Full-Field Material Calibration Using LS-OPT®

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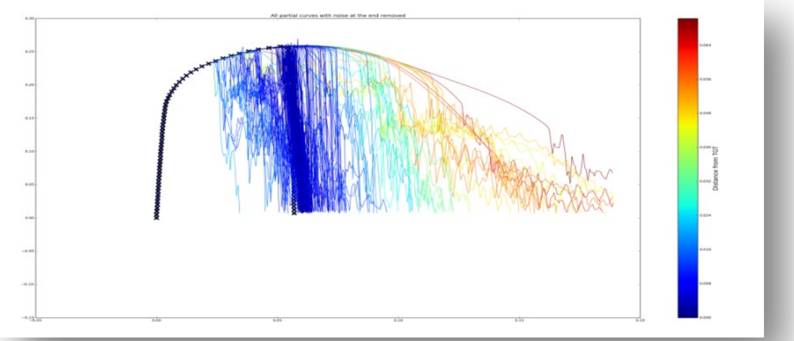
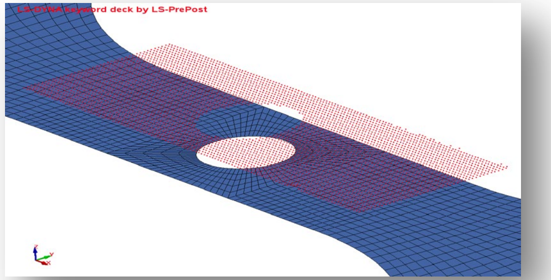
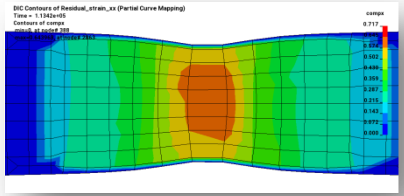
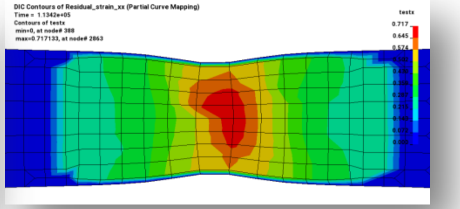








German LS-DYNA Forum

Bamberg, Germany

October 16, 2018

Parameter Identification: Overview

- New curve matching algorithm

  Dynamic Time Warping

- Digital Image Correlation

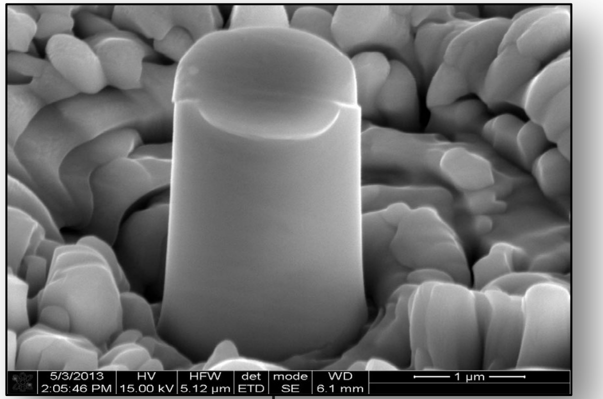
  Nearest Neighbor Cluster: Reduce resources

- Post-processing

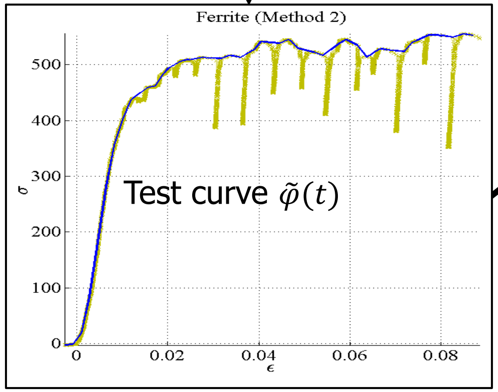
  Automated Contour History display (LS-PrePost) using Similarity Measure

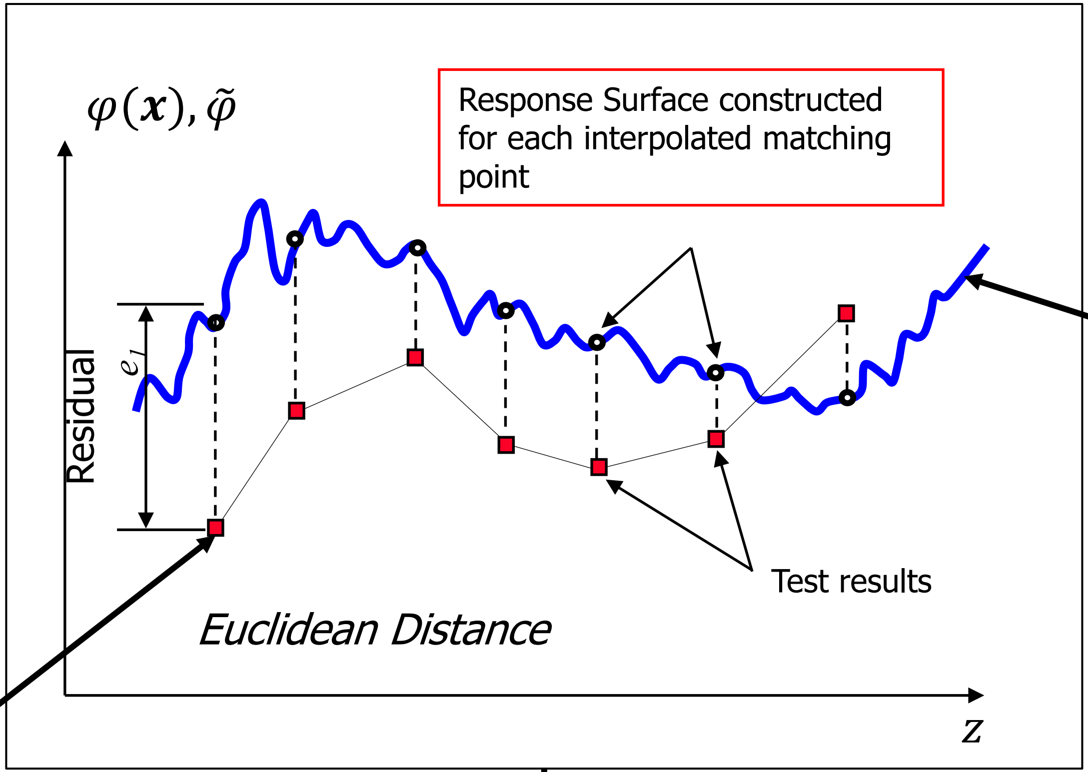
Material Calibration: Introduction

Experiment (single crystal micropillar)



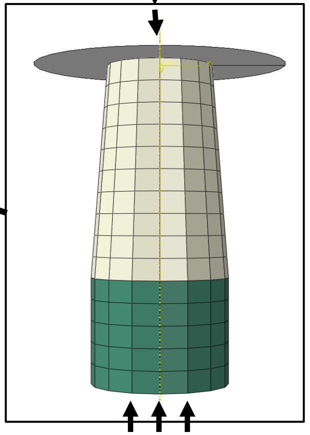
Result





Material parameters $\boldsymbol{x}$

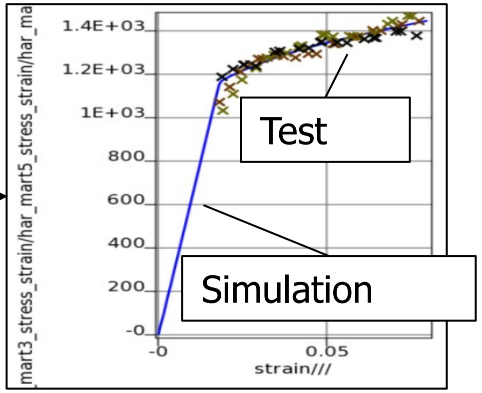
Computed curve: $\varphi(\boldsymbol{x}, t)$



FE model

$$\min_{\boldsymbol{x}} \sum_{j=1}^{n} (\varphi_j(\boldsymbol{x}) - \tilde{\varphi}_j)^2$$

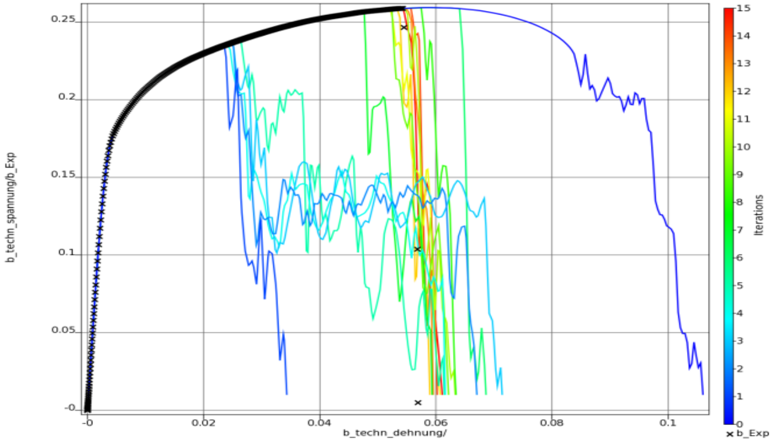
$$\boldsymbol{x}^*$$

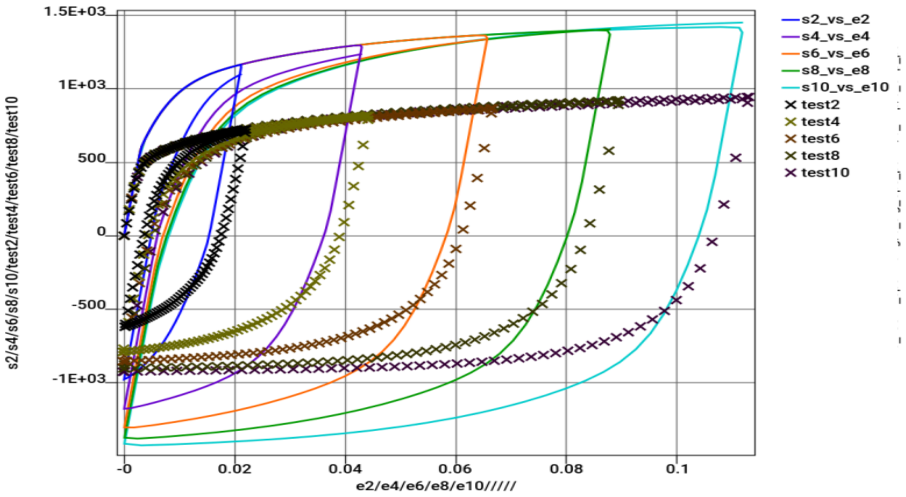


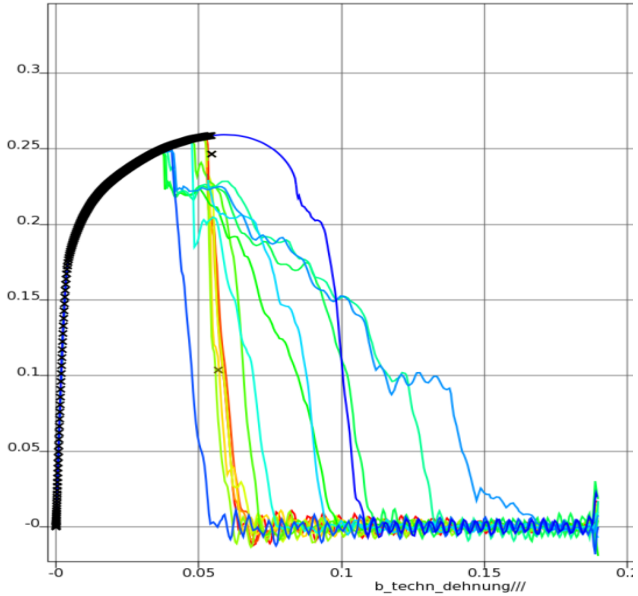
Prof. S. Kumar,
Dr. H. Ghassemi-Armaki
(Brown U.)
Prof. F. Pourboghrat (OSU)

Calibration: Computational challenges

Experimental and computational results can be difficult to compare







Noise
Failure model: GISSMO — element erosion a discrete process

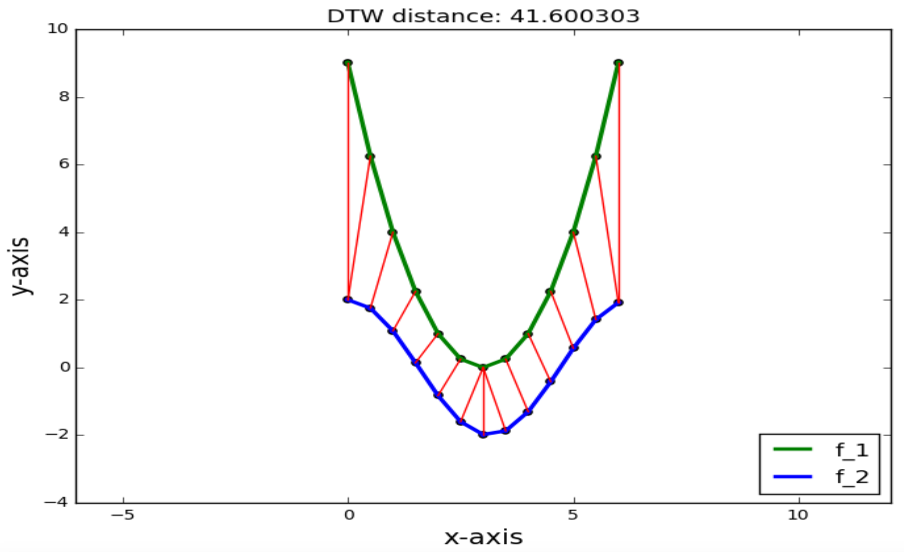
Hysteresis
Material 125 — Loading/Unloading (5 cases)

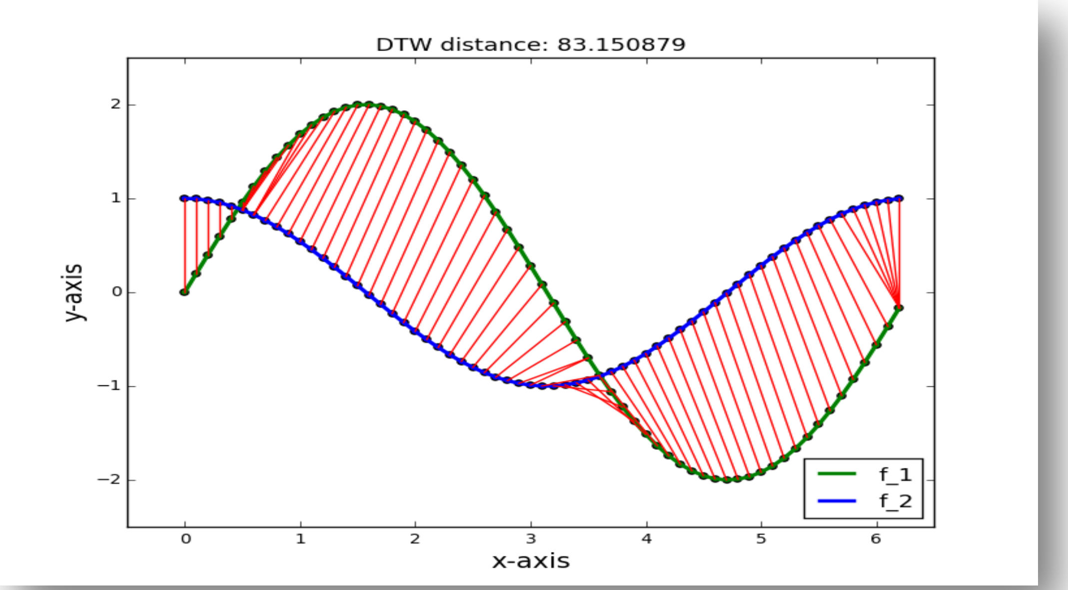
Partial Matching
Failure model: GISSMO — post-failure oscillation of coupon

Addressing noise: Dynamic Time Warping

- DTW calculates the distance between two data sets, which may vary in time, via its corresponding warping path.
- This path is the result of the minimum accumulated distance which is necessary to traverse all points in the curves.
- The matching is end-to-end.
- While the Euclidean distance measure is a strict one-to-one mapping, DTW also allows one-to-many mappings.
- Mathematically, optimize the path:

$$DTW(P,Q) = \frac{1}{l} \min_{W} \left\{ \sum_{i=1}^{l} \delta(w_i) \right\}$$





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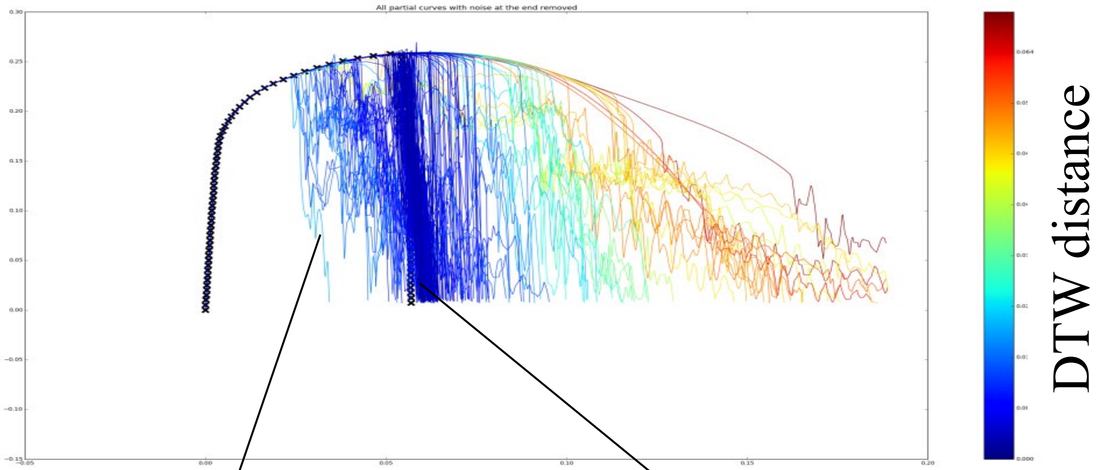
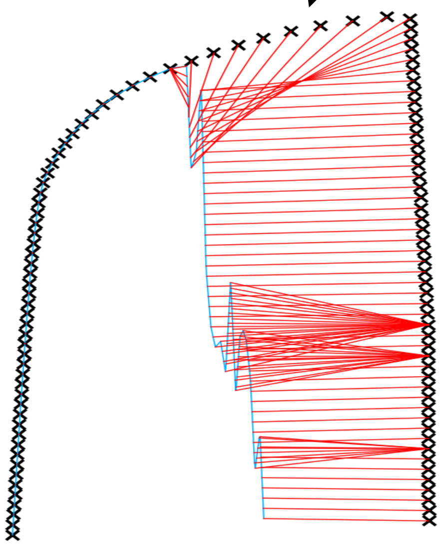
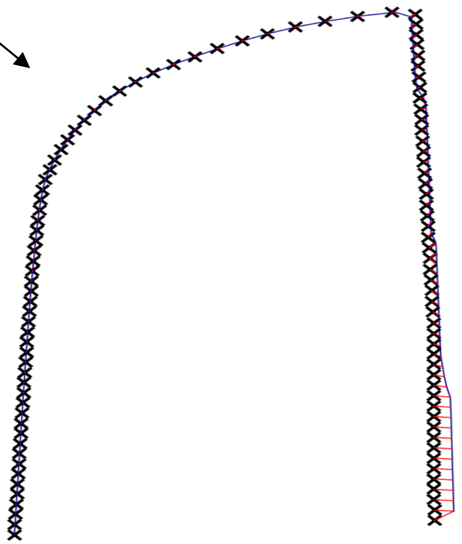
Dynamic Time Warping: DTW mapping

