LS-OPT: Status and Outlook

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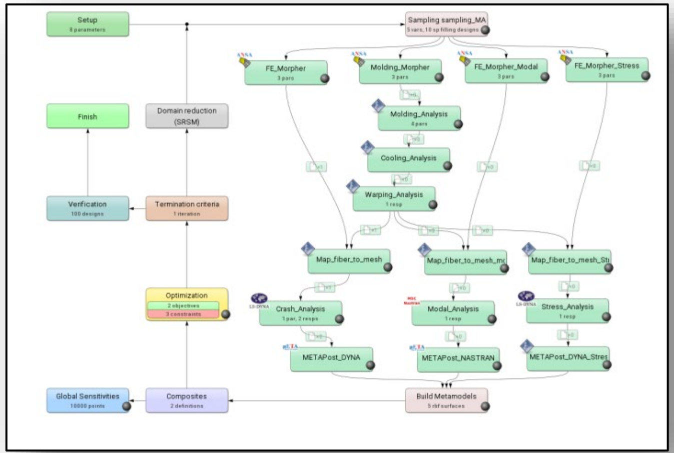
Outline

- LS-OPT Overview
- Current Production Features (LS-OPT 7.0)
- Future Versioning and Licensing: LS-OPT Pro YYYY R1/2
- Current 2022 R1/R2 Developments
  - Unified Extractor with LS-Reader Interface
  - Element Interpolation for Results Extraction
  - Automatic Metamodel Selection: MOP
  - CORA Interface
  - Reduced Order Modeling
  - Pareto Optimality based Classifier
  - Point Cloud Mapping
- Summary & Outlook

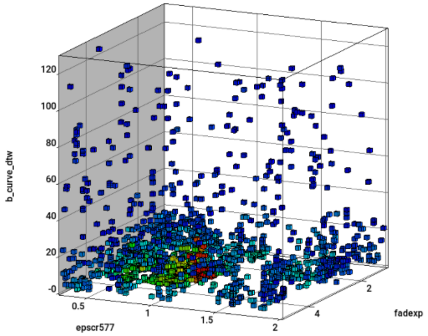
LS-OPT® | Optimization, Probabilistic Analysis & System Calibration

Integrates LS-DYNA® in a *multi-stage, multi-case, multi-level* process

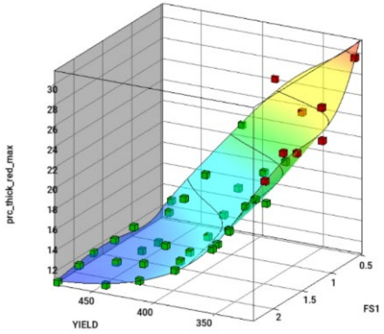
- **Process**
  - Multi-case
  - Multi-stage
  - Multi-level



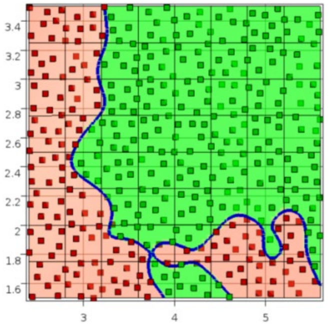
- **Modeling: Direct, Metamodel, Classification**



Direct Optimization



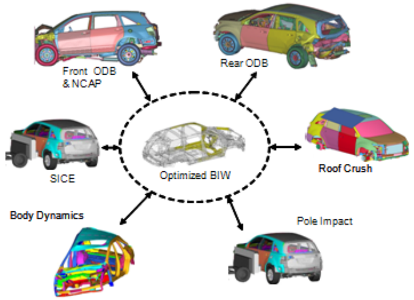
Neural Net



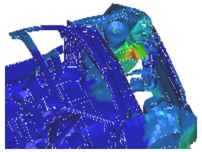
Support Vector Classifier

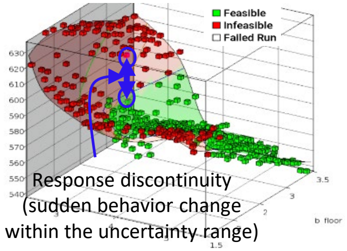
- **Optimization**
  - MDO
  - MOO
  - Discrete variables

Multi-case Vehicle MDO

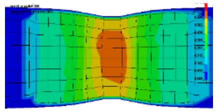


- **Statistics & Uncertainty**
  - Robust & Reliable Design
  - Tolerance Optimization
  - Sensitivity Analysis
  - LS-DYNA® Statistics
    - Outlier Analysis

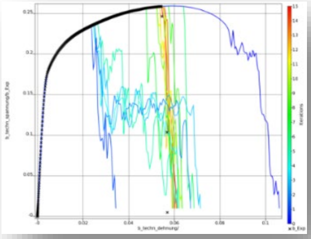




- **Material Calibration**
  - Hysteresis: Loading-Unloading
  - Curve Matching with noise e.g. GISSMO
  - Full-field Calibration w. Digital Image Correlation (DIC)



