

Aachen, 2026-10-06

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(Key Ward)

 AACHEN AUTOMOTIVE
COLLOQUIUM
OCTOBER 05-07TH, 2026



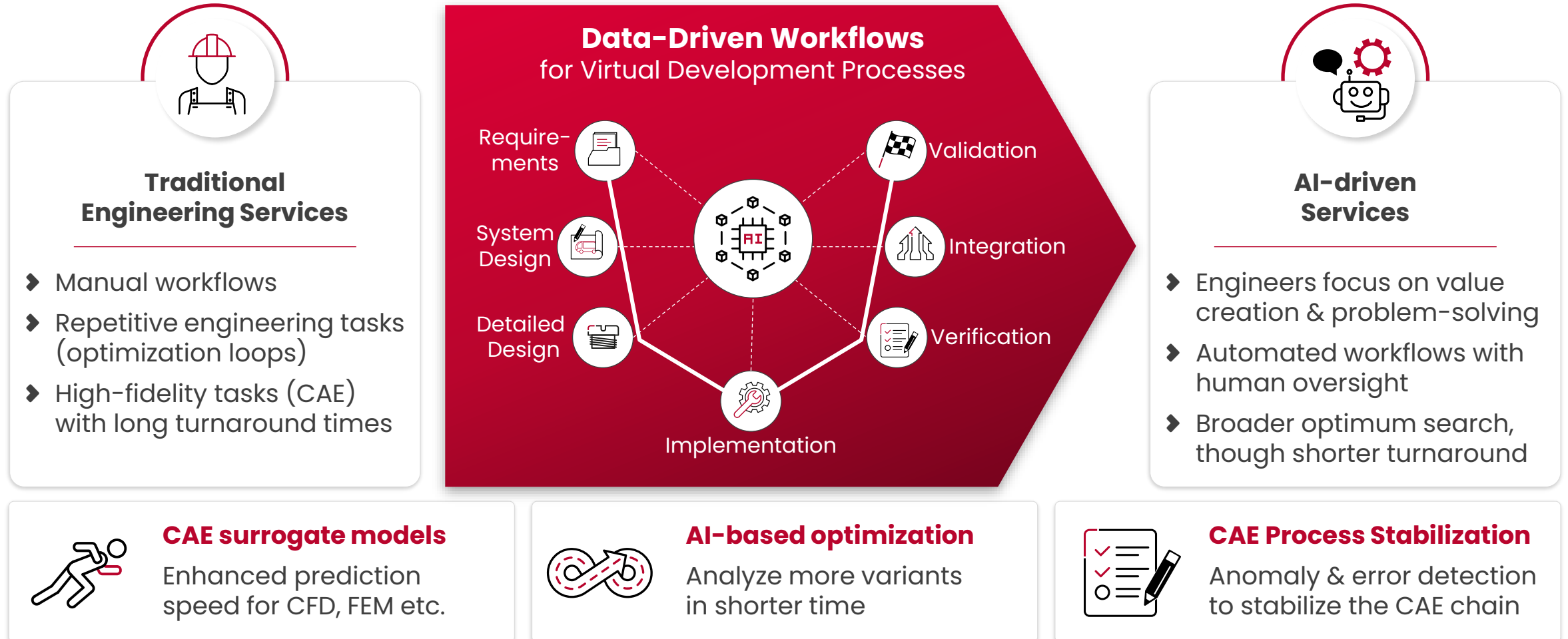
Next-Generation CAE: Leveraging Data-Driven Workflows for Virtual Development



Transformation from classical engineering services with accelerated CAE by AI Surrogates & Agentic Orchestration



TRANSFORMATION OF ENGINEERING OPERATIONS



AGENDA

- **Achieving Shorter Turnaround Times in CAE-Loops**
- AI-Driven Design Space Exploration to Identify the Best Candidate
- Establish Standardized Quality Control in Your CAE Toolchain



CAE surrogate models

Enhanced prediction speed for CFD, FEM etc.



AI-based optimization

Analyze more variants in shorter time

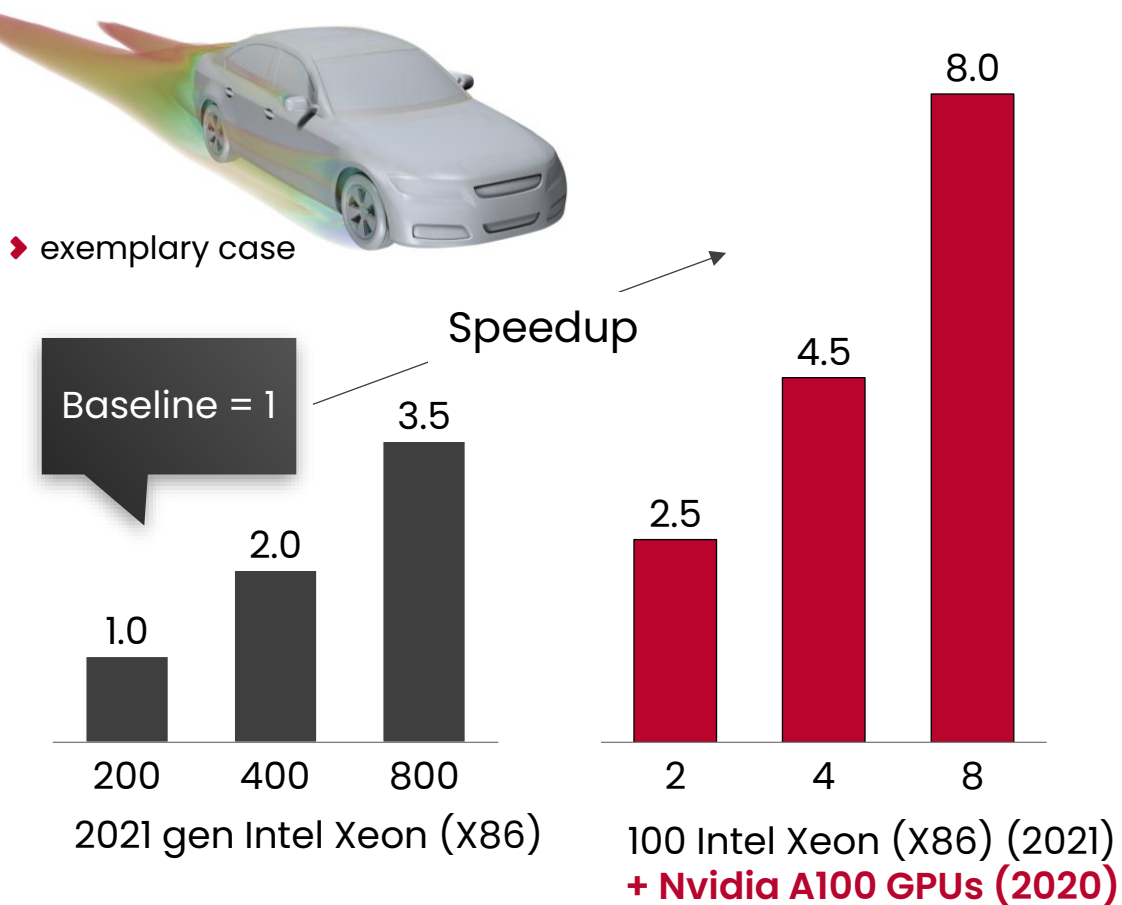


CAE Process Stabilization

Anomaly & error detection to stabilize the CAE chain

Leveraging AI Hardware for Solver Acceleration

UTILIZING GPU FOR CFD COMPUTATION CAN LEAD TO SIGNIFICANTLY INCREASED SPEEDUPS



- Application: high cell count, e.g. aerodynamics
- Utilized solver: **OpenFOAM** (GPU enabled at FEV)
- **Further** speedup potential achievable with modern chip architectures, e.g. Grace Hopper GH200:



- FEV in pre-access program on Europe's largest HPC, exascale-sized **JUPITER**

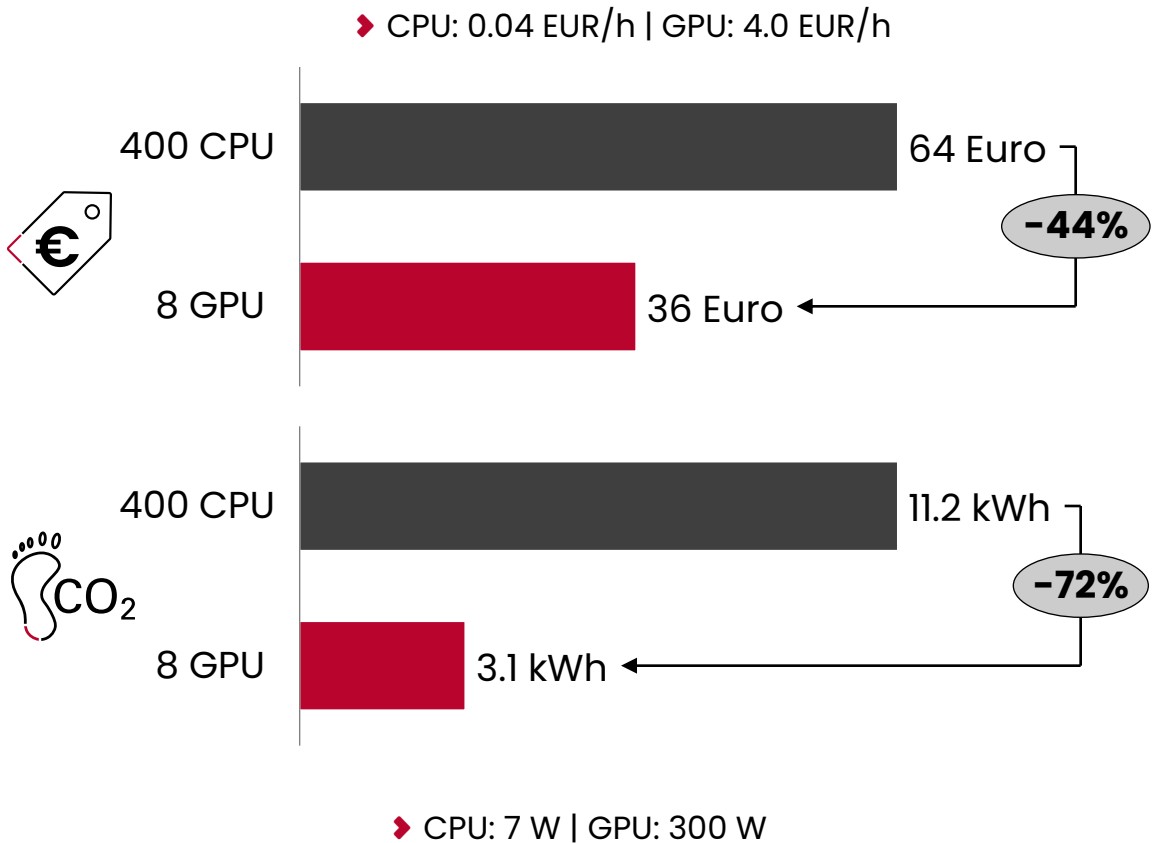
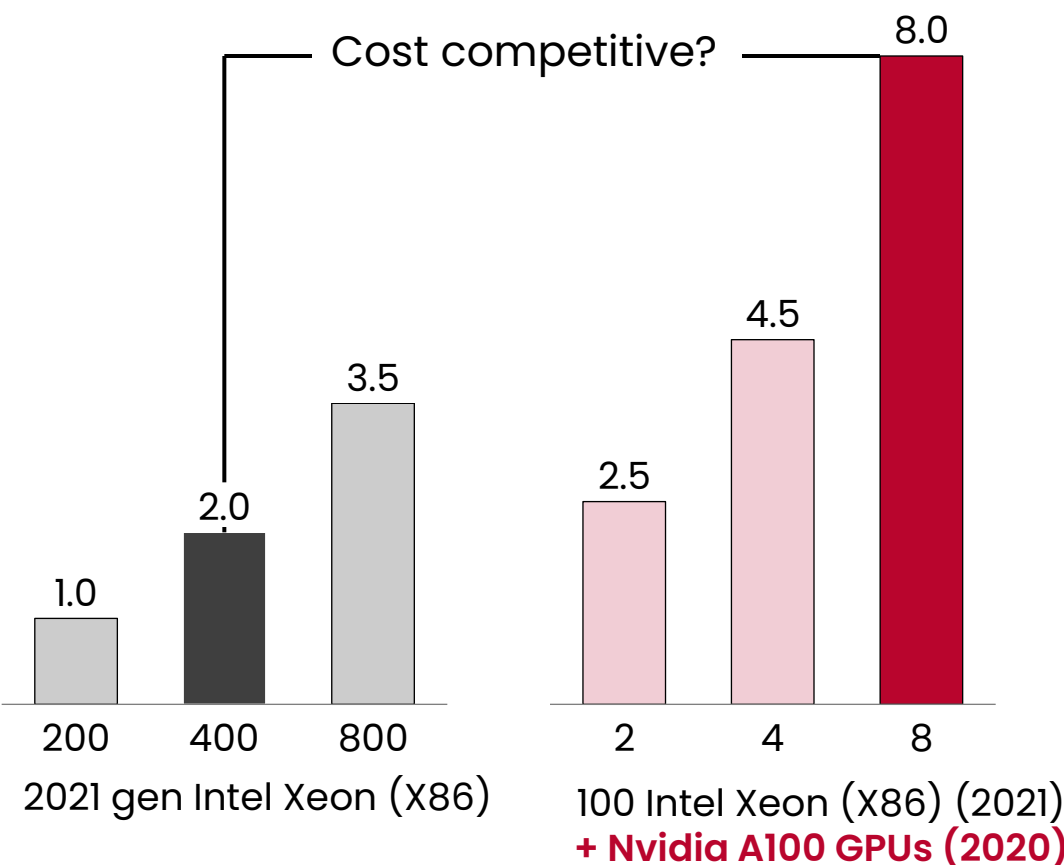


Reduction of Turnaround Times While Saving Cost & Energy



DAY-TO-DAY SAVINGS AS WELL AS ENABLER FOR DATABASE GENERATION FOR AI MODEL TRAINING

Speedup



Data Infrastructure for Engineering & AI

Engineering data is fragmented across simulation, test, manufacturing and fleet systems. Key Ward turns that chaos into governed datasets and reusable AI-ready workflows, so your engineers go from data to decisions in minutes, not days.

