Applications & Potential of Classifiers In LS-OPT 6.0

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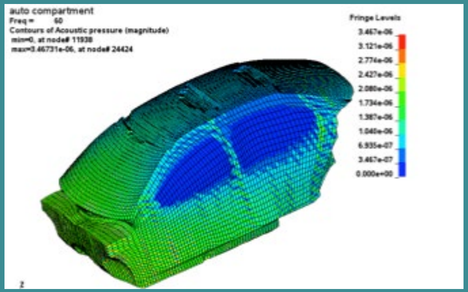
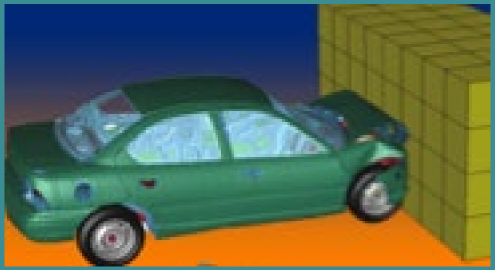
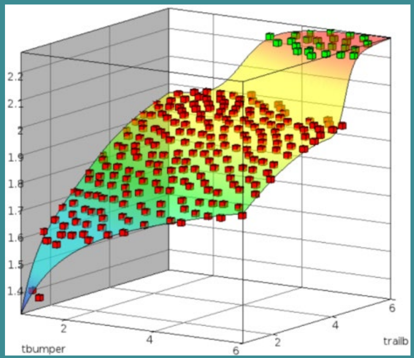
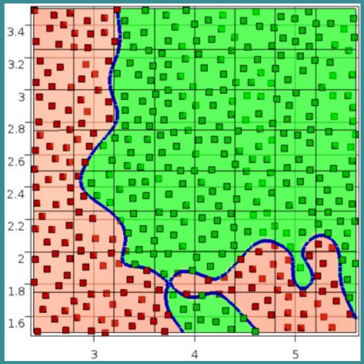




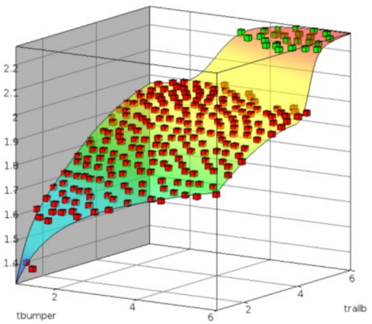




15th German LS-DYNA Forum, October 2018

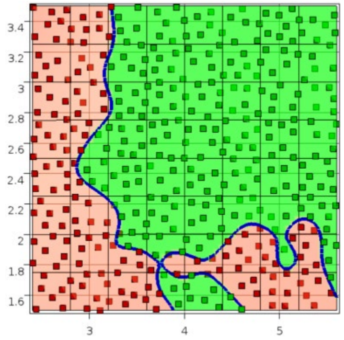
Overview

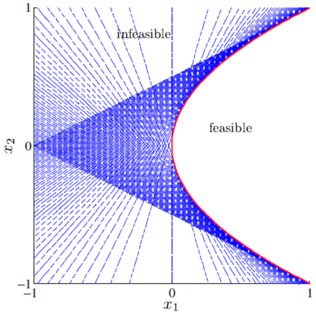
- Metamodeling Challenges



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

- Support Vector Machines (SVM)



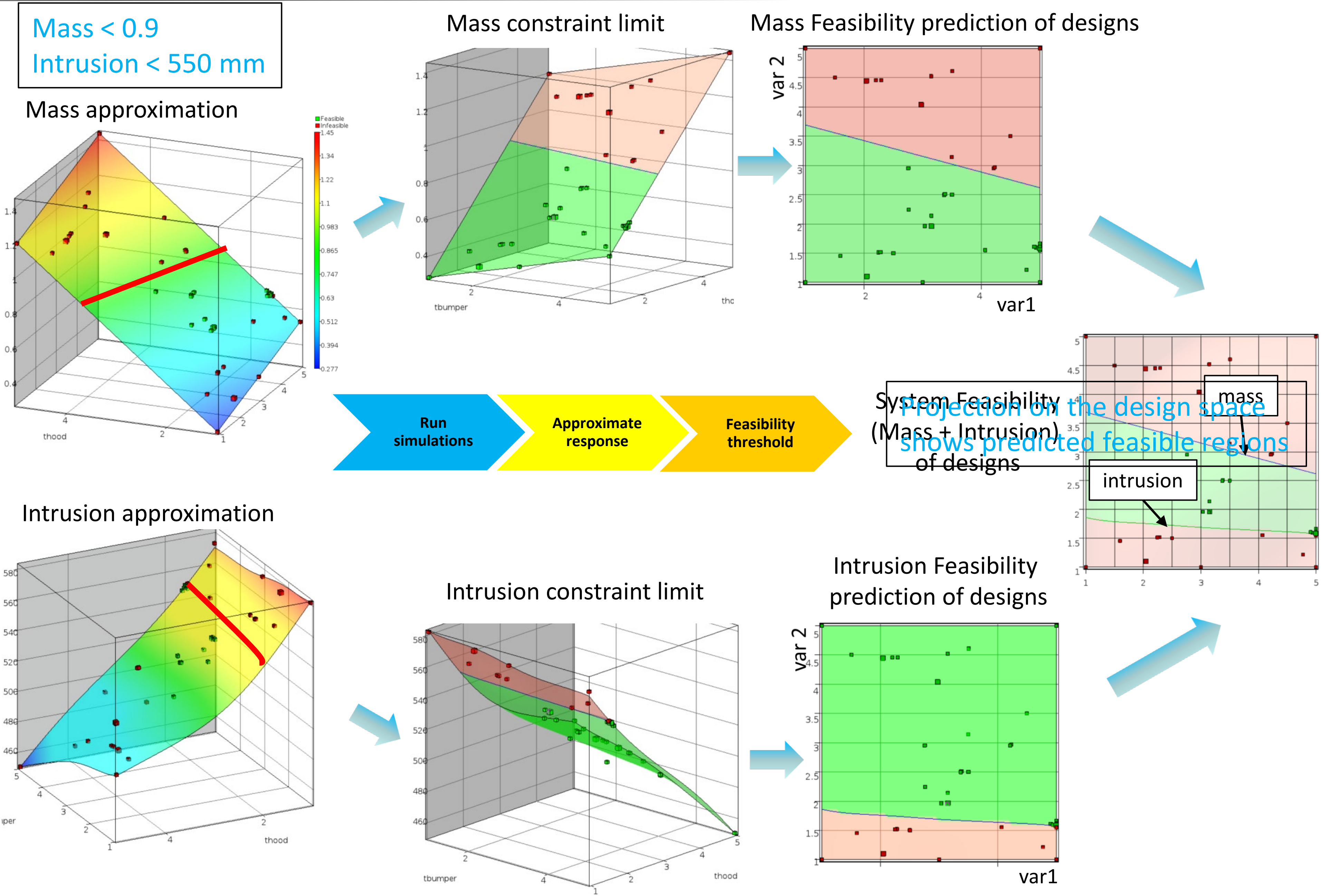


- Examples – discontinuous responses, hidden/binary constraints, multidisciplinary constraints, system reliability

- Future enhancements/Potential Applications/Summary

Constraint Approximation Using Metamodels

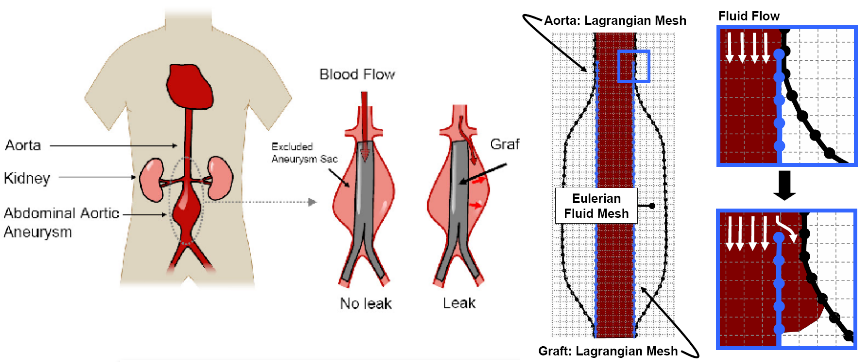
Mass < 0.9
Intrusion < 550 mm



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)



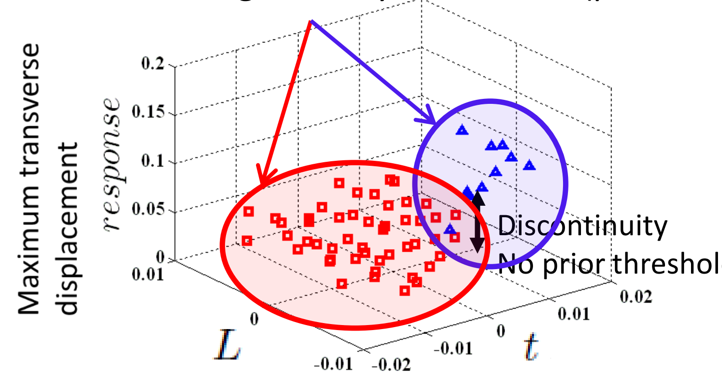
Binary information:

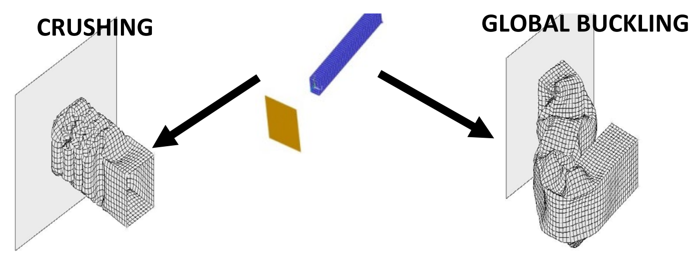
Failed (leaked) or not (no leakage)

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)



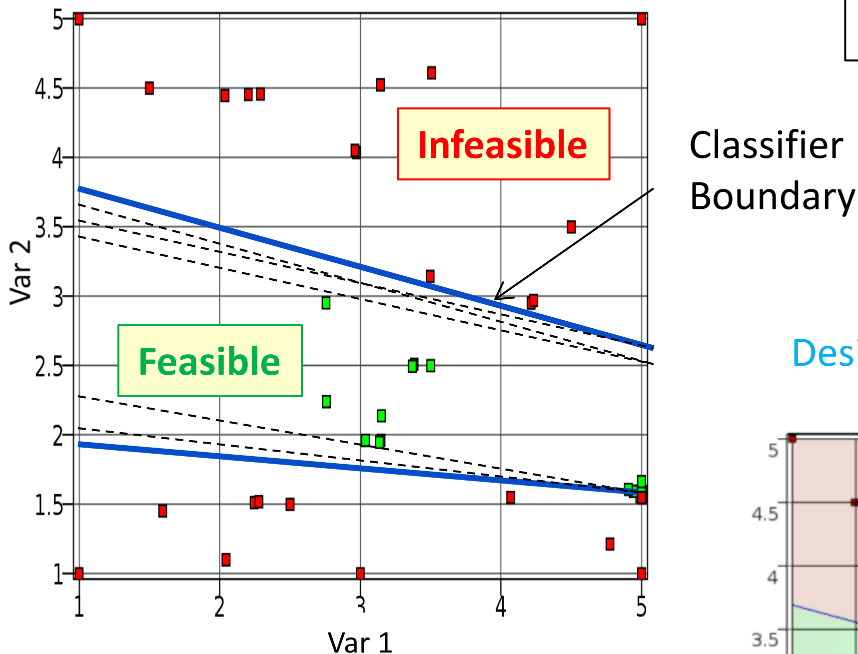


Basudhar, Anirban, and Samy Missoum. "A sampling-based approach for probabilistic design with random fields." *Computer Methods in Applied Mechanics and Engineering* 198.47-48 (2009): 3647-3655.