DIC



GISSMO

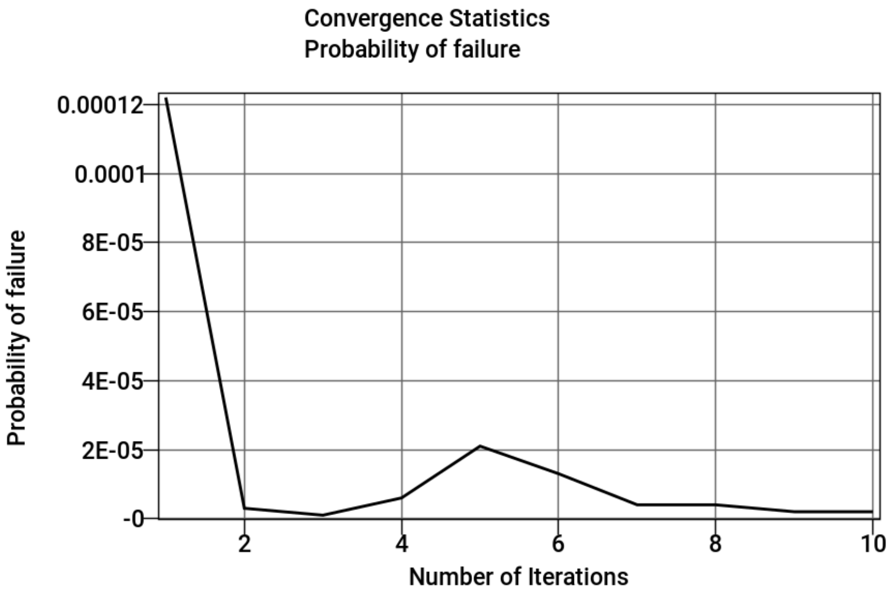
LS-OPT 7.0 Developments

- Improved Flexibility/Usability/Robustness
- Algorithm Technology Advances

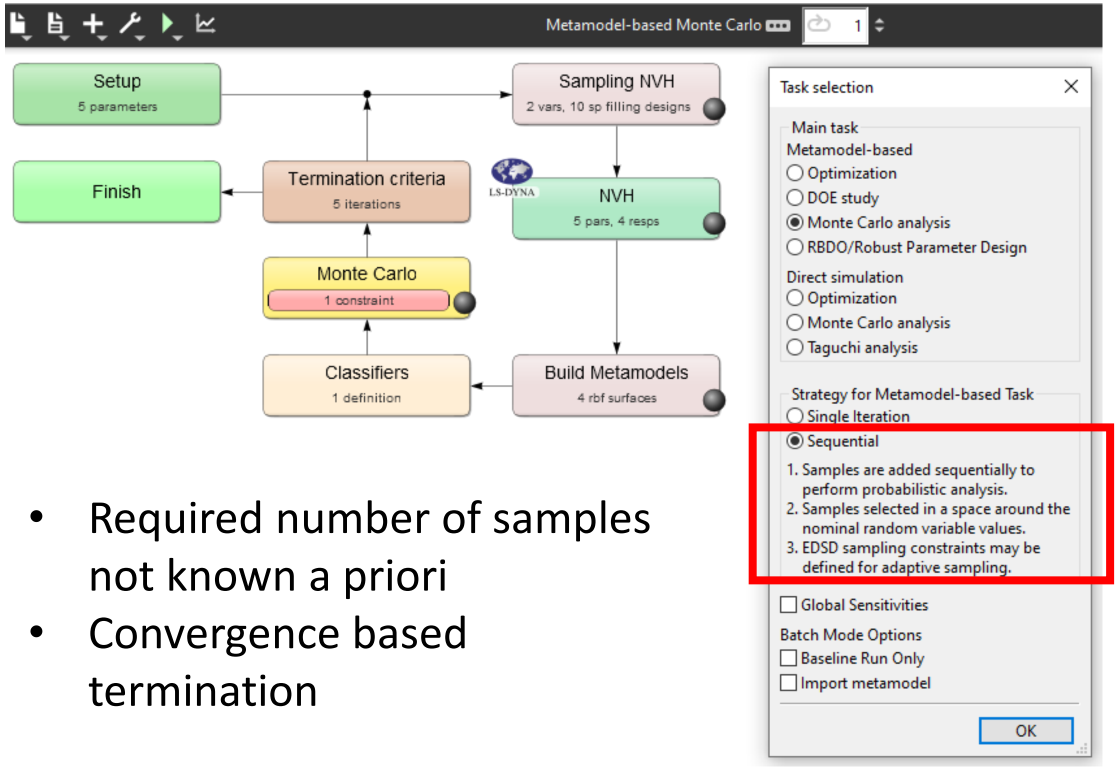
Ansys

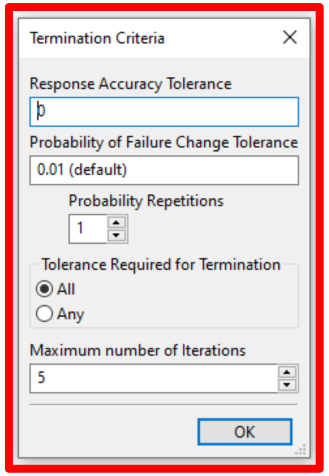
7.0: Sequential Monte Carlo Analysis For Convergence & Efficiency

- Convergence history of failure probability (failure probability termination criterion)



Convergence based on failure probability & Response Accuracy; failure probability repetitions may be specified

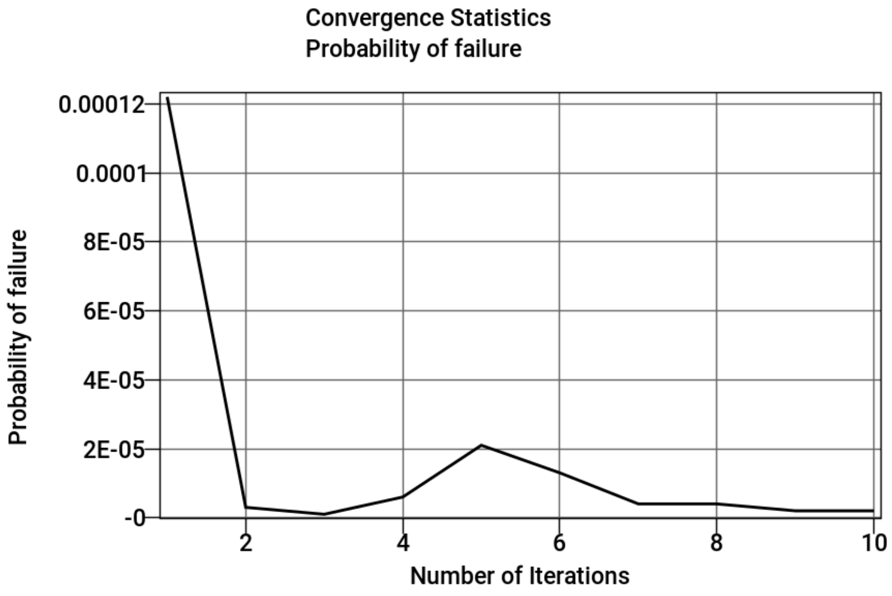




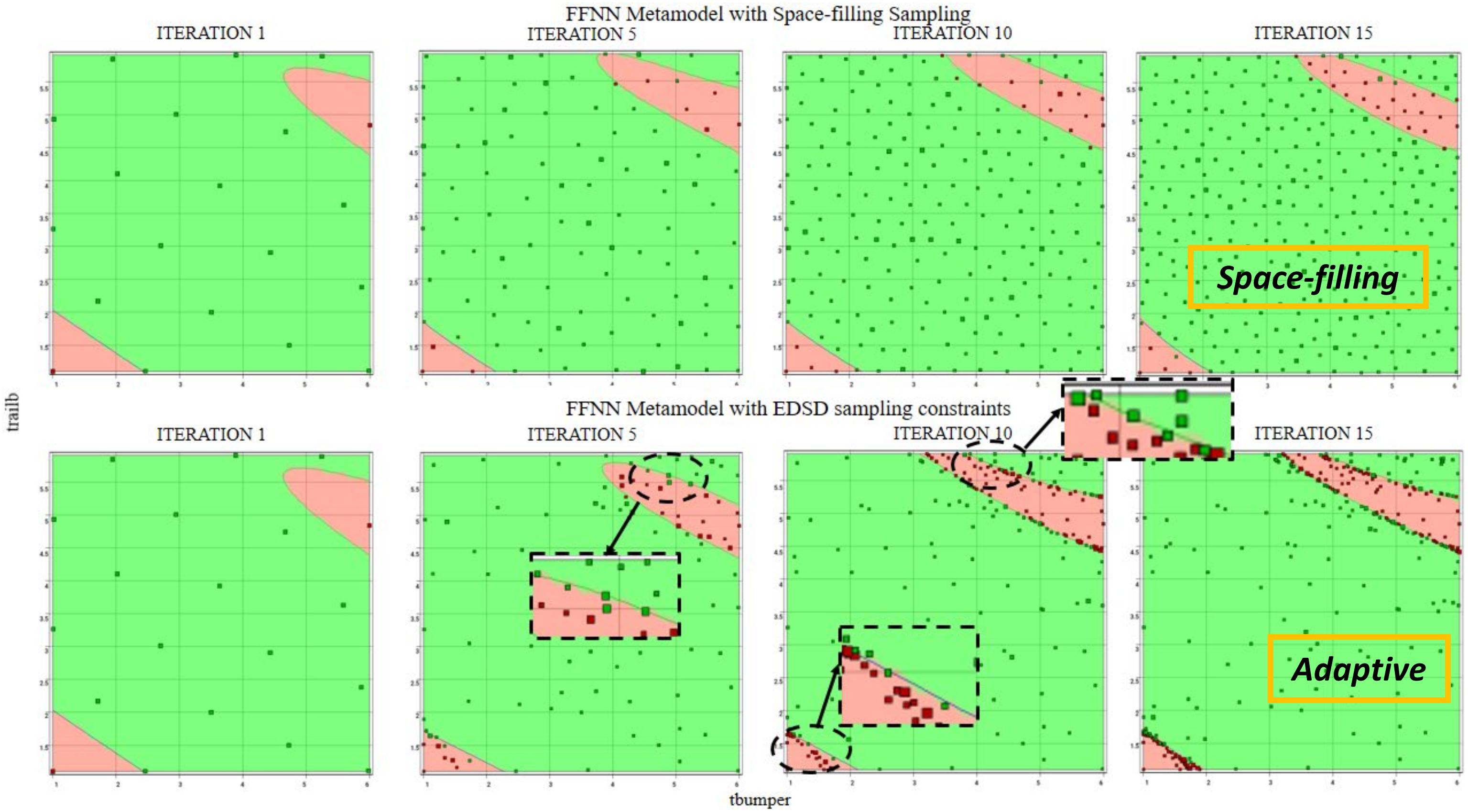
- Required number of samples not known a priori
- Convergence based termination

