Machine Learning Tools for accelerating CAE and unleashing Design Exploration



Challenges

more complex phenomena, more physics, more Optimization, more design iterations

costly FE Analysis of multi million element models

complicated Data Management and design exploration



Benefits

speeding up CAE simulation through simulation results prediction

speeding up Optimization through machine learning Response Surface Models

benefit from history data using them for ML training

speeding up CAE modeling through ML assisted clips recognition

streamlined data handling



ML solutions

Optimization Tool DOE in DM

KOMVOS Data management and design exploration

easy to use Machine learning tools

coupled Data Analytics Technics and Simulation Data Management

API for customization and automation

Remote ML training and prediction



ML solutions

a unique Feature Based ML for elastic and local modes prediction

a unique mode classification ML for mode shape type prediction

data driven ML for key values, curves and 3d simulation results prediction



A unique "cross-model" approach (i.e. not parametric) that can generalize

Inputs:

- Geometric and engineering features extracted from CAE data.
- Labeled responses

Supports only scalar / 1d outputs (e.g):

- First torsional mode
- First Vertical Bending mode
- First lateral Bending mode
- Local modes

Feature Based

General information



Feature Based

Predict Elastic modes for Simulation Runs

KPIs

- Accuracy vs Datasize
- Target vs Prediction
- Residuals
- Confidence

Details Feature Based Predictio... Feature Based Predictio... Beferences Changeset **Feature based Predictor** ground nested40 Feature based predictor ground nested40 001 First Torsional value (Mean Absolute Error: 0.32641936337387384) Feature based predictor ground nested#0 001 first Vertical Bending value (Mean Absolute Error: 0.4547619992844324) Feature based predictor, ground, nested40,001, First, Lateral, Bending, value (Mean Absolute Error: 0.5703218774842165) Import and Predict Reri Name First Torsional value +/- Variance First Torsional First Vertical Bending value +/- Variance First Vertical First Lateral Bending value +/- Variance First Lateral Bending 008 Imported data 1 A 001 01 0001 008 22.8683 34.3117 0.7539 1.0939 0.5411 31.6092 009 imported data 1 A 001 01 0001 009 20 5946 0.6261 30.0375 0.8722 28.4835 0.9455

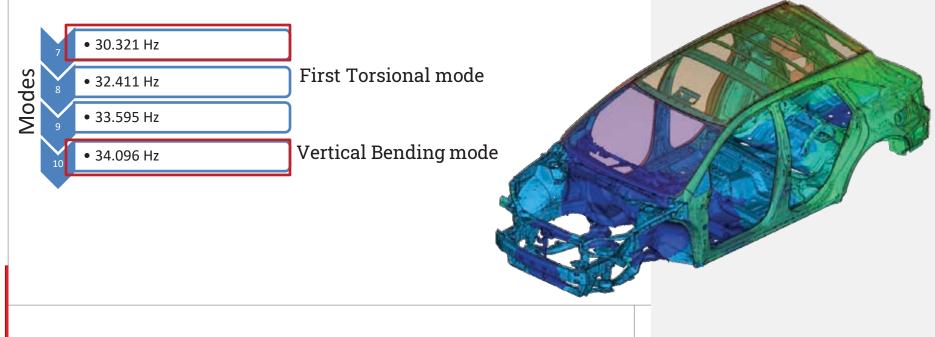
Feature Based

Predict Elastic modes for Simulation Runs

Elastic and local mode values prediction

Load case

✓ 103 Normal modes Analysis



Feature Based

Application

Elastic and local mode values prediction

Dataset Creation with ANSA Optimization Tool

ML Train	ing Dataset	Feature Based Application		
FE Model	First torsional va	lue (Hz)	Vertical bending (Hz)	
Sim Run 1	32.411		38.492	
Sim Run 2	34.096		39.123	
FE Model	First torsional va	lue (Hz)	Vertical bending (Hz)	
Sim Run 1	30.123		36.893	
Sim Run 2	32.321		37.923	

Elastic and local mode values prediction

"Unseen" data elastic mode prediction

Feature Based Application

FE Model	First torsional value (Hz)	Vertical bending (Hz)
Prediction	39.74	40.88
FE Result	39.73	40.78
Abs Error	0.01	0.1

"Cross-Model" approach (i.e. not parametric) that can generalize. This classifier is able to Predict the modeshape types of FE models

Inputs:

- Normal modes result files of FE models
- Classification

Supports 1d outputs (e.g):

• Mode shape types like Torsional, Bending, Lateral, etc.