Simulated GISSMO model: force-displacement curves for tensile test





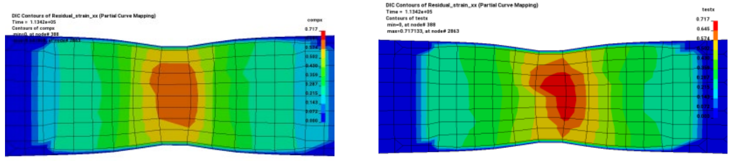
Poor fit DTW map



Best fit DTW map

<u>Contour Mapping</u>

- Multi-point histories: Apply to multiple points (full field): ε vs. force
- Use DTW *map* to construct test contours for comparison



simulation experiment

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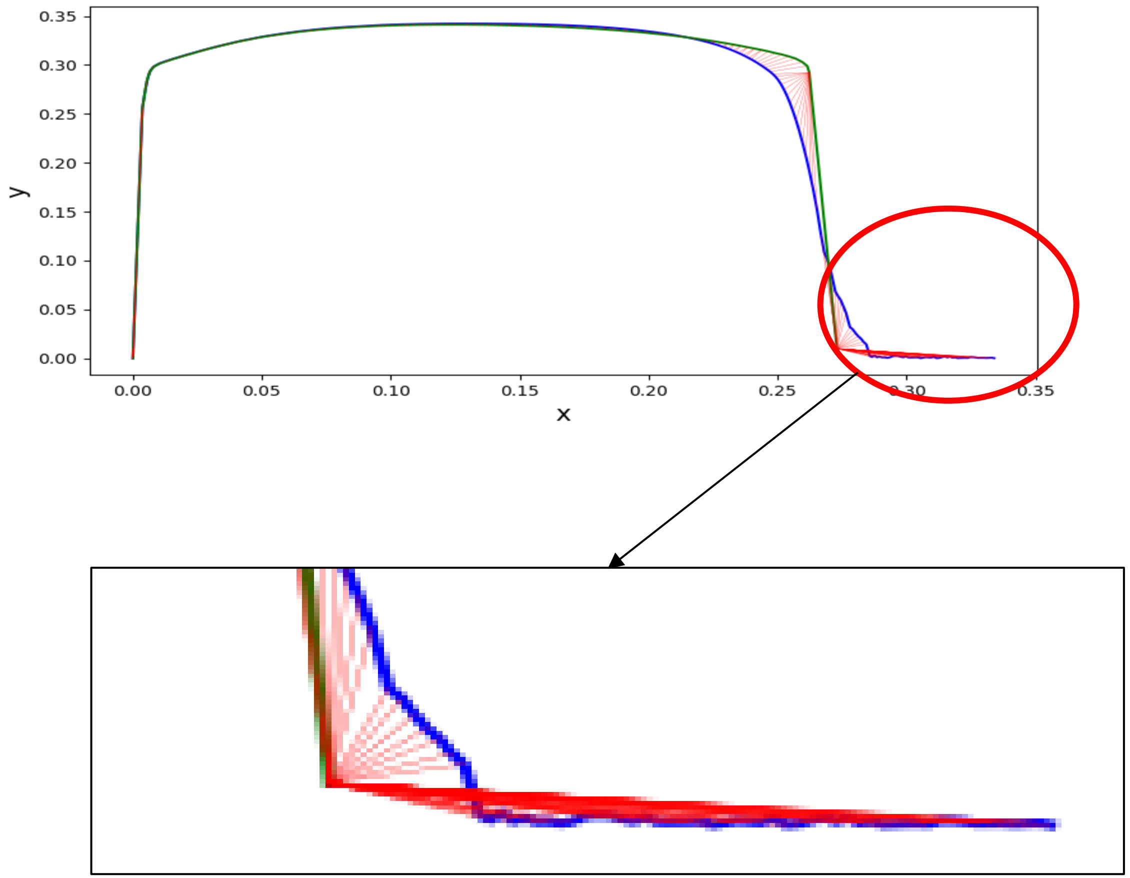
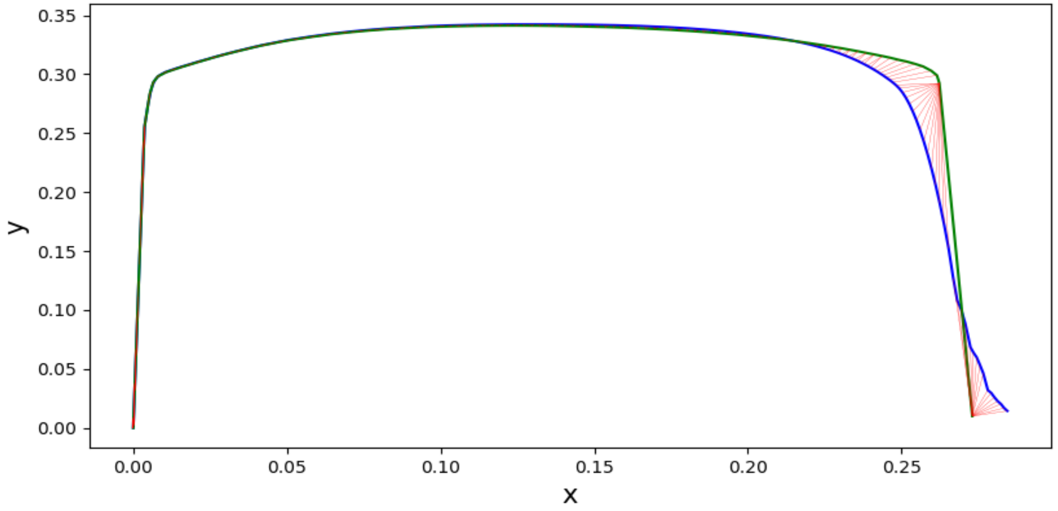
Dynamic Time Warping: Partial curves

Partial curve pairs can distort the DTW result



- In DTW, red connectors are summed
- Curve length difference artificially distorts mismatch
- Truncation required

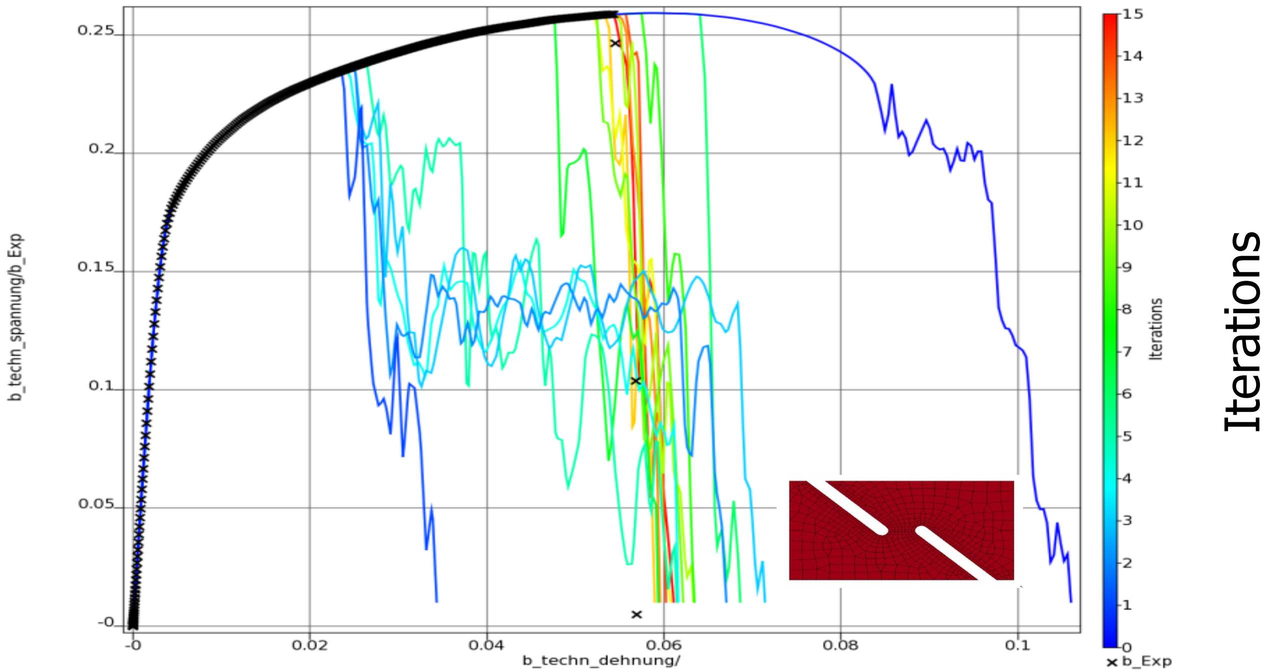


Example: GISSMO model

The GISSMO failure model requires special treatment for curve matching

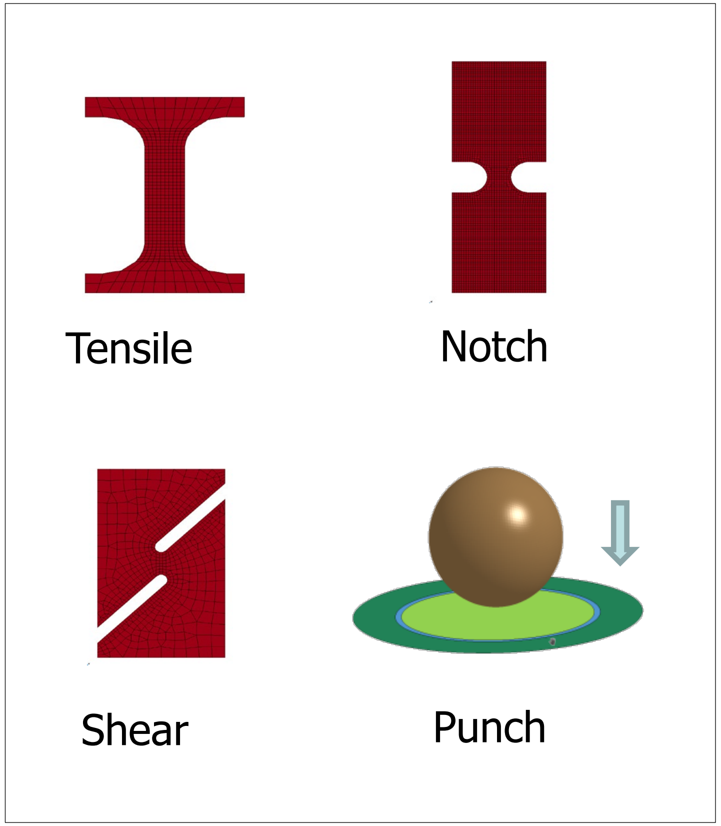
- Parameters: 7, Material Model: GISSMO
  - Uses discrete (element-by-element) erosion
- Curve Matching
  - Dynamic Time Warping (DTW)
  - Does not address partial curves ⇨ Truncate Force history at failure
- Optimization
  - SRSM (fast local optimizer)

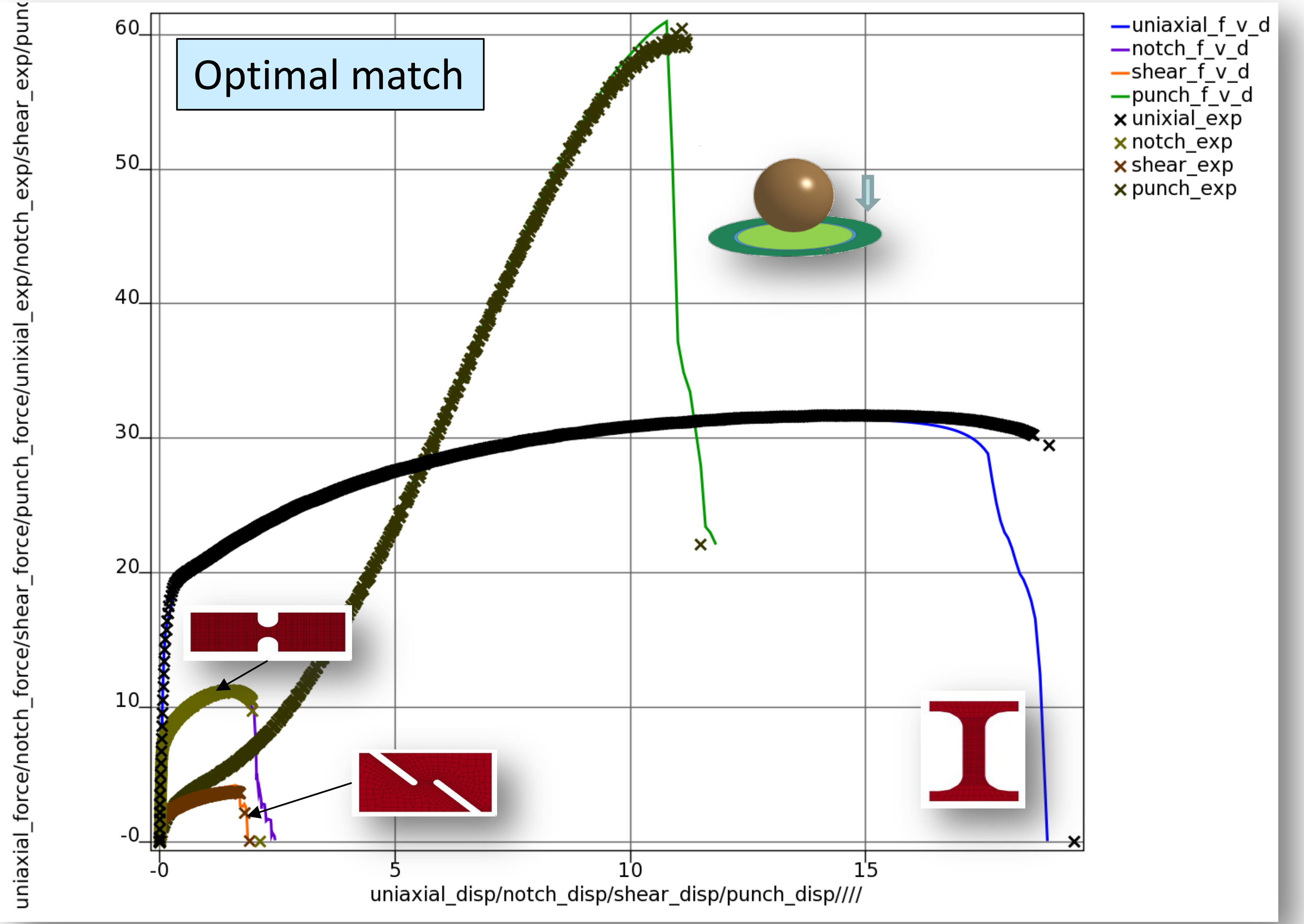
Shear: single case calibration history



Calibration: GISSMO model

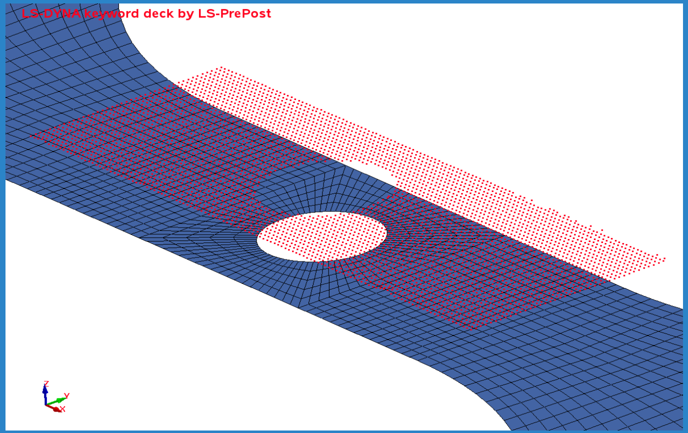
In industry, the calibration of the GISSMO model typically involves multiple cases





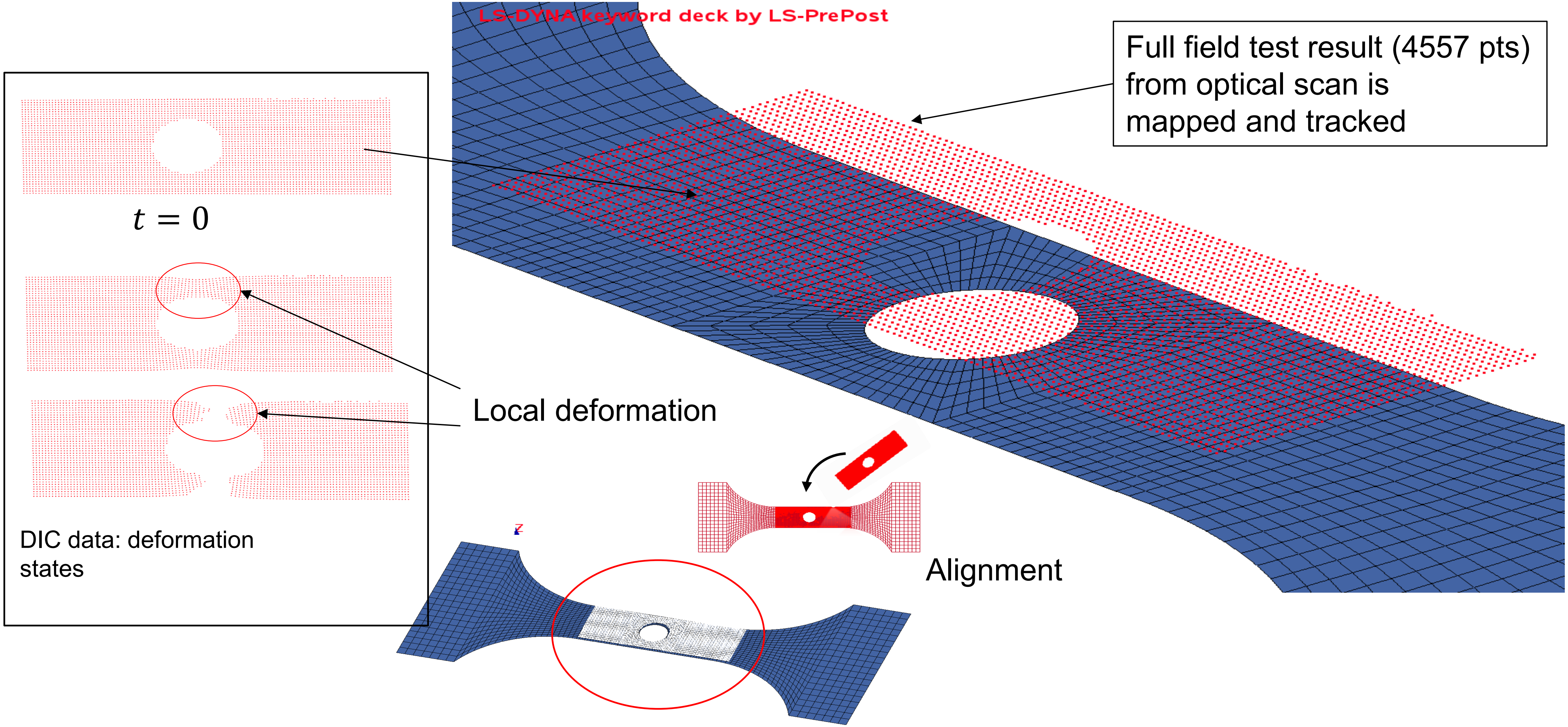
Courtesy: FCA

Digital Image Correlation



Digital Image Correlation (DIC)

Align and *map* optical data to the Finite Element model



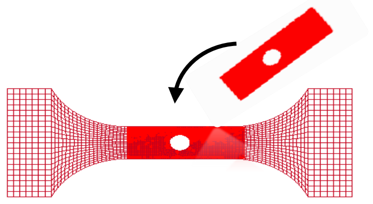
Digital Image Correlation: LS-OPT technologies (1)

- ***Alignment*** *in 3D of test to FE model.* Least Squares solution:

$$\boxed{\min_{\boldsymbol{T},\hat{s}} \|\hat{s}\boldsymbol{X}_1\boldsymbol{T} - \boldsymbol{X}_2\|}$$

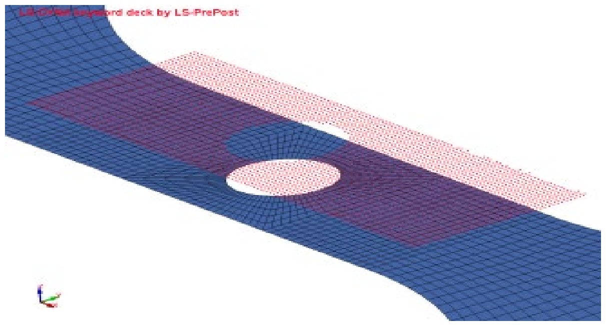
$\boldsymbol{X}_1$:Test pts (subset), $\boldsymbol{X}_2$: FE model pts, $\boldsymbol{T}$: transform, $\hat{s}$: Isotropic scaling. Typically 3 or 4 points

  - *Alternative*: LS-PrePost® to translate, rotate and scale test points.