WITHOUT KEY WARD

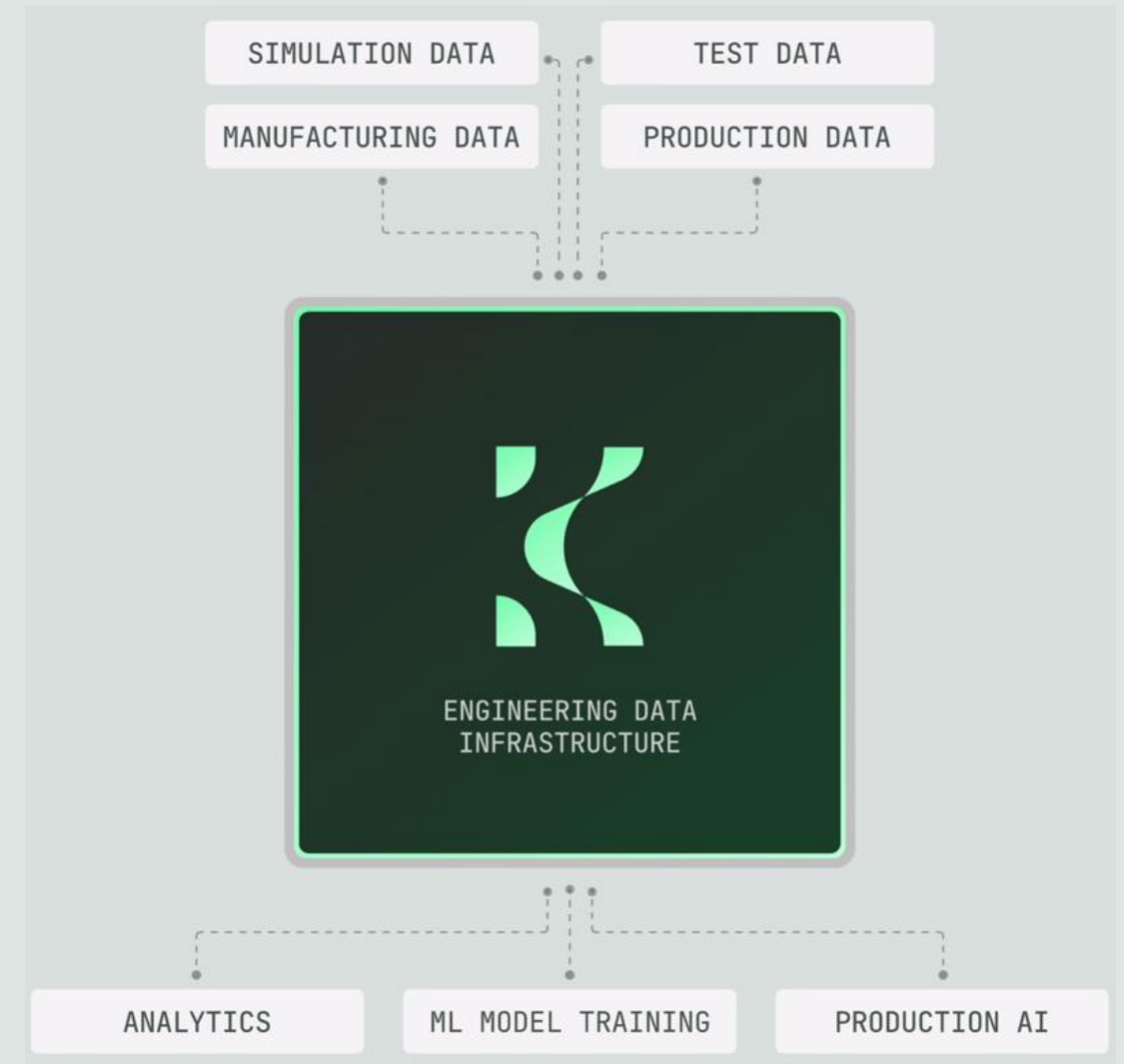
5%

of engineering organizations move AI/machine learning from pilot to production at scale

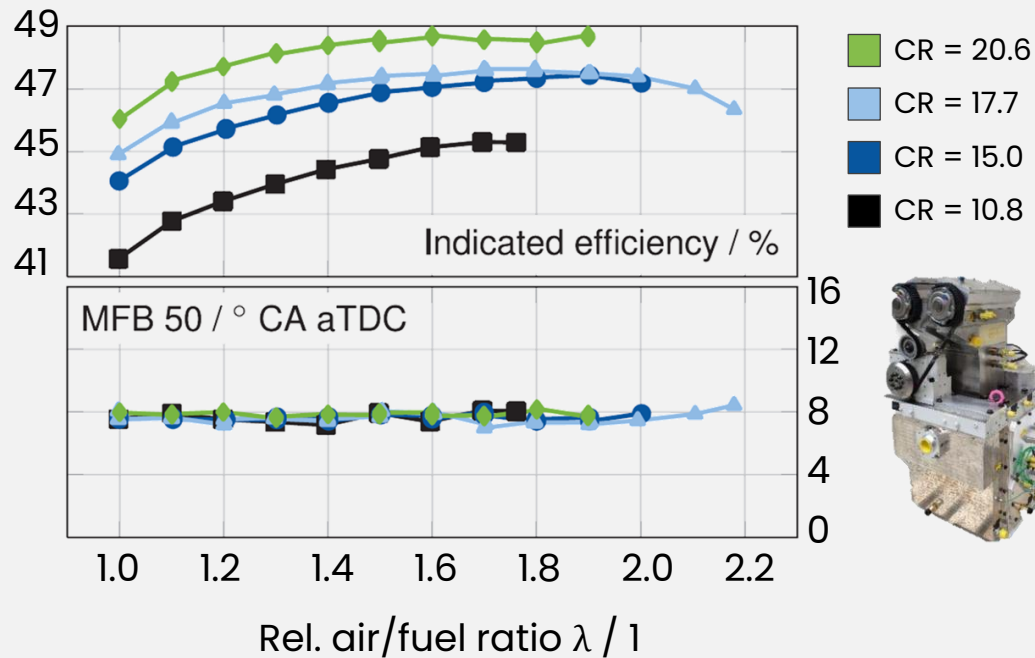
WITH KEY WARD

100%

AI scales across engineering teams and programs



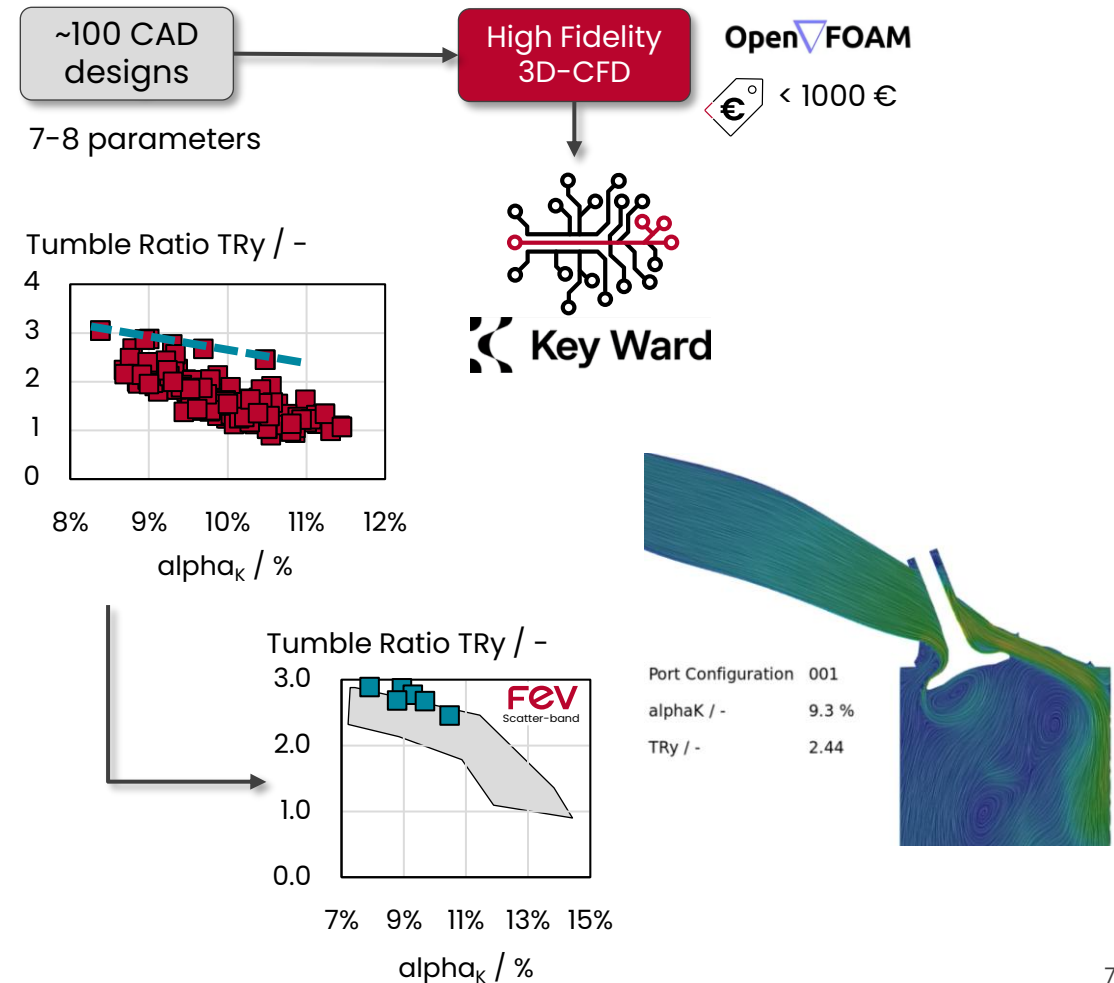
Methanol ICE: Road to 50 % ITE



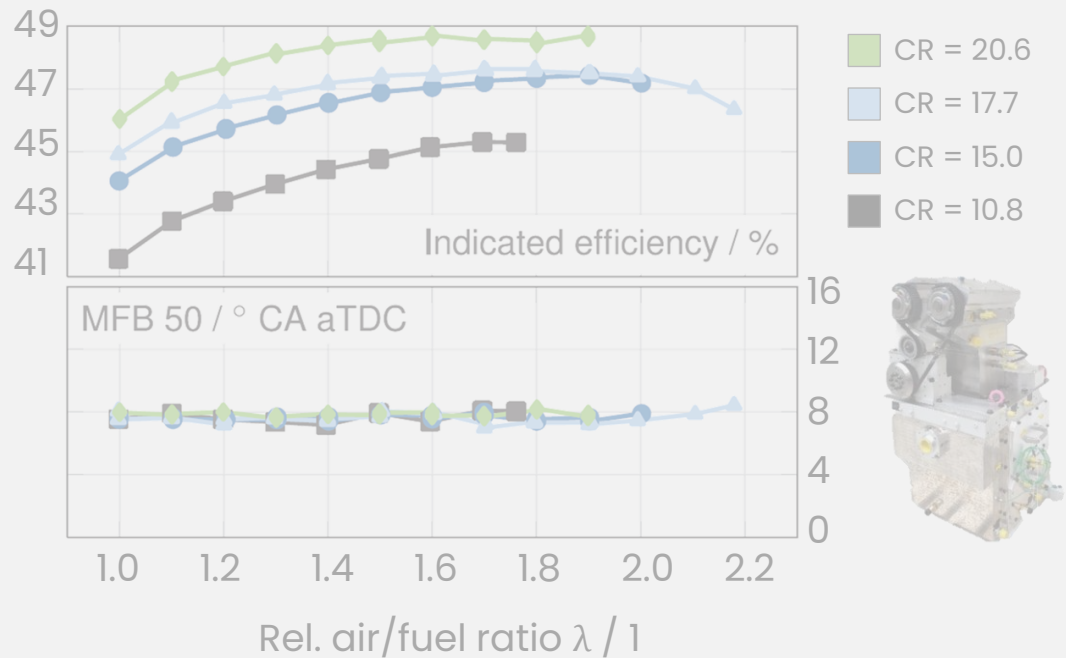
$V_H = 0.5 \text{ l, s/B-ratio} = 1.5, n = 2500 \text{ 1/min, IMEP} = 16 \text{ bar, } p_{in} = p_{ex}$
 $p_{rail} = 200 \text{ bar, SOI} = 300^\circ \text{ CA bTDC, } T_{in} = 25^\circ \text{ C, } T_{oil} = T_{coolant} = 90^\circ \text{ C}$