Mode Classifier

General information

Mode-shape type classification training

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Mode Classifier

Imported data with labeling

Mode-shape type classification prediction



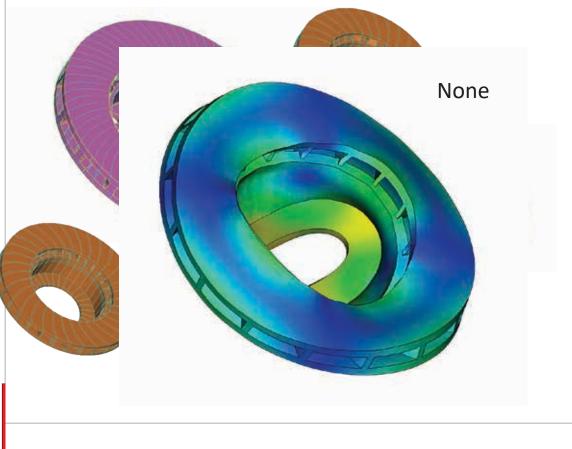
Mode Classifier

Mode shape type Prediction

KPIs

- Classes Histogram
- Confusion Matrix
- ROC Curve
- Accuracy curve

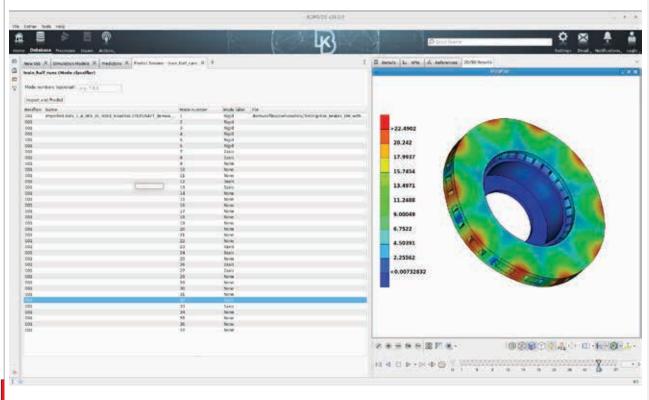
Disk Brakes mode classification



Mode Classification Application

Data set creation Mode shape labeling

Disk Brakes mode classification



Mode Classification Application

KOMVOS Data view Mode classifier with KPIs Prediction Data driven machine learning for keyvalue, curves and 3d simulation results prediction (parametric)

Inputs:

- Design Variables and their values
- Responses extracted from FE Analysis

Supports:

- 1d results (Scalar Key Values)
- 2d results (Any available curve results)
- 3d results (Any available field results. Scalar, Deformation, Vector)

Design Variable Based

General information

Key values prediction

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Design Variable Based

Predict Key Values, Curves and 3D Field results on theoretical designs

KPIs

- Ranking of DVs with Importance
- Accuracy vs Datasize
- Target vs Prediction
- Residuals
- Confidence