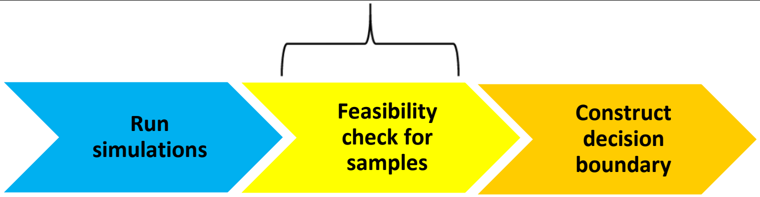
Conventional Metamodel Approximation Not Possible!

Constraint Boundary Using Classification

Design Space



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



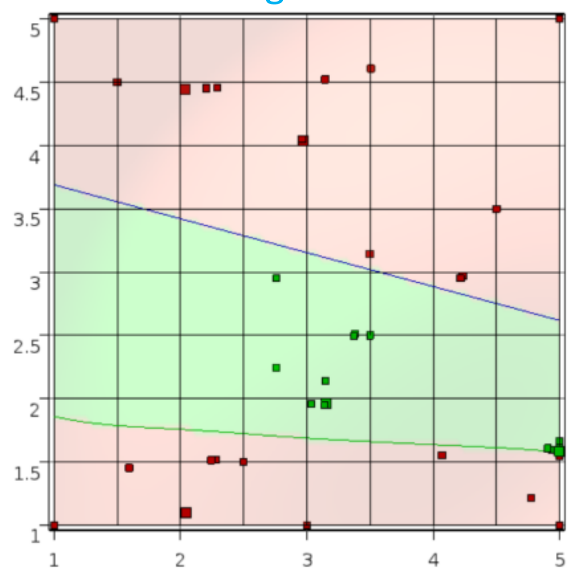
Available Information:

- 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.

Design Space Decomposition Using LS-OPT



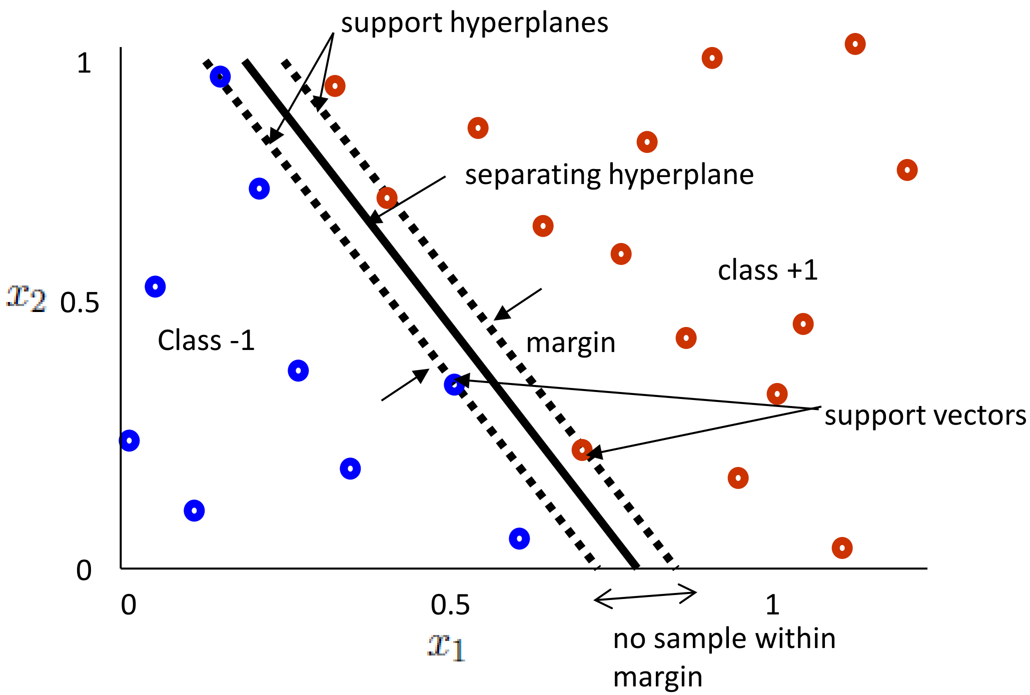
Pattern Recognition

Infinite number of boundaries possible!!

Need Optimal boundary

Optimal Boundaries Using Support Vector Machine

Machine learning technique for pattern recognition

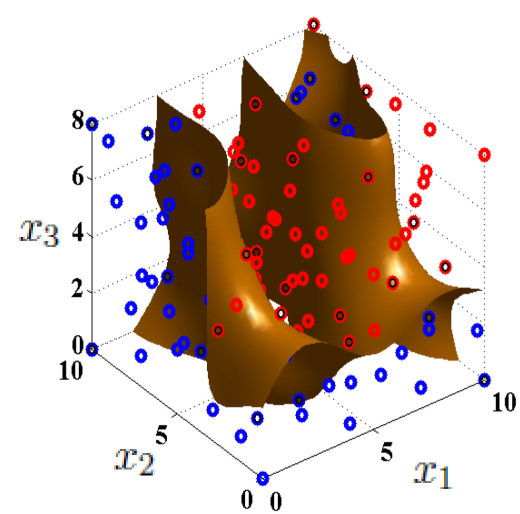


Optimal SVM maximizes the margin

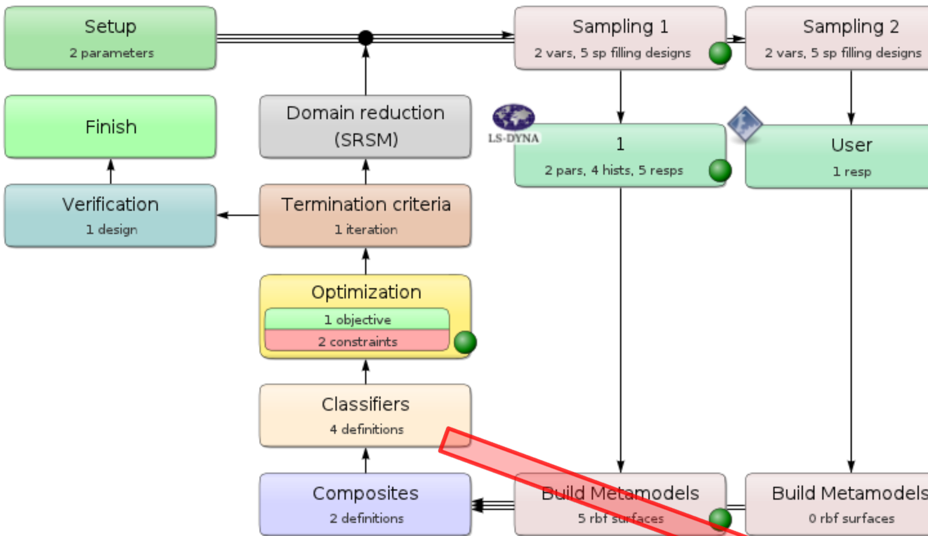
- Separating Hyperplane
  $s(\mathbf{x}) = \mathbf{w}.\mathbf{x} + b = 0$
- Support Hyperplanes
  $s(\mathbf{x}) = +1$ and $s(\mathbf{x}) = -1$
- Margin = $2/||\mathbf{w}||$

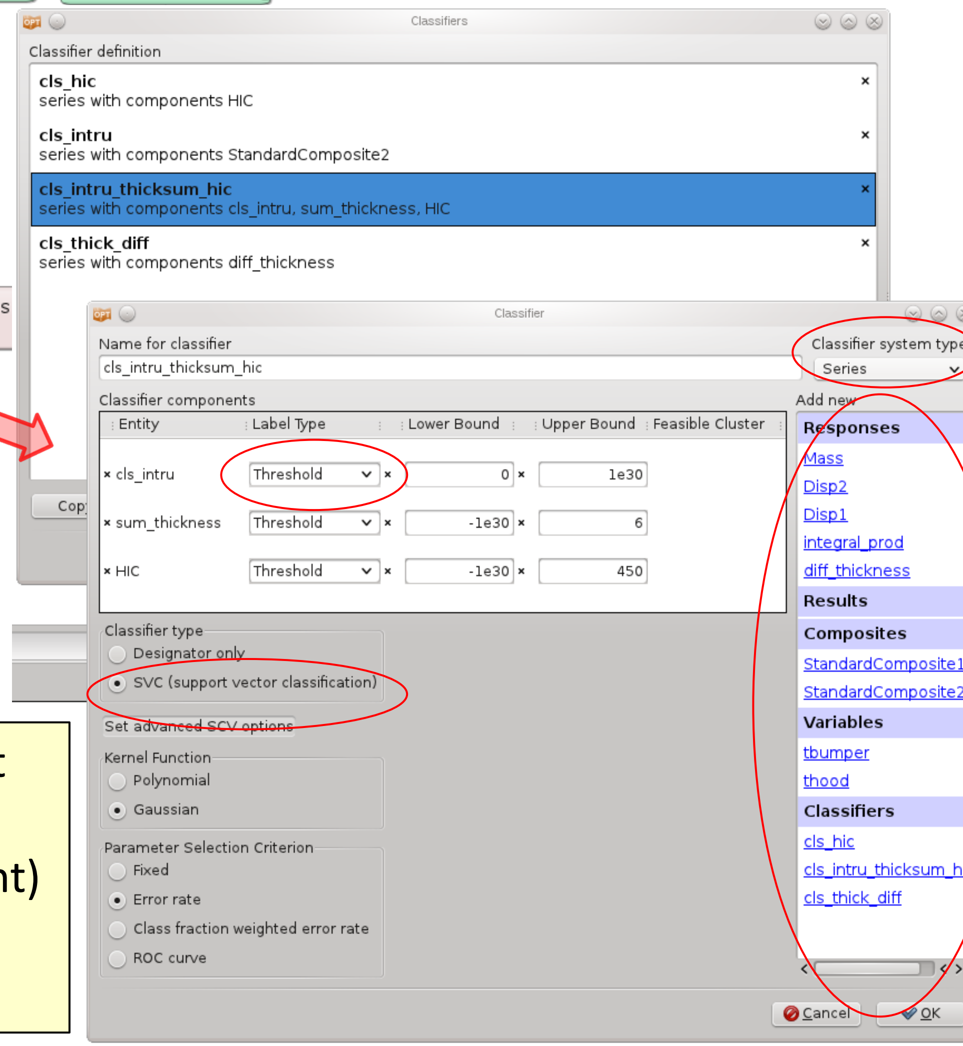
- General nonlinear separating function:

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



Classifier GUI In LS-OPT





<u>Information for Classifier definition:</u>

- Underlying response
- Feasibility criterion
- Classifier Type

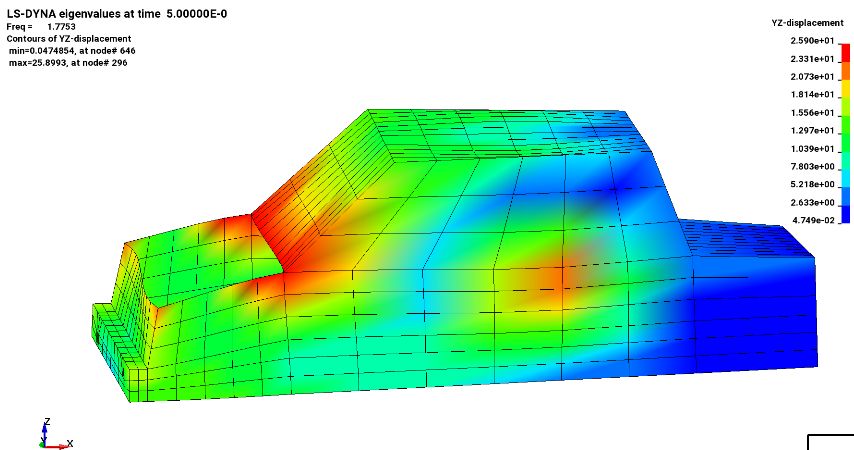
Any entity type can be a classifier component

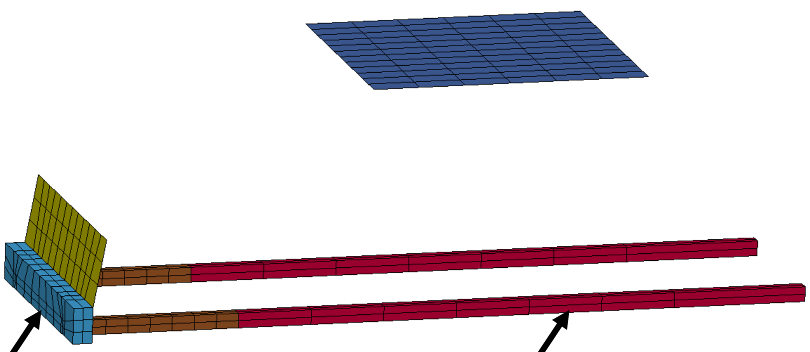
Classifiers can be nested (classifier component)

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

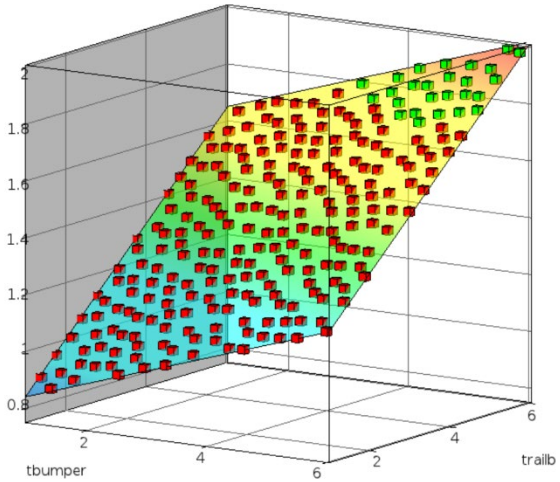
Back rail thickness
trailb

$$\begin{aligned} &\min \quad \textit{Mass} \\ &s.t. \quad 1^{st}\ \text{Torsional Mode Frequency} \geq 2.2 \end{aligned}$$

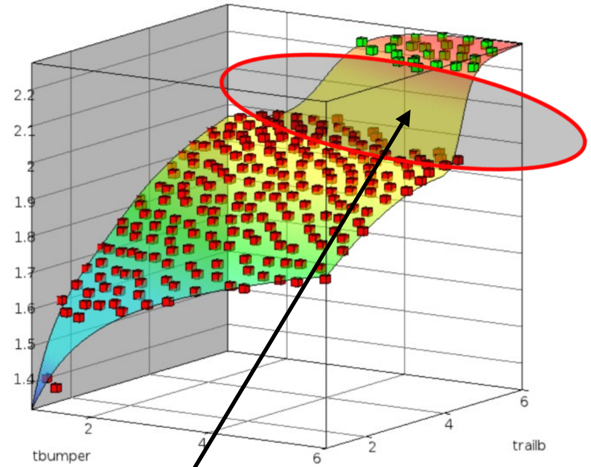
Mode switching causes discontinuity in the frequency response

Ex 1: Metamodel for Discontinuous Constraint

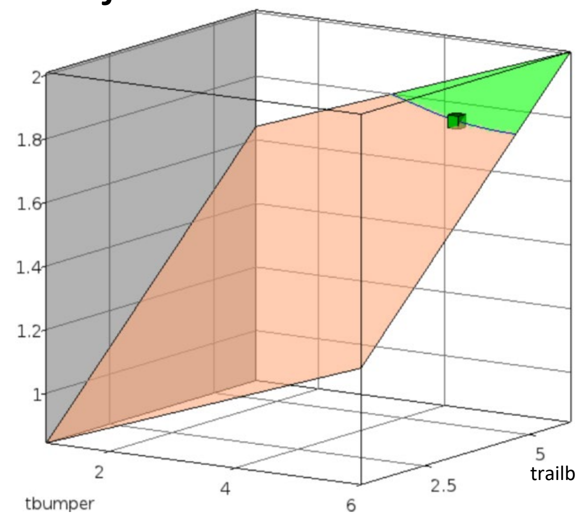
Obj fun approximation

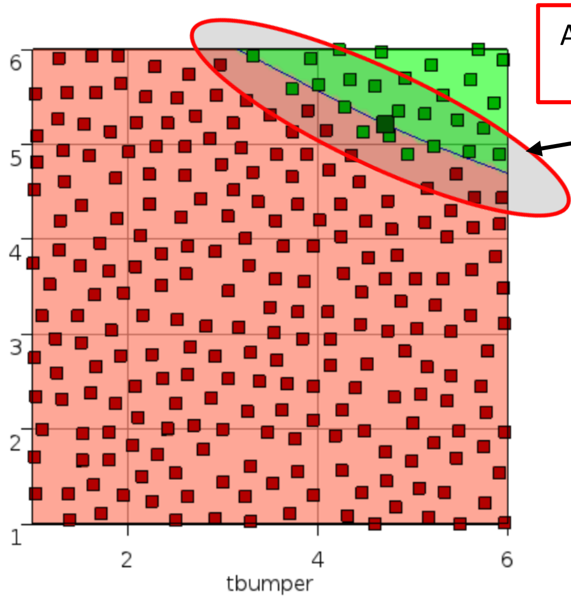


Con fun approximation



Obj fun + Con limit state





Approximating discontinuous functions can compromise accuracy

Obj Fun: Mass

Con: Frequency of 1st torsional mode

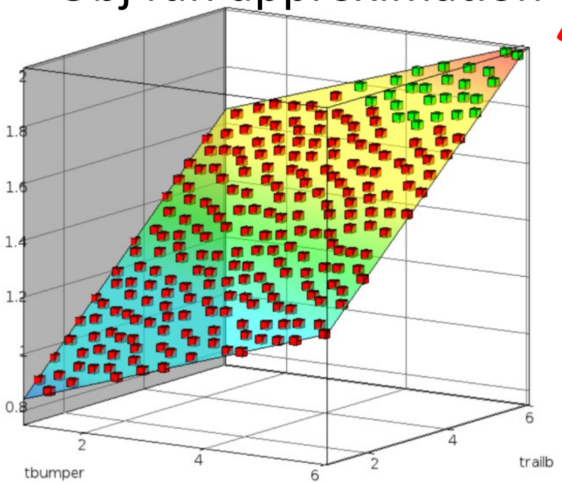
Discontinuity due to mode switching

<u>Metamodel-based Approach:</u>

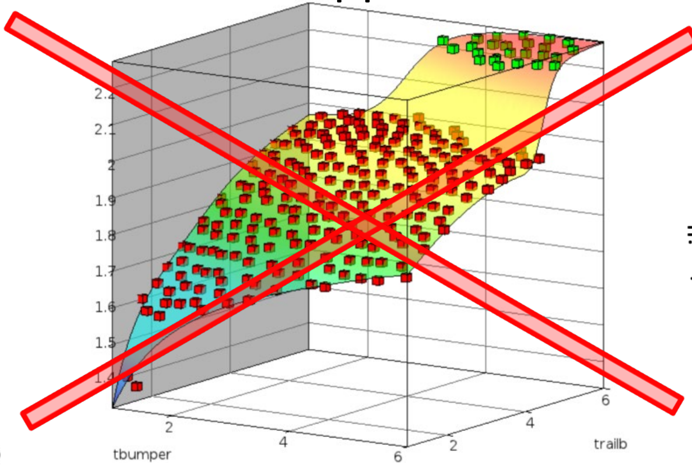
Approximate objective function and constraints