- Optimum piston layout to maintain charge motion
- **Revise port layout to reduce stress on boosting system**

Workflow for Port Development



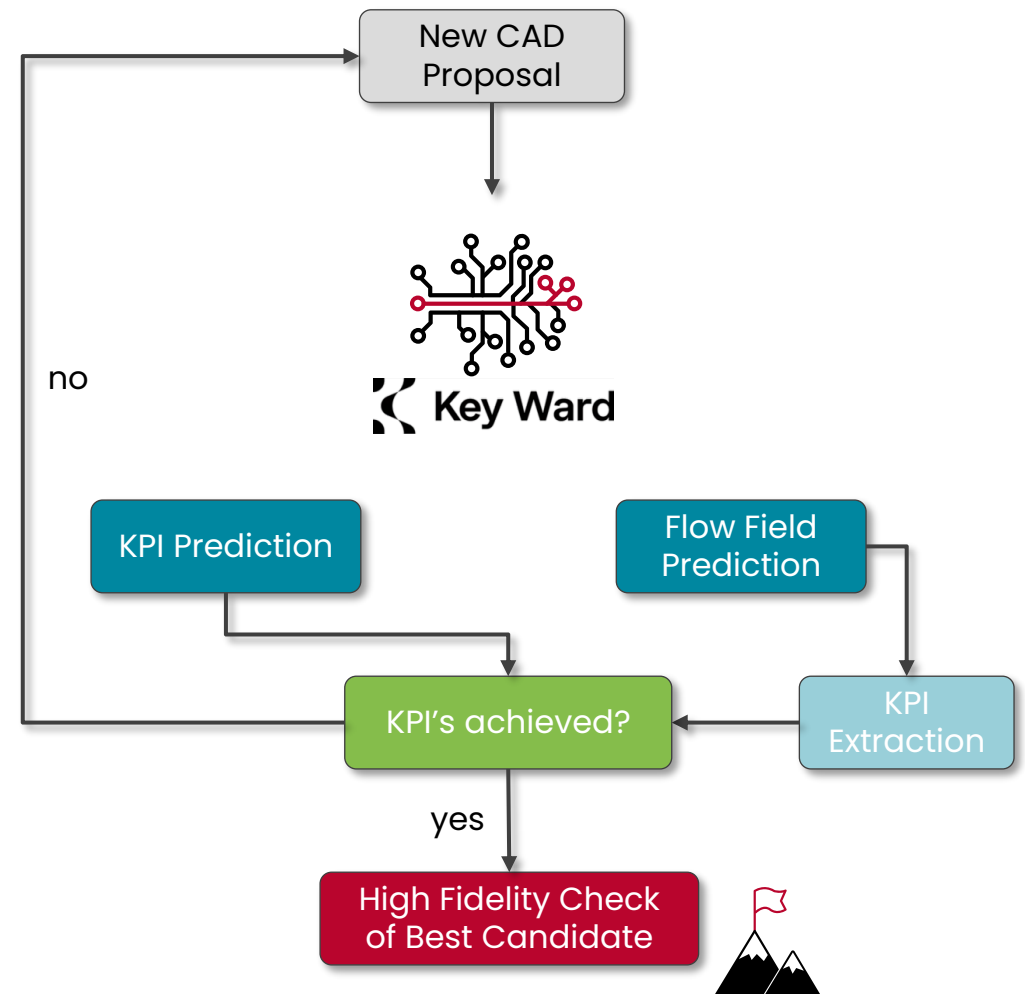
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Workflow for Port Development



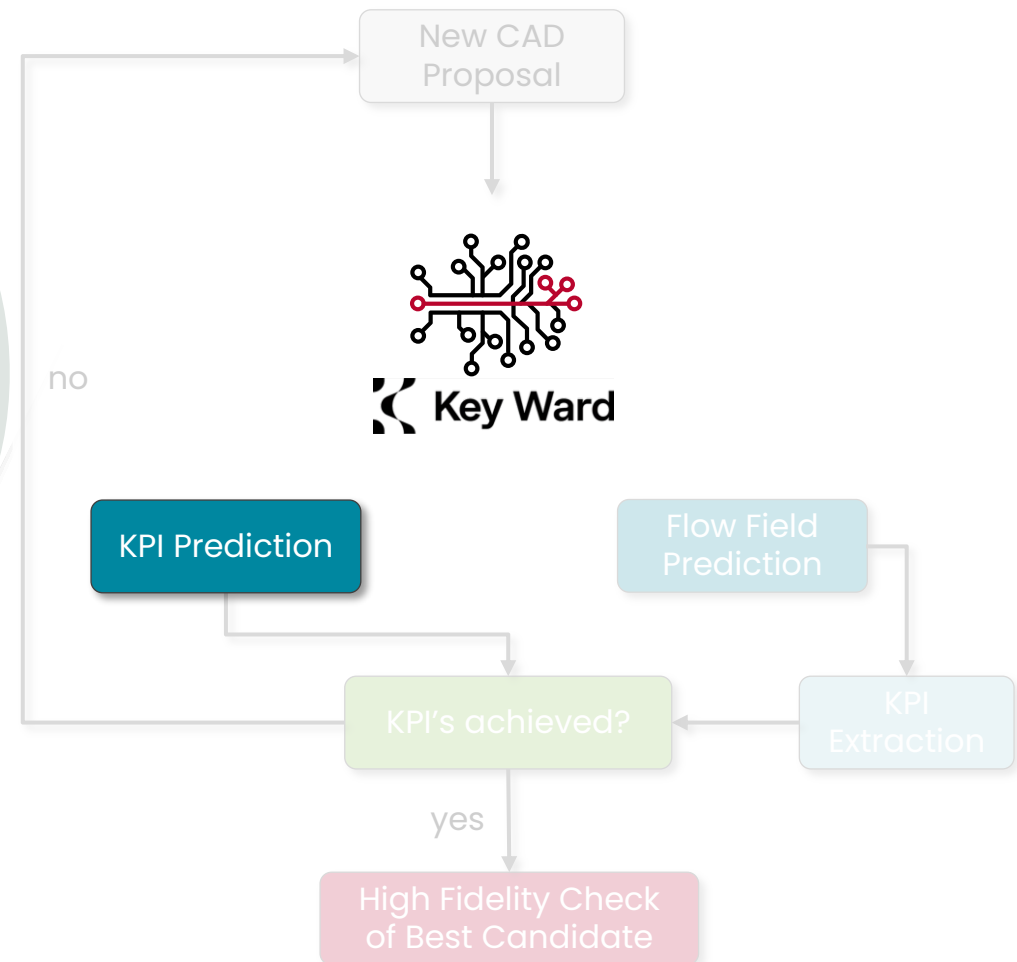
Modeling within Key Ward

• Direct KPI Prediction:

- Simulation data is processed to be compatible with CNN architecture.
 - Signed Distance Field (SDF) computed to represent the shape variation.
- Convolutional Neural Network (CNN) trained to learn correlations between varying shapes and KPIs (α_K , TRy, etc.).

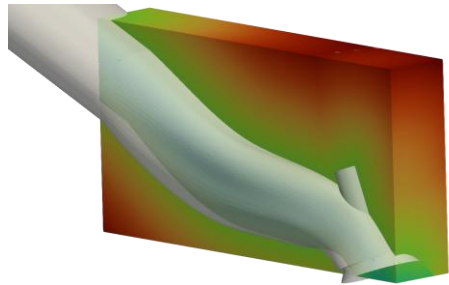
• Flow Field Prediction: GeoTransolver

- Approach initially developed at NVIDIA Corp.
- Simulation data (volume and surface meshes) are used directly as model input to predict pressure and velocity fields on those meshes.

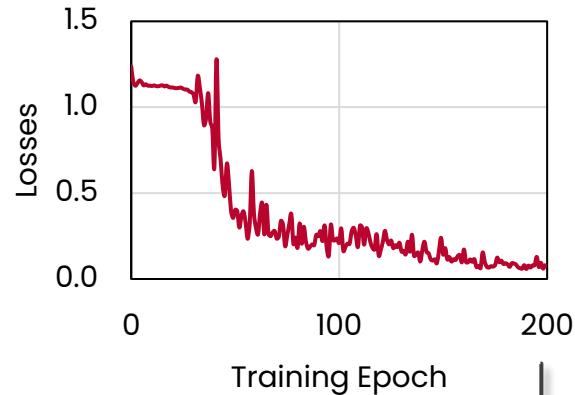


Successful KPI-Prediction Achieved with the CNN Workflow

TRAINING DATASET SIZE OF >80 REQUIRED TO ACHIEVE SUFFICIENT ACCURACY

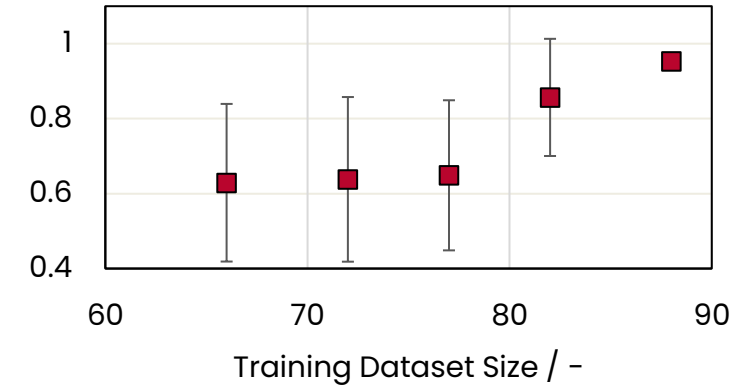


► SDF Representation

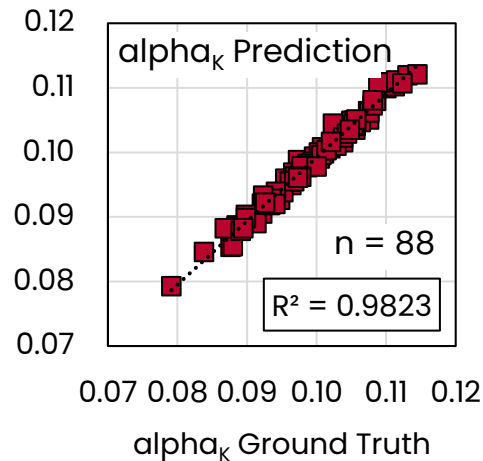


How much training data do we need?

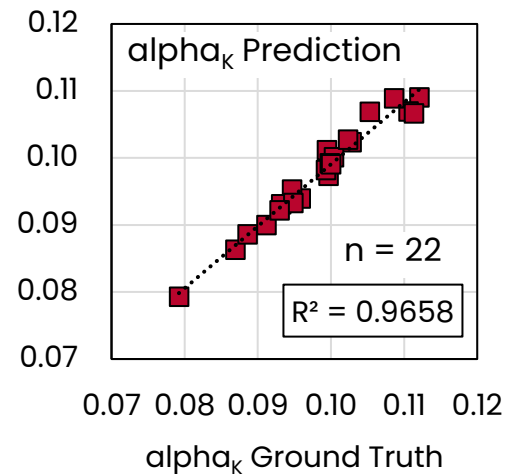
Validation R^2 : Port Coeff. α_k



► training data



► valid. Data (20 %)



How do we implement this into our routine?