Align Test points

- ***Map:*** *Test → FE mesh:*
  - Exact Nearest Neighbor (bin tree) search and element interpolation ($10^7 \rightarrow 10^7$ pts). (Practice: ~ 10^6)



- ***Optimization:*** *Minimize Similarity Measure:*

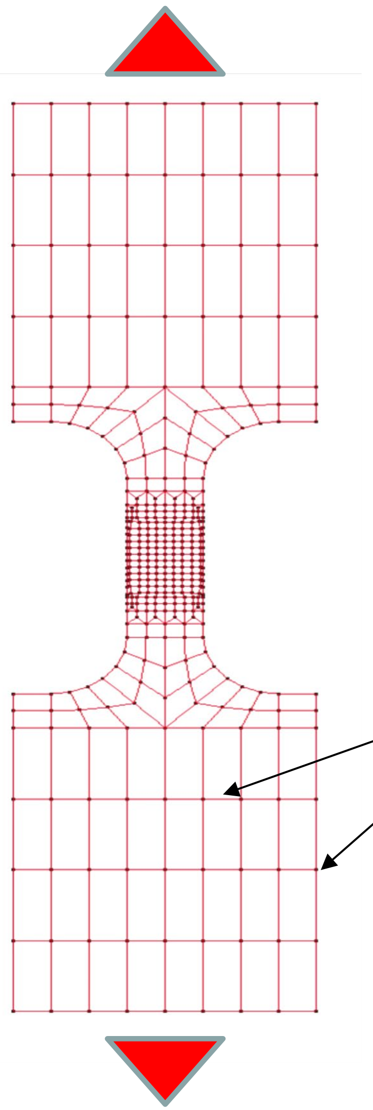
$$\boxed{\min_{x} \sum_{p=1}^{points} DTW(P,Q)_p}$$

Validation of a Synthetic Problem

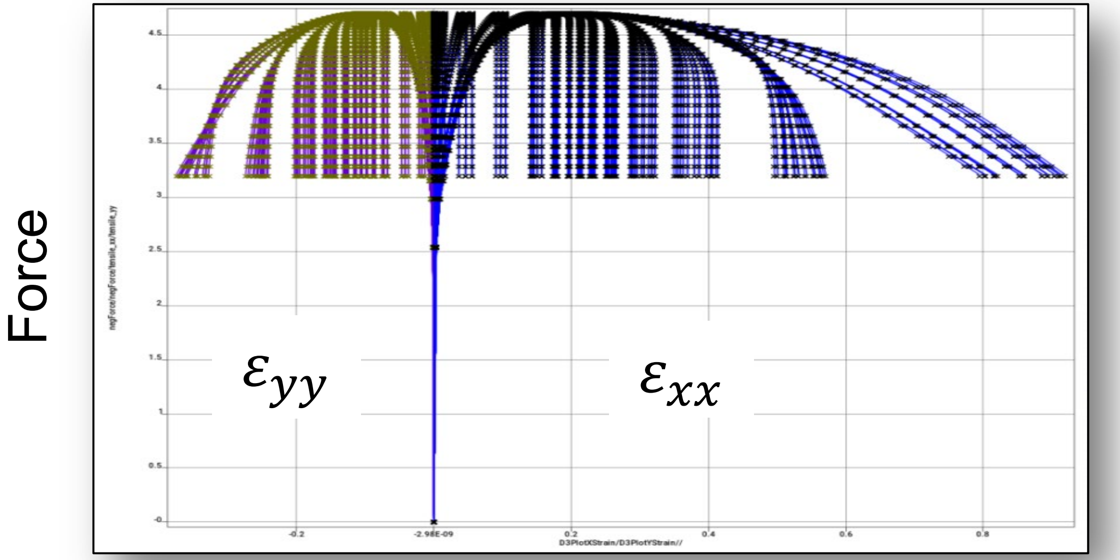
Material 24 with *Hockett-Sherby* flow curve extrapolation

$$f(\varepsilon_p) = A - Be^{-c\varepsilon_{pl}^n}$$

- c **and** n **are variables**



Test pts & nodes coincide



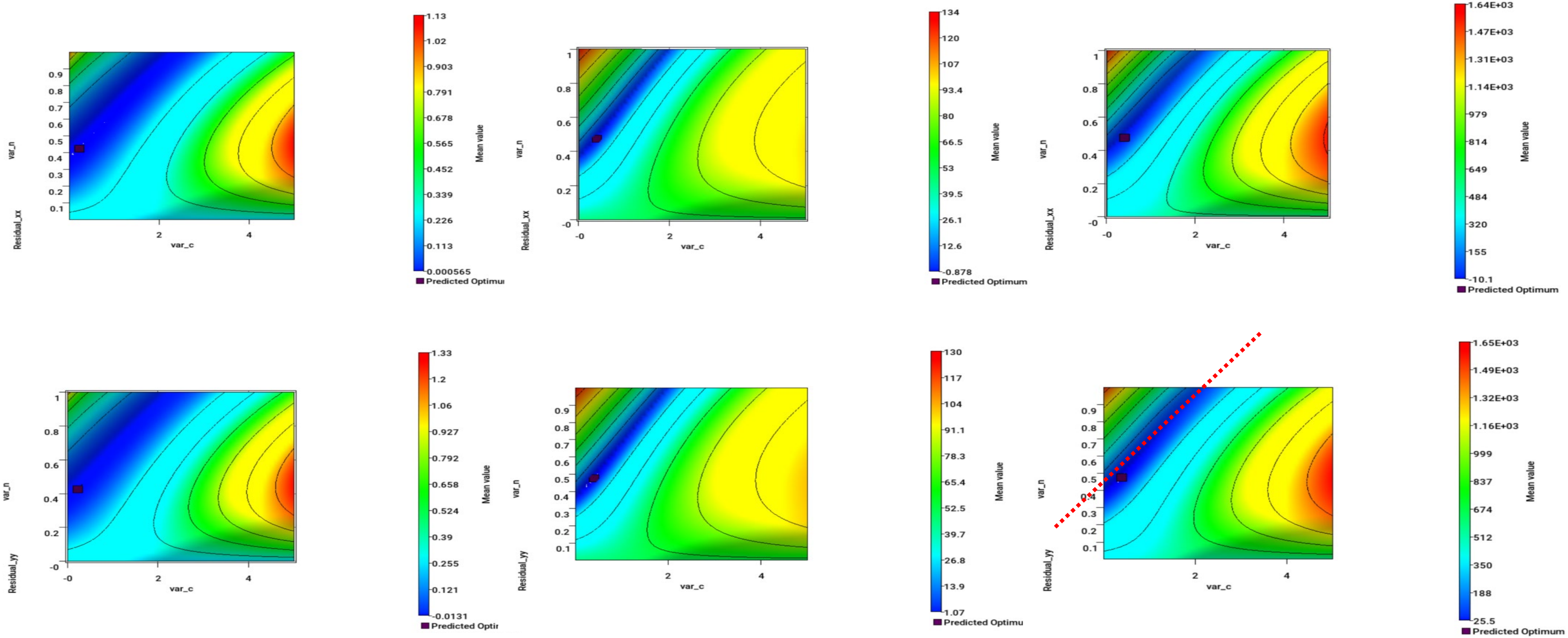
Full-field deformation

	c^*	n^*
Start	4.0	0.9
PCM	0.502	0.501
DF	0.500	0.500
DTW	0.497	0.499
Exact	0.500	0.500

Distance vs. parameters

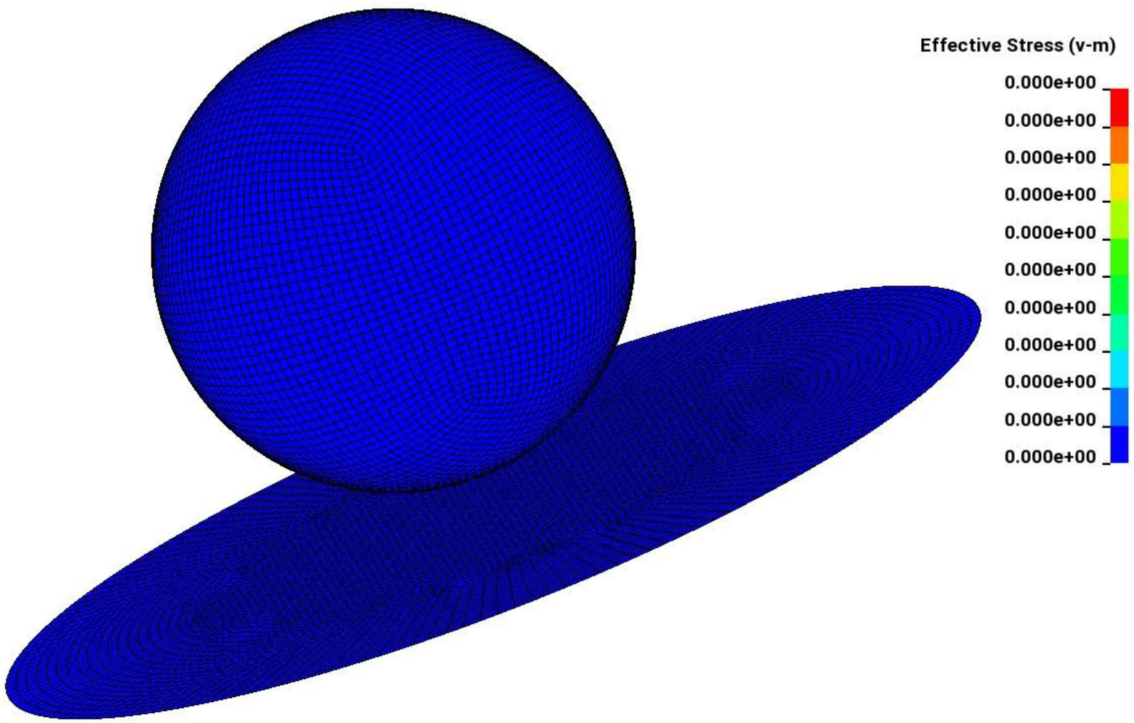
Different similarity measures compared

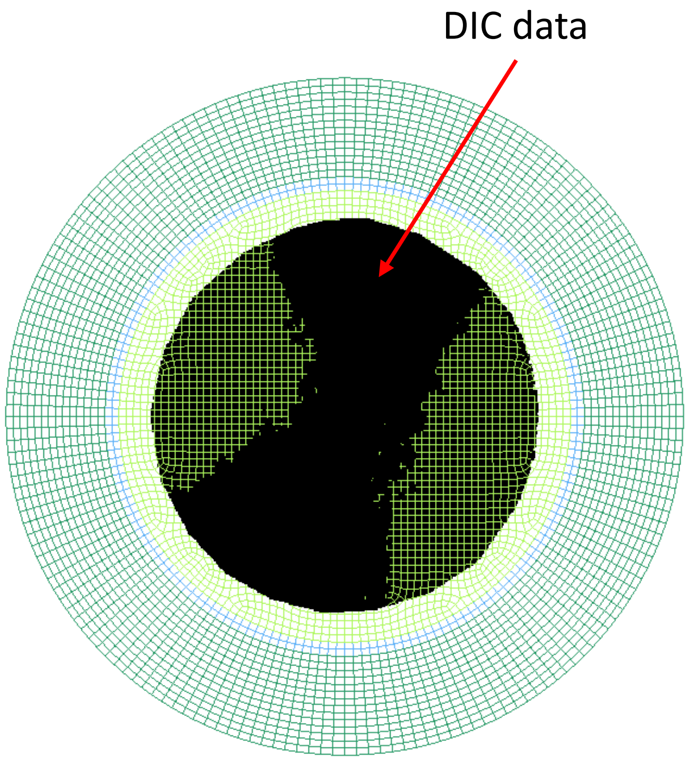
Partial Curve Mapping	Discrete Fréchet	Dynamic Time Warping



Example 1: DIC Validation: Punch example

Calibrate GISSMO material properties using strains/transverse displacement

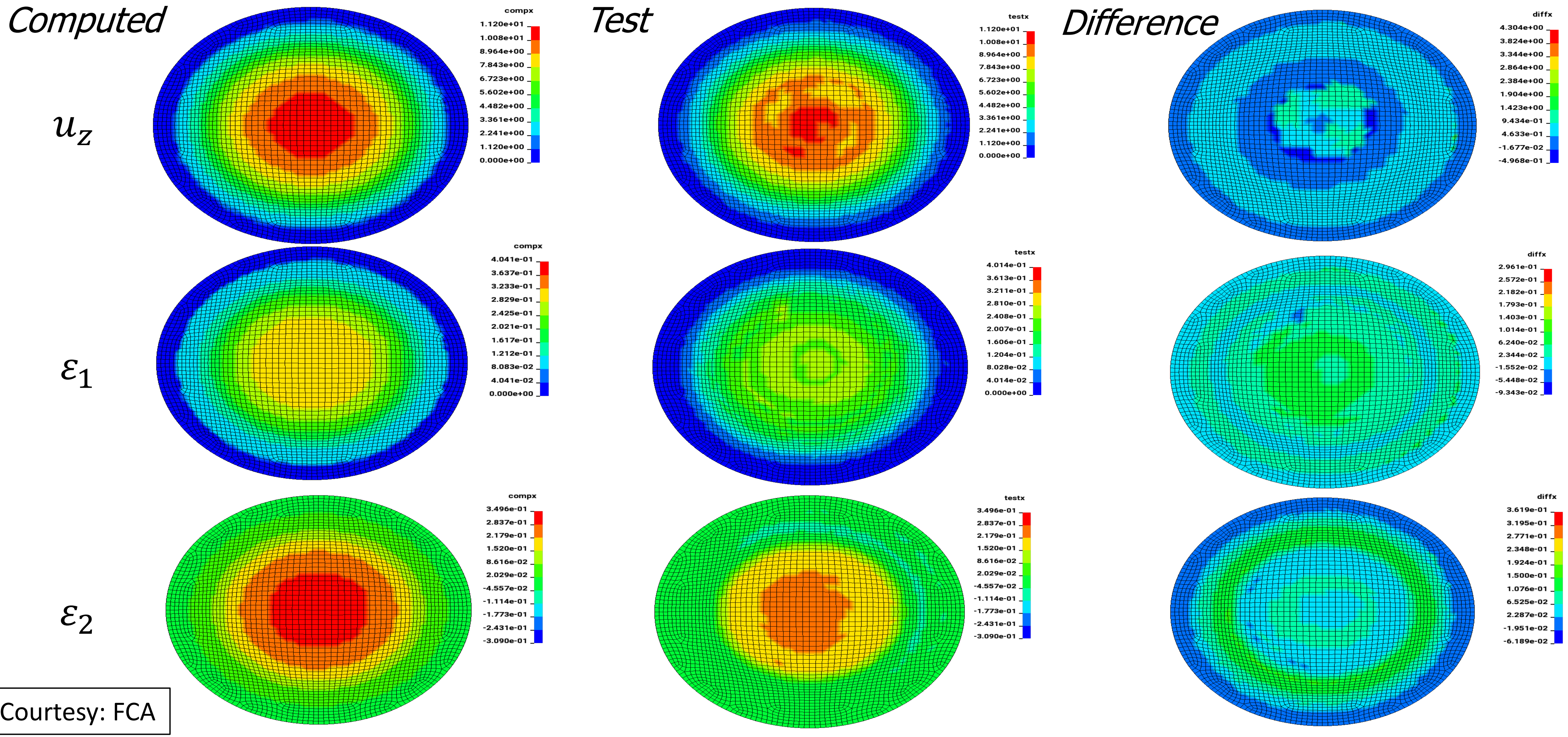




Courtesy: FCA

Example 1: DIC Validation: Punch example

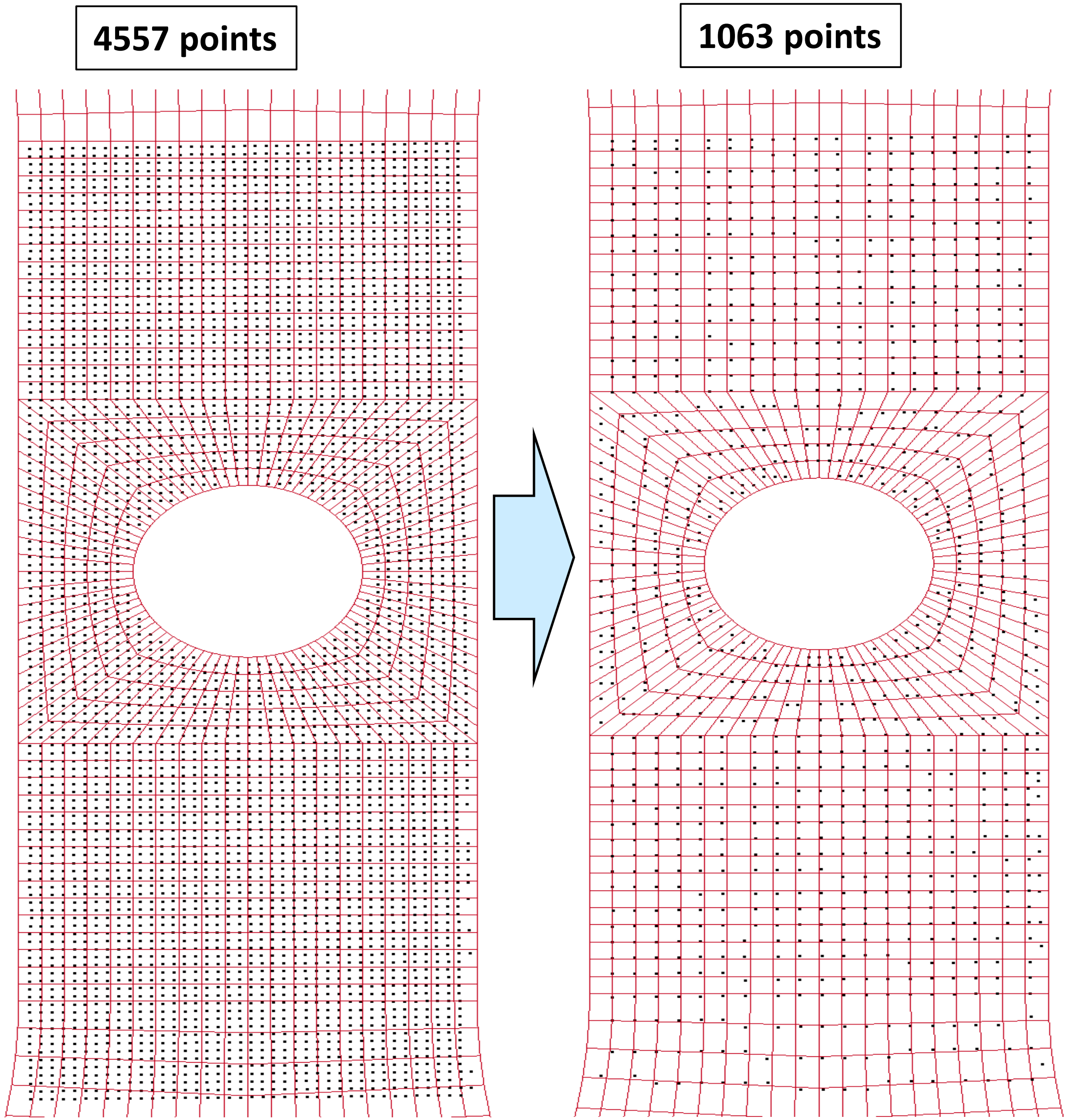
The calibration was done using a Force-Displacement similarity match (GISSMO)



