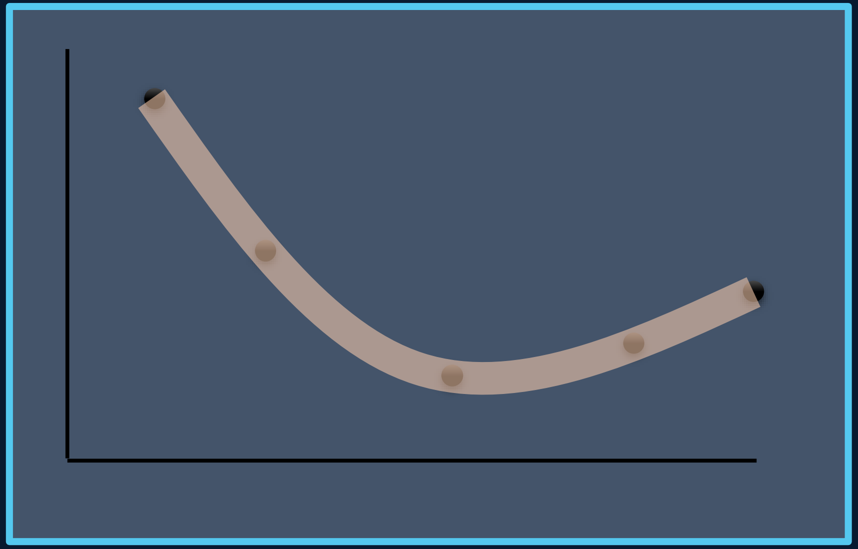
VOLTA

MADO Supplier M&S Challenge

Supplier

Weeks to Months

- Engineering Change
- Validation Testing
- Engineering Approval
- Contracts
- …



Save the date

um 2020

ESTECO
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Trieste, ITALY » **29-30 SEPT**

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See you in 2021

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NORTH AMERICA
USERS' MEETING

um 2021

Detroit area, MI

36TH AMERICA'S CUP
PRESENTED BY
PRADA
AUCKLAND 2021

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Thank you!

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