7.0: Sequential Monte Carlo Analysis For Convergence & Efficiency

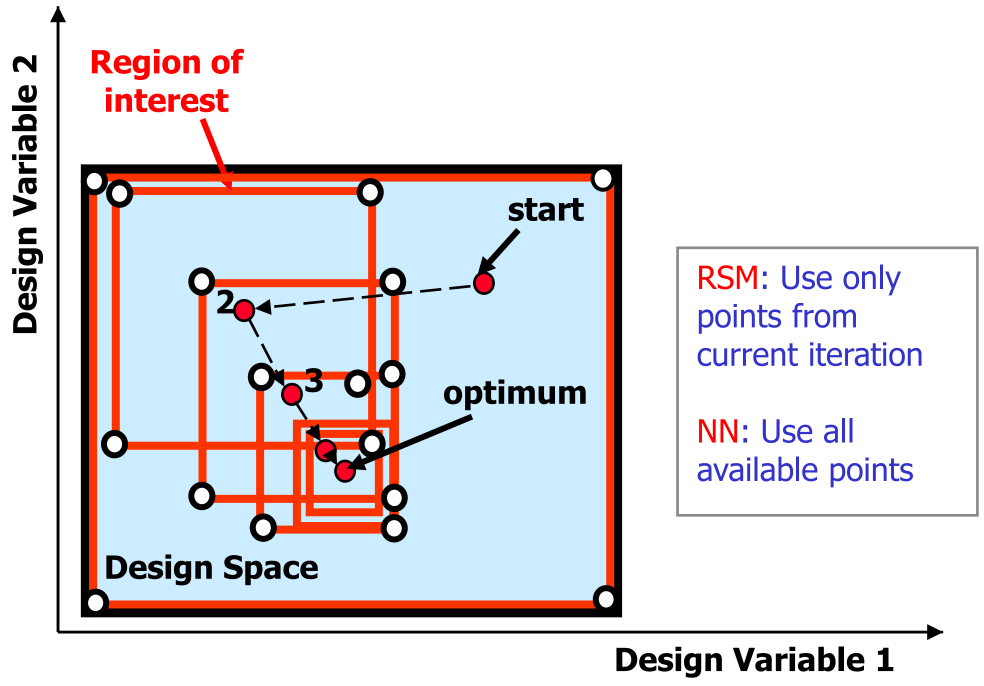
- Convergence history of failure probability (failure probability termination criterion)
- Iteratively add <u>space-filling</u> or <u>adaptively selected</u> samples



Convergence based on failure probability & Response Accuracy; failure probability repetitions may be specified

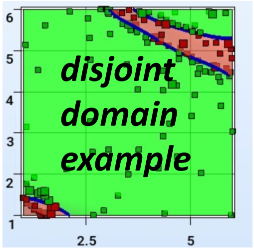


7.0: Adaptive Sampling Constraints For Improving Efficiency



- Previously, adaptive sampling was available in LS-OPT as Sequential with Domain Reduction optimization strategy
- Avoids unnecessary samples (focuses on important region)
- Applicable to optimization only – focuses around optimum
- Constraints may be inaccurate
  - Not applicable to reliability assessment
  - Applicable to RBDO with low order reliability methods only

- Classifier-based sampling constraints for <u>irregular domains</u>
  ***E**xplicit **D**esign **S**pace **D**ecomposition (EDSD) sampling constraints*



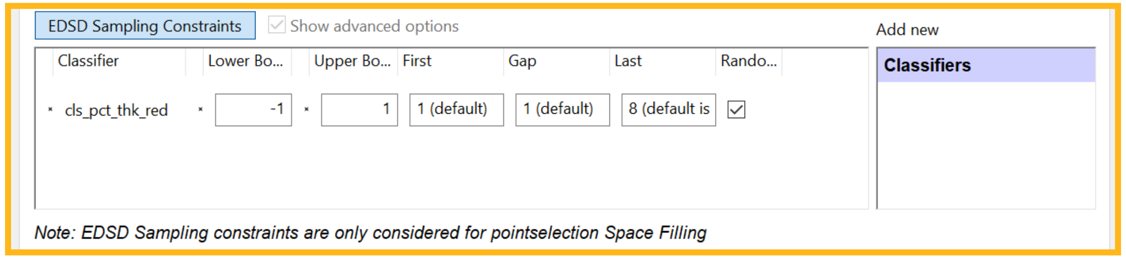
- Depending on the application, sampling targeted at:
  - Refinement of the constraint boundary approximation
    Sample in the vicinity of classifier boundary
  - Generating samples of a particular type/class
    Sample on one side of the classifier boundary
- Regions of interest can be disjointed and can result from discontinuous, binary or hidden constraints

- Adaptive sampling feature is now more generalized
- The adaptively refined constraints can be used for any LS-OPT task, e.g. probabilistic analysis or optimization
- Can be used along with Sequential with Domain Reduction strategy

Ansys

7.0: Adaptive Sampling Constraints For Improving Efficiency

- Constraint boundaries approximated using a support vector machine (SVM) classifier used to define (irregular) sampling region
- Sampling based on the SVM decision boundary prediction, which evolves as more samples are added

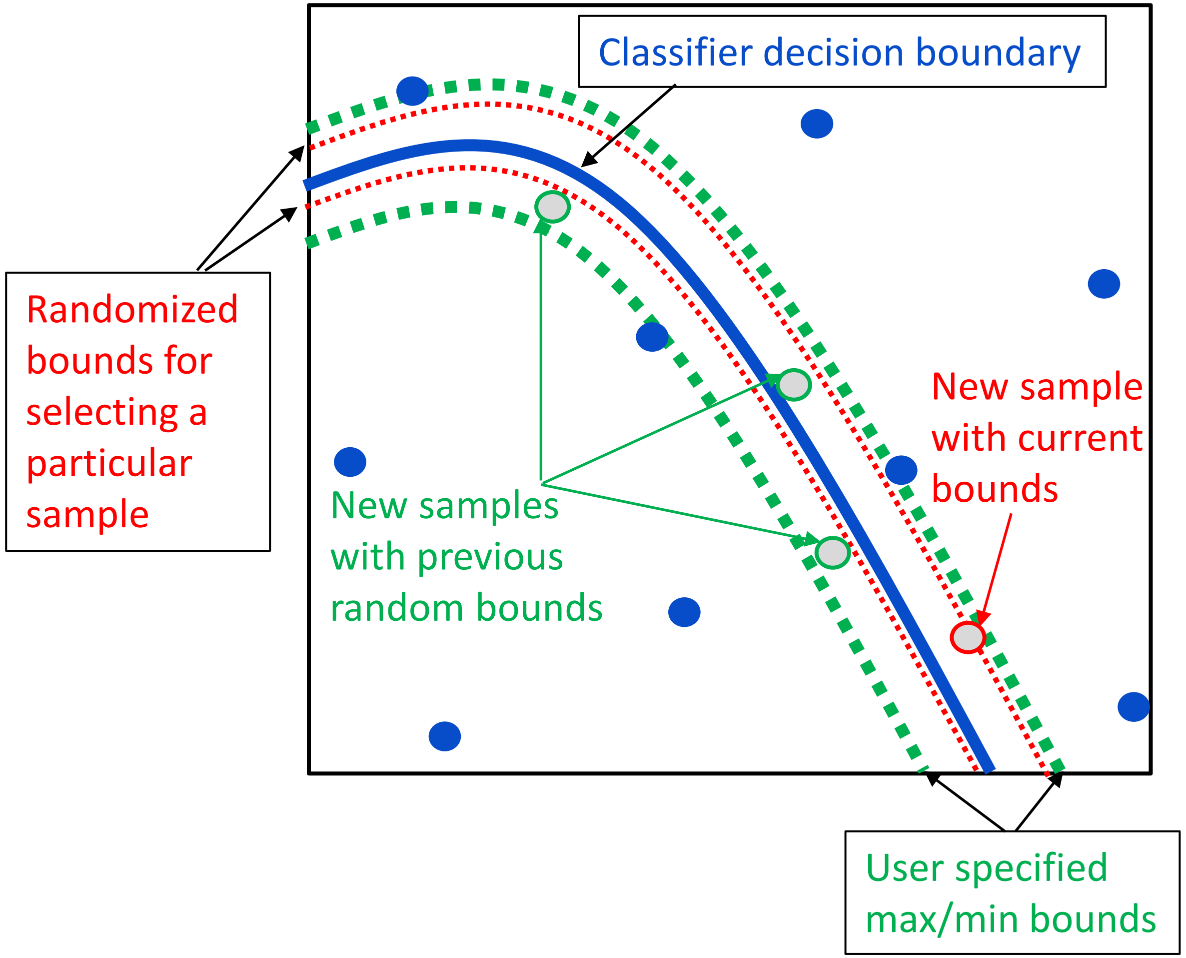


Sampling constraint attributes may be customized

Adds application-based flexibility and robustness (local-global balance)