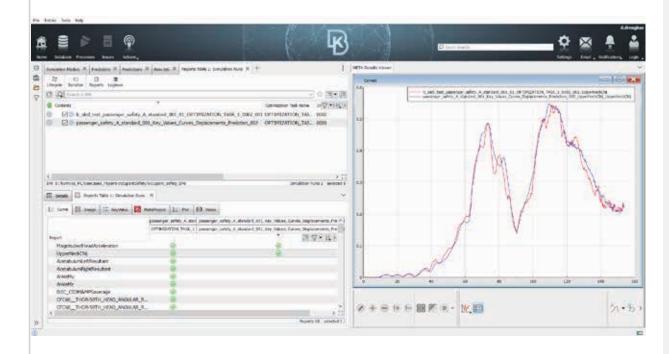
3D Results prediction



Design Variable Based

Predict Key Values, Curves and 3D Field results on theoretical designs

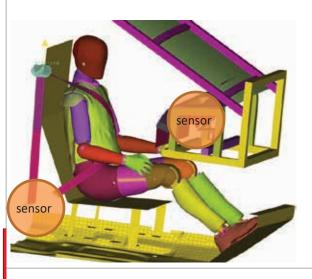
2D Results prediction and comparison

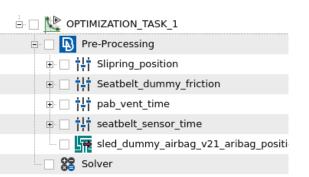


Design Variable Based

Predict Key Values, Curves and 3D Field results on theoretical designs

- Slip ring position (Z axis).
- Friction coefficient between seat belt and ATD
- Airbag venting trigger time
- Seatbelt sensor trigger time

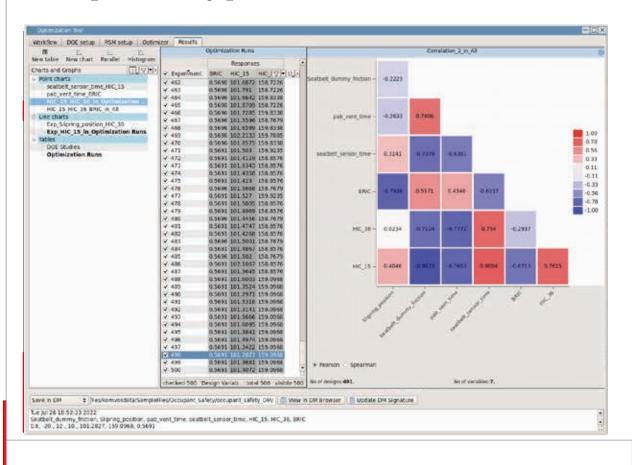




Design Variable Based Application

Design Variables

Optimization task



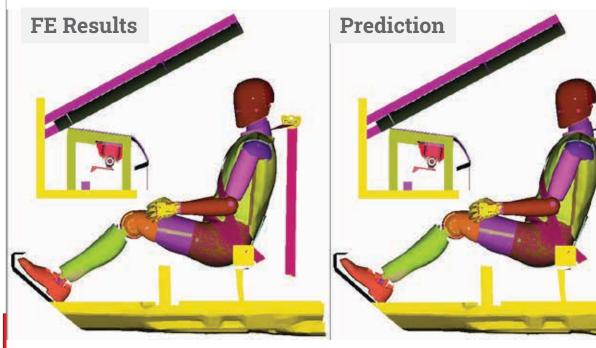
Design Variable Based Application

Response Surface Method Optimization - Predictor Objective Constraints

Correlation

Design Variable Based Application

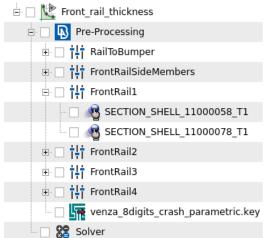
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Head accele	Head acceleration (mm)		38.905		38.5627	0.88%
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Upper neck	Upper neck nij		0.3988		0.4022	0.84%
Thorax rib U	L (<i>mm</i>)		65.597		66.321	1.09%
Thorax rib U	R (<i>mm</i>)		43.722		43.421	0.69%