- CFD engineer performs high fidelity DoE and trains CNN model in Key Ward
- CAD engineer checks intermediate designs for flow performance/charge motion trade-off and aligns with target values. This avoids additional CAE loops.
- **Vision: upload of all available solution fields, no project-specific training but one single database**

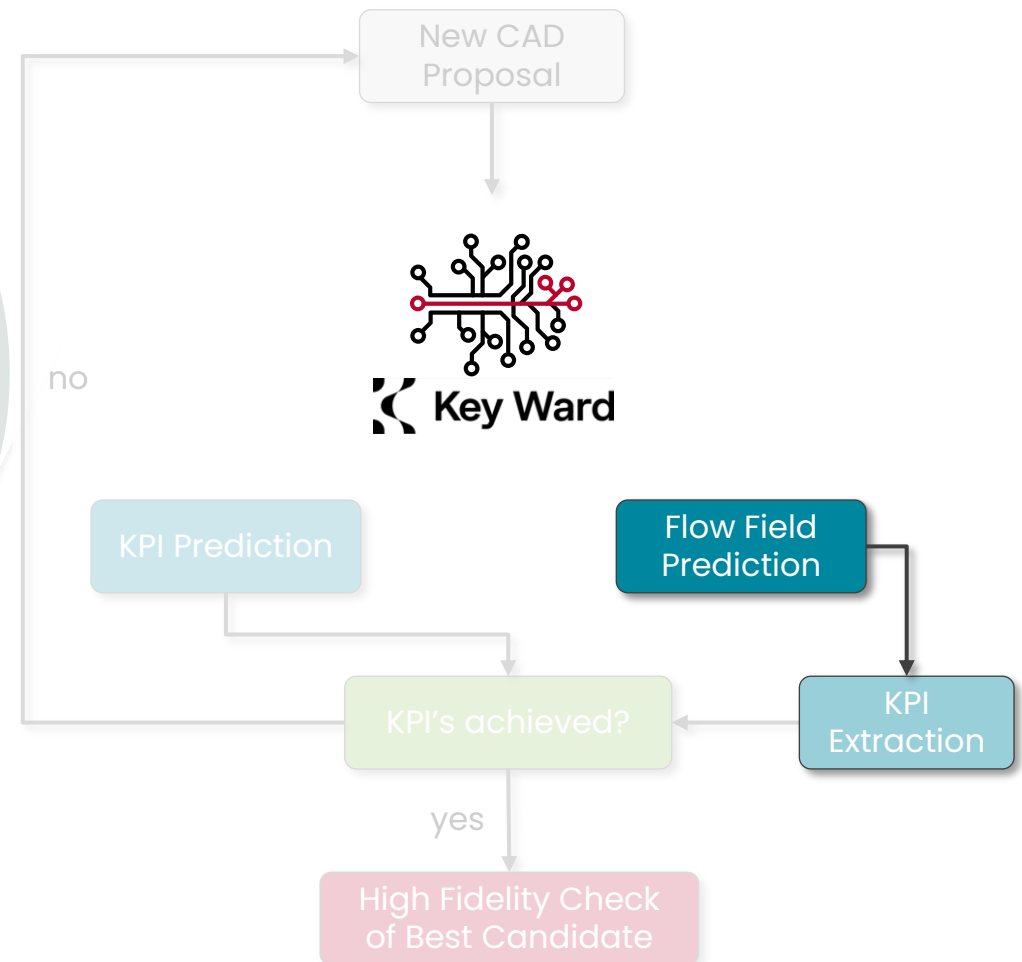
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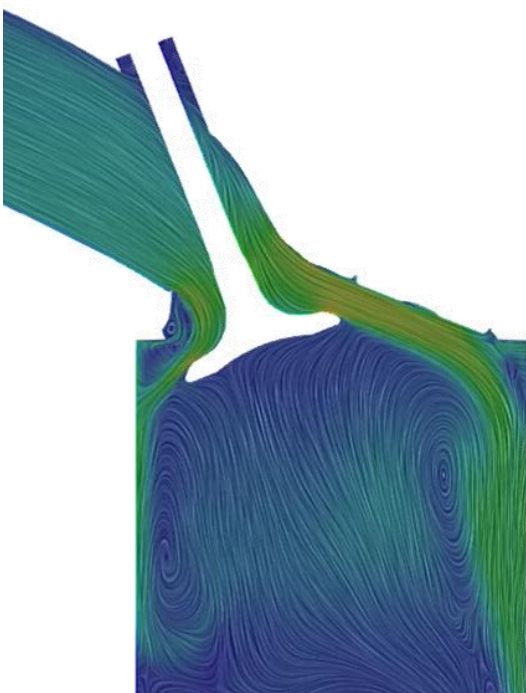


GeoTransolver Workflow: A Deep Learning Method to Predict of the Flow Field



FLOW FIELD PREDICTION & KPI EXTRACTION – TYPICAL ACCURACY IN THE ORDER OF +/- 5 % DEVIATION

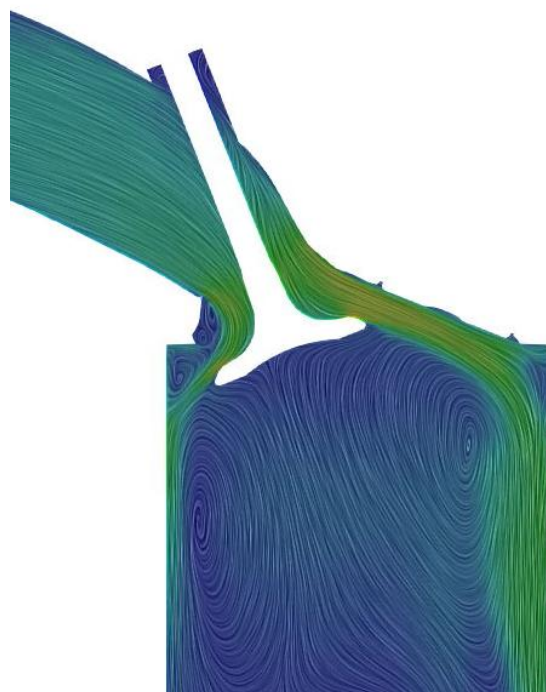
Prediction



alpha_k
9.7 %

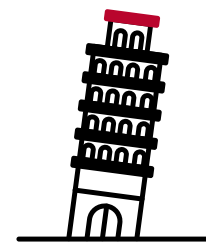
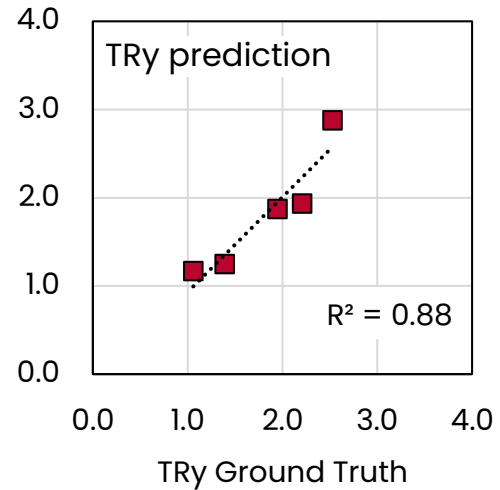
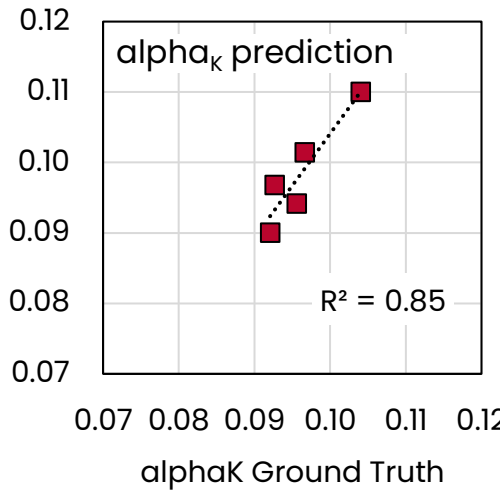
TR_y
1.39

CFD field



alpha_k
10.2 %

TR_y
1.25

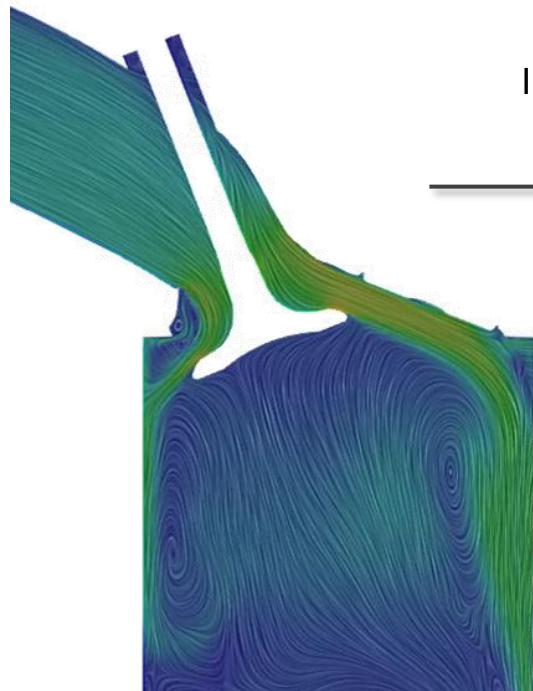


Is this sufficiently accurate?

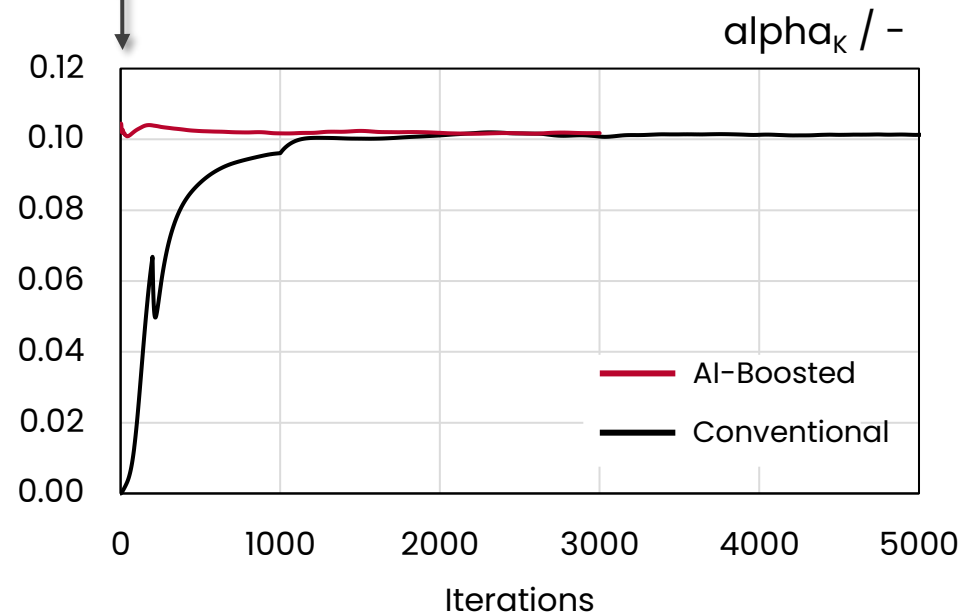
Closing the Gap or Accelerating CFD: AI-boosted Initialization of Flow Fields

40 % REDUCED NUMERICAL EFFORT ACHIEVED IF THE INITIAL FLOW FIELD IS TAKEN FROM AI

► Prediction



Initialization



- Conventional CFD solvers can be initialized with arbitrary solution fields via mapping
- Utilizing AI-predicted flow fields enables a much faster convergence into the same, high fidelity solution
- **Savings potential of ~40 %** observed for multiple use cases