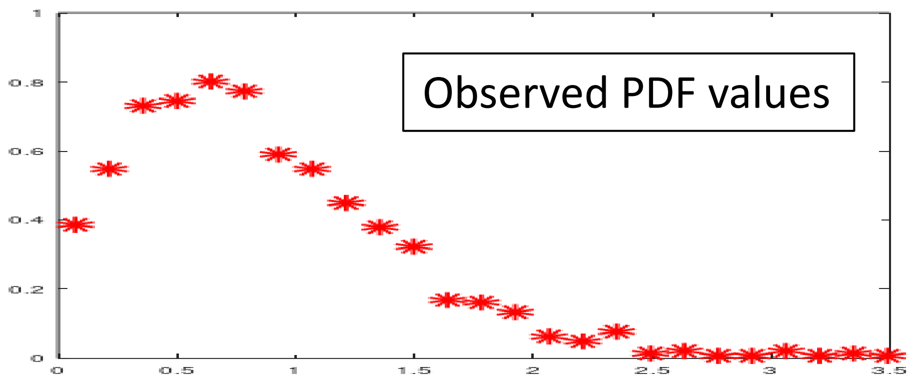
- Max/Min SVM bounds defined by user
- Actual bounds may be randomized between the max/min values - each sample to be selected has a different set of bounds due to randomization
- Maximin distance sample selected within the bounds
- Bounds may be deactivated for specific samples using appropriate "First", "Gap" and "Last" parameters

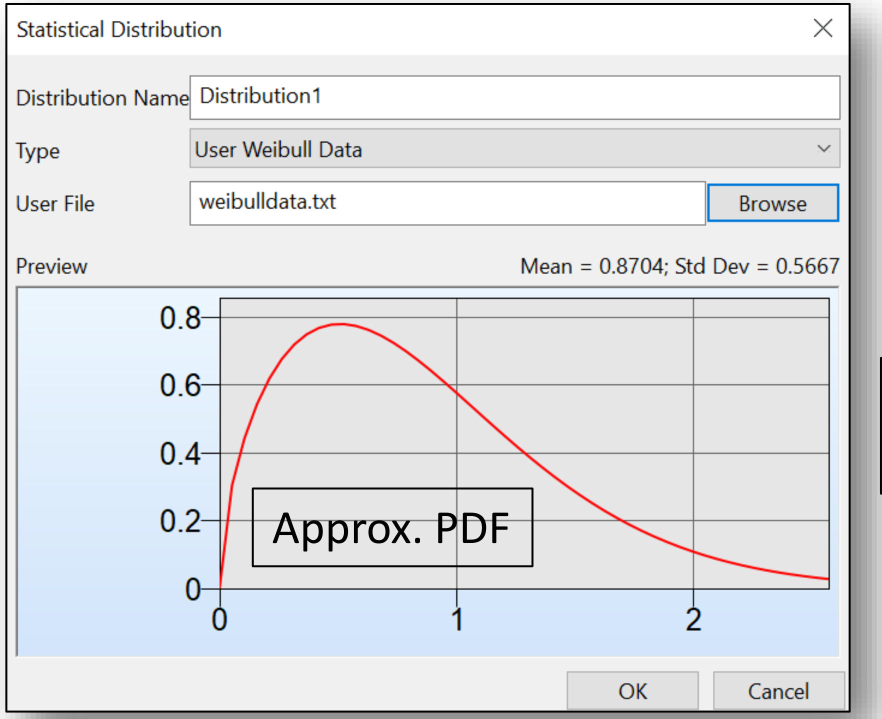
The adaptively refined constraints can be used for any LS-OPT task, e.g. probabilistic analysis or optimization



7.0: Distribution Fitting

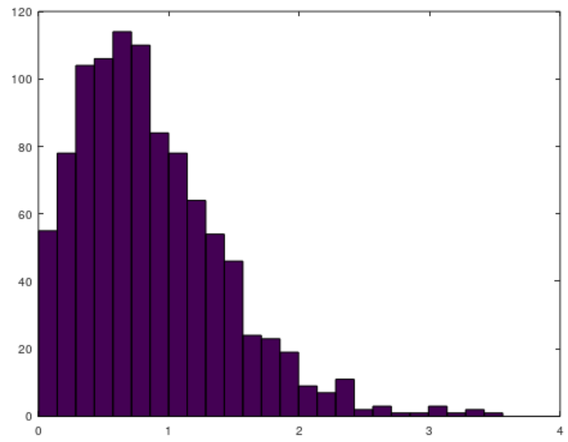
- Possible to provide observed data instead of pre-defined distribution parameters.
- Normal & Weibull distribution fitting
  - Moment matching for Normal distribution
  - Maximum likelihood estimate for Weibull distribution