Design Variable Based Application

ML Prediction vs FE Results

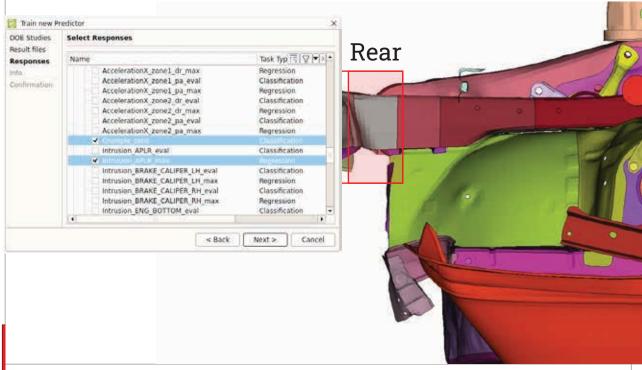




Design Variable Based Application

Design Variables

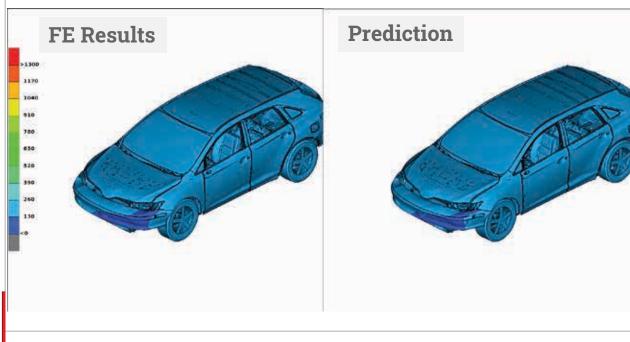
Optimization task



Design Variable Based Application

Key Value Predictors

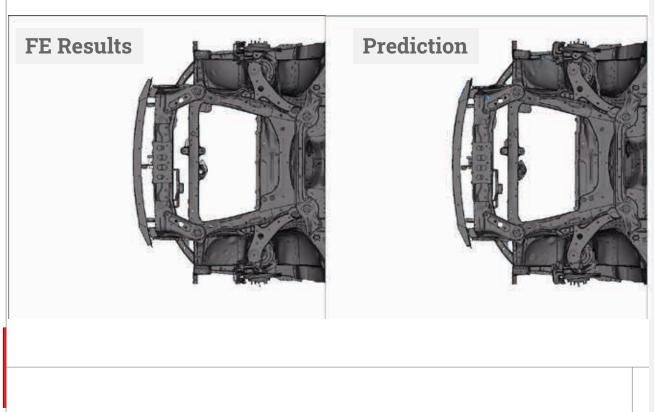
Classification type predictors



Design Variable Based Application

ML Prediction vs FE

Results



Design Variable Based Application

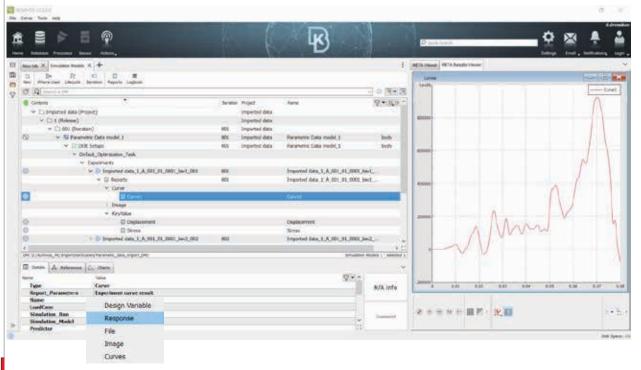
ML Prediction vs FE

Results

DOE Studies

Doe studies dedicated tab for design exploration

- Parallel Coordinates filtering
- 2nd level filtering checkbox
- 2D,3D charts
- Reports table



Import Parametric Data

Import existing excel sheet with parametric data

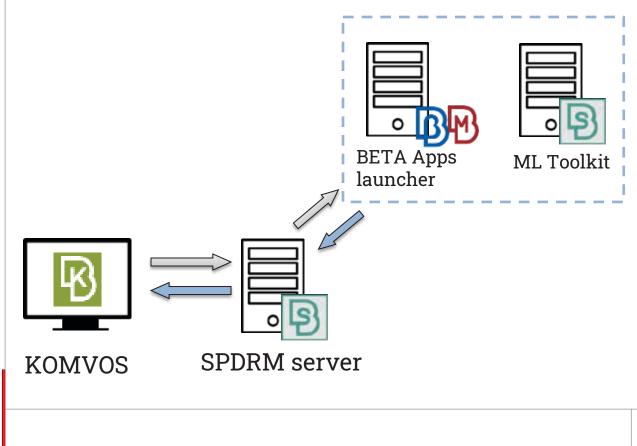


Direct Access to all aspects of the Machine Learning processes through python script interface