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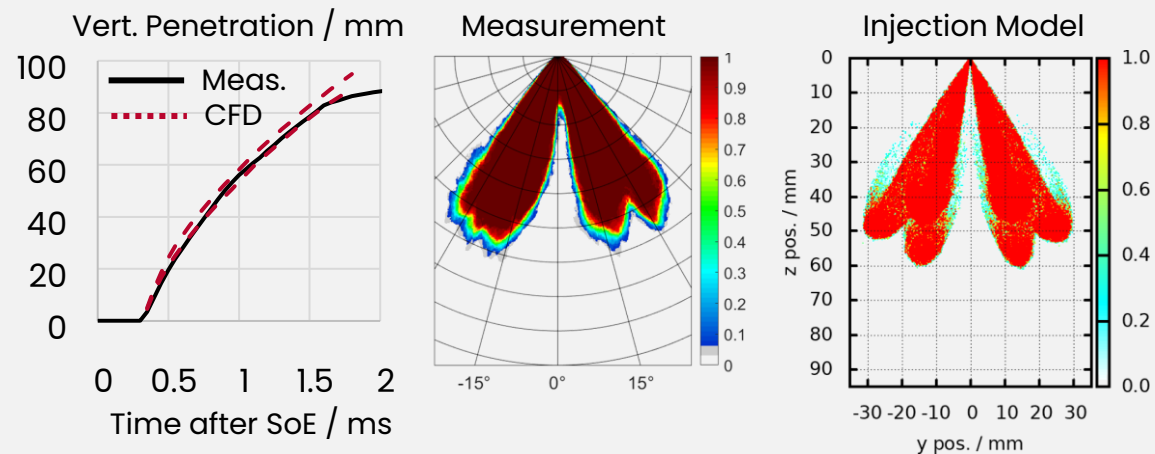


CAE Process Stabilization

Anomaly & error detection to stabilize the CAE chain

Application: Methanol ICE (Injection)

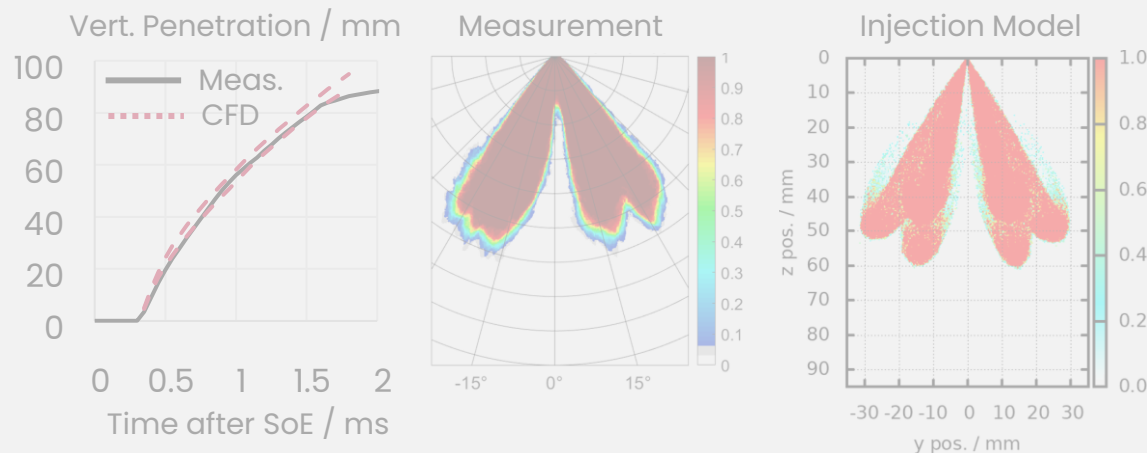
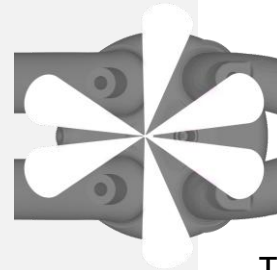
- Second single cylinder engine being optimized for MeOH
- Significantly less charge motion than engine #1
- High pressure on mixture formation and avoidance of wall film formation w/ long injection times
- In focus: injection system with following KPI:
 - Global Homogeneity – Local homogeneity
 - Wall wetting – Local turbulence intensity



$p_{\text{chamber}} = 1 \text{ bar}$, $p_{\text{inj}} = 200 \text{ bar}$

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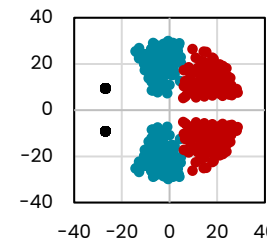
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$p_{chamber} = 1 \text{ bar}$, $p_{inj} = 200 \text{ bar}$

Workflow for Injection Optimization

~50 Spray Targets



InCylinder
Spray Sim.

Training set

CONVERGE
CFD SOFTWARE

€ < 1500 €



Key Word

AI
Recommendation

High Fidelity DoE
(CFD)

Internal
Optimization Loop

KPI's achieved

No

Yes



Targeting
variation

Modeling within Key Ward

- **Tabular surrogate models:**

A foundational tabular regression model applied on results of high fidelity DoE.

- Training individual KPI for highest accuracy expected
- Ranking based on KPI weighting

- **Design Space Exploration on Surrogate model:**

Space-filling sampling strategy that covers the injection design space across multiple degrees of freedom.

- Visual response surface exploration to understand fundamental dependencies

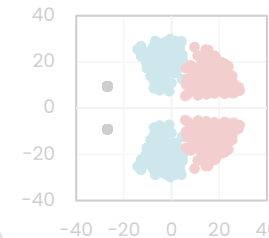
- **Targets w/ highest total ranking to be checked in high fidelity CFD**



Workflow for Injection Optimization



~50 Spray Targets



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Key Ward

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Recommendation

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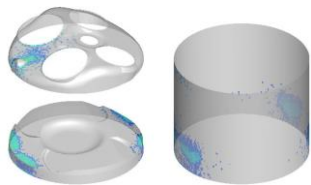
Yes



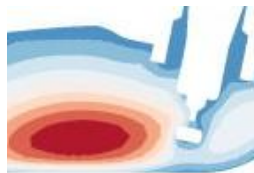
Introduction of 4 KPI to Establish a Ranking System

FOUNDATIONAL MODEL SURROGATE SELECTED AND APPLIED TO THE INDIVIDUAL KPI

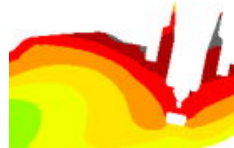
4 KPI used for model training:



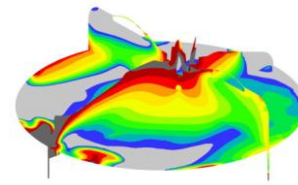
▶ Liner film



▶ Local TKE



▶ Local AFR



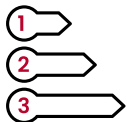
▶ Global Homogeneity

Ratings:

0 = worst result of DoE
1 = best result of DoE

Training:

- ▶ Input: 4 Target Angles
- ▶ Output: 4 KPI Ratings



less is better

more is better

lower is better

lower COV is better

Introduction of 4 KPI to Establish a Ranking System

FOUNDATIONAL MODEL SURROGATE SELECTED AND APPLIED TO THE INDIVIDUAL KPI

4 KPI used for model training:



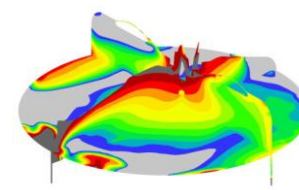
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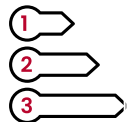
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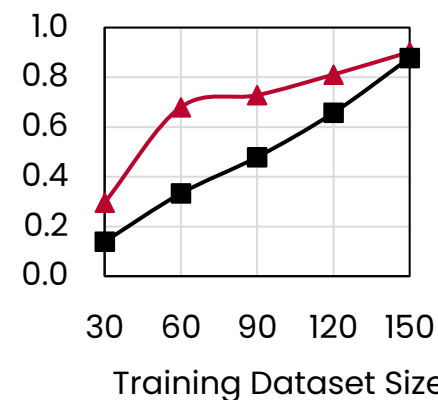
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R^2 of $COV(\lambda)$



— Training
— Validation

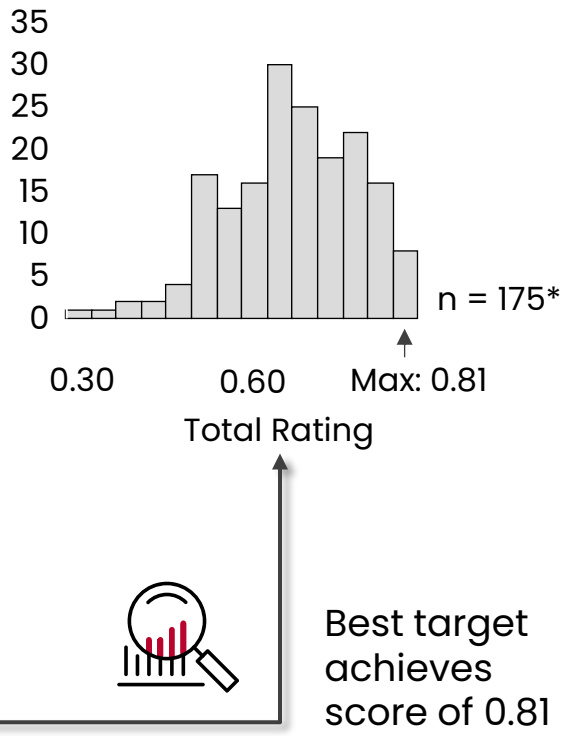
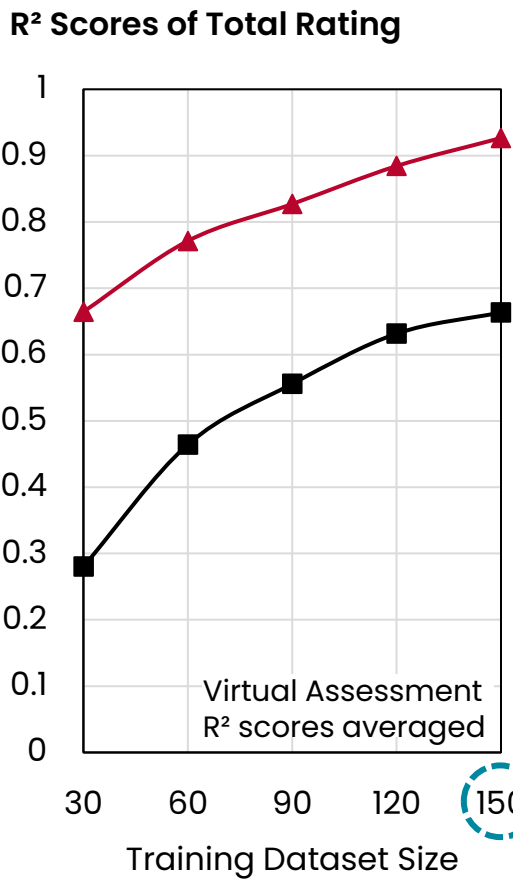
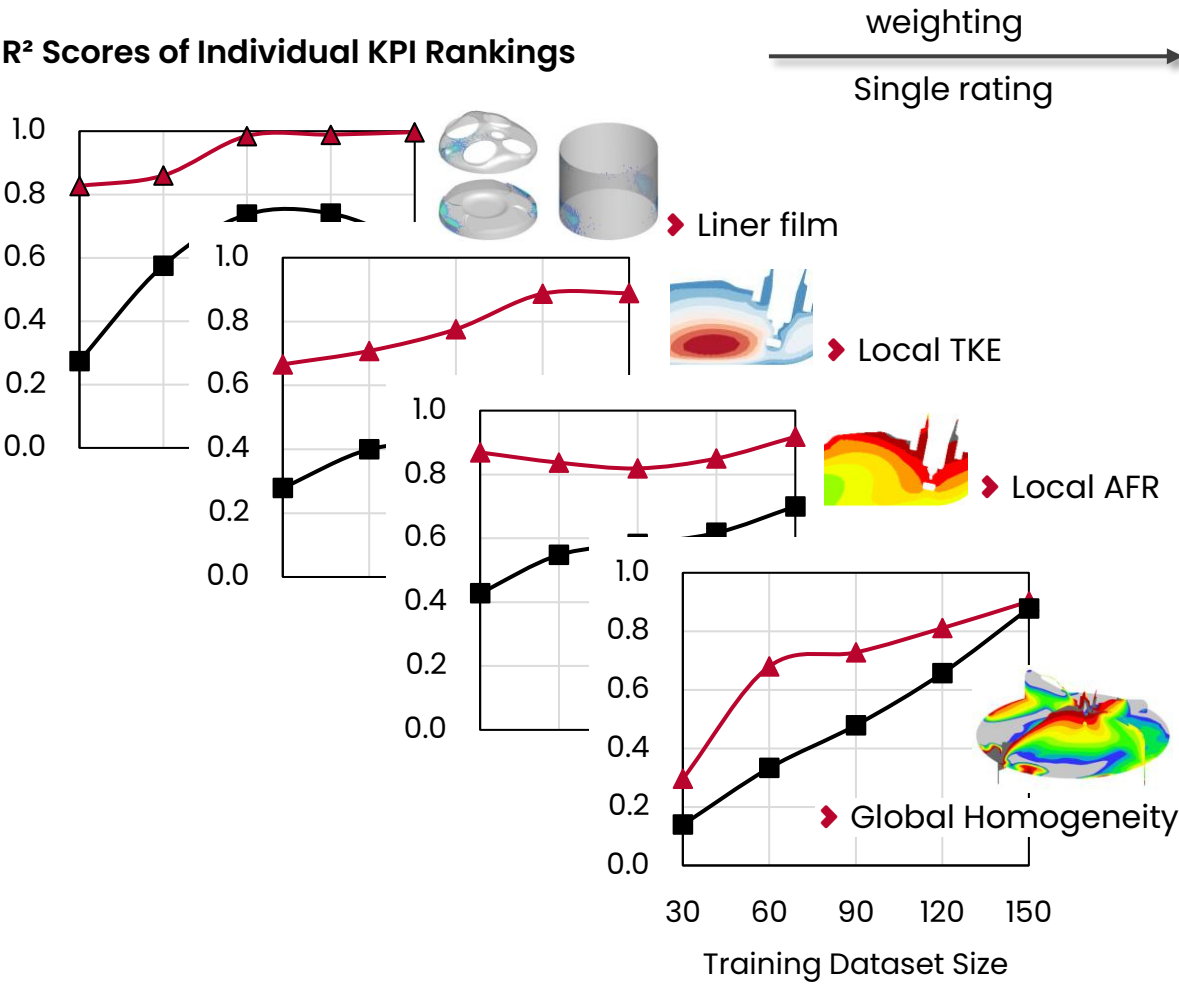
Full DoE: 175 Cases
for Model Sensitivity
Analysis