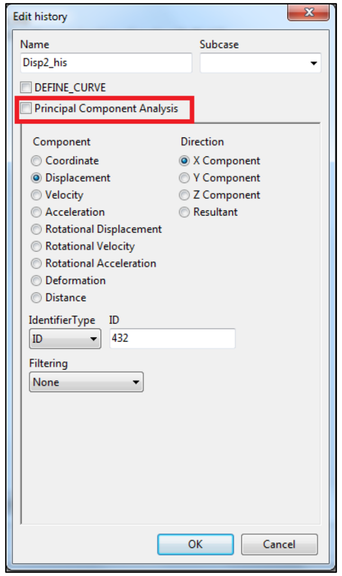
LS-OPT Weibull fit

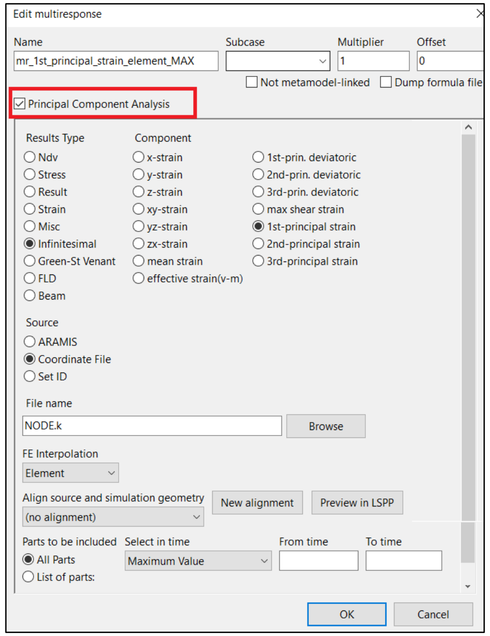
Observed data

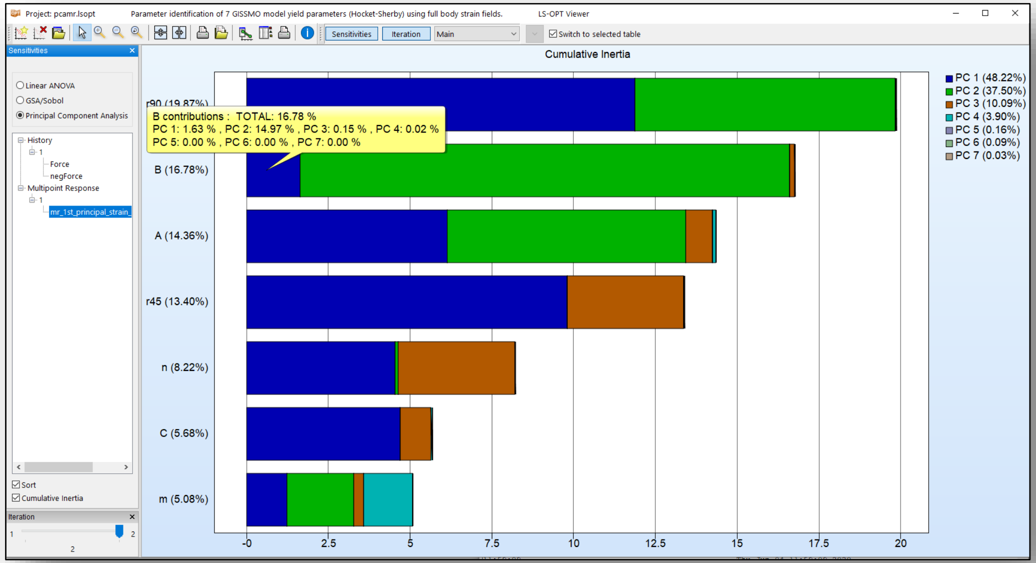


7.0: Variable Importance: Sensitivity of Multi-Responses/Histories

- Correlation Matrix Proper Orthogonal Decomposition
- Shows contribution of each principal component and cumulative history/multiresponse sensitivity measure
- Variable Importance
- Multi-point response (spatial field) extraction added

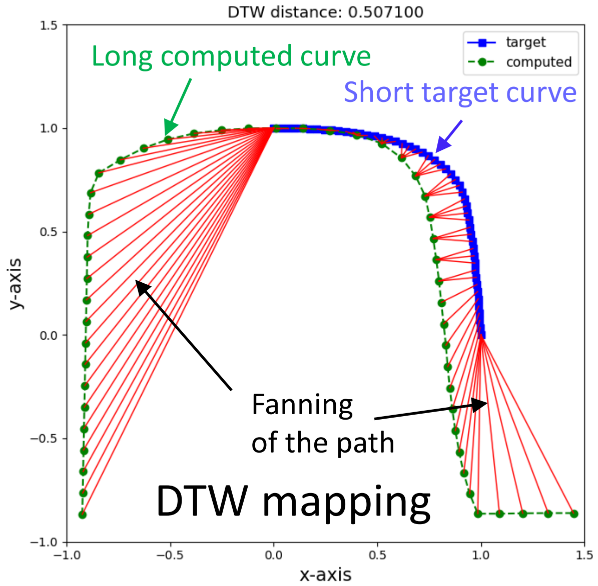




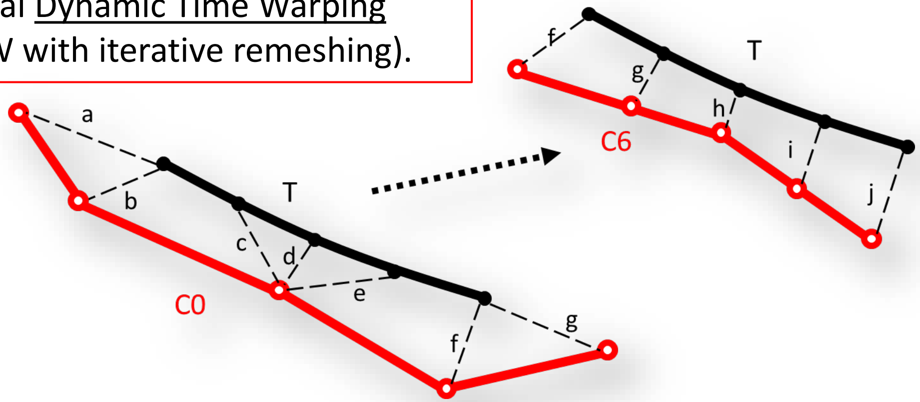


Material Calibration Using Partial Curves

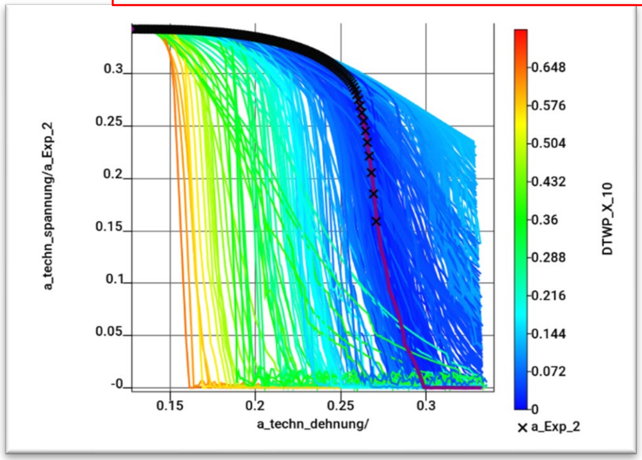
- Partial curves confound the error source (shape vs length mismatch)
- Trimming improves curve compatibility and can reduce optimization complexity



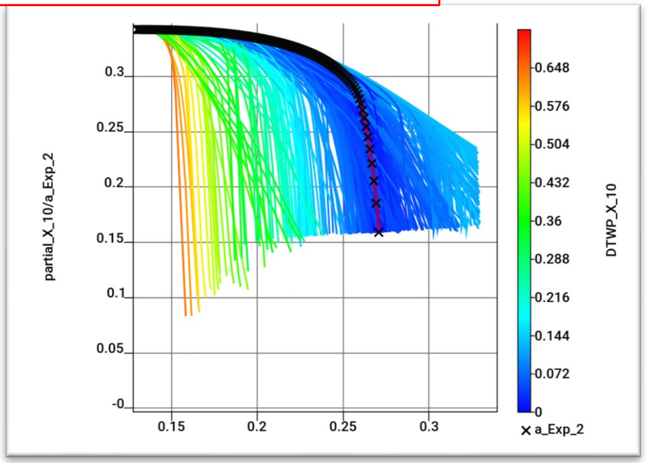
Partial Dynamic Time Warping (DTW with iterative remeshing).



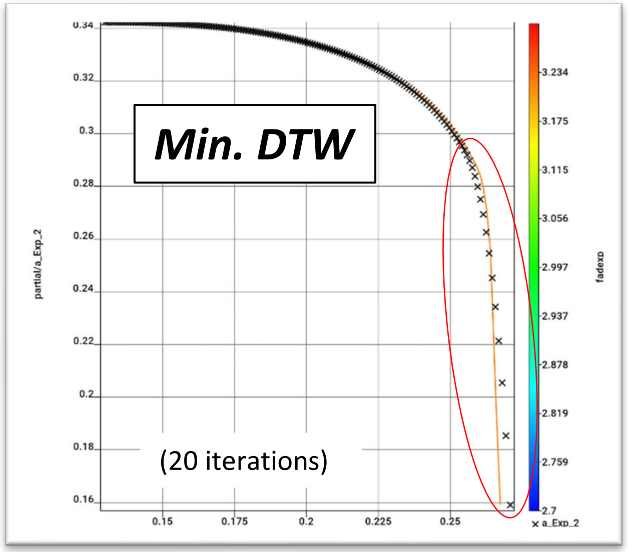
LS-DYNA® GISSMO failure model with element erosion