Ex 1: SVM Classifier for Discontinuous Constraint

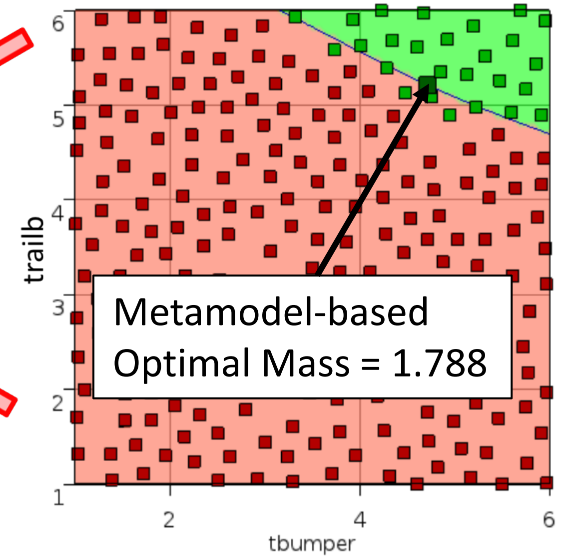
Obj fun approximation

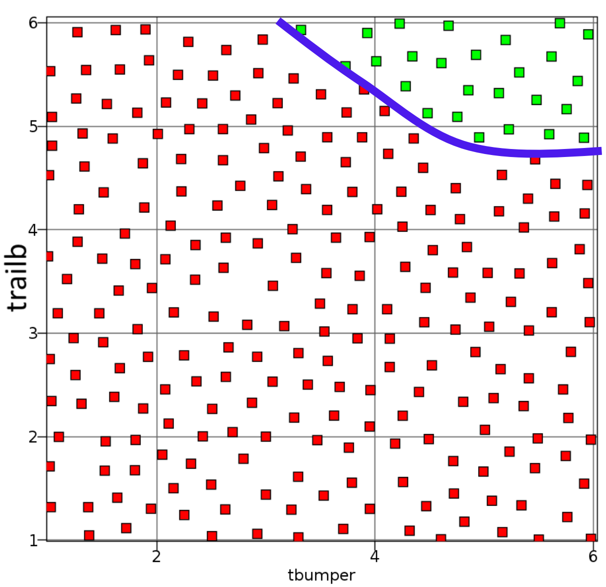


Con fun approximation

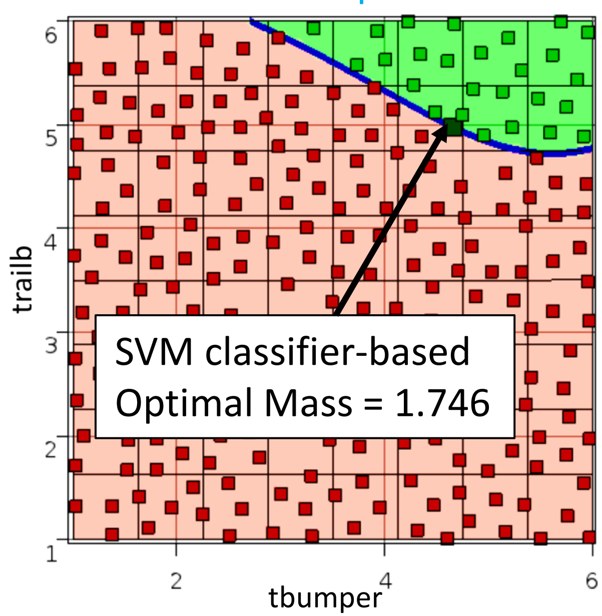


250 samples

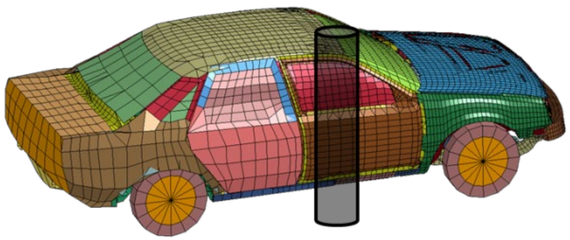




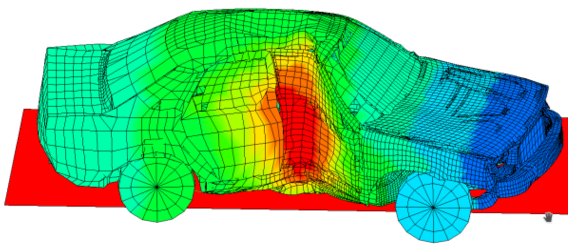
250 samples



Ex 2: Non-convex discontinuous constraint reliability



Side Pole Impact



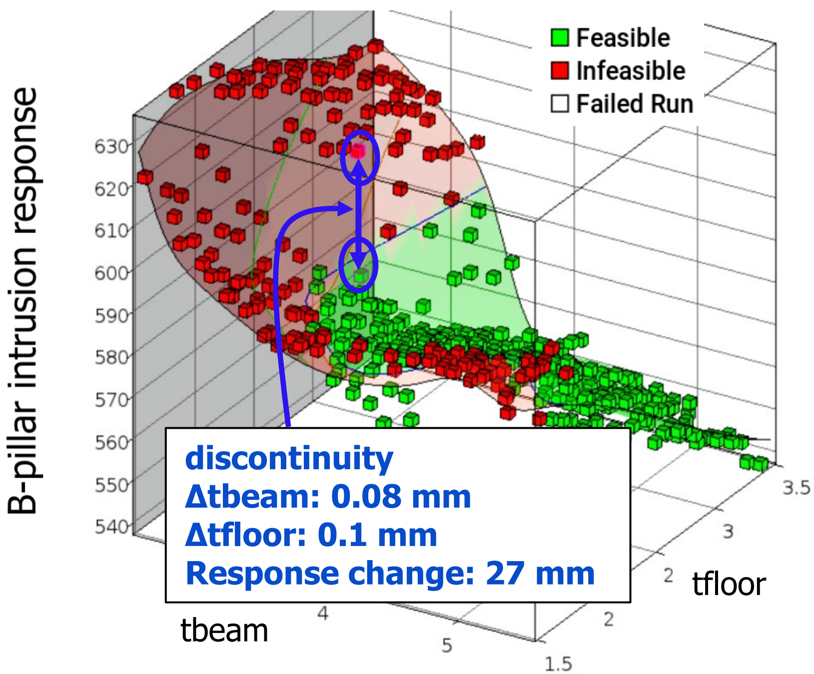
Reliability Assessment

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

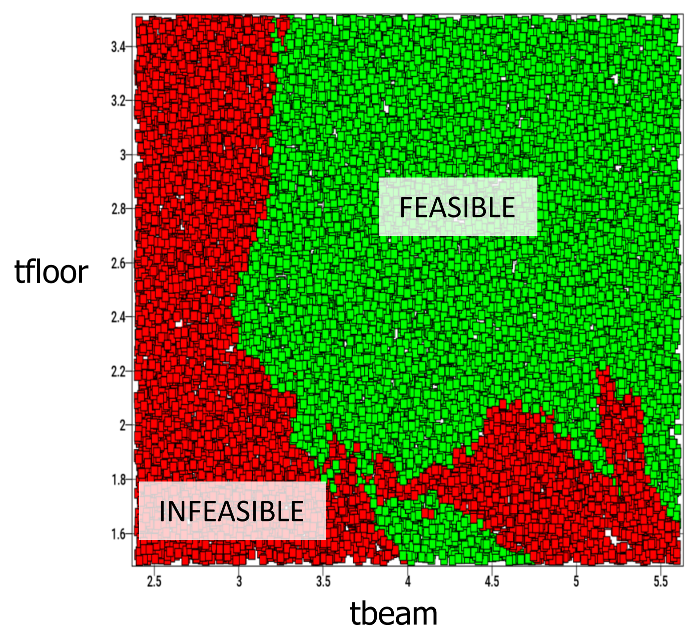
Random/Noise Variables:

Beam Thickness
tbeam N(4,0.4)

Floor Thickness
tfloor N(2.5,0.25)



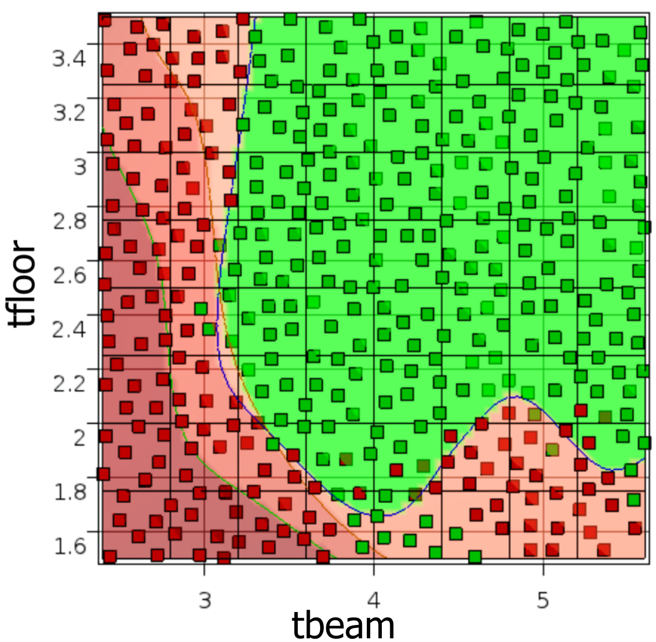
Actual constraint feasibility
(20,000 LS-DYNA runs)



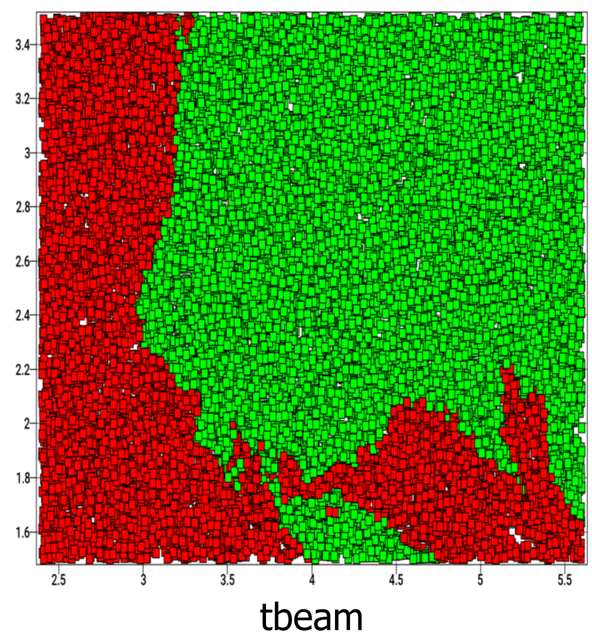
Ex 2: Non-convex discontinuous constraint reliability

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

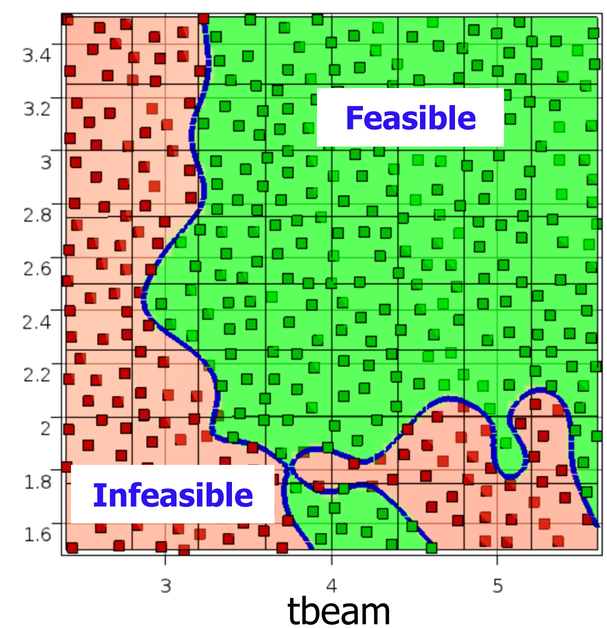
Failure probability using Neural Network Metamodel (400 samples): 0.0217
Failure probability using SVM Classifier (400 samples): 0.0218
Actual Failure probability: 0.0219