Courtesy: FCA

Digital Image Correlation: *Nearest Neighbor Cluster*

- **Accuracy and cost**
- **Nearest Neighbor Clustering**
  - Pre-processing feature
  - Reduce resources for large point set ($\sim 10^6$)
    - Storage space
    - CPU time: mapping is done at each time step (vanishing nodes/points)
  - Nodal 1-to-1 map
  - Can also apply a proximity tolerance for removing outlier points
- **Algorithm** $(\boldsymbol{t} = \boldsymbol{0})$
  - Nearest node to each point → *reduced node set*.
  - Prune *reduced node set* → *nearest points*
  - 1-to-1 map



Digital Image Correlation: *Nearest Neighbor Cluster*

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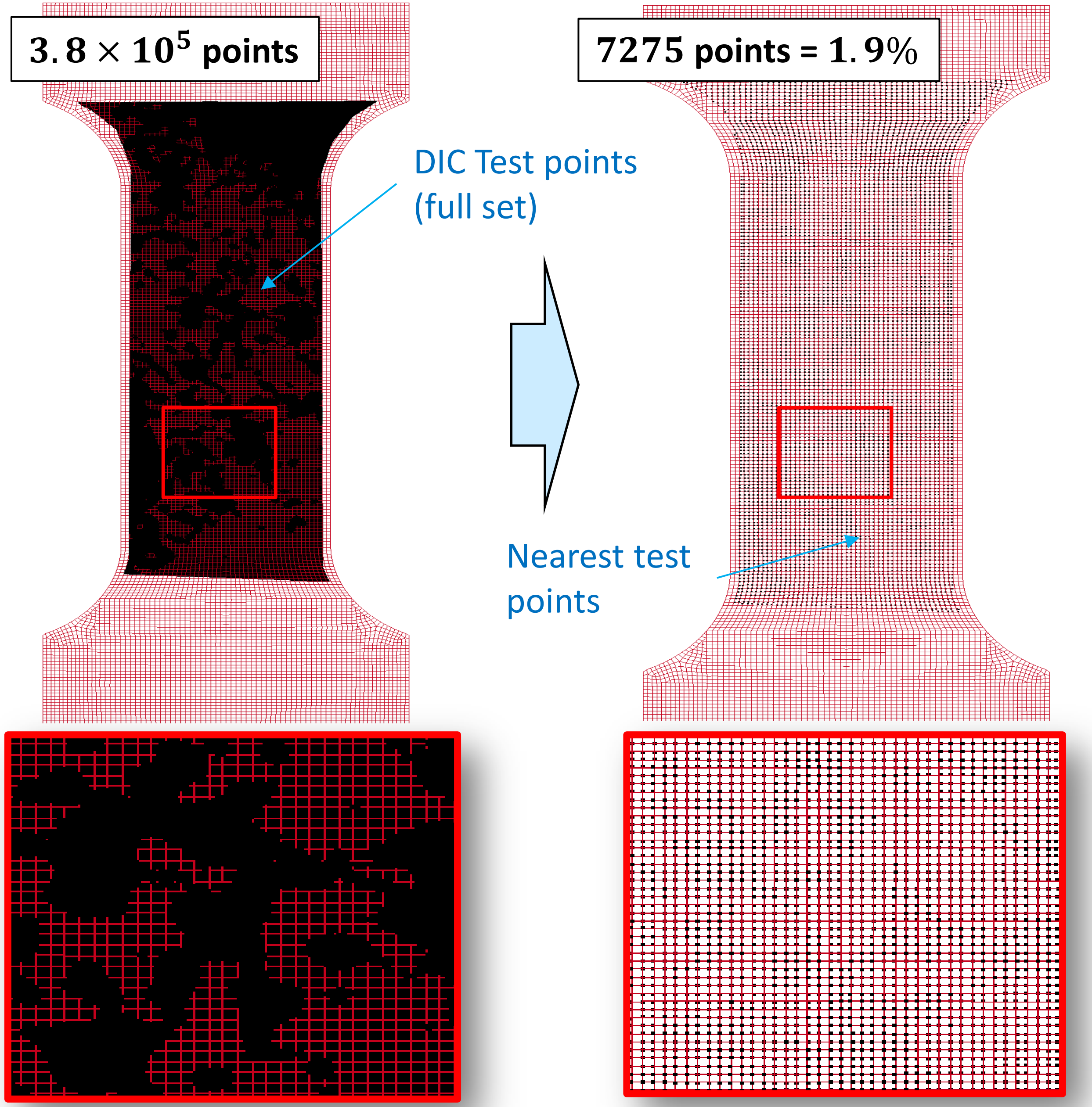
Enlarged

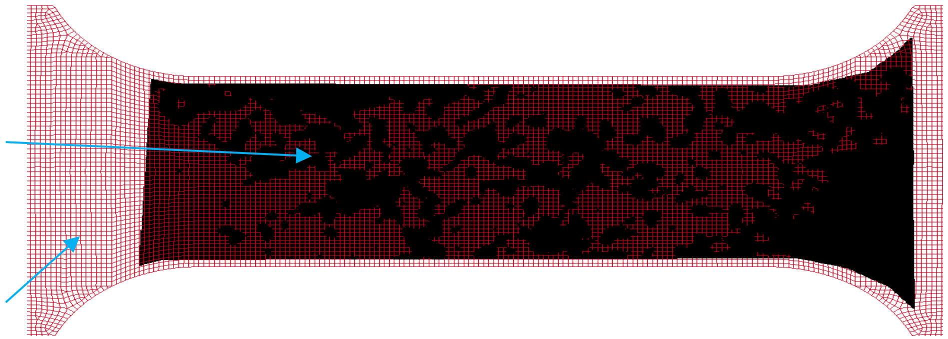


Example 2: Tensile test

The contour comparison uses *Dynamic Time Warping:* 3.8×10^5 DIC points

DIC Test points

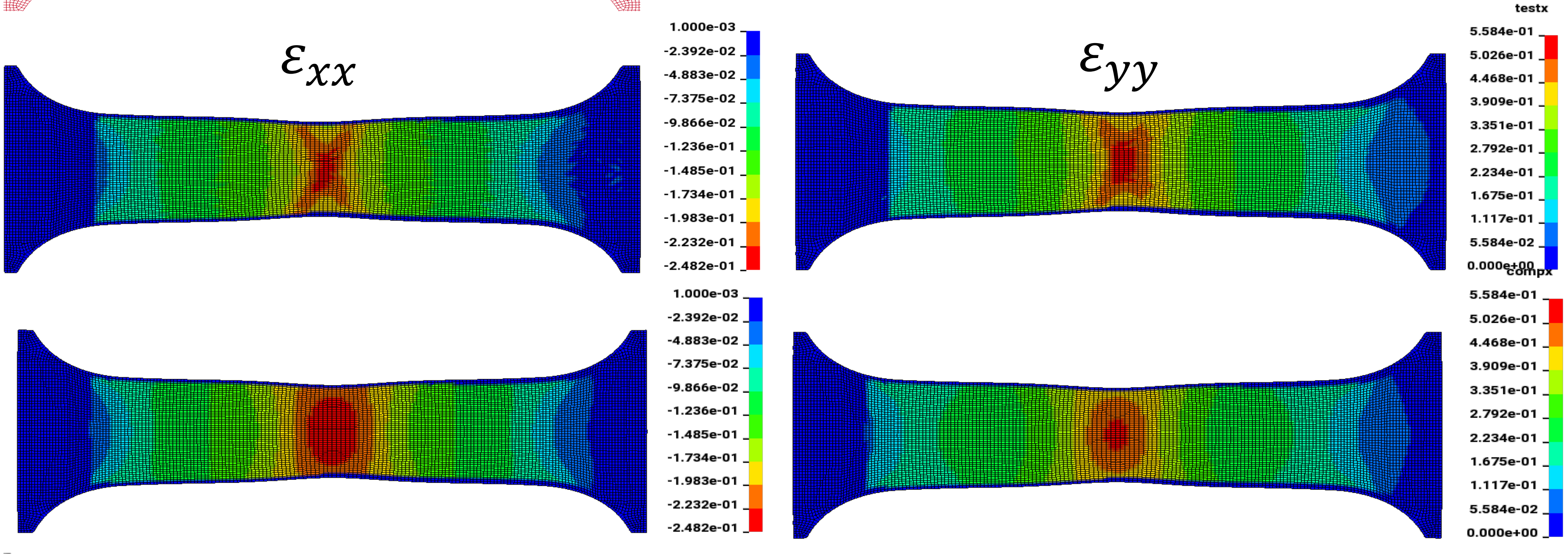
FE model



- Reduces 380,000 DIC points to 7275 points with nodal neighbors
- Reduces extraction time from 2 hours → 6 minutes

DIC

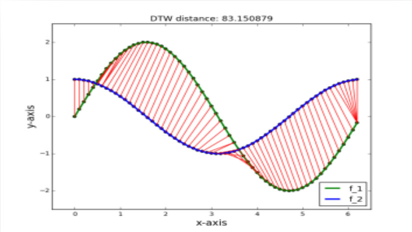
Computed



LS-OPT *DIC* calibration feature summary (v6.0)

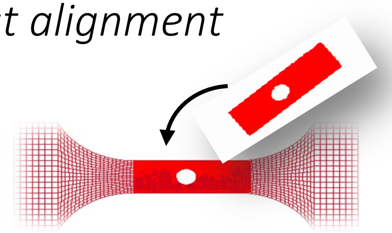
- DIC Interfaces:
  - gom/ARAMIS
    - v6 CSV
    - v7 XML
  - Fixed Format (LS-PrePost)
  - Free Format (LS-OPT/GenEx parser)
- LS-DYNA interface
  - Multi-point histories (d3plot)
  - Entities
    - Nodal
    - Shell
    - Solid
  - *Exact nearest neighbor point* mapping ($\sim 10^7$ pts). Test pt → FE pt

- Curve similarity methods
  - Euclidean, Fréchet, *DTW*, PCM

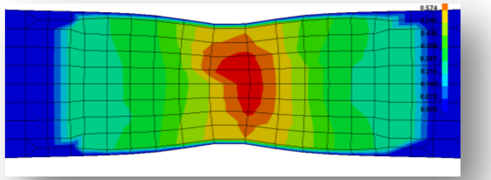


DTW

- Filtering
  - Online filtering (SAE, Ave)
- GUI
  - Test pre-view
  - *Test alignment*



  - *Strain fringe plot* (LS-PrePost)
    - Simulation
    - Experiment
    - Error



Outlook

- General feature: Improved pre-viewing/pre-processing of experimental data.

  Interactive filtering and truncation of test results

- Partial DTW-based curve mapping

  DTW-LCS method

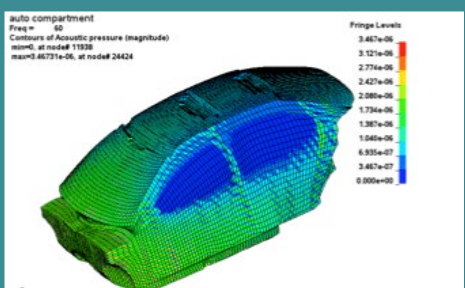
- Further speedup

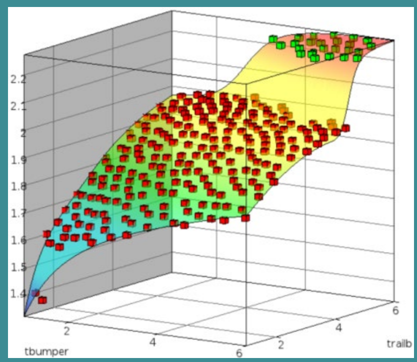
  Multiple similarity responses typically have the same mapping

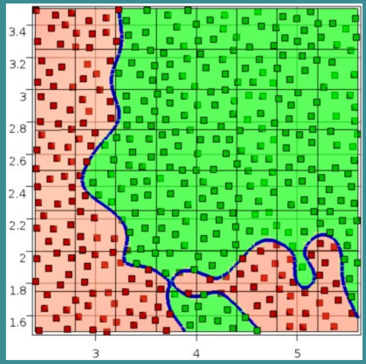
Applications & Potential of Classifiers In LS-OPT 6.0

Anirban Basudhar (LSTC),

K. Witowski (DYNAmore GmbH) , I. Gandikota, N. Stander, D. Kirpicev (LSTC)



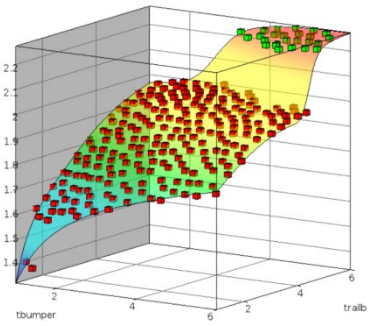




15th German LS-DYNA Forum, October 2018

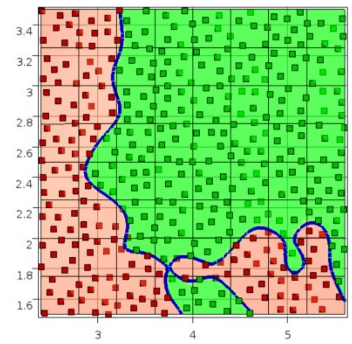
Overview

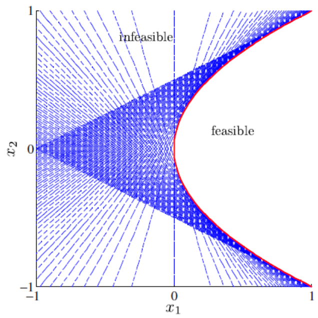
- Metamodeling Challenges



- Statistical Classification-based Constraint Definition in LS-OPT 6.0

- Support Vector Machines (SVM)



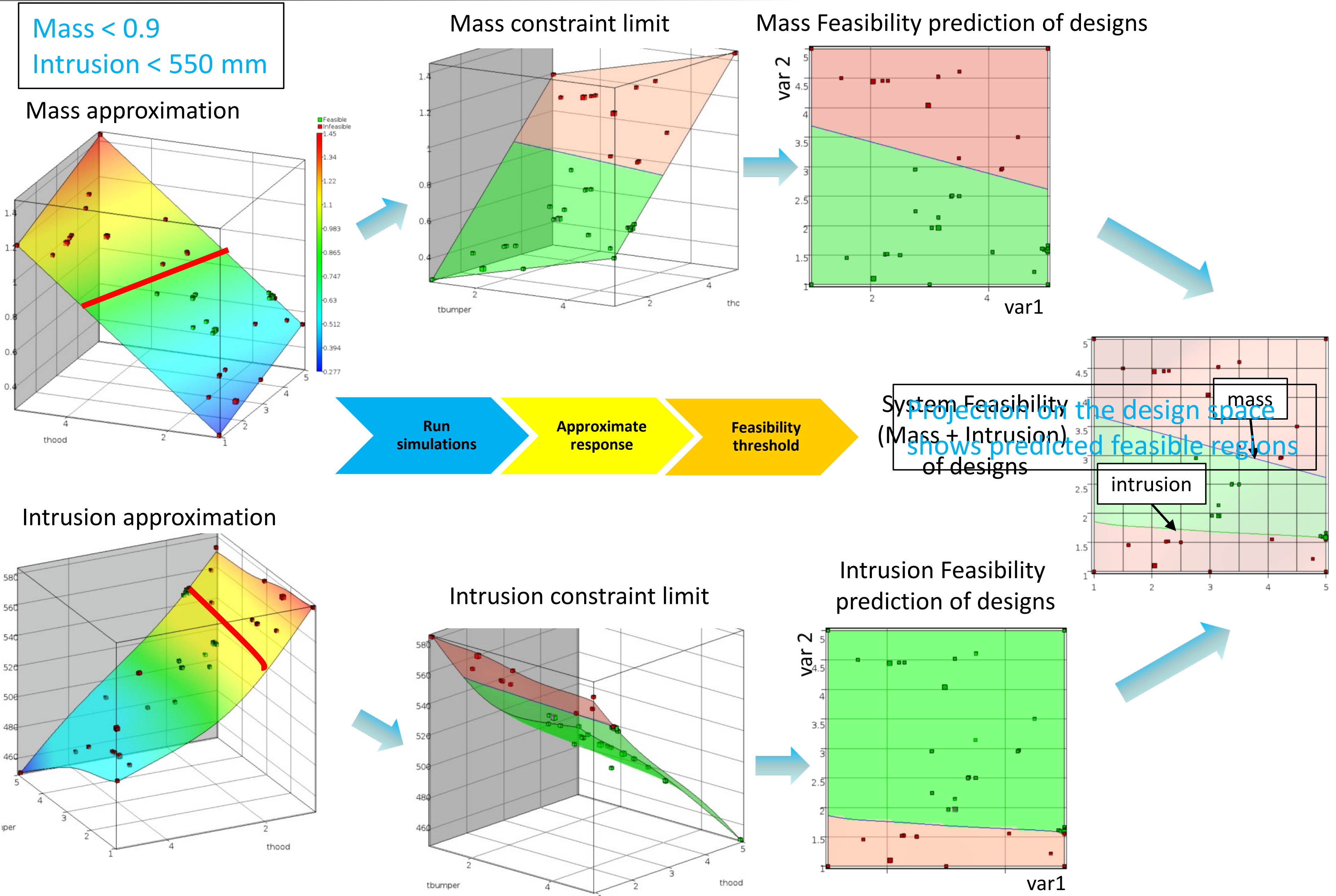


- Examples – discontinuous responses, hidden/binary constraints, multidisciplinary constraints, system reliability

- Future enhancements/Potential Applications/Summary

Constraint Approximation Using Metamodels

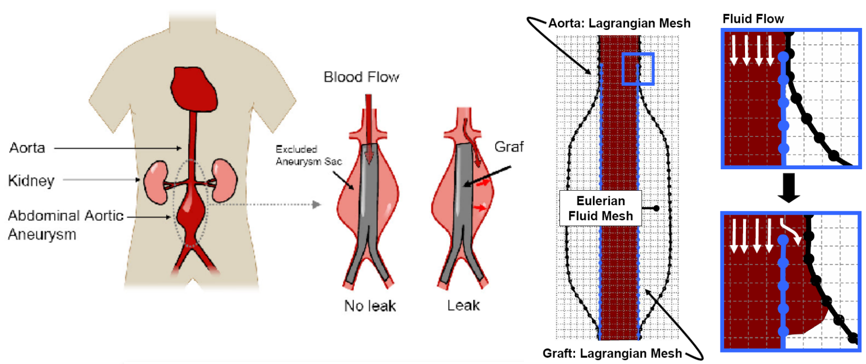
Mass < 0.9
Intrusion < 550 mm



Metamodeling Challenges

What if simulation does not provide quantifiable response values?
– Failed simulations
– Binary pass/fail information (e.g. 3rd party proprietary response values)
– Failure determined through prior experience

Biomedical Binary application (Blood leakage from Stent)



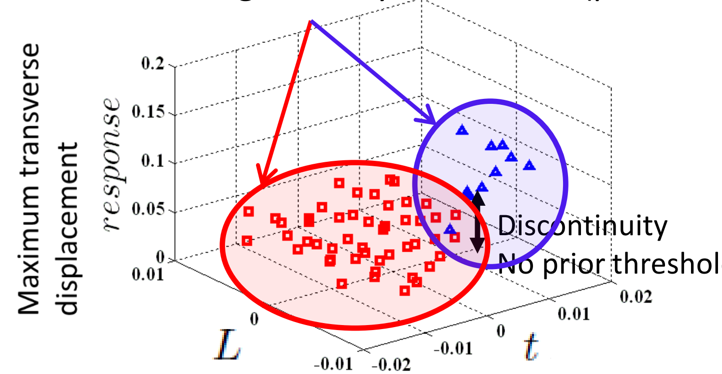
Binary information:

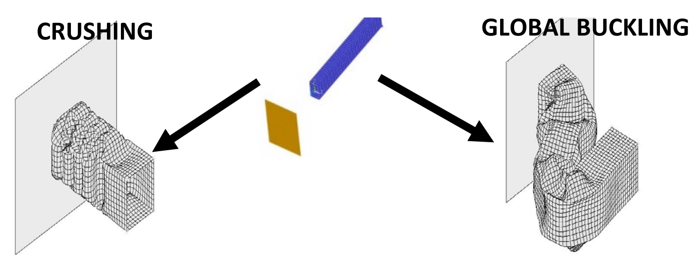
Failed (leaked) or not (no leakage)

Layman, R. et al. "Simulation and probabilistic failure prediction of grafts for aortic aneurysm." *Engineering Computations* 27.1 (2010): 84-105.