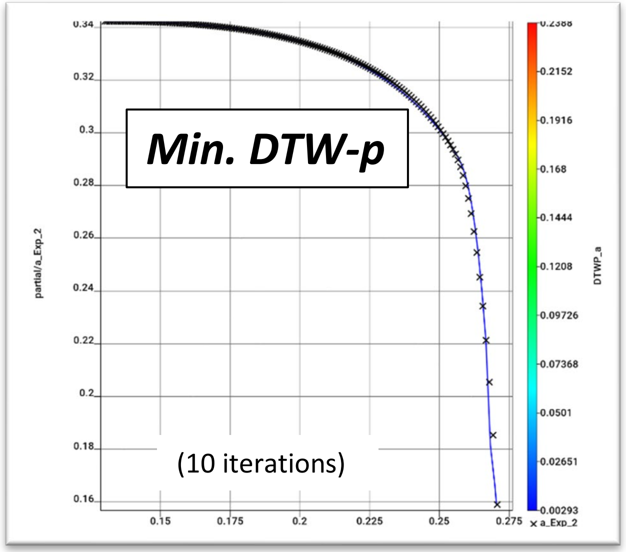


Baseline



Truncated curves





Optimum

Summary of the similarity measures available in LS-OPT®

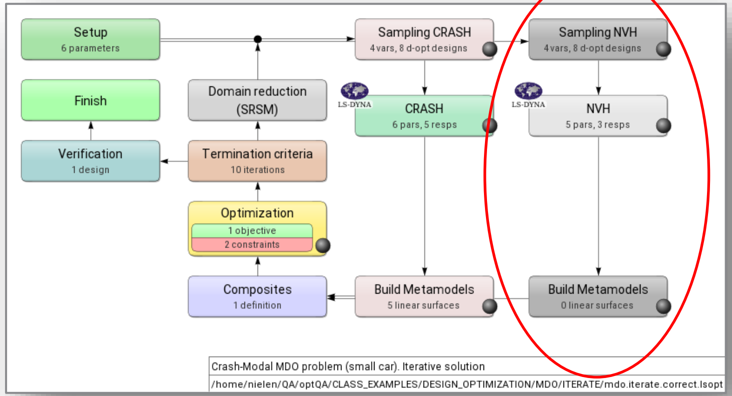
Distance Metric	Principle	Advantage	Disadvantage
Euclidean Distance (MSE)	**Mean Squared Error** of the difference in curve ordinates	Noise, partial curves	Hysteresis: the curves must be functions such as time histories.
Partial Curve Mapping (PCM)	**Area between curves.** Preserves the arc length.	Curves of unequal geometric length and hysteresis	Noise. Due to arc length preservation.
Discrete Fréchet (DF)	**Minimum of the maximum** of all possible edge lengths along a path which connects all given data points, taking into account the location and ordering of the points.	Noise and hysteresis	Curves of unequal geometric length (incompatible).
Dynamic Time Warping (DTW)	Minimizes the sum of path connectors between the curves in a **one-to-many mapping** end to end.	Noise and hysteresis	Incompatible curves. More complicated to code. More expensive to compute.
Modified Dynamic Time Warping (DTW-p)	Recursively **trims coincident end connectors** of DTW.	Noise, hysteresis, incompatibility. Simple extension of DTW	None

LS-OPT 7.0: Process Management: Case and Stage (de)activation

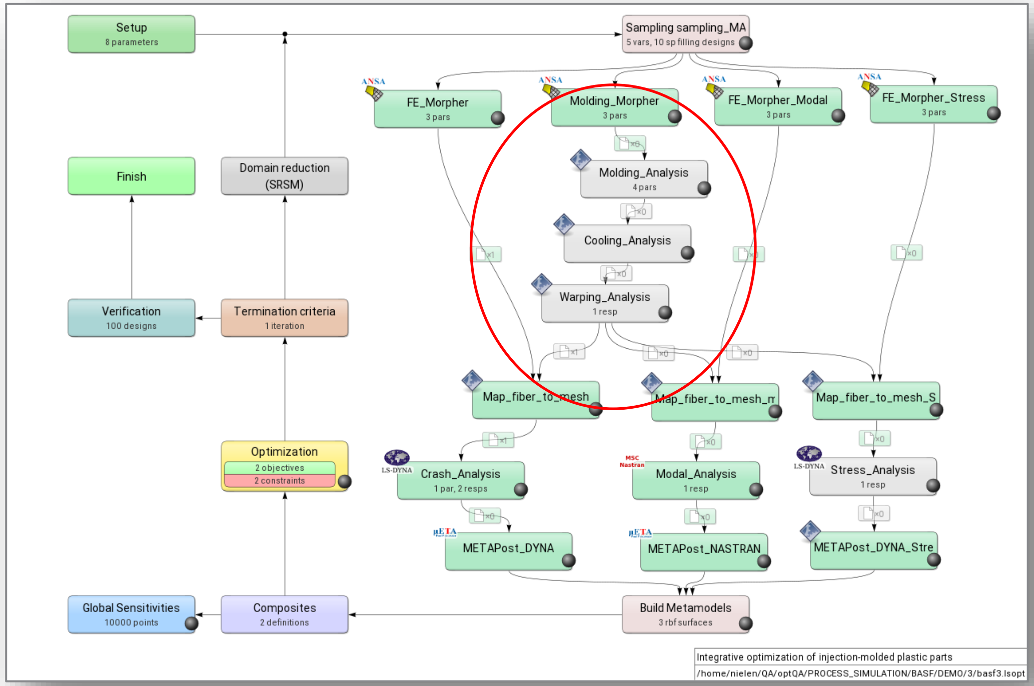
- LS-OPT provides a flexible process integration & optimization framework: multidisciplinary, multiobjective, multilevel
- In large groups, there may be a need to execute a certain part of the process, e.g. a particular discipline. Goal is to reduce manual work.

LS-OPT process flow

- Deactivate selected MDO cases or stages for an Optimization/Reliability run
- Automatic (de)activation of dependent Classifiers and Composite expressions
- Requests to extend as debugging tool



Case deactivation



Stage deactivation

LS-OPT 7.0: Job scheduler

SSH support and simplify customization for remote scheduling (e.g. Blackbox system)

- **Parallel limit**
  - Increase number of simultaneous runs — 300 parallel limit no longer valid
- **SSH Support**
  - *SSH is the default access into UNIX systems*
  - Well understood by IT staff. Maintained and secure
    - Run job directly on remote machine
    - Submit job to cluster via proxy machine
    - Supports OpenSSH or PuTTY binaries (common)
  - SSH host configuration is saved in user settings as opposed to project-file.
  - Authentication using SSH-agent is highly recommended (streamlines security handling)
  - GUI settings in lieu of environment variables

- **Simplified BLACKBOX queuing system**
  - No need to implement LsoptJobCheck script
    - No job progress
  - User-defined termination criteria from GUI
    - Job executable return code
    - Line in stdout (e.g. N o r m a l)
    - File existence
    - Line in file
- **User-defined port range for runqueuer**
- ***Destined for WorkBench, LS-Run, LS-TaSC, LS-Form***

Courtesy: Åke Svedin

LS-OPT Pro 2022 R1/2

Ansys

LS-OPT Pro

- Version Naming will change to **YYYY R1 or R2**
- *LS-OPT Pro* part of 3-Tiered licensing system
  - **LS-OPT Pro (Licensed)**
  - optiSLang Premium
  - optiSLang Enterprise
- Integration: LS-OPT Pro & optiSLang (an Ansys product) will exchange technology
  - <u>From optiSLang:</u>
    - A single best metamodel selection option is added.
      - "Best" metamodel, Metamodel of Optimal Prognosis (MOP), selected using coefficient of prognosis (CoP).
  - <u>To optiSLang:</u>
    - Integrates Extractor (LS-DYNA interface) including Response GUI, Variable parsing and special functions such as injury criteria, time integration, similarity measures, etc.
    - Incorporates LS-OPT metamodels in MOP (MOP-X)
    - Integrates Classification