- Data collection
- Training
- Prediction
- Predictor Life Cycle

Machine learning API

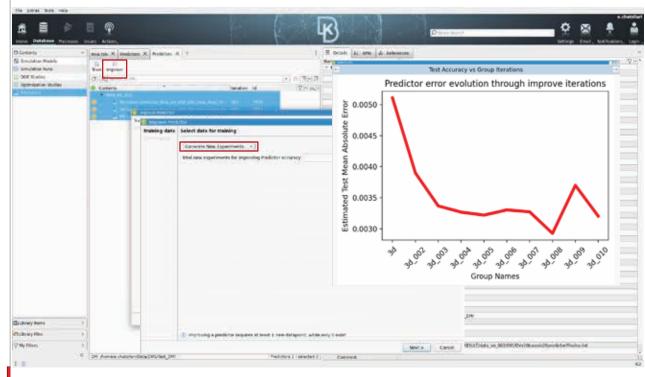
v24.0.0 New Features



Remote Training and Prediction

ML Training and Prediction actions can be performed remotely through SPDRM SERVER

Simplified Predictor Improvement interface



Unified Predictor Improve tool

Incremental Retrain and Smart sampling Now in a simple unified interface

Data visualizations

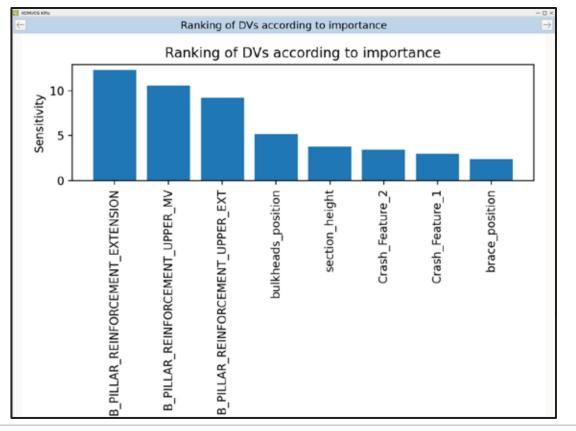
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Data analysis charts

- Pair plots
 - Correlation
 - Predictive Power Score
 - **Mutual Information**
 - **Dataset Statistics**

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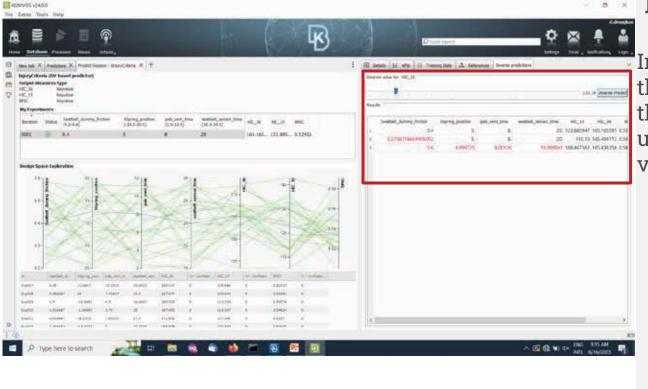
Interpretable Machine Learning



More clarity on a predictors behavior

- Partial dependence
- What-if plots
- Breakdown plots
- SHAP (Shapley) plots
- Permutation Feature Importance

Inverse Prediction



Asking for the best DV values

Inverse predictions show the Design Variable values that would result in the user defined Response value

Control and Transparency

- Tuning ML hyper-parameters
- Specify ML algorithms
- User designed ML modules
- Access through API

Mode classification

- Trim body models
- Modal Map Generation

Physics informed Machine learning

- CFD
- Extend to other disciplines

Future Developments

Smart Sampling

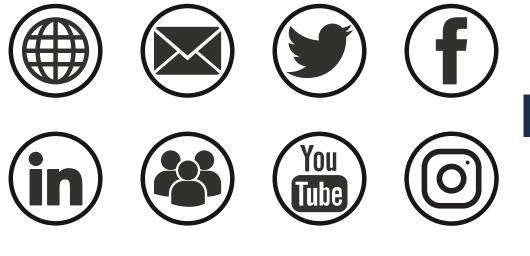
- Better performance with fewer experiments
- More effective exploration of the Design Space during Optimization
- Effective exploration of data coming from real tests

Optimization

- Start and supervise Optimization studies in KOMVOS
- Post process Optimization results

Future Developments





Stay connected