Weighting of the 4 KPI to Obtain a Single Rating Factor



FOUNDATIONAL MODEL SURROGATE SELECTED, TOTAL RATING ESTABLISHED

Validation Training



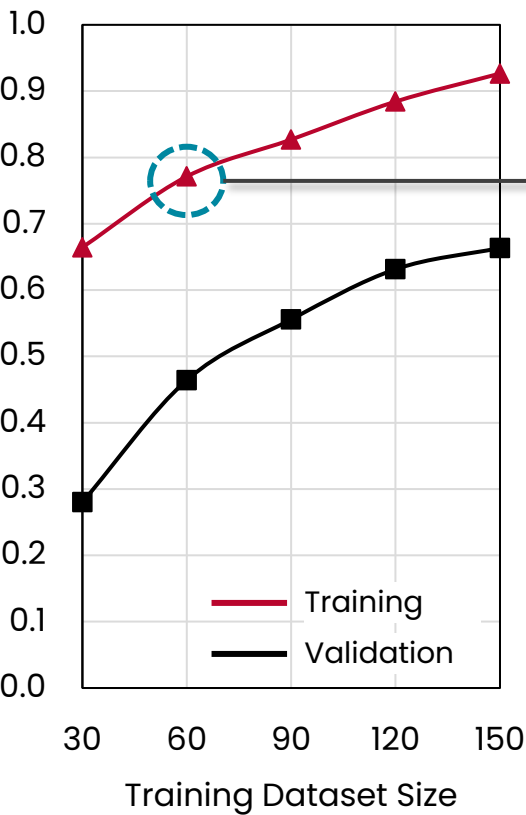
* Training + Validation Data

Target Recommendation w/ Medium Dataset Size Outperforms Large CFD DoE

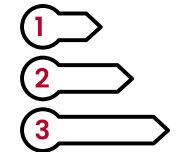
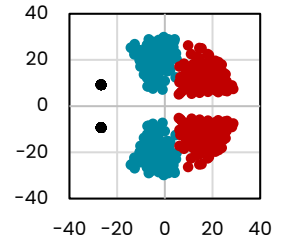


FOUNDATIONAL MODEL SURROGATE USED TO PREDICT PERFORMANCE OF 2500 TARGETS

R² Scores of Total Rating



Virtual DoE with n = 2500 Targets

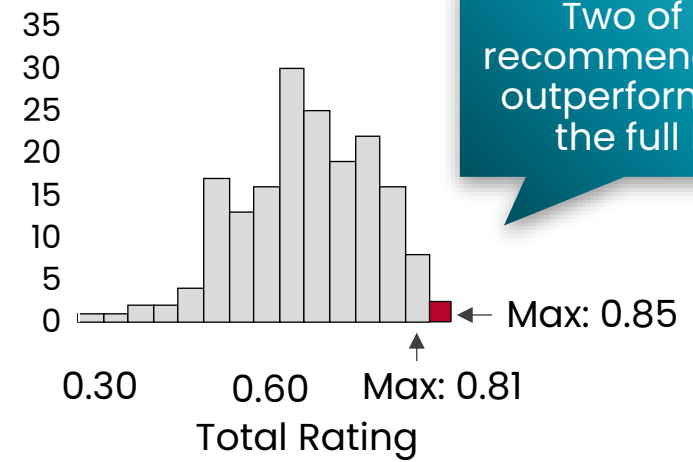
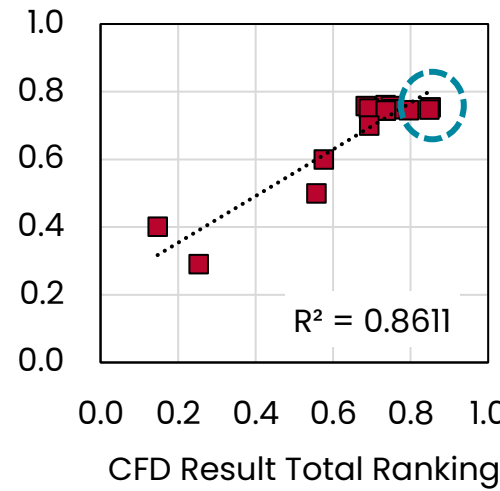


High Fidelity



Top 10

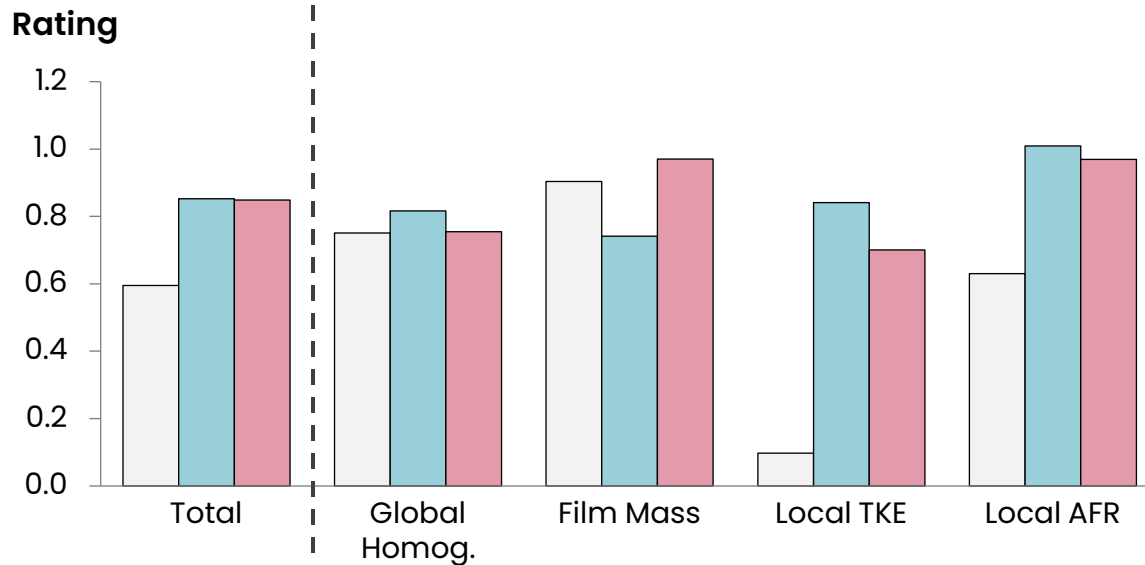
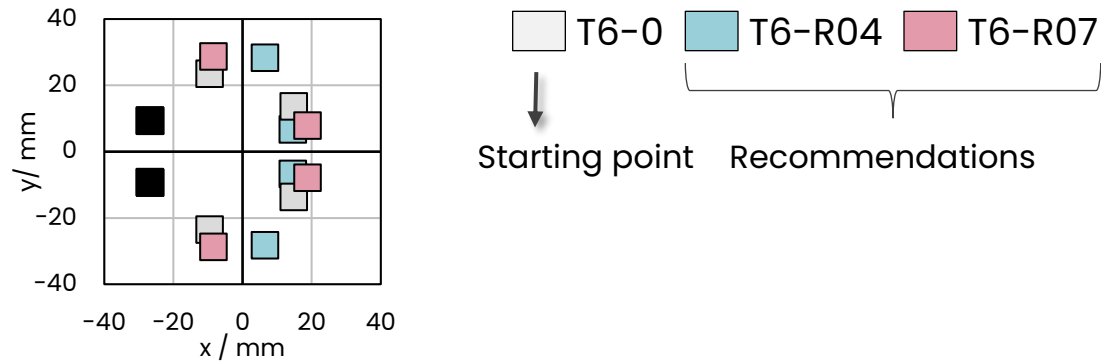
Predicted Ranking



Two of the recommendations outperform even the full DoE

Final Candidate Selection by Engineer

Target Coordinates in $z = 30$ mm



Following steps:

- Engineer to select the target based on the individual strengths, e.g. R07 for suppression of wall film
- Further optimization with individual hole size trimming possible (virtual DoE)

Comparison to experience-based approach:

- Higher numerical effort
- Highly automated, much faster turnaround time
- Much higher certainty to have identified ideal solution

Outlook:

- Automated, ML-enhanced DoE approach applicable to various optimization problems in CAE

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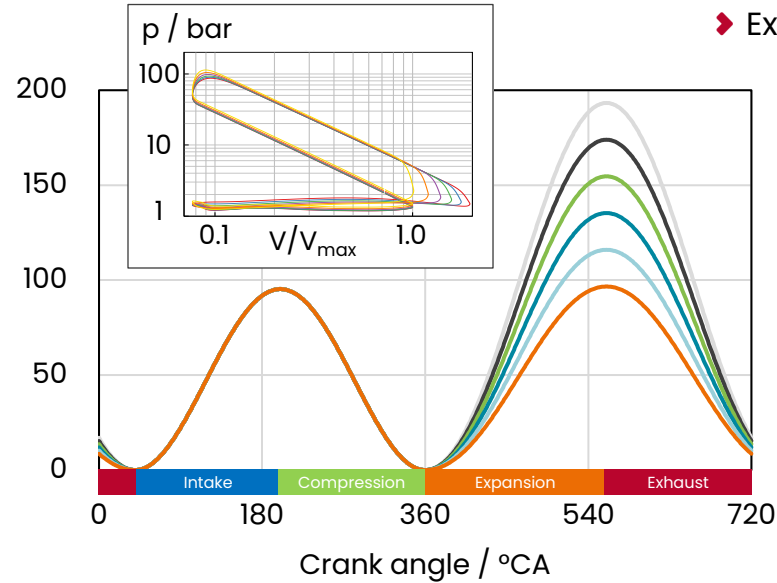


CAE Process Stabilization

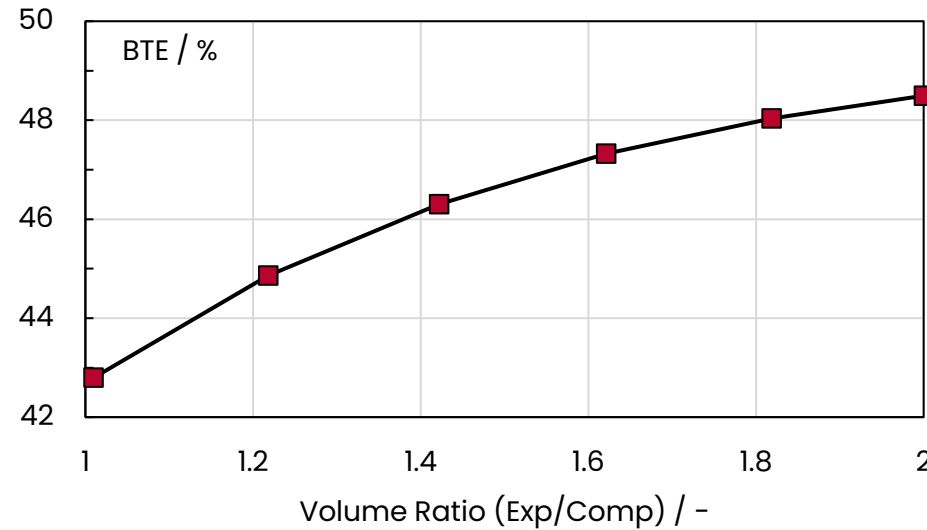
Anomaly & error detection to stabilize the CAE chain