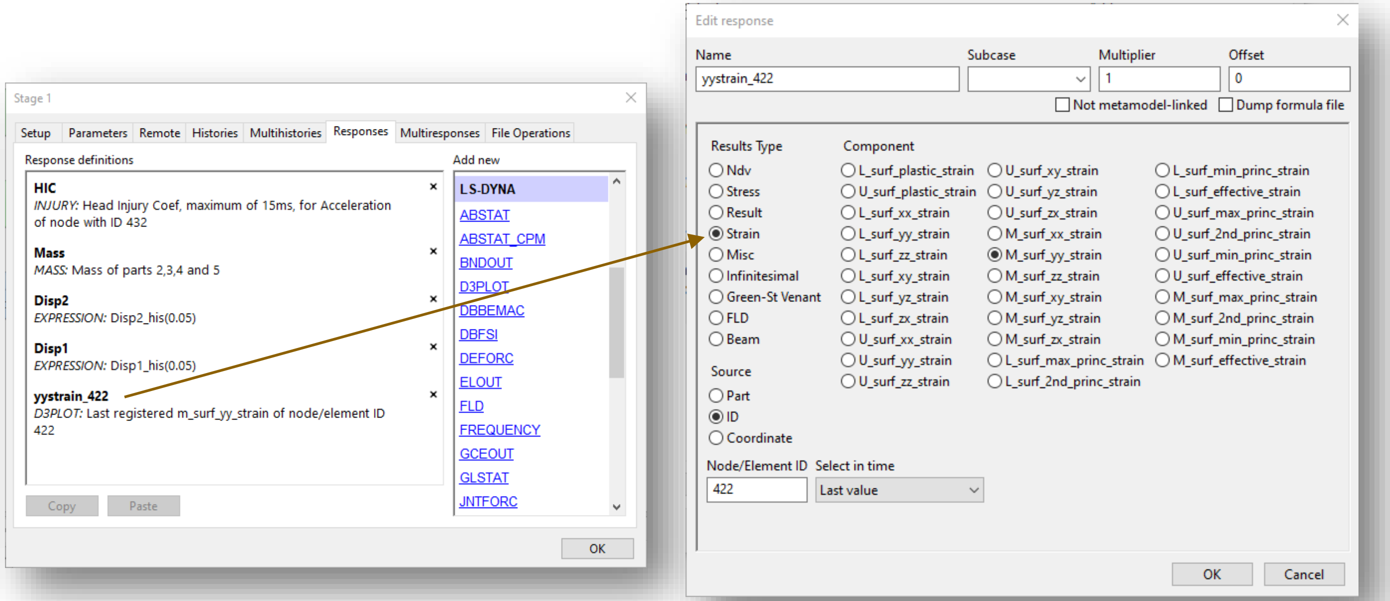
- The first version of LS-OPT Pro is 2022 R1
  - Released Jan, 2022
    - MOP: automatic problem specific metamodel selection
    - CORA stage: standardized parameter identification metrics.
    - Element interpolation features for point mapping (DIC)
    - LS-Reader integration
- Current R&D focus on reduced order modeling for approximating histories and spatial fields, cloud mapping (Point Registration) and adaptive sampling

R2022 R1 Development (next release)

Unified Extractor with LS-Reader Interface

- Extractor is now part of a bigger ecosystem shared by *LS-OPT Pro*, LS-TaSC and optiSLang (other Ansys code)
- Results are now extracted using independently maintained *LS-Reader* API (also integrated with LS-PrePost, LS-TaSC)
- **Updates to LS-DYNA database automatically supported, thus improving stability of the optimization software**
- Special functions such as operators (integration, differentiation), *Injury criteria* and *Similarity measures* also supported
- Commands are generated by a GUI

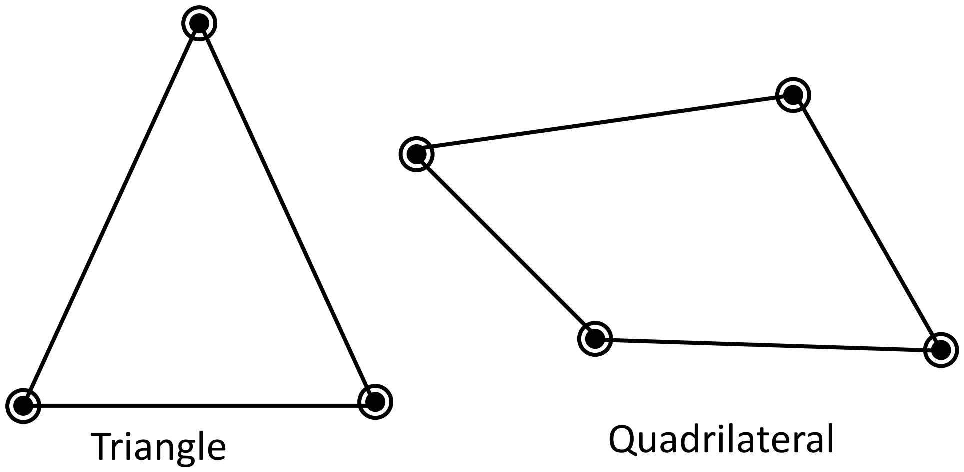
- Additional response types not currently supported in LS-OPT will be added in 2022 R2.
  - **Acoustics, CFD, Thermal etc.**
- Extractor will thus become a complete package for LS-DYNA based multi-disciplinary analysis.



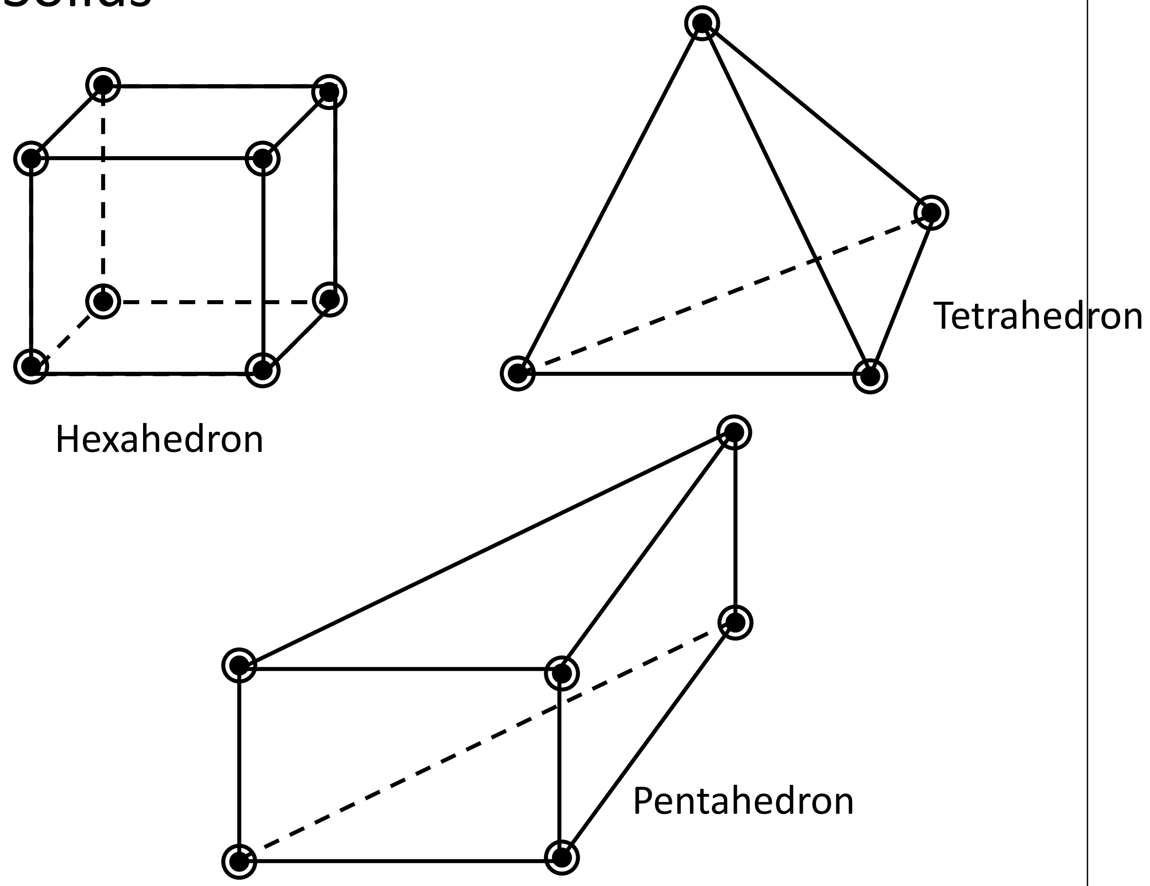
Result extraction LS-DYNA®: Point mapping in shells and solids