Neural net approximation of constraint (inaccurate)

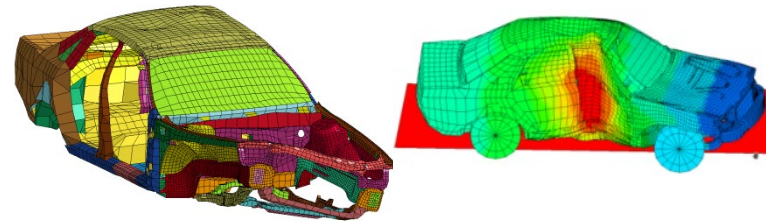


Actual constraint feasibility (LS-DYNA)



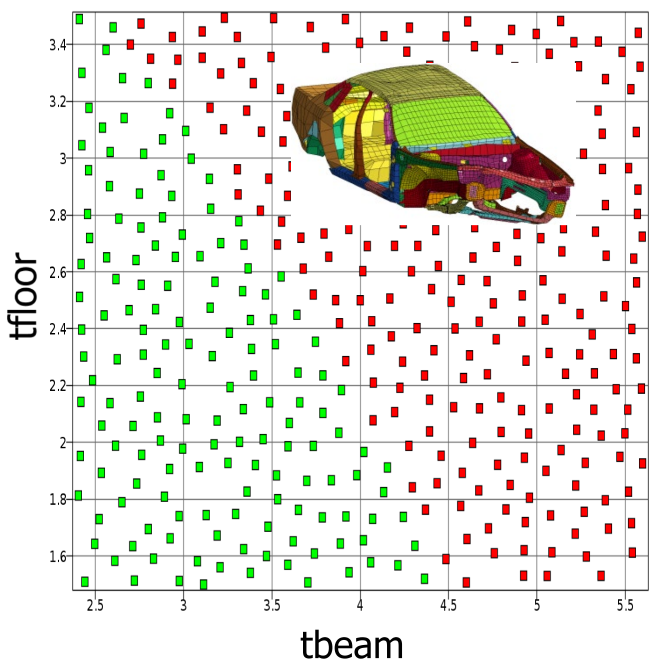
SVM classifier-based constraint (accurate)

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

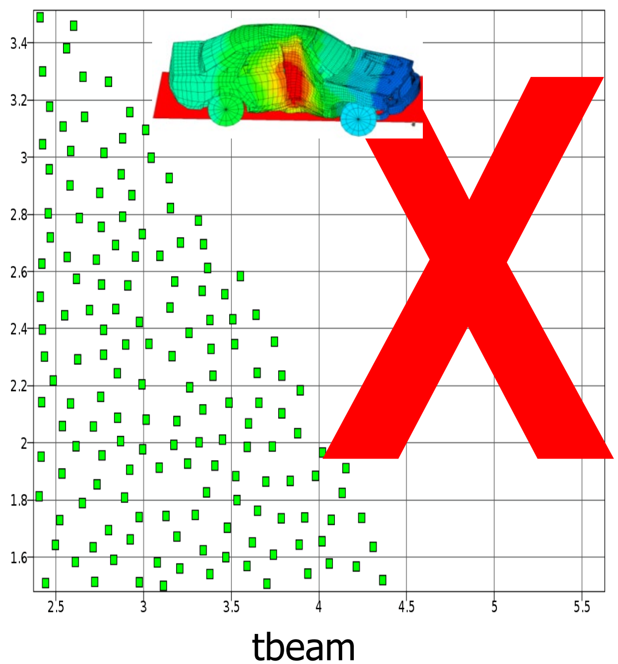


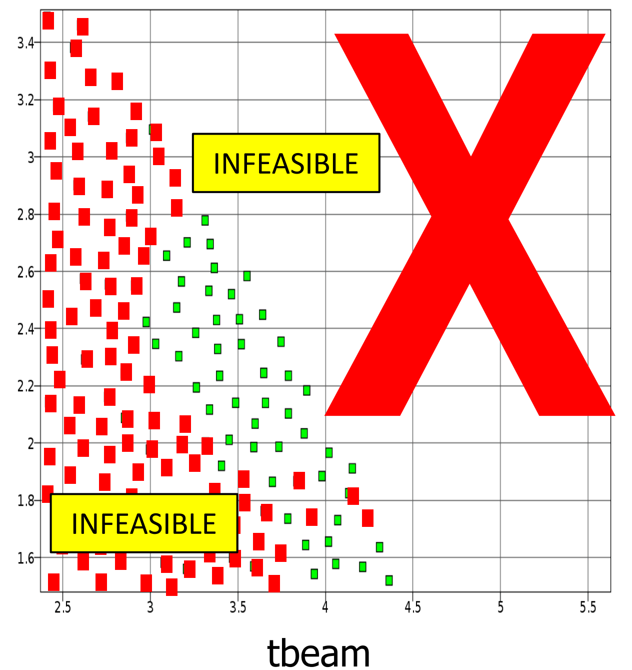
- Torsional mode frequency constraint added (frequency > 41.6)
- NVH analysis followed by crash analysis
- Because classifier is used, *crash analysis needed only at feasible NVH points*
- Crash simulation savings: 246 out of 400 (61.5 %)

NVH Samples (400)



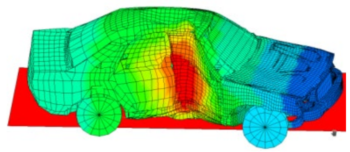
Crash Samples (154)



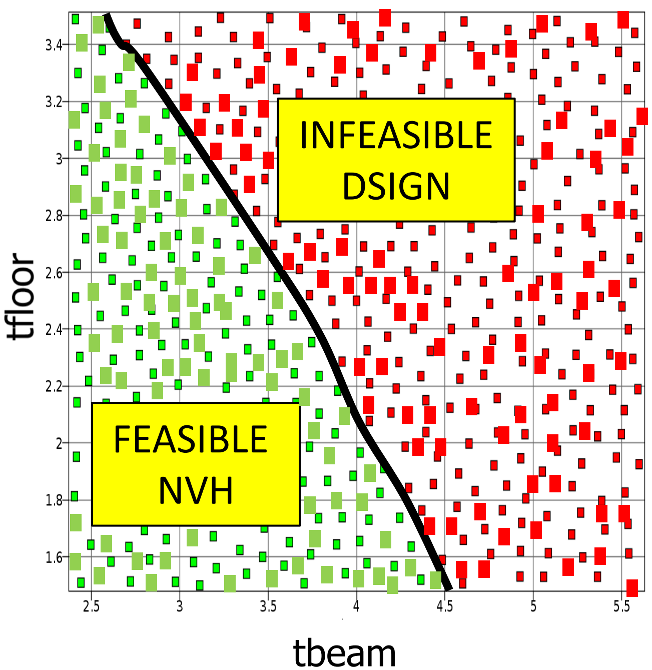


Ex 3: 2-disciplinary System Reliability (Unequal Costs)

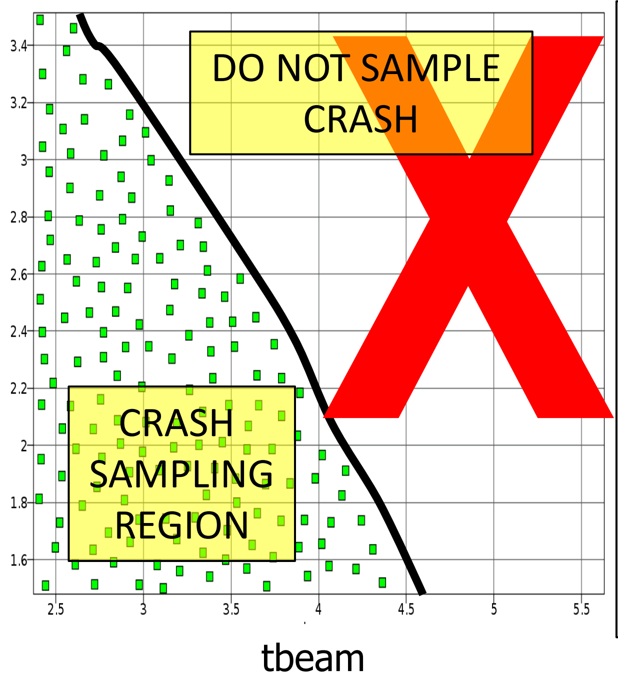
- We can get a very accurate decision boundary for inexpensive load cases
- Expensive cases sampled within the domain defined by the classifier



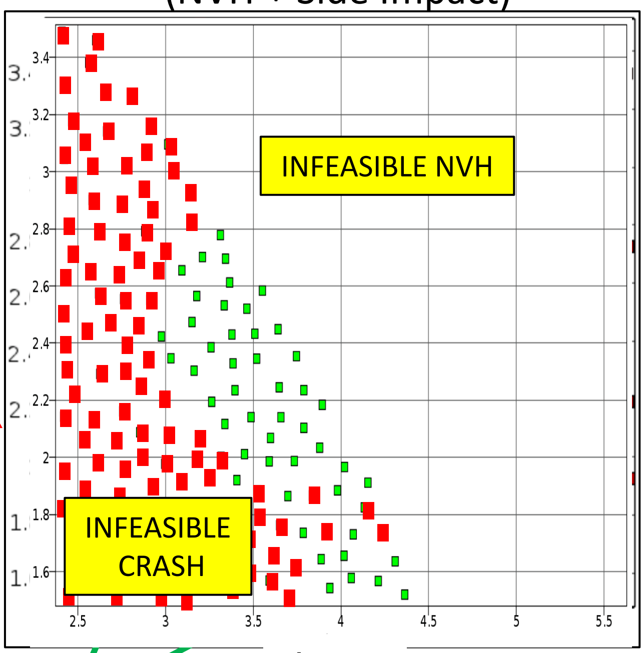
NVH Samples (400+)



Crash Samples (154)