Extended expansion concept as enabler for >48% BTE

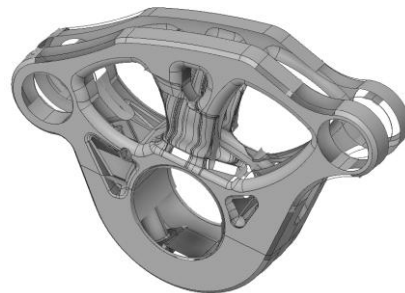
CHALLENGE: CRANKTRAIN DESIGN FOR HIGH EXPANSION RATIOS



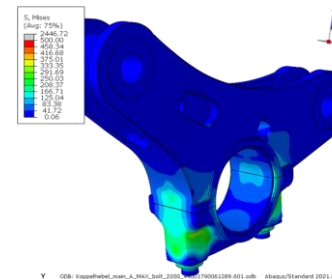
Example: 1.5 l, pre-optimized valve lifts and TC at exp/Comp = 2



► bionic design optimization



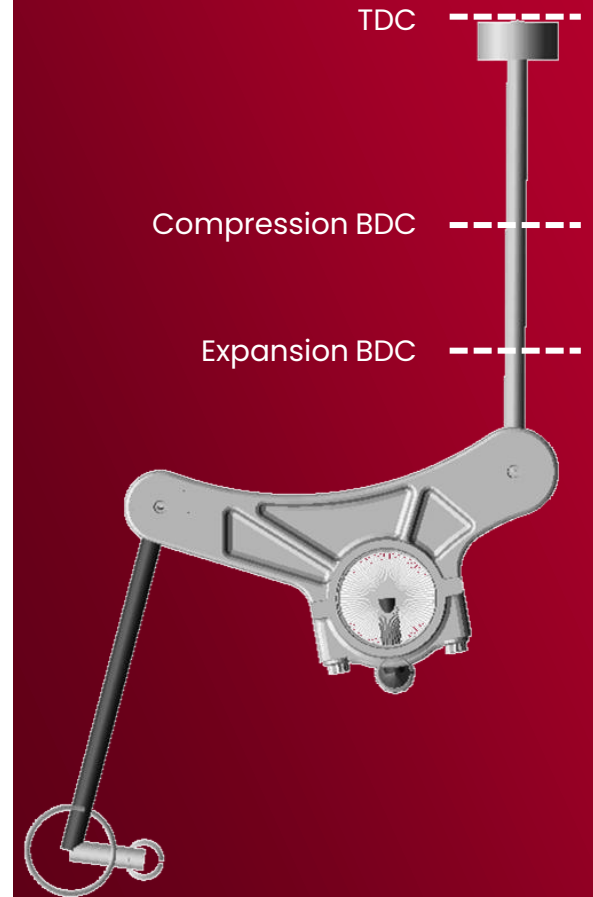
► manufacturable design



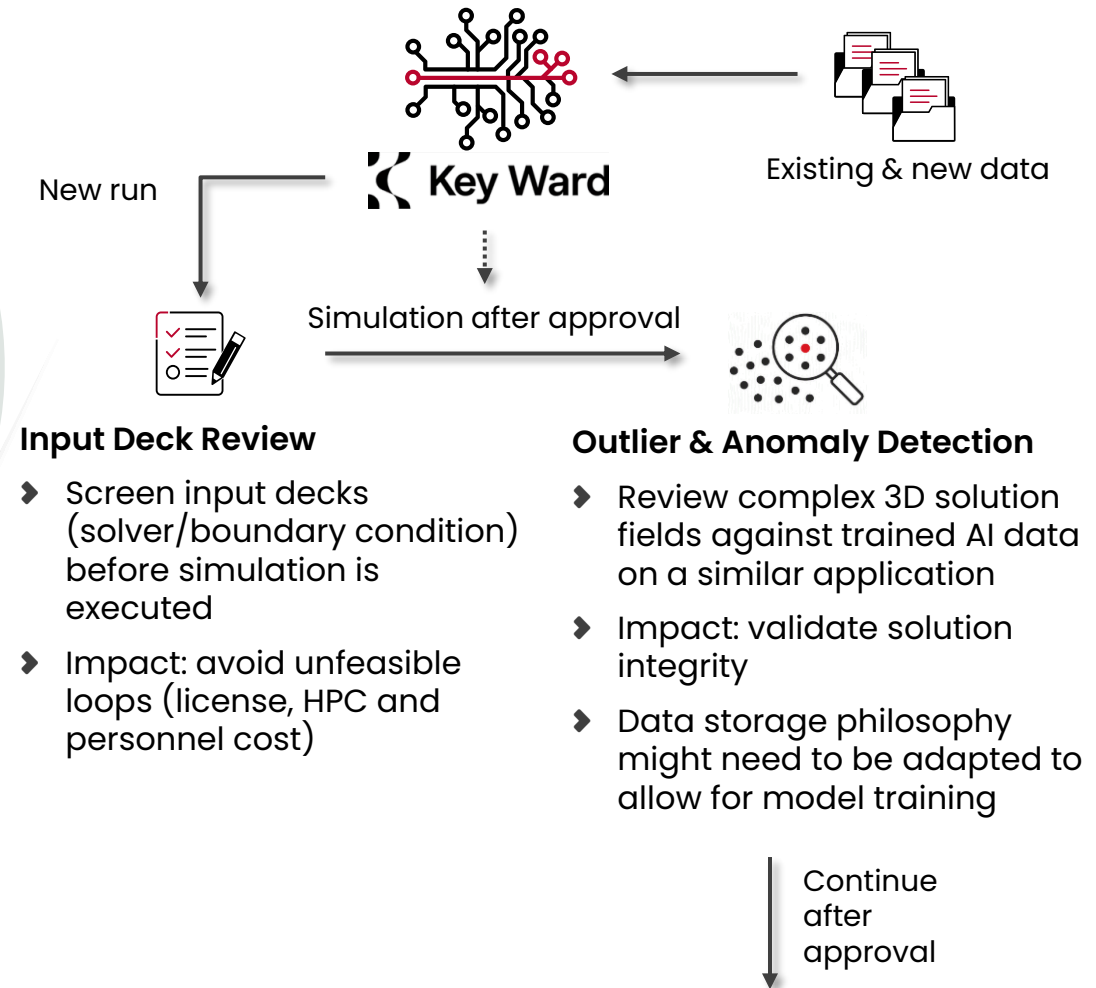
► FE analysis

FEV

► Dynamic MBS Simulation Model with flexible Trigonal Link



Workflow for Anomaly Detection

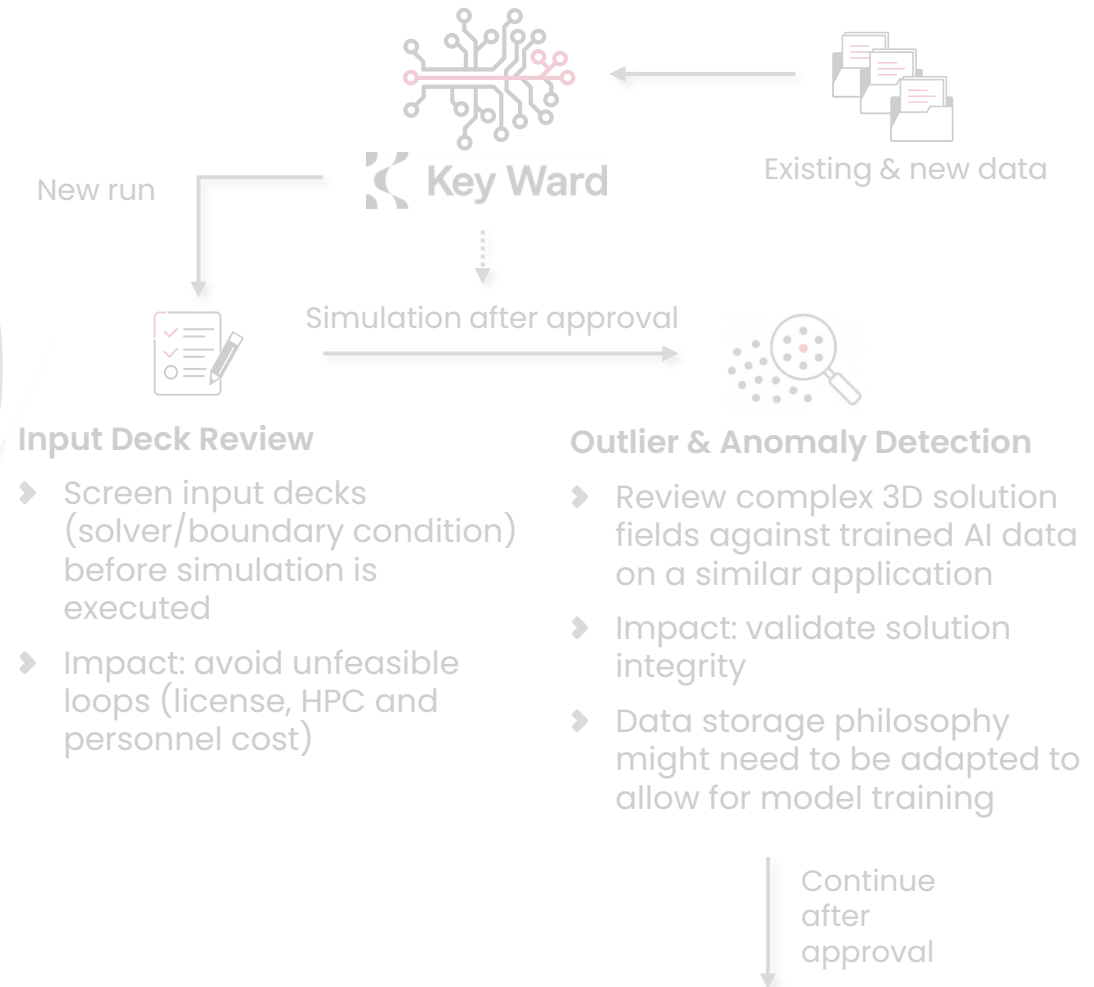


Simulation Quality Control Pipeline

- **Stage 0: Input Deck Review**
 - Pattern recognition (based on boundary conditions/solver settings)
- **Stage 1: Fleet-wide KPI Score Assessment**
 - Statistical anomaly detection in seconds after upload
 - Automated severity classification
- **Stage 2: Region-Level Field Analysis**
 - 3D field analysis via PyVista, extracting region-level statistics
 - Identification of affected component
- **Stage 3: Full-Assembly Spatial Deviation**
 - Assembly-wide field comparison
 - Spatial deviation assessment
 - Heat-map based visualization

This is what standardised simulation quality control looks like at scale.