Discontinuity with unknown threshold

Clustering: Identify two classes (pass/fail)



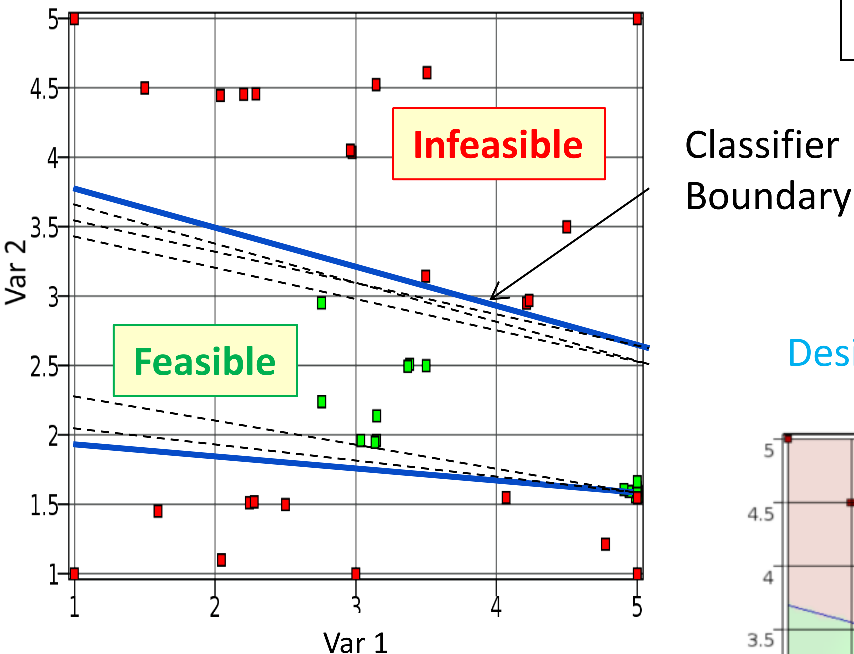


Basudhar, Anirban, and Samy Missoum. "A sampling-based approach for probabilistic design with random fields." *Computer Methods in Applied Mechanics and Engineering*198.47-48 (2009): 3647-3655.

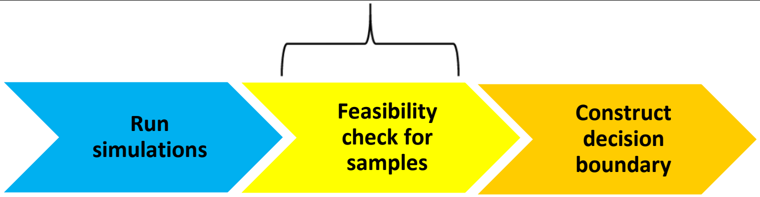
Conventional Metamodel Approximation Not Possible!

Constraint Boundary Using Classification

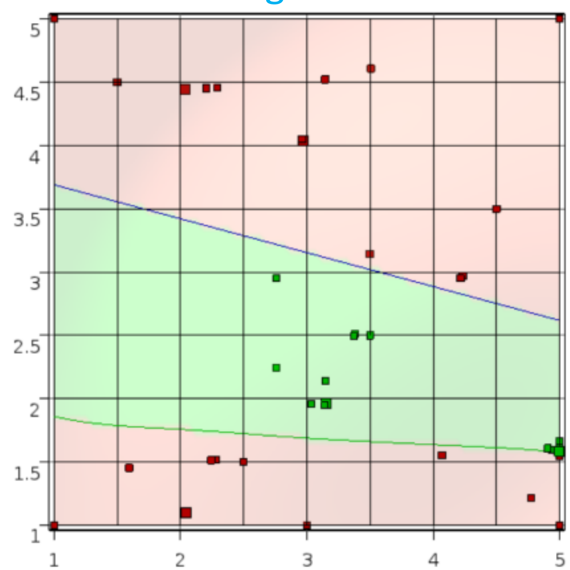
Design Space



Response value not necessary
when using classifier (only feasibility information)



Design Space Decomposition
Using LS-OPT



Pattern Recognition

Available Information:
– Design point (variable values)
– Feasibility of each design
(e.g. red vs green)

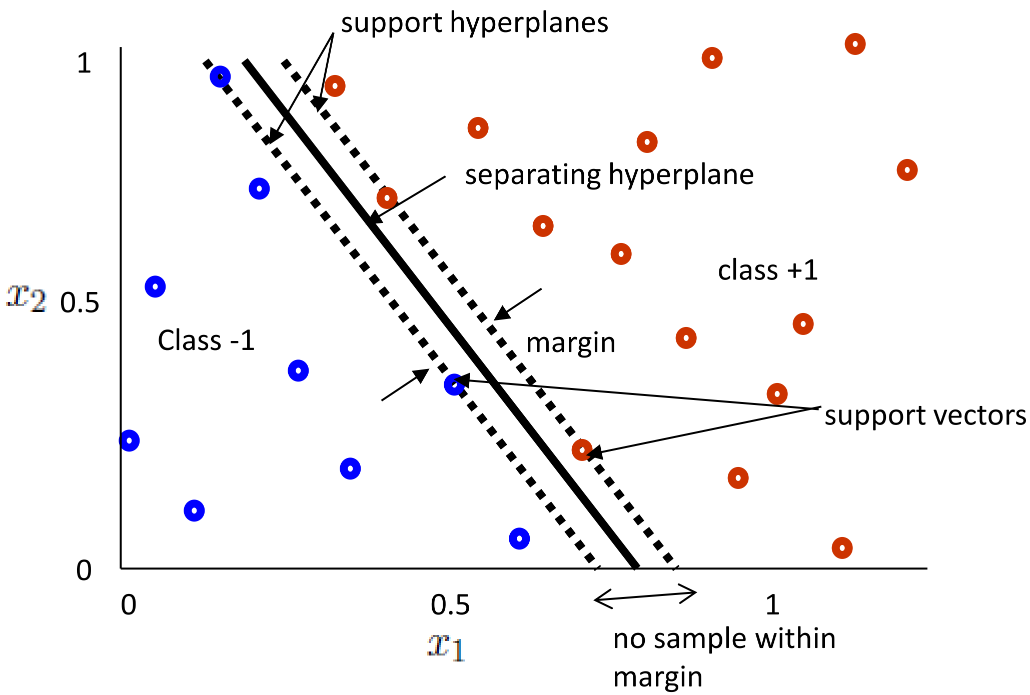
Examples:
- Simulation failure,
- 3rd party proprietary information
- Unknown threshold
- Combining experience with simulations etc.

Infinite number of boundaries possible!!

Need Optimal boundary

Optimal Boundaries Using Support Vector Machine

Machine learning technique for pattern recognition

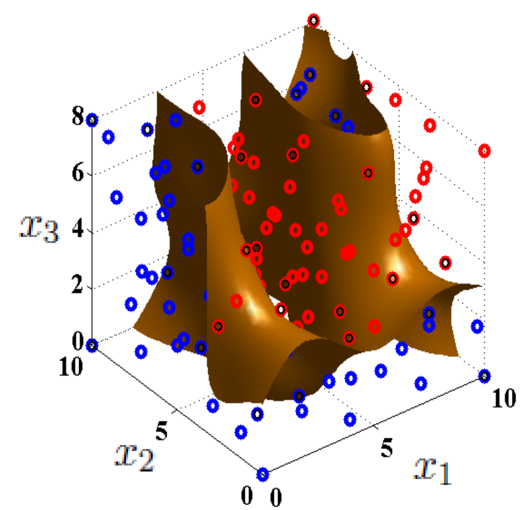


Optimal SVM maximizes the margin

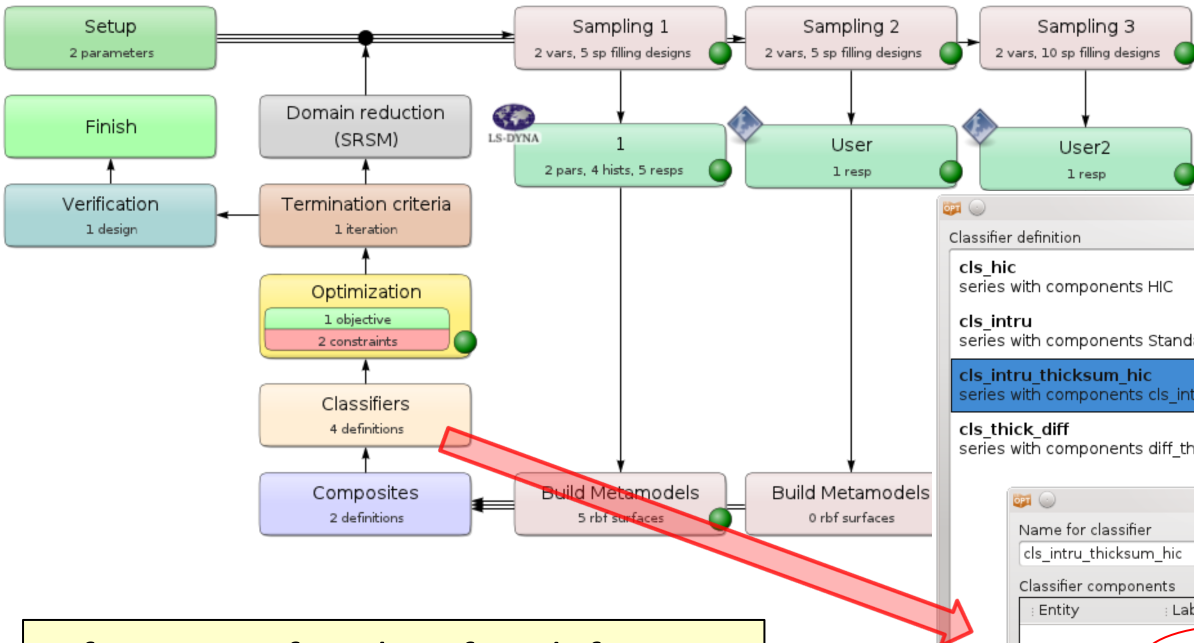
- Separating Hyperplane
  $s(\mathbf{x}) = \mathbf{w}.\mathbf{x} + b = 0$
- Support Hyperplanes
  $s(\mathbf{x}) = +1$ and $s(\mathbf{x}) = -1$
- Margin = $2/||\mathbf{w}||$

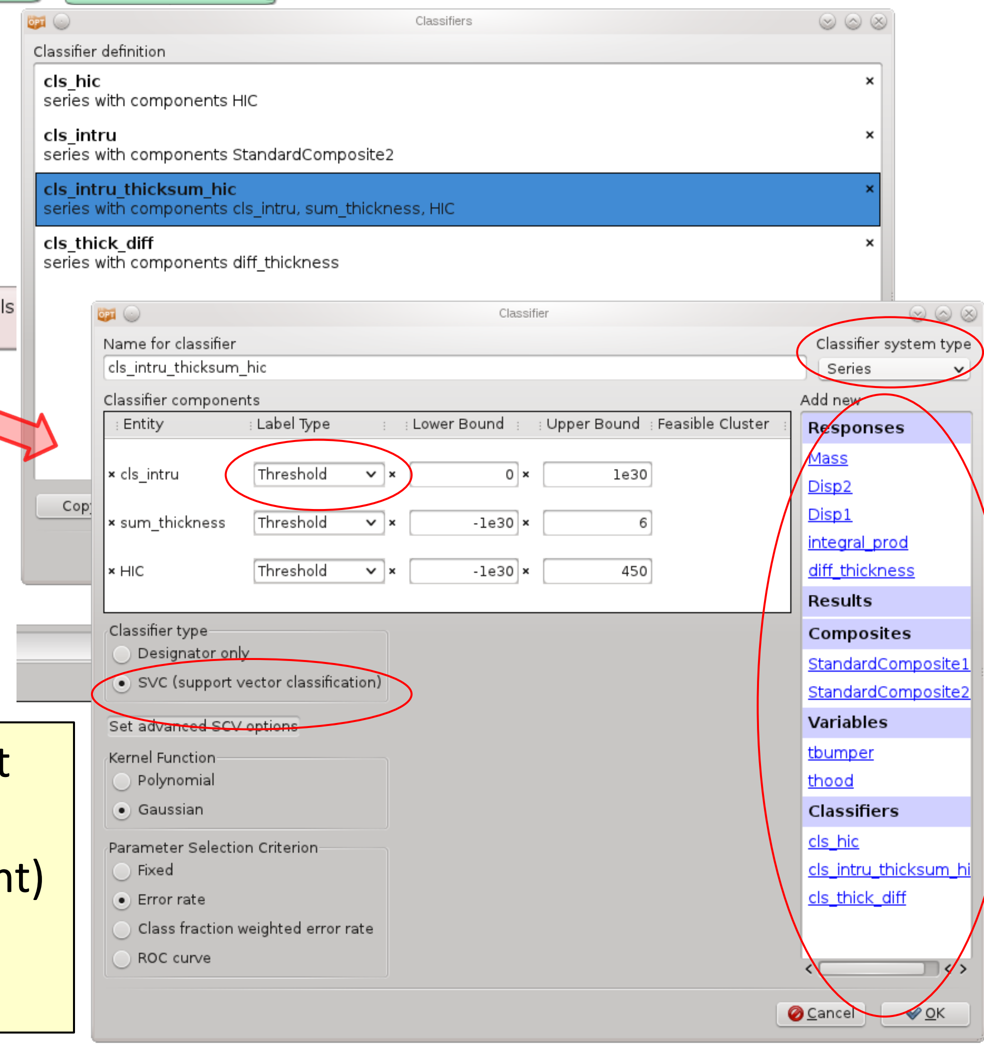
- General nonlinear separating function:

$$b + \sum_{i=1}^{NSV} \lambda_i y_i K(\mathrm{x}_i, \mathrm{x}) = 0$$



Classifier GUI In LS-OPT





Information for Classifier definition:

- Underlying response
- Feasibility criterion
- Classifier Type

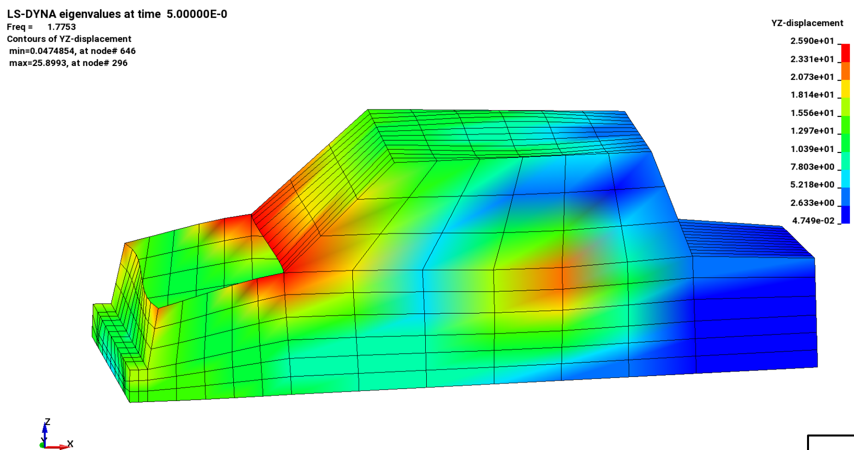
Any entity type can be a classifier component

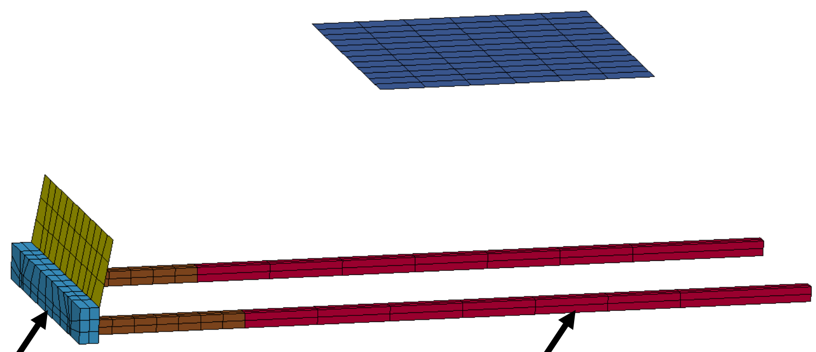
Classifiers can be nested (classifier component)