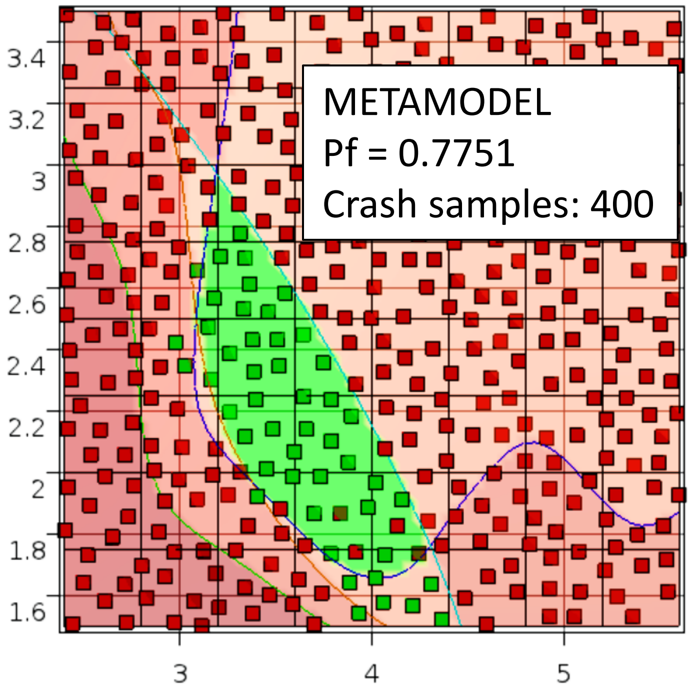


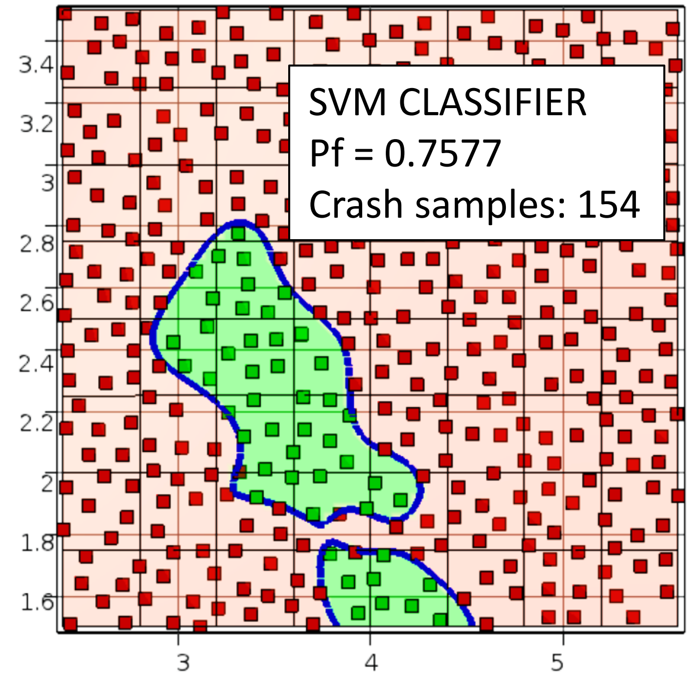
Dual-disciplinary Classification (NVH + Side Impact)



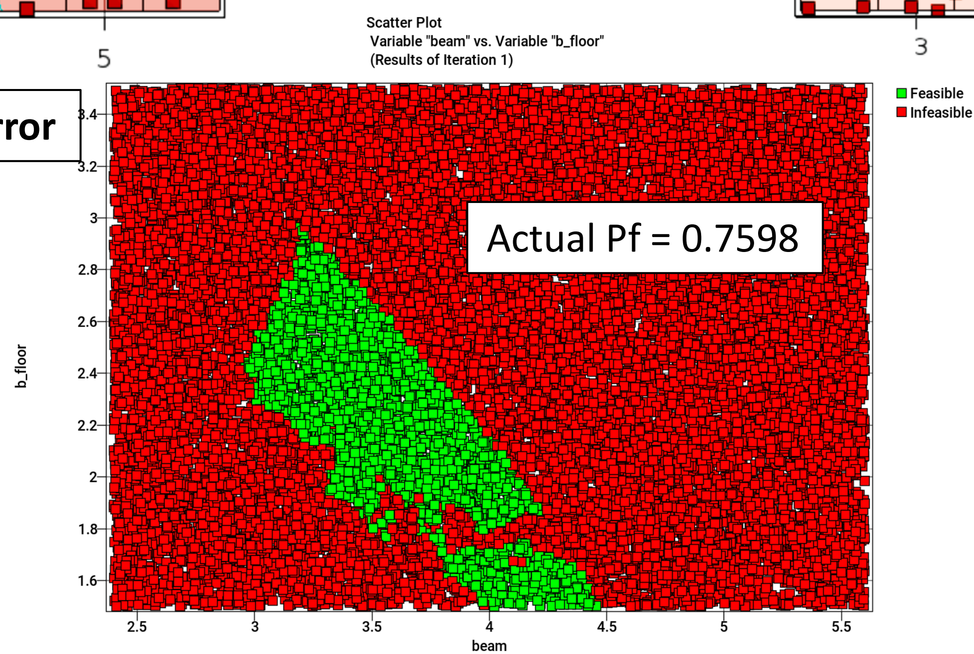
Sampling region for subsequent load case

Ex 3: 2-disciplinary Constraint Comparison





Metamodel: 2.01% error



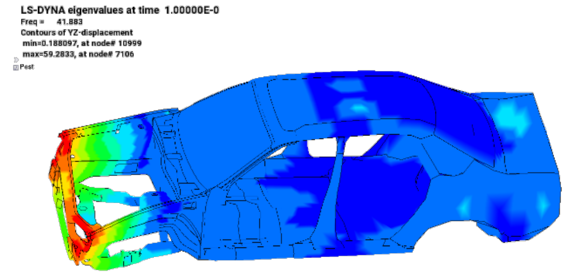
Classifier: 0.28% error

Ex 4: Multidisciplinary Optimization (MDO) Cost Savings

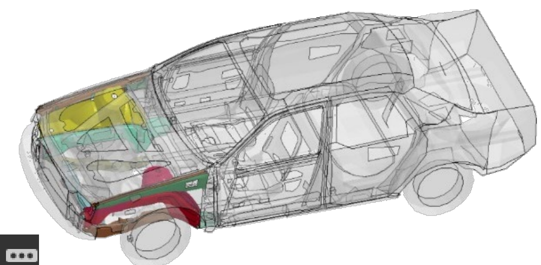
$$
\begin{aligned}
&min && Mass\,(x_{1,2..7}) \\
&s.t. && 41.38Hz < b_{freq} < 42.38Hz \\
& && Stage\ 1\ pulse > 13.94g \\
& && Stage\ 2\ pulse > 19.17g \\
& && Stage\ 3\ pulse > 21.3g
\end{aligned}
$$

where

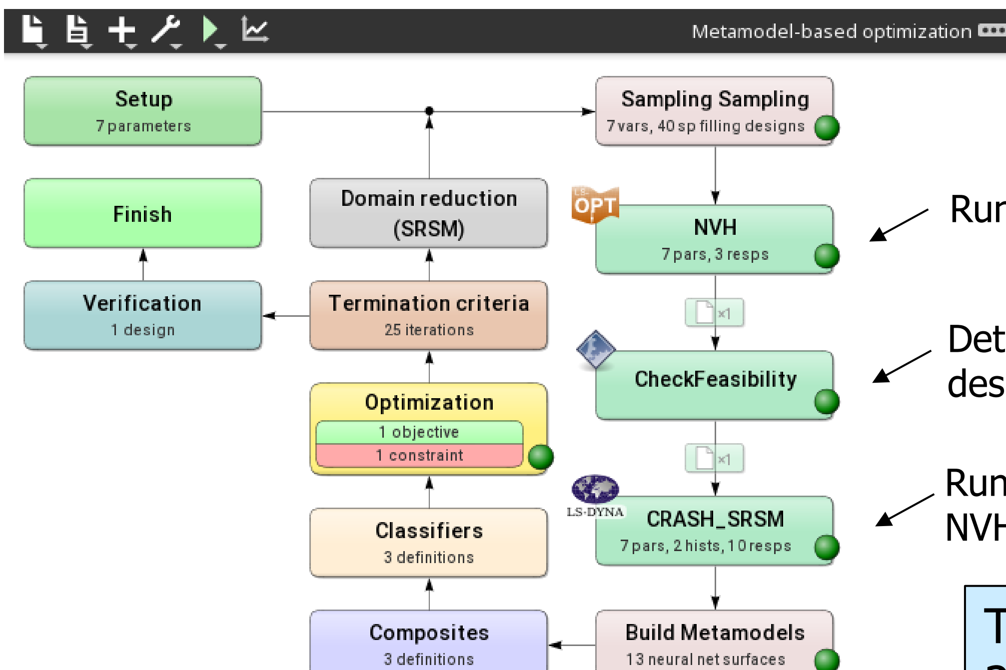
- $x_{1,2..7}$ *are the design part thicknesses*
- b_{freq} *is the first torsional frequency*



Baseline Torsional Mode



Crash model and MDO design parts



Run cheaper NVH analysis first

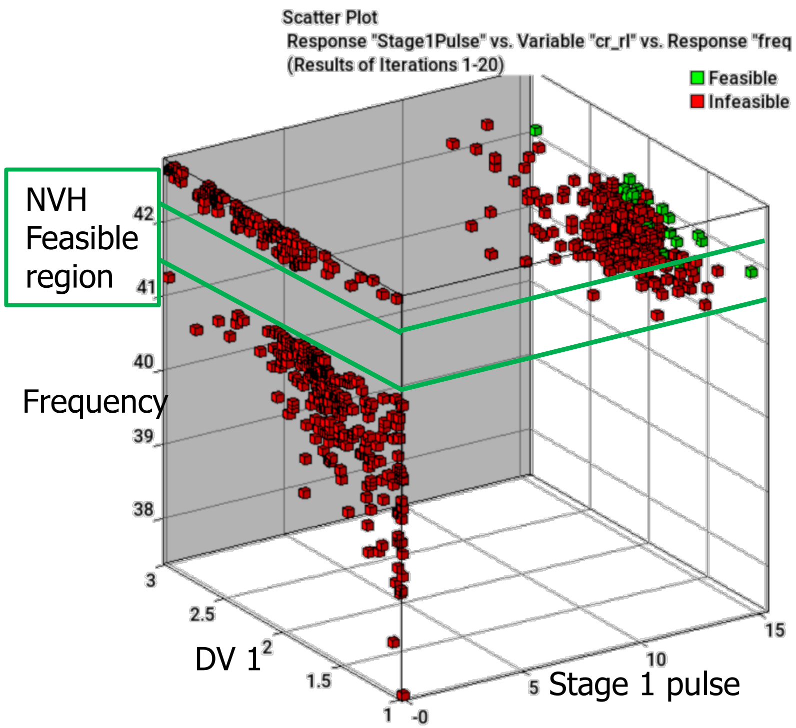
Determine feasibility of the NVH designs