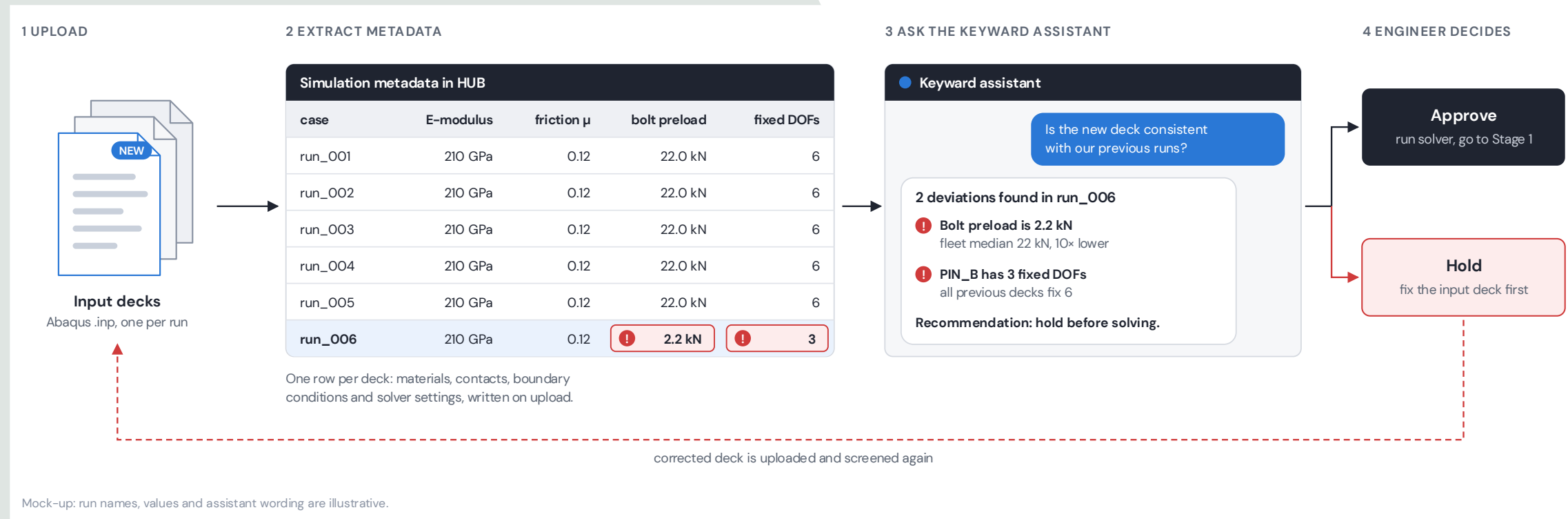
Workflow for Anomaly Detection



Stage 0: Input Deck Review before Job Submission

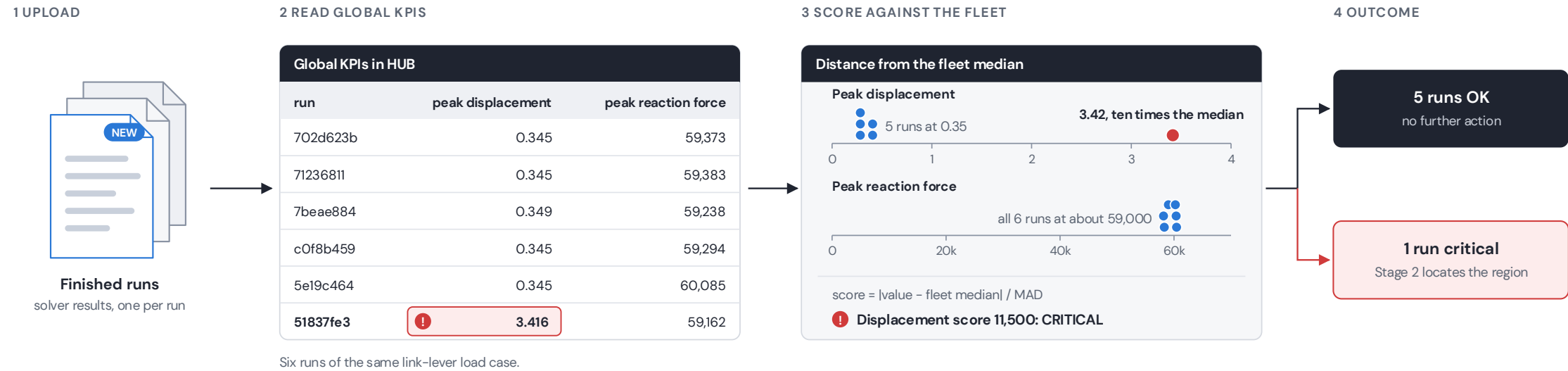
Read each input deck into a metadata table

Key Ward assistant compares the new deck w/ previous runs and flags potentially faulty Boundary conditions



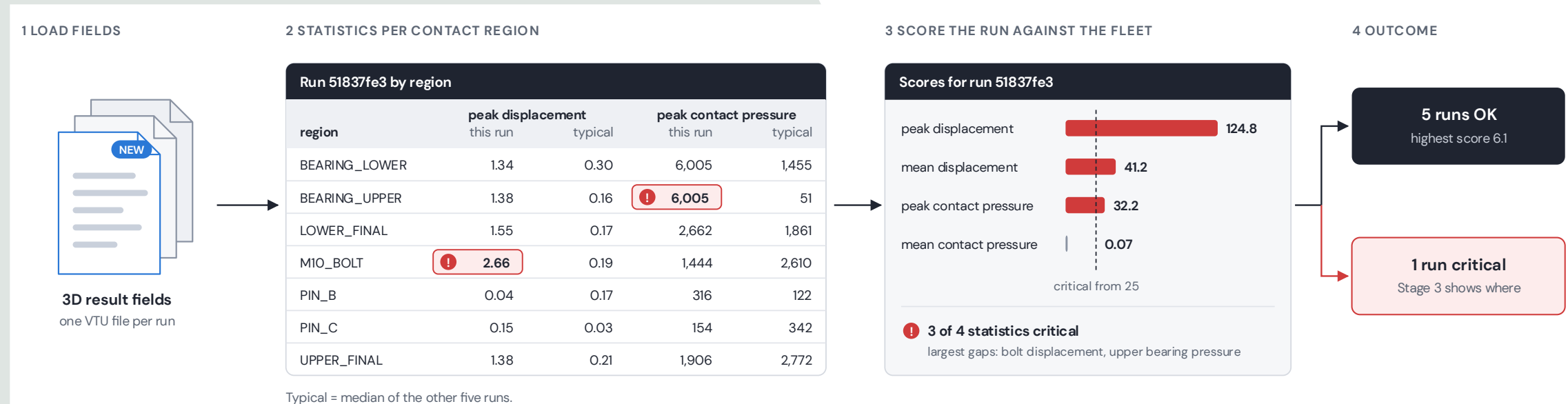
Stage 1: Fleet-Wide KPI Screening

Seconds after solution upload, each run's global KPI are compared with all previous runs and the run is classified automatically.



Stage 2: Region-Level Field Analysis

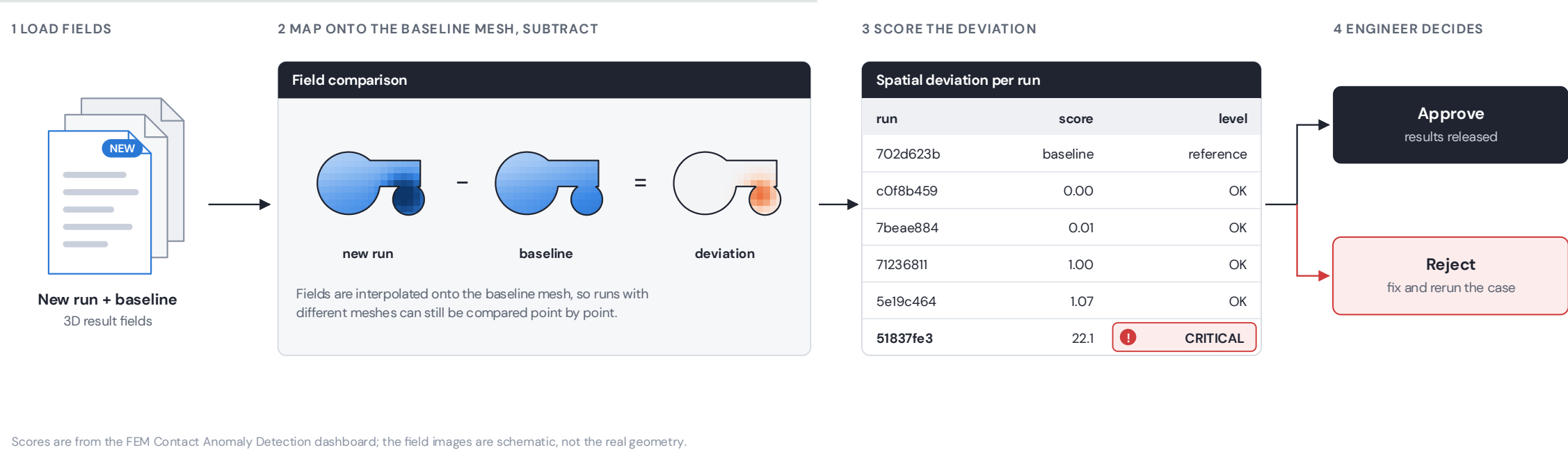
The 3D result-fields are split by contact region. This allows for an effective back-tracing to the components which behave differently.

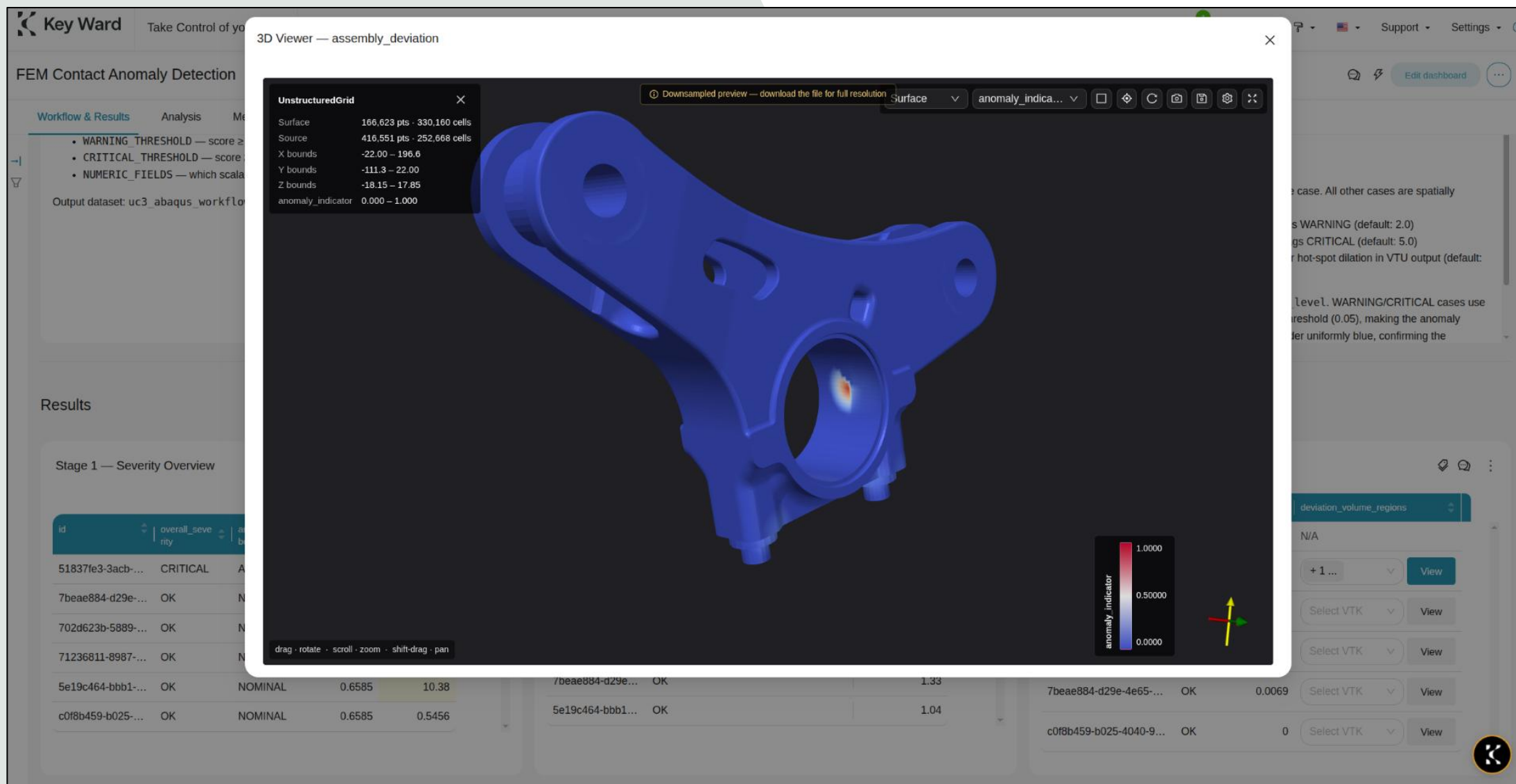


Values are from the FEM Contact Anomaly Detection dashboard data; the two highlighted cells mark the largest gaps and are added for illustration.

Stage 3: Full-Assembly Spatial Deviation

Each run is compared node-by-node with a validated baseline. The deviation is shown as a heat map on the assembly.





SUMMARY

Leveraging Data-Driven Workflows for Virtual Development



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Enhanced prediction speed for CFD, FEM etc.



AI-based optimization

Analyze more variants in shorter time



CAE Process Stabilization

Anomaly & error detection to stabilize the CAE chain



- AI hardware can significantly reduce turnaround times & cost (GPU solving)
- Surrogate models offer the possibility to fast-screen geometry variants w/o initiation of full CAE loop
- Enabled by more efficient CAE, larger DoE for model training is possible
- Enhanced by ML regression models, high confidence in the optimization is achieved and best candidates identified w/ less effort
- Automated feasibility check of simulation setups, output KPI and 3D solution fields
- This can function as a scalable, standardized CAE quality control



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Stop by
Booth 17 · Lichthof
for a demo on real
engineering data.



SCAN TO SAVE CONTACT



Interested? Get in touch with us!



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