Classifiers can be series or parallel or mixed

Ex 1: Optimization with Discontinuous Constraint

Modal Analysis of a simple car - mode shape tracked to account for switching





Bumper thickness
tbumper

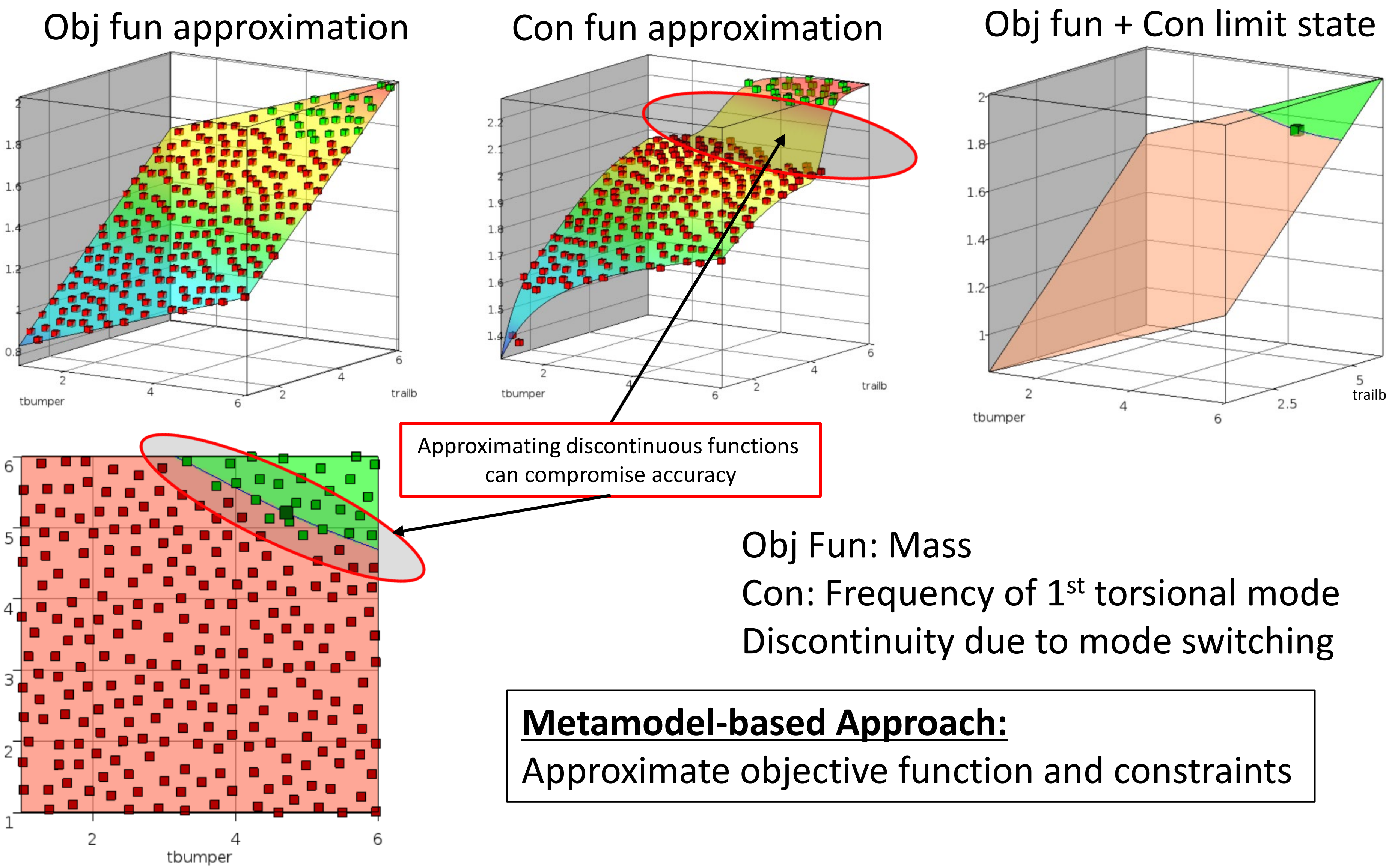
Back rail thickness
trailb

$$\min \quad Mass$$

$$s.t. \quad 1^{st} \text{ Torsional Mode Frequency} \geq 2.2$$

Mode switching causes discontinuity in the frequency response

Ex 1: Metamodel for Discontinuous Constraint



Obj Fun: Mass

Con: Frequency of 1^{st} torsional mode

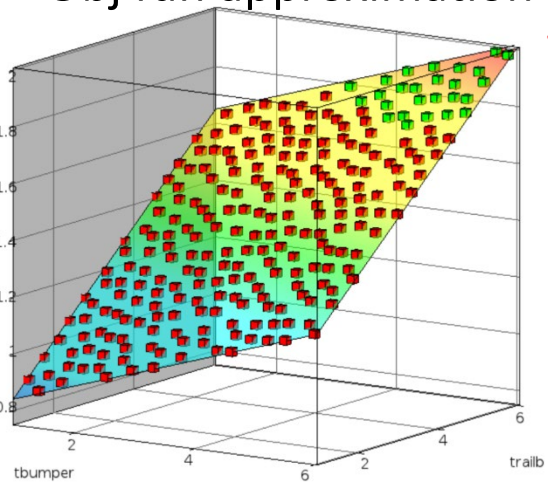
Discontinuity due to mode switching

Metamodel-based Approach:

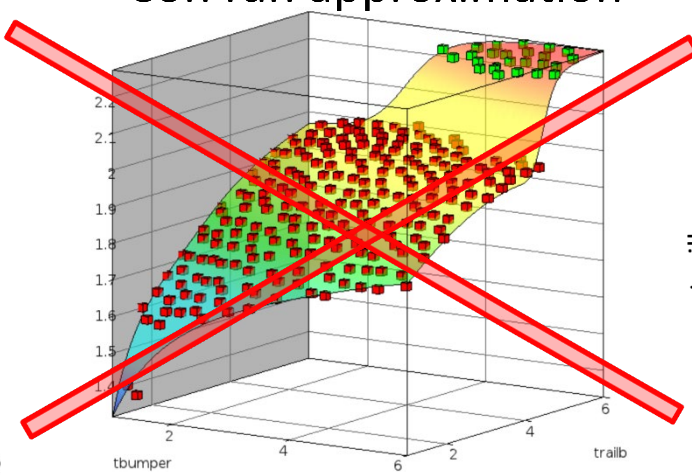
Approximate objective function and constraints

Ex 1: SVM Classifier for Discontinuous Constraint

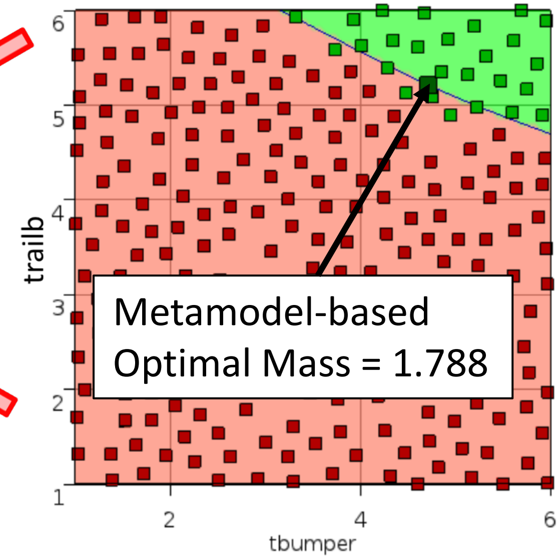
Obj fun approximation

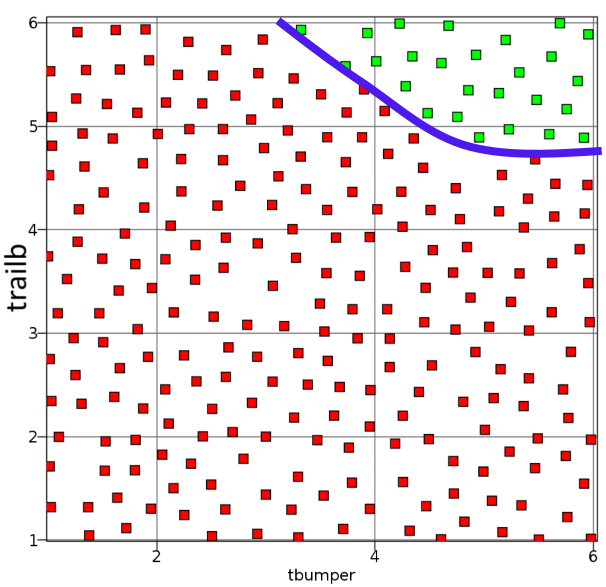


Con fun approximation

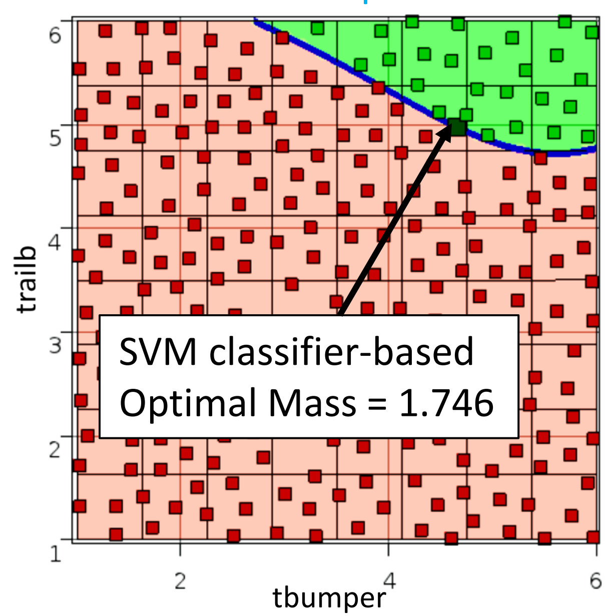


250 samples

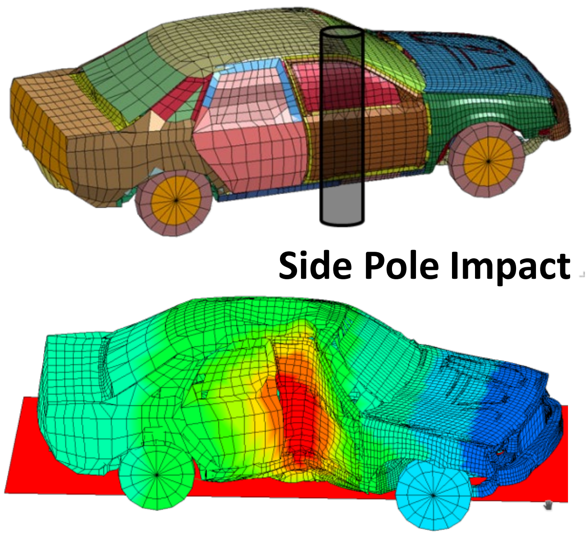




250 samples



Ex 2: Non-convex discontinuous constraint reliability



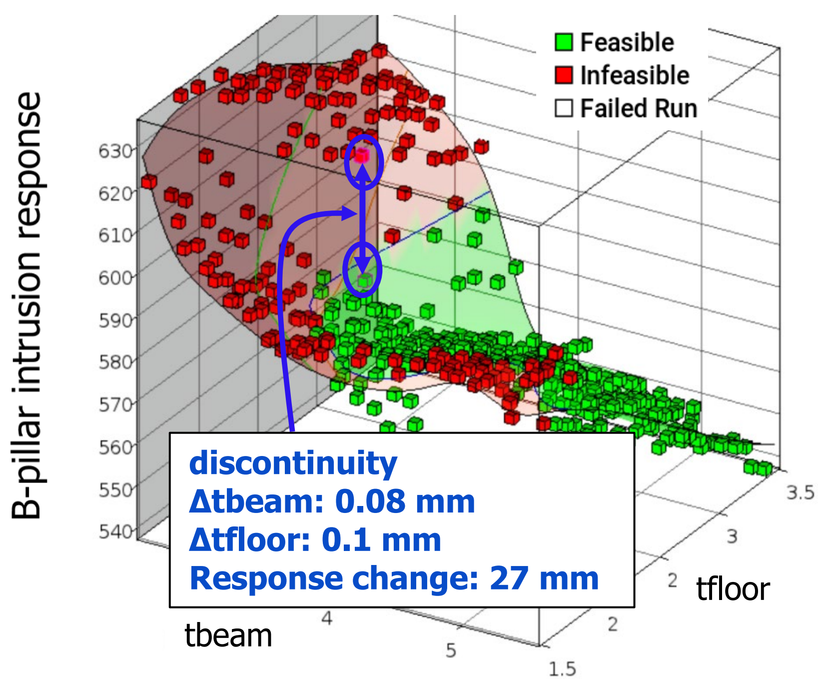
Reliability Assessment

B-pillar intrusion < 585 mm
Lower beam intrusion < 710 mm
Door intrusion < 638.23 mm

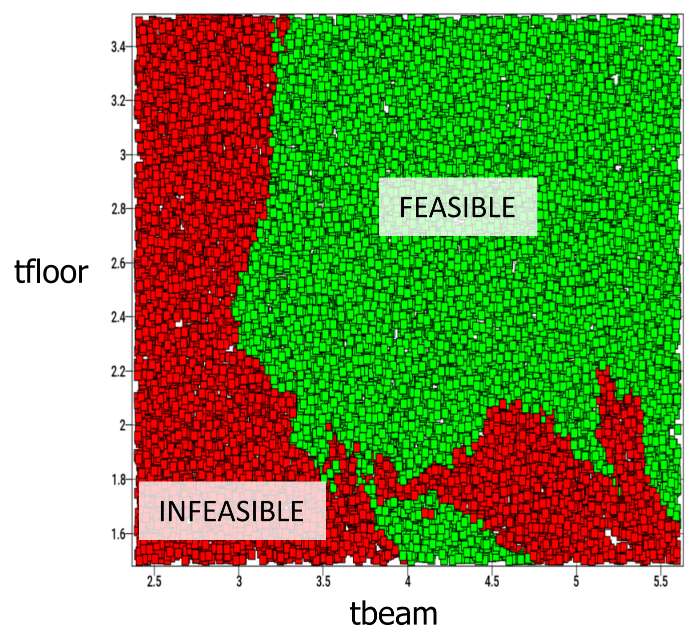
Random/Noise Variables:

Beam Thickness
tbeam N(4,0.4)

Floor Thickness
tfloor N(2.5,0.25)



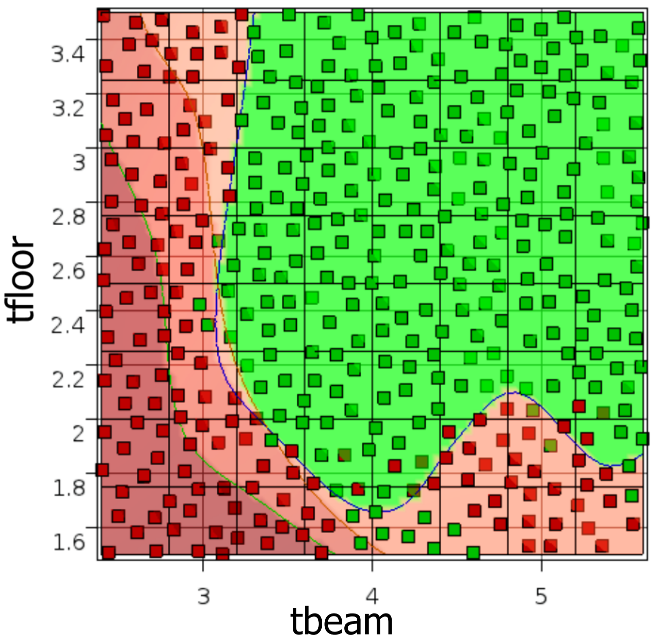
Actual constraint feasibility
(20,000 LS-DYNA runs)



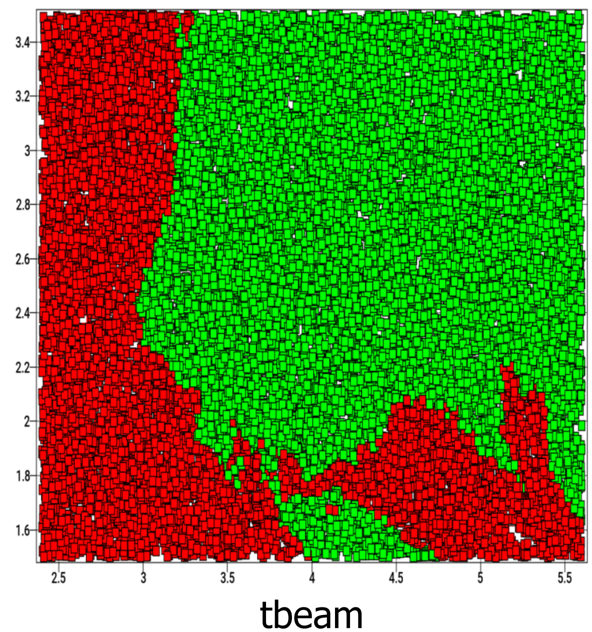
Ex 2: Non-convex discontinuous constraint reliability

- SVM able to approximate highly nonlinear boundaries accurately
- Single classifier represents 3 intrusion constraints (system reliability)

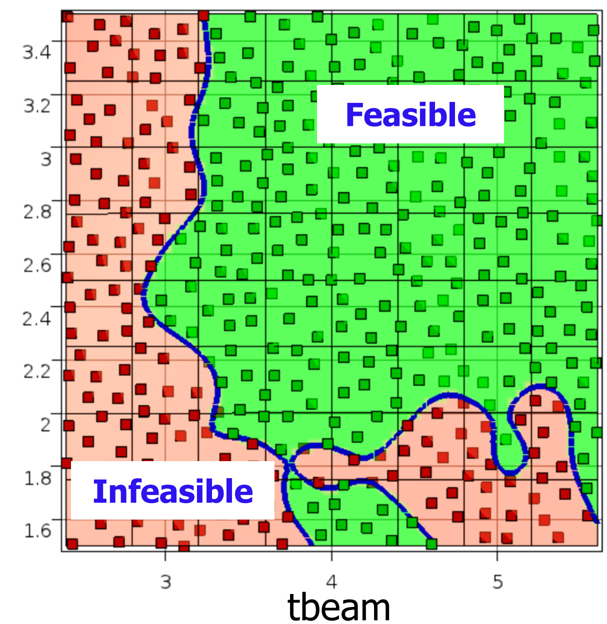
Failure probability using Neural Network Metamodel (400 samples): 0.0217
Failure probability using SVM Classifier (400 samples): 0.0218
Actual Failure probability: 0.0219



Neural net approximation of constraint (inaccurate)



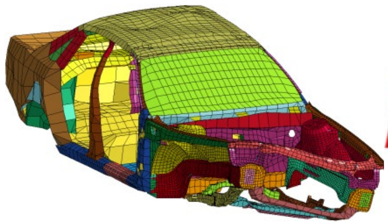
Actual constraint feasibility (LS-DYNA)

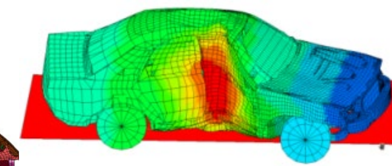


SVM classifier-based constraint (accurate)

Ex 3: 2-disciplinary System Reliability (Unequal Costs)

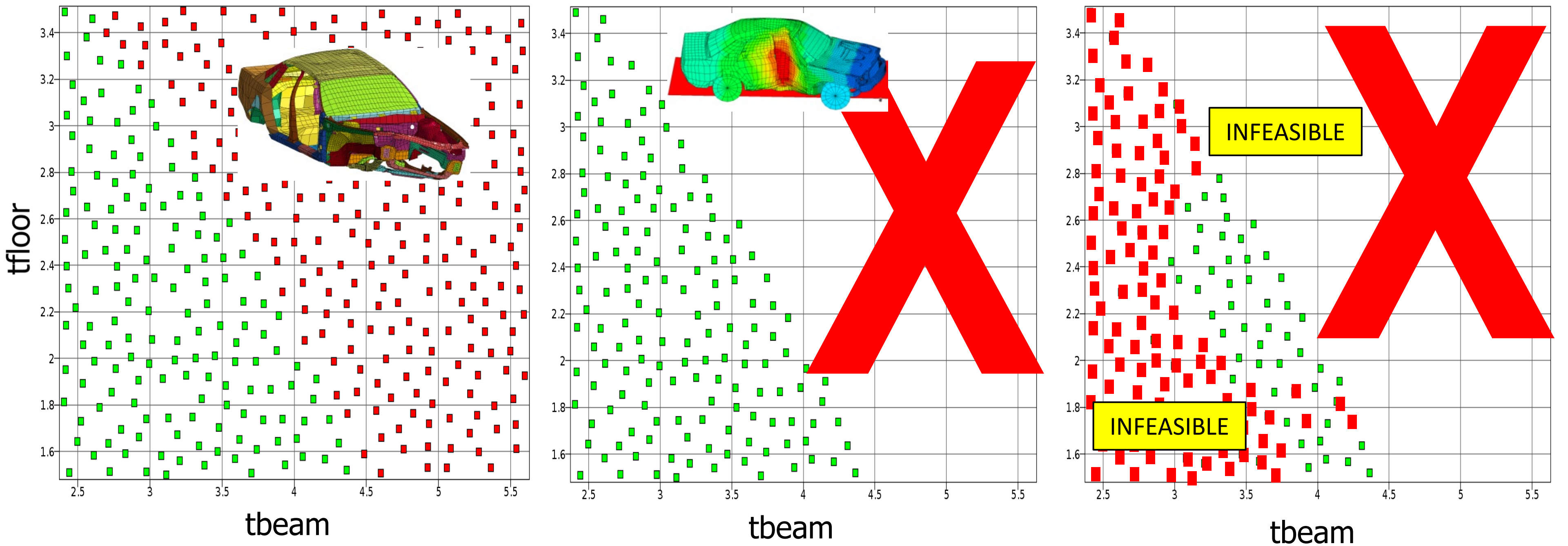
- Torsional mode frequency constraint added (frequency > 41.6)
- NVH analysis followed by crash analysis
- Because classifier is used, *crash analysis needed only at feasible NVH points*
- Crash simulation savings: 246 out of 400 (61.5 %)