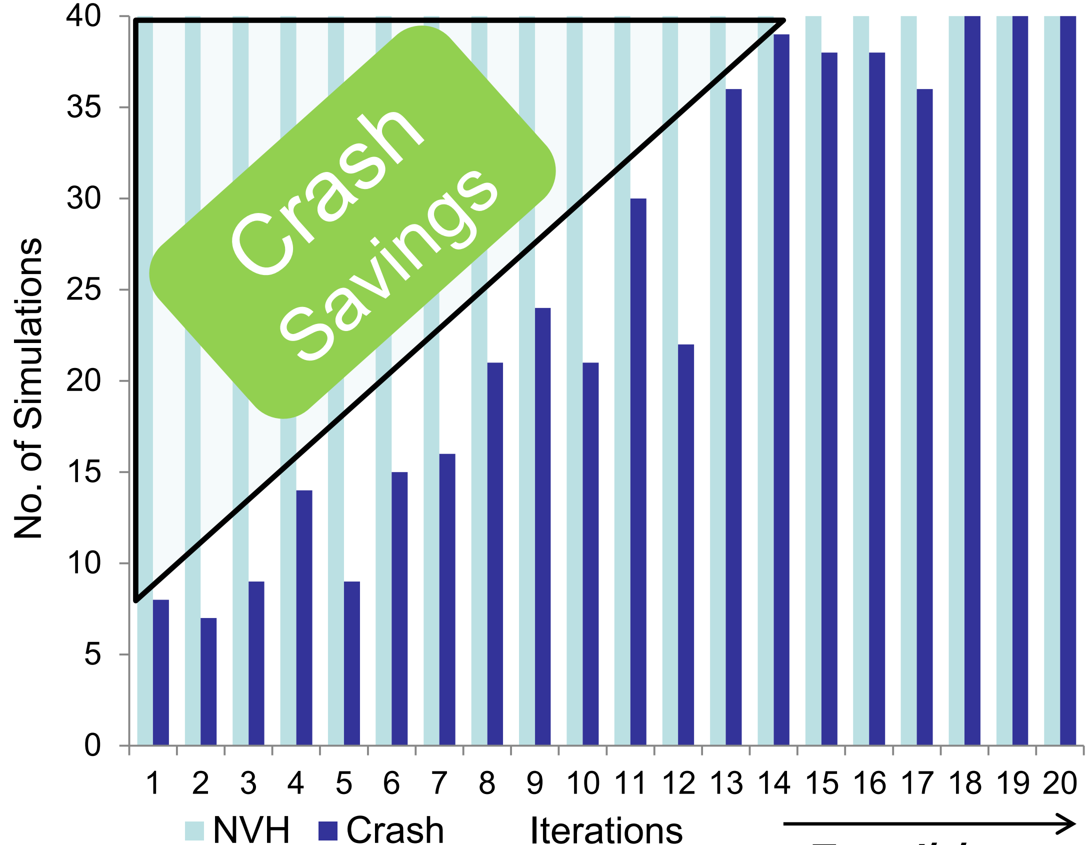
Run crash analysis only for feasible NVH designs

Total crash runs saved: 297 (37%)

Ex 4: Multidisciplinary Optimization (MDO) Cost Savings

Computation cost savings using classifiers





Feasible NVH sub domain

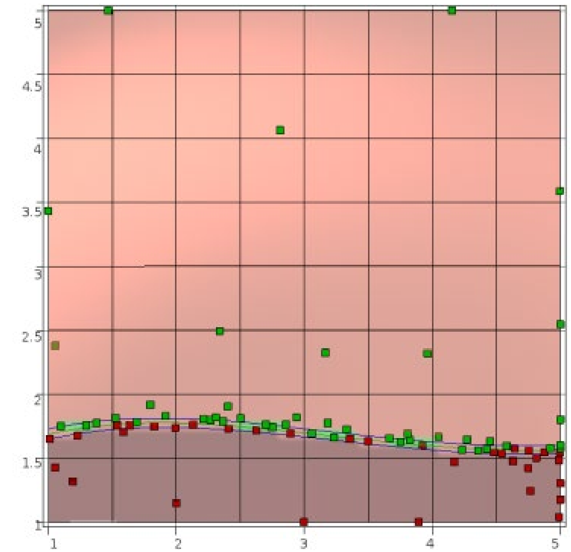
Load Case	Runs per iteration	Total runs (without classifiers)	Total runs using classifiers	Savings
NVH	40	800	800	0
Crash	40	800	503	297 (37%)

Other Applications & Enhancements

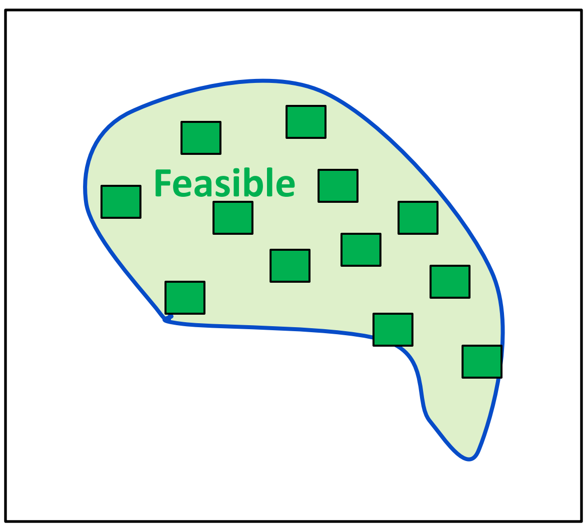
Adaptive Sampling

- 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.



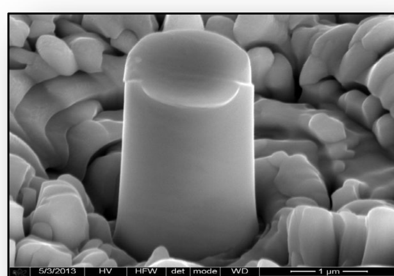
- Sampling the feasible regions

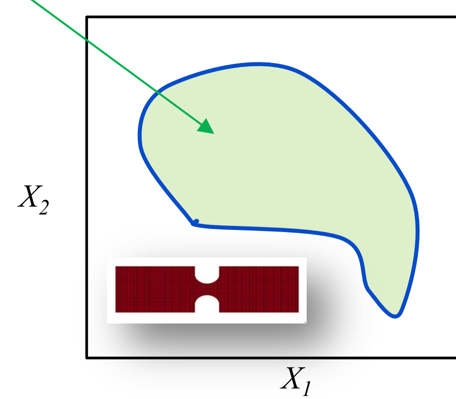


$\boldsymbol{x}$

Micro scale Material model → $\boldsymbol{x}^*$ → Macro scale Material model

$\boldsymbol{X}$

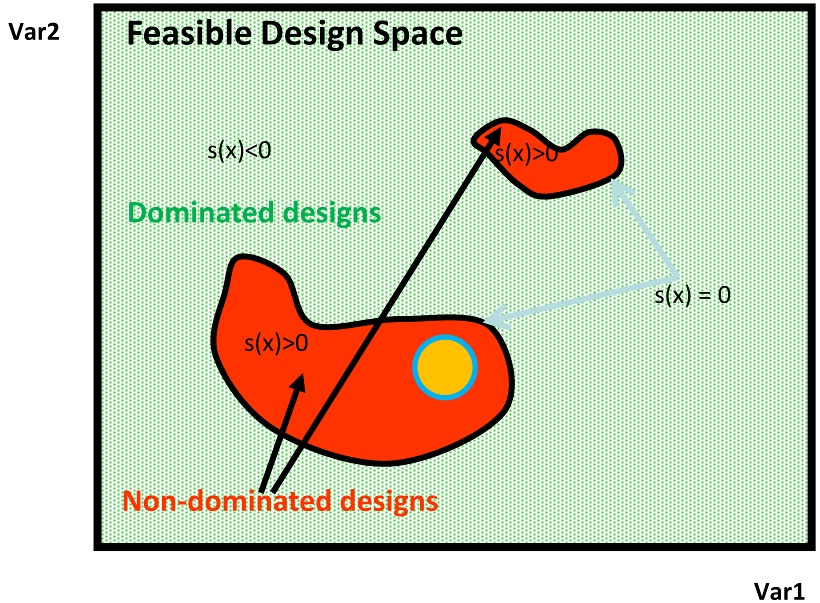




Prof. S. Kumar, Dr. H. Ghassemi-Armaki (Brown U.), Prof. F. Pourboghrat (OSU)

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.

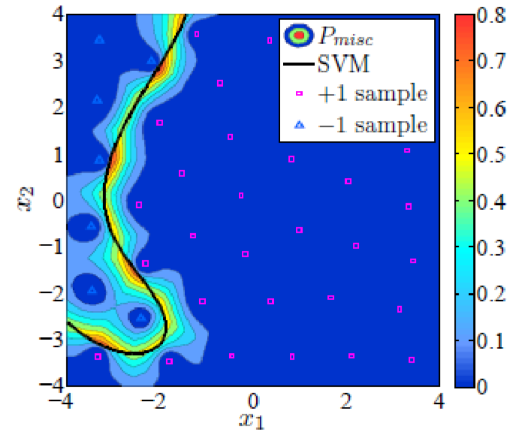
MOO considered as a classification problem:

DOMINATED vs NON-DOMINATED

Other Applications & Enhancements

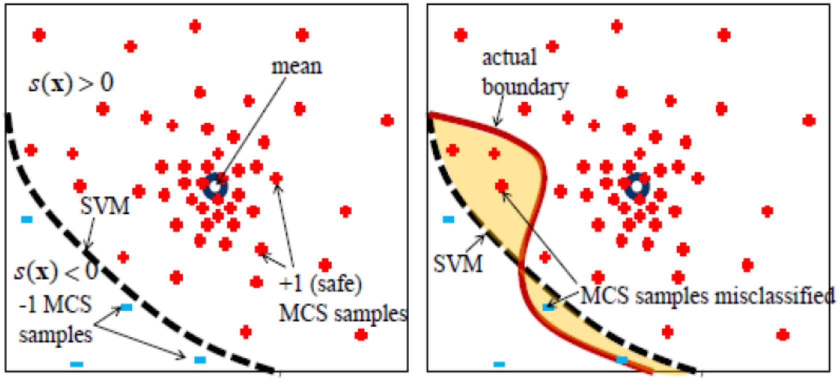
Probabilistic Classifiers

- Constrained Efficient Global Optimization



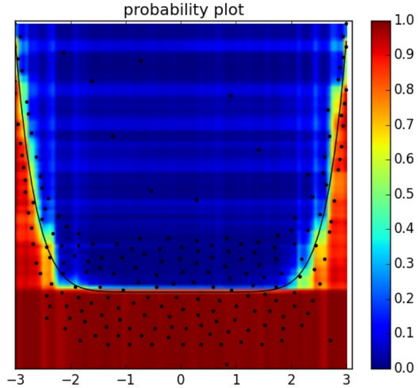
Basudhar, Anirban, et al. "Constrained efficient global optimization with support vector machines." *Structural and Multidisciplinary Optimization* 46.2 (2012): 201-221.