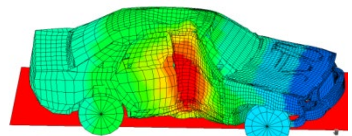
NVH Samples (400)

Crash Samples (154)

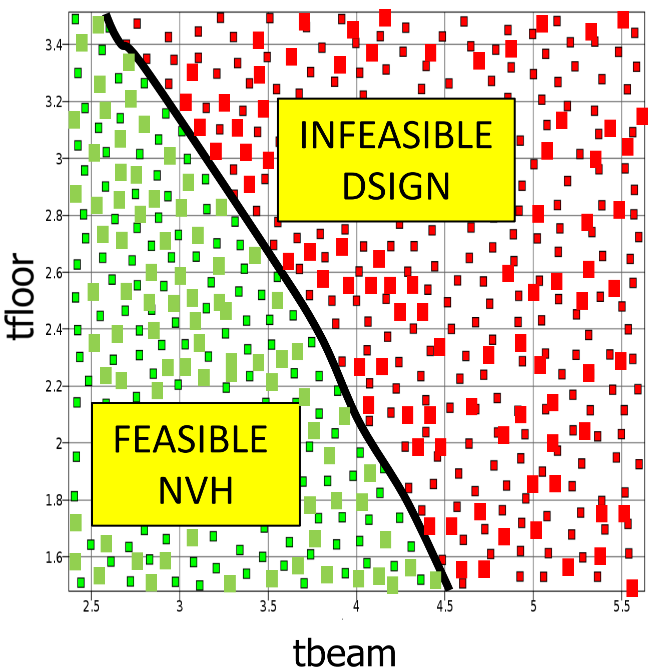


Ex 3: 2-disciplinary System Reliability (Unequal Costs)

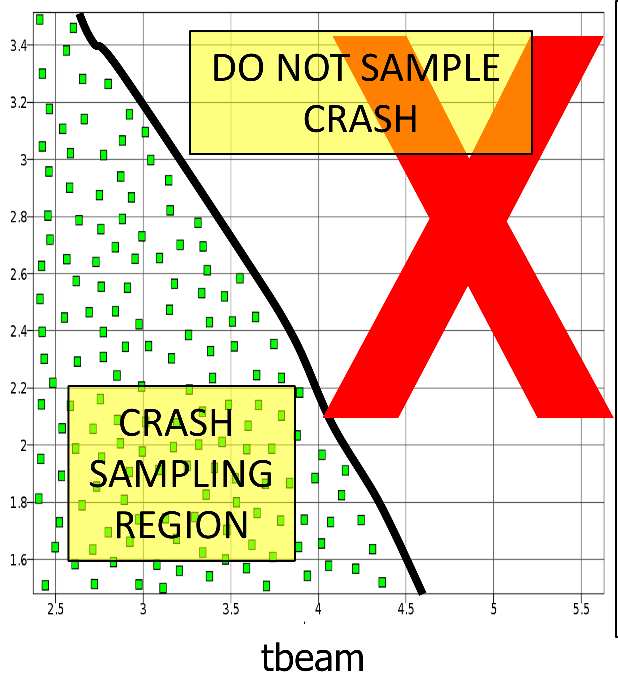
- We can get a very accurate decision boundary for inexpensive load cases
- Expensive cases sampled within the domain defined by the classifier



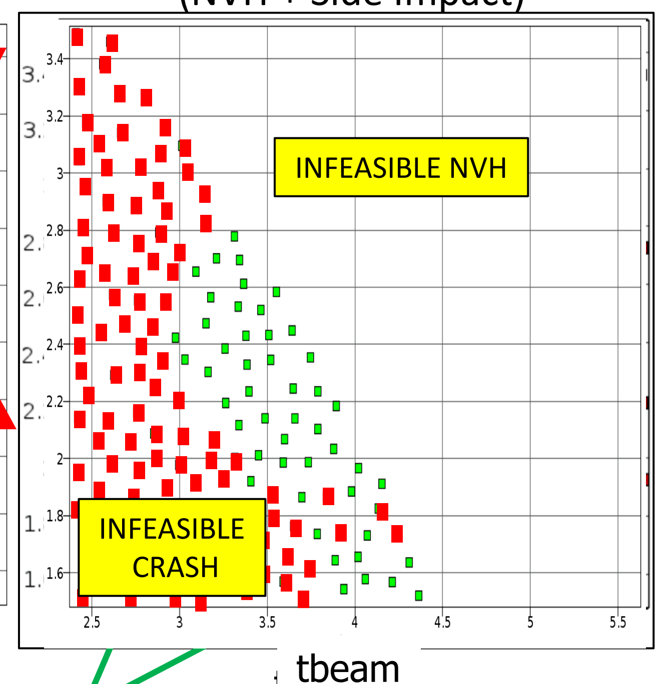
NVH Samples (400+)



Crash Samples (154)

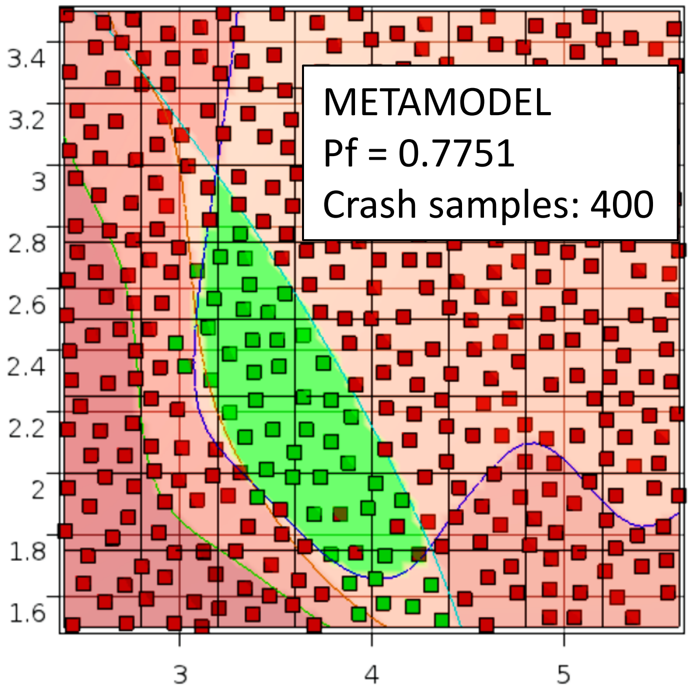


Dual-disciplinary Classification
(NVH + Side Impact)

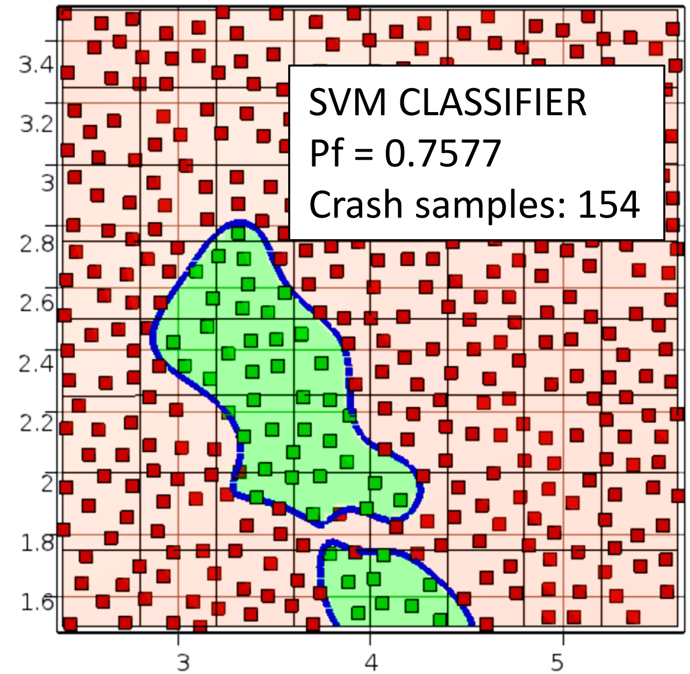


Sampling region for subsequent load case

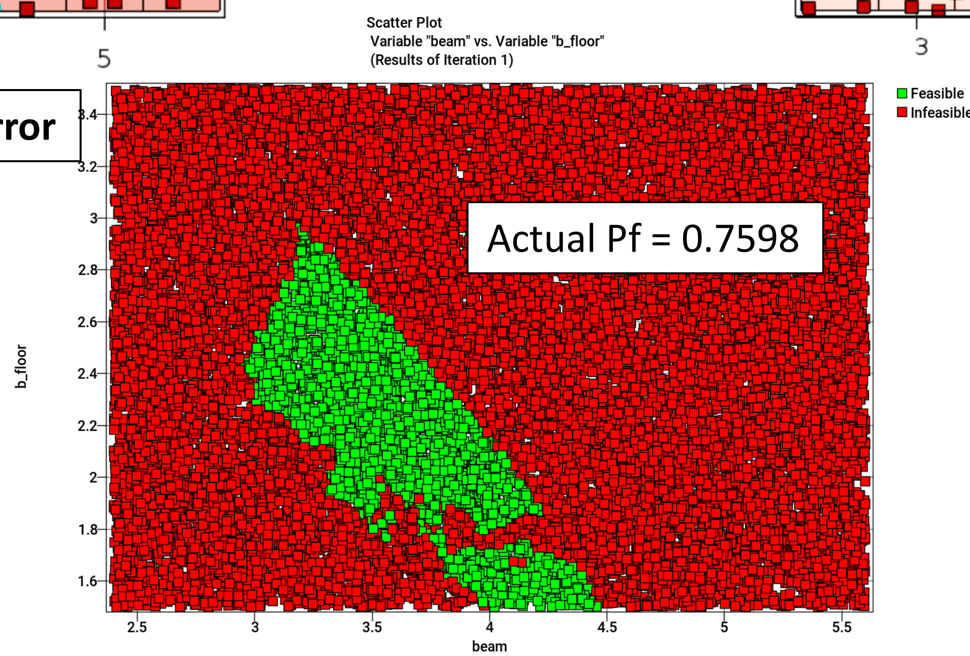
Ex 3: 2-disciplinary Constraint Comparison



Metamodel: 2.01% error



Classifier: 0.28% error

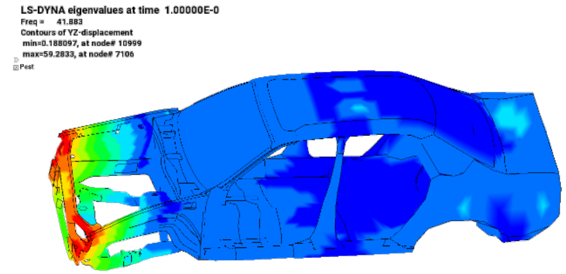


Ex 4: Multidisciplinary Optimization (MDO) Cost Savings

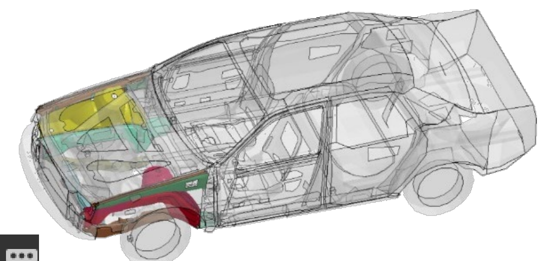
$$
\begin{aligned}
&min && Mass\,(x_{1,2..7}) \\
&s.t. && 41.38Hz < b_{freq} < 42.38Hz \\
& && Stage\ 1\ pulse > 13.94g \\
& && Stage\ 2\ pulse > 19.17g \\
& && Stage\ 3\ pulse > 21.3g
\end{aligned}
$$

where

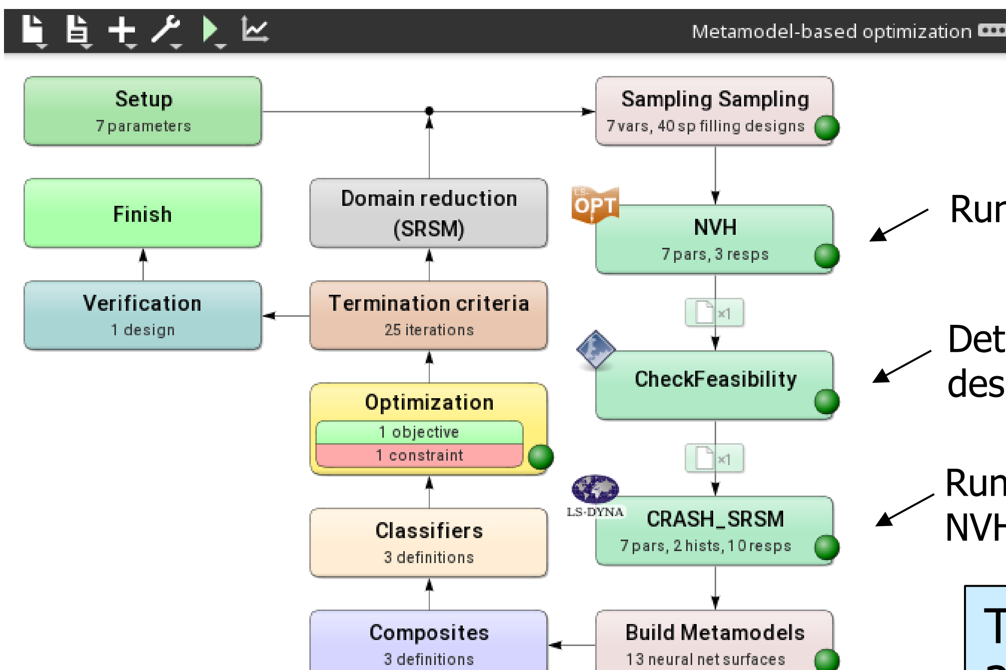
- $x_{1,2..7}$ *are the design* part thicknesses
- b_{freq} *is the first torsional frequency*



Baseline Torsional Mode



Crash model and MDO design parts



Run cheaper NVH analysis first

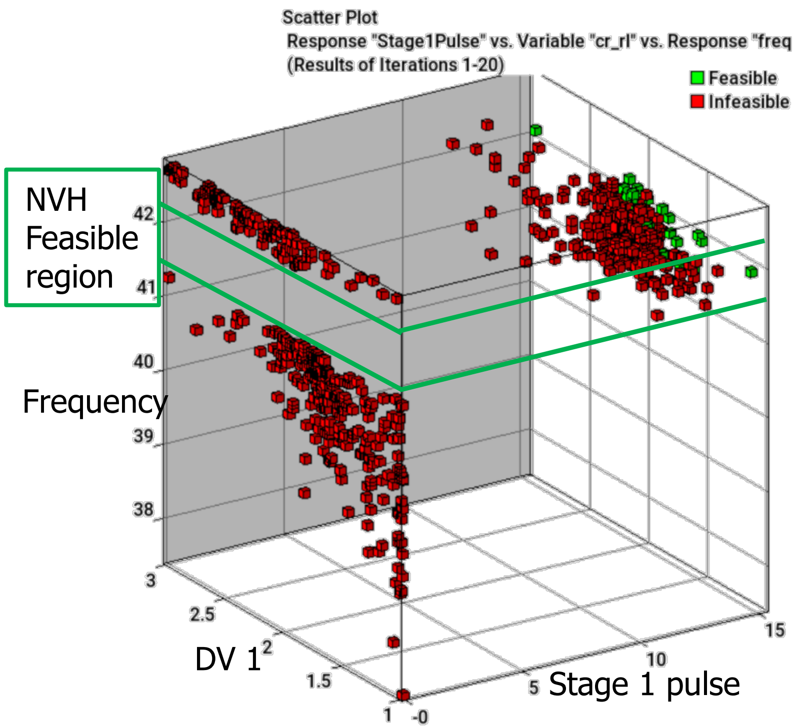
Determine feasibility of the NVH designs

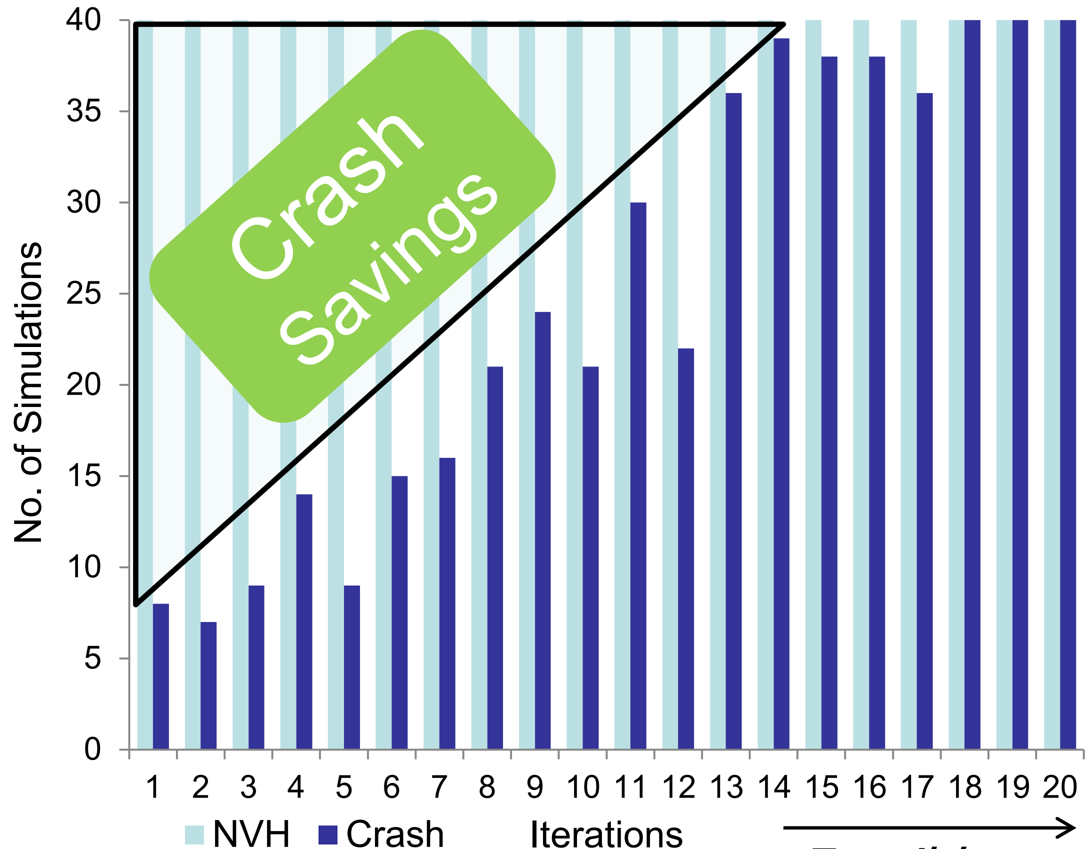
Run crash analysis only for feasible NVH designs

Total crash runs saved: 297 (37%)

Ex 4: Multidisciplinary Optimization (MDO) Cost Savings

Computation cost savings using classifiers





Feasible NVH sub domain

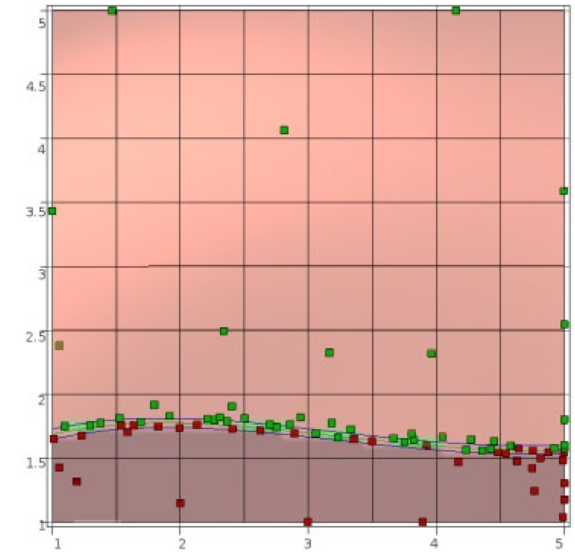
Load Case	Runs per iteration	Total runs (without classifiers)	Total runs using classifiers	Savings
NVH	40	800	800	0
Crash	40	800	503	297 (37%)