- 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.

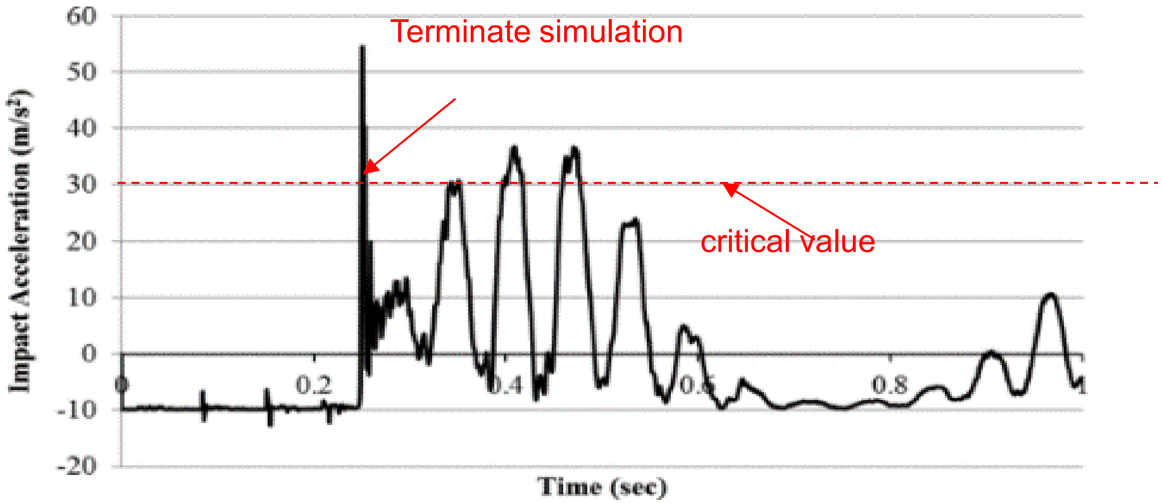
- Probabilistic SVM, Random Forest Classifier



Other Applications & Enhancements

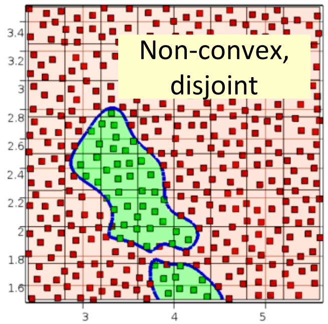
Adaptive simulation time reduction

Check failure criteria during simulation

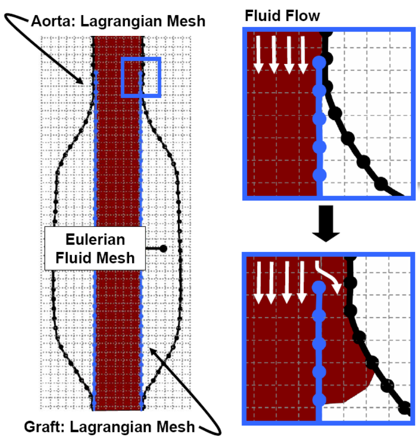


Summary

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



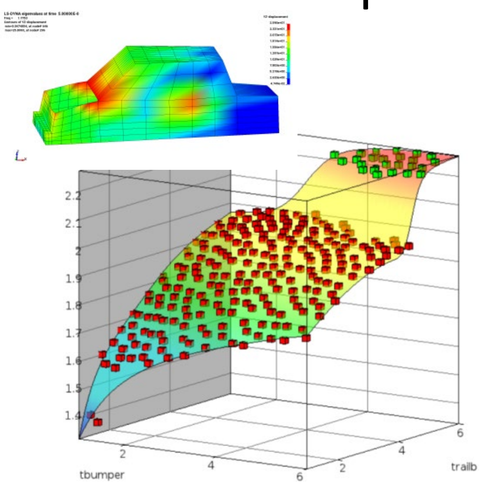
- Support Vector Machines used for classification
- Benefits shown for binary/discontinuous response & MDA/MDO

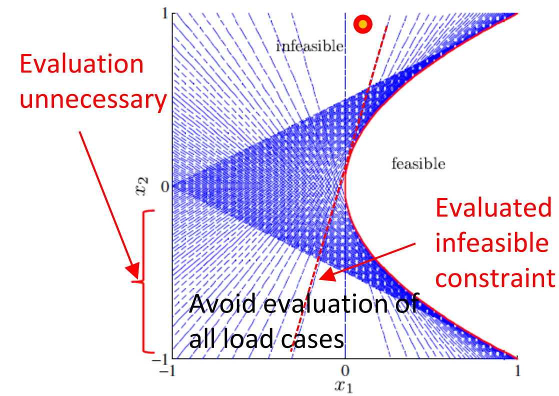


Binary information:

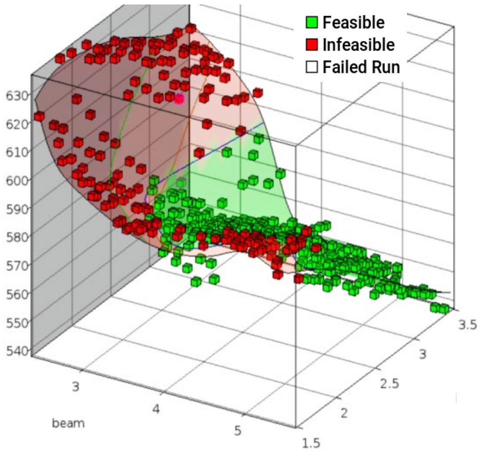
Failed (leaked) or not (no leakage)

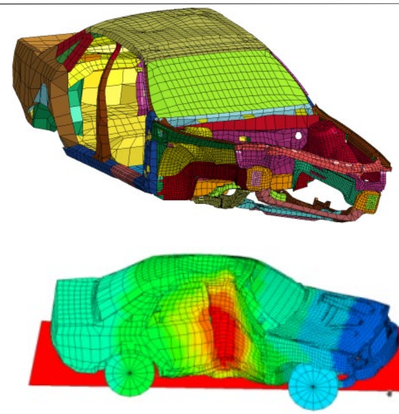
Layman, R. et al. "Simulation and probabilistic failure prediction of grafts for aortic aneurysm." *Engineering Computations* 27.1 (2010): 84-105.

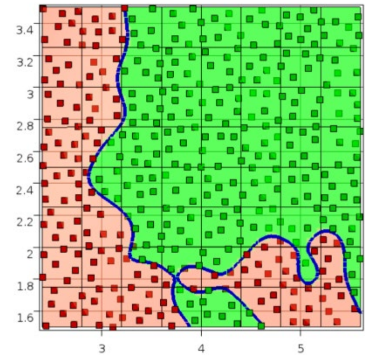


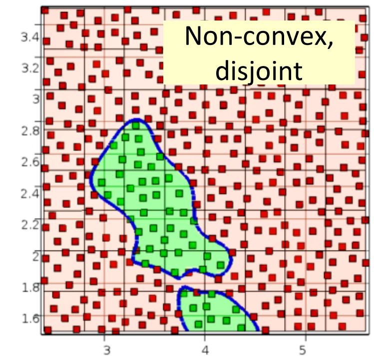


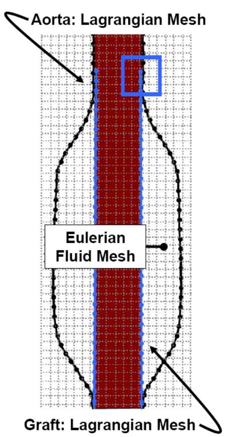
- Series/parallel or mixed system constraints can be defined
- Classifiers can be used for optimization or for reliability

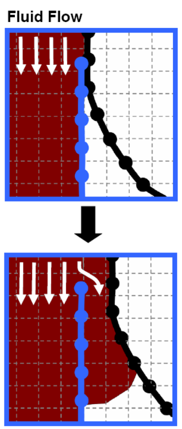

Feasible
Infeasible
Failed Run
beam



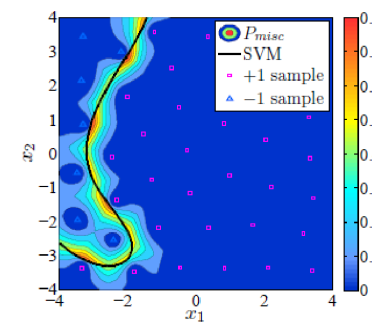


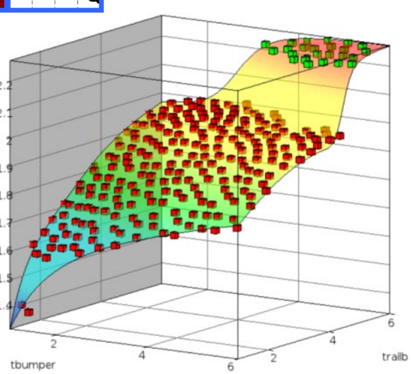

Non-convex,
disjoint

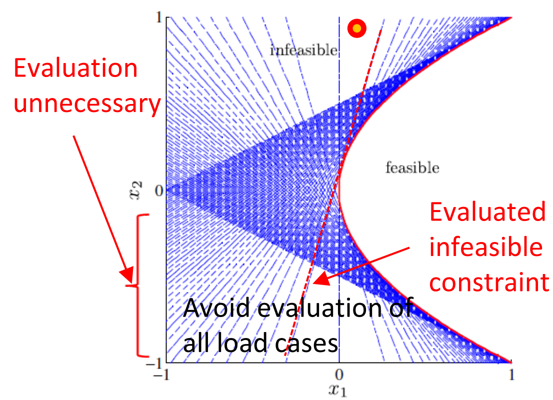

Aorta: Lagrangian Mesh
Eulerian
Fluid Mesh
Graft: Lagrangian Mesh

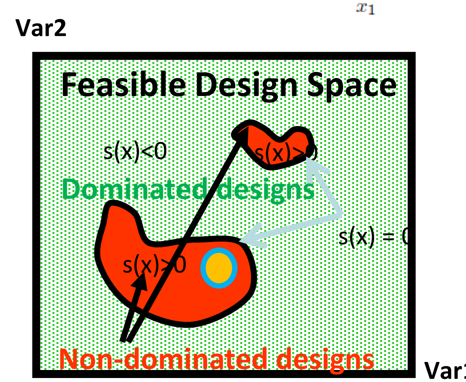

Fluid Flow

THANK YOU!


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


tbumper
traílb


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
Non-dominated designs
Var1