Other Applications & Enhancements

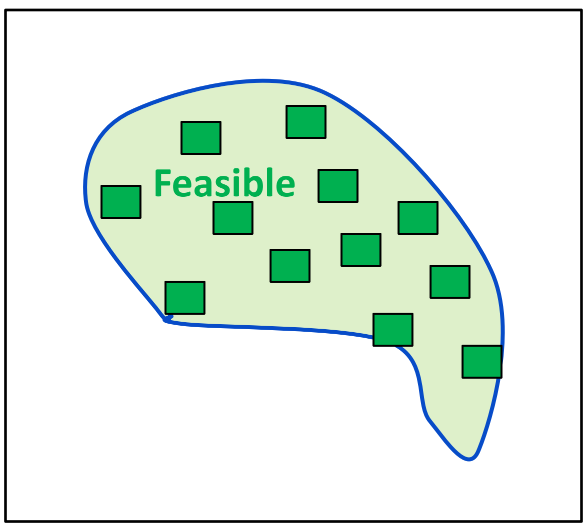
Adaptive Sampling

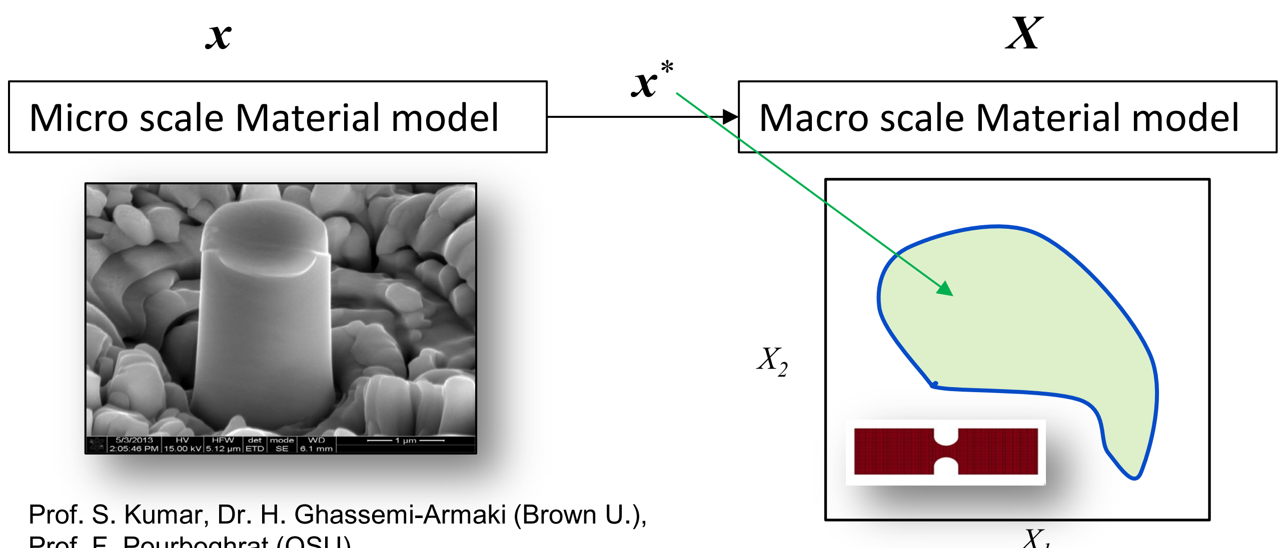
- Sampling near classifier boundary

Basudhar, Anirban, and Samy Missoum. "An improved adaptive sampling scheme for the construction of explicit boundaries." *Structural and Multidisciplinary Optimization* 42.4 (2010): 517-529.



- Sampling the feasible regions

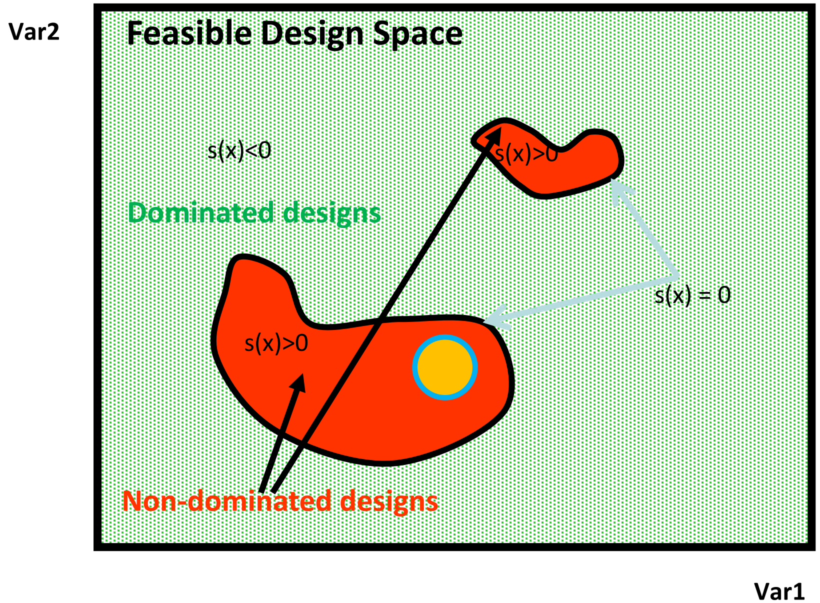




Prof. S. Kumar, Dr. H. Ghassemi-Armaki (Brown U.),
Prof. F. Pourboghrat (OSU)

Other Applications & Enhancements

Adaptive Explicit Multi-Objective Optimization (MOO)



Basudhar, Anirban. "Multi-objective Optimization Using Adaptive Explicit Non-Dominated Region Sampling." *11th World Congress on Structural and Multidisciplinary Optimization*. 2015.

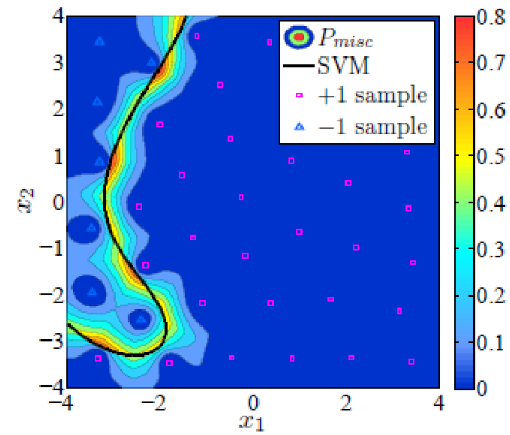
MOO considered as a classification problem:

DOMINATED vs NON-DOMINATED

Other Applications & Enhancements

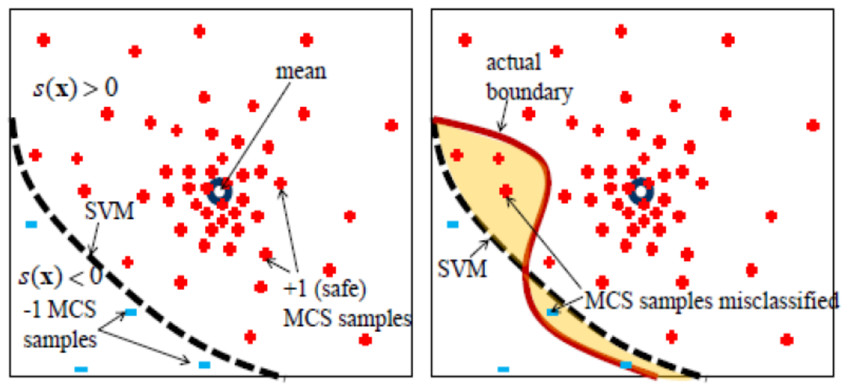
Probabilistic Classifiers

- Constrained Efficient Global Optimization



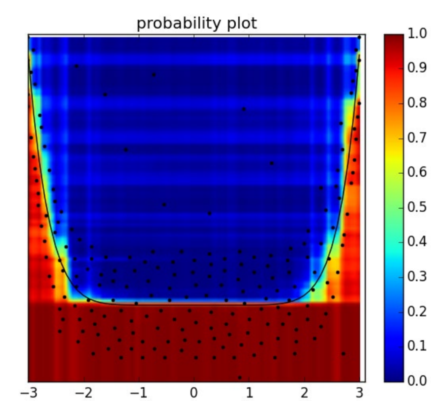
Basudhar, Anirban, et al. "Constrained efficient global optimization with support vector machines." *Structural and Multidisciplinary Optimization* 46.2 (2012): 201-221.

- Conservative Failure Probability Estimate



Basudhar, Anirban, and Samy Missoum. "Reliability assessment using probabilistic support vector machines." *International Journal of Reliability and Safety* 7.2 (2013): 156-173.

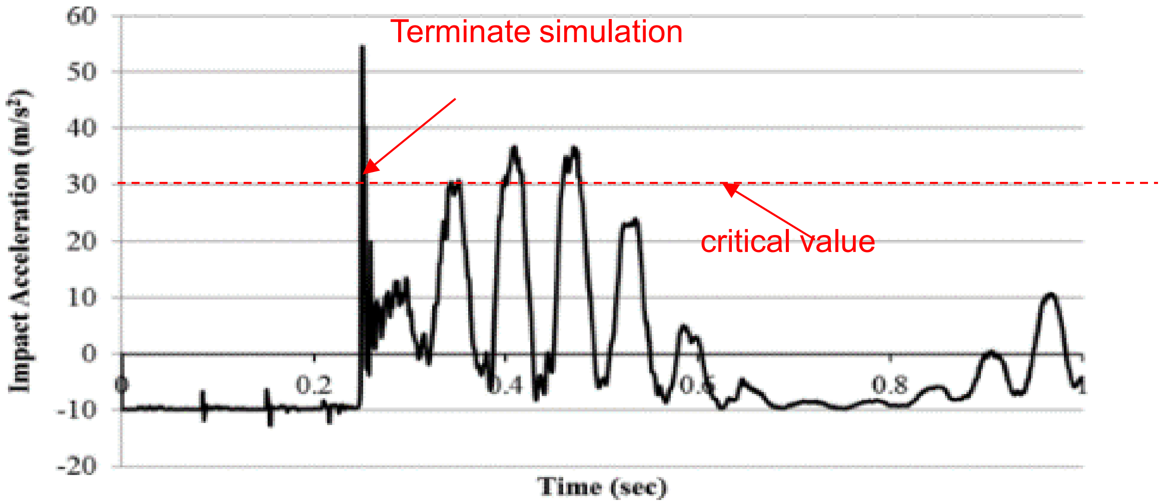
- Probabilistic SVM, Random Forest Classifier



Other Applications & Enhancements

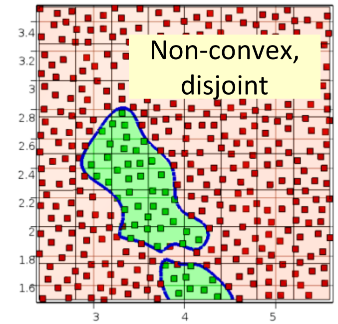
Adaptive simulation time reduction

Check failure criteria during simulation

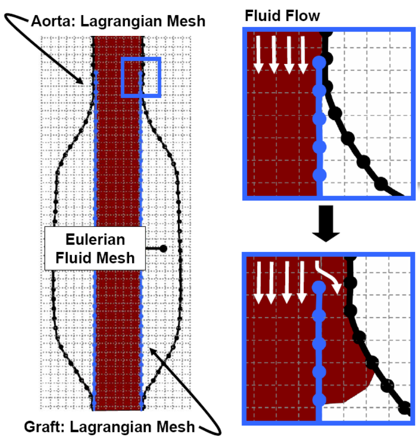


Summary

- Classifier-based constraint definition method in LS-OPT 6.0



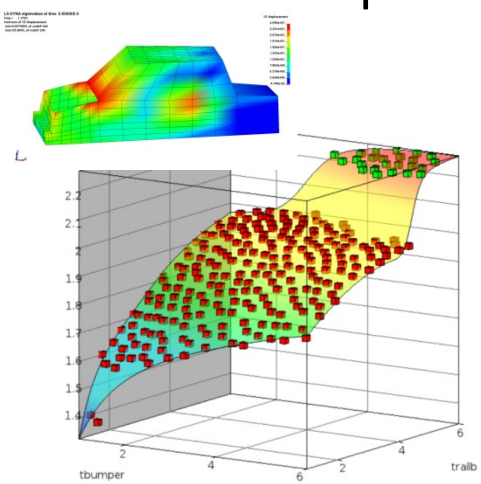
- Support Vector Machines used for classification
- Benefits shown for binary/discontinuous response & MDA/MDO

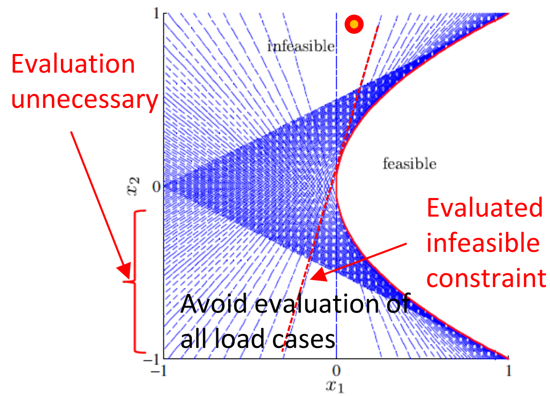


Binary information:

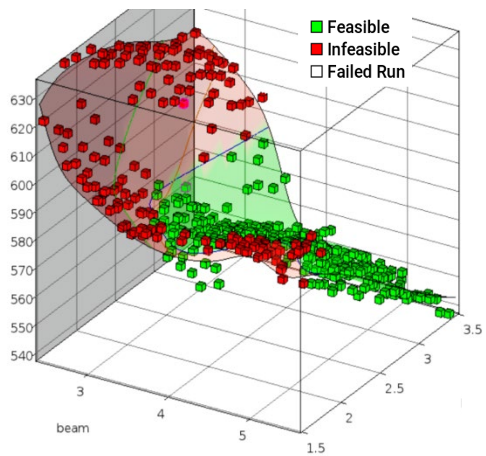
Failed (leaked) or not (no leakage)

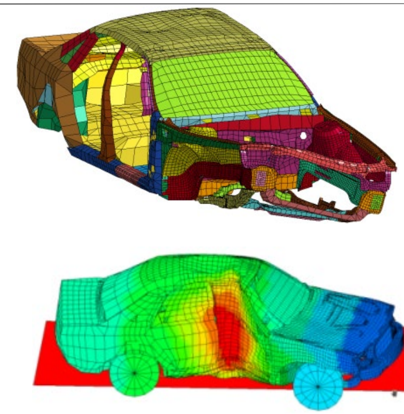
Layman, R. et al. "Simulation and probabilistic failure prediction of grafts for aortic aneurysm." *Engineering Computations* 27.1 (2010): 84-105.

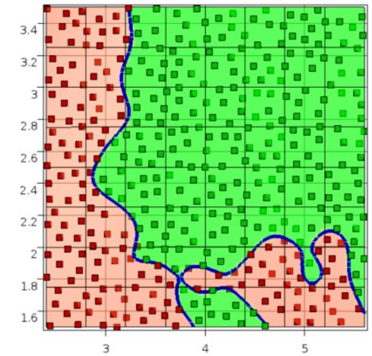


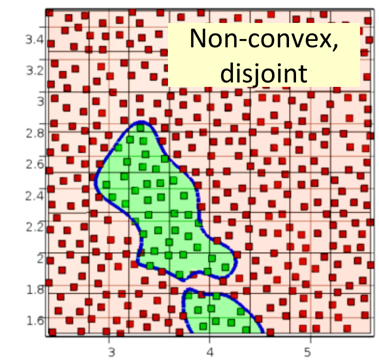


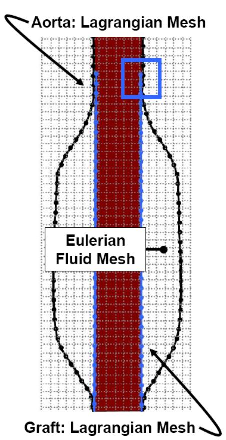
- Series/parallel or mixed system constraints can be defined
- Classifiers can be used for optimization or for reliability

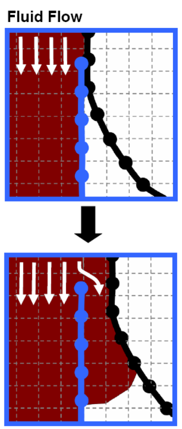

Feasible
Infeasible
Failed Run
beam



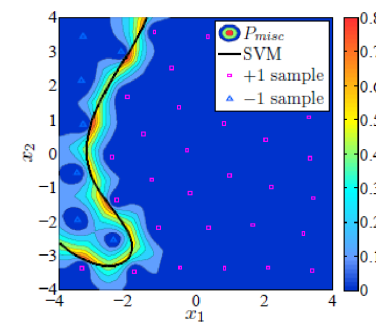


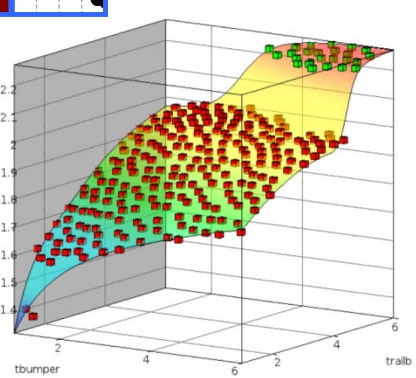

Non-convex,
disjoint

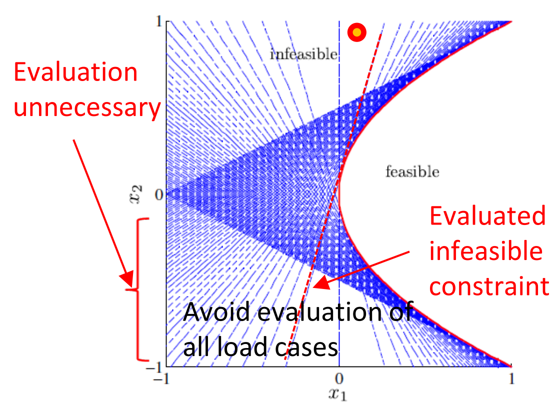

Aorta: Lagrangian Mesh
Eulerian
Fluid Mesh
Graft: Lagrangian Mesh

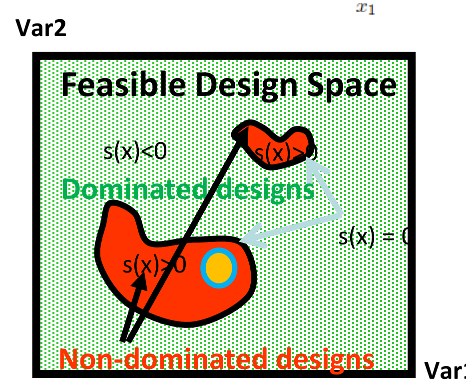

Fluid Flow

THANK YOU!


P_{misc}
SVM
+1 sample
−1 sample
x_1
x_2


tbumper
trailb


Evaluation
unnecessary
infeasible
feasible
Evaluated
infeasible
constraint
Avoid evaluation of
all load cases
x_1
x_2


Var2
Feasible Design Space
s(x)<0
s(x)>0
Dominated designs
s(x) = 0
s(x)>0
Non-dominated designs
Var1