- Applications
  - Models often have mixed element facetypes
  - Interpolate values at specified coordinates
  - Applies to responses, histories, fields, field histories (Digital Image Correlation)

- Shells

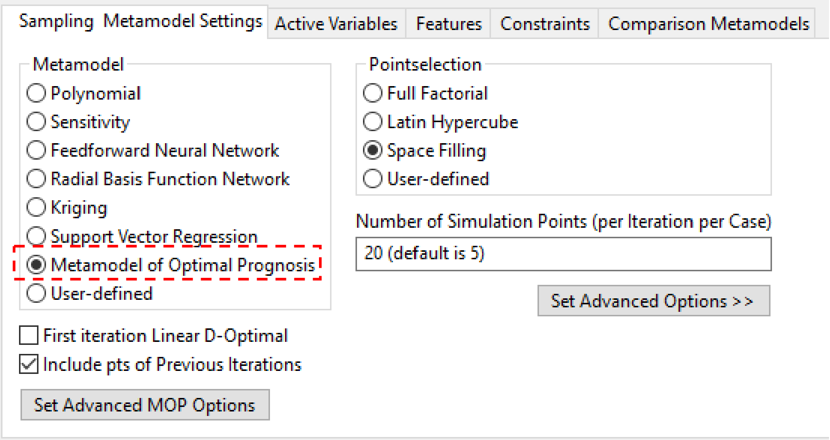


- Solids



Metamodel of Optimal Prognosis (MOP): Automated Selection

- The most suitable metamodel type is generally problem dependent (not known a priori)
- The best metamodel is selected automatically using the new MOP feature.
- Feature imported from optiSLang, which uses a Coefficient of Optimal Prognosis to evaluate the metamodel quality.



- 2022 R1 supports:
  - Linear
  - Quadratic
  - Kriging
- 2022 R2 MOP-X will expand the options to include:
  - *Feed Forward Neural Networks (FFNN)*
  - *Radial Basis Function Networks (RBFN)*
  - *Support Vector Regression (SVR)*
  - *Support Vector Classification (SVC)*

MOP: Comparison to Existing Metamodels (2 variable Taurus)

	RBF Predicted	NN Predicted	Kriging Predicted	MOP Predicted	MOP Model	Direct Optimum (20 iterations, 30pts/iter)
b_floor	1.72454	1.69784	1.73095	1.73458		1.74959
beam	3.5436	3.52277	3.47564	3.51511		3.45645
ref_node	-715.042	-716.952	-716.809	-716.212	MLS	-716.956
RMS	2.28	2.69	2.74	2.18		
lwr_beam	-10.7259	-10.4128	-11.9367	-10.9651	Kriging	-12.206
RMS	1.79	2.16	1.85	1.71		
upr_beam	-66.2104	-69.0849	-68.2547	-67.247	Kriging	-68.7782
RMS	3.38	3.46	4.14	3.28		
door	-76.7483	-78.6579	-78.5151	-77.9186	Kriging	-78.7444
RMS	2.87	3.11	3.43	2.9		
bpillar	-133.018	-132.955	-137.282	-134.063	Kriging	-137.015
RMS	3.9	5.09	4.74	3.7		
Int_bpillar	582.024	583.997	579.527	582.149		579.941
Int_lwrbeam	704.316	706.539	704.872	705.247		704.75
Int_door	638.294	638.294	638.294	638.293		638.211
Mass	0.0639212	0.06333	0.063541	0.0637139		0.0632154

Metamodel built using 200 points and RMS error evaluated using 800 check points.

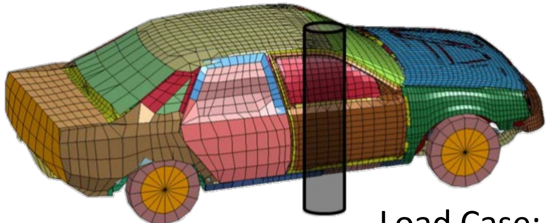
$\min \quad$ Mass (six parts, two variables)

$\text{s.t.} \quad \text{Intrusion}_{\text{bpillar}} \le 585\text{mm}$

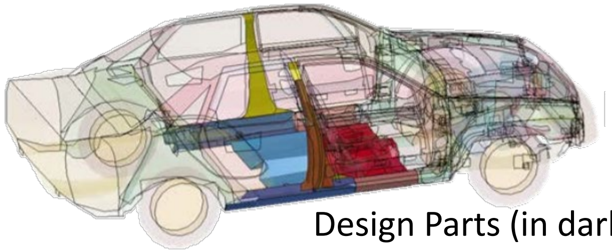
$\text{Intrusion}_{\text{lowerbeam}} \le 710\text{mm}$

$\text{Intrusion}_{\text{door}} \le 638.23\text{mm}$

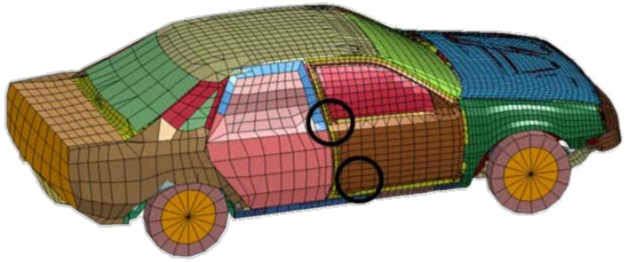
(Intrusion measured with respect to a reference node)



Load Case: Side pole crash



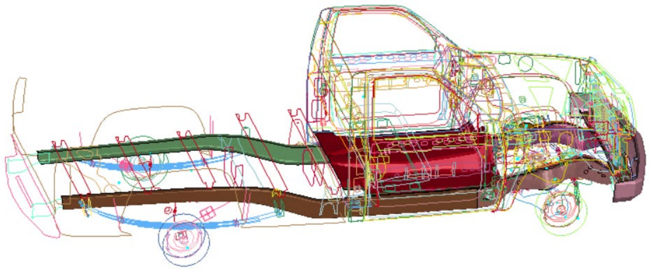
Design Parts (in darker shade)



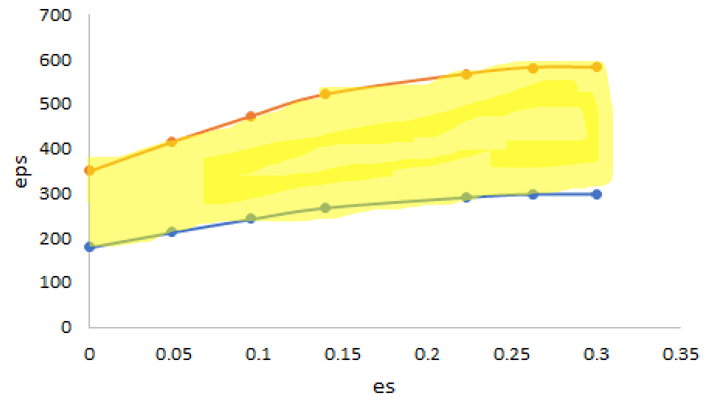
MOP: Comparison to Existing Metamodels (22 variable truck)

	RBF Predicted	NN Predicted	Kriging Predicted	MOP Predicted	MOP Model	Direct Optimum (20 iter., 100pts/iter.)
t1, m1	2.510, 349.5	2.510, 349.7	2.510, 327.6	2.510, 348.1		
t2, m2	2.398, 315.4	2.398, 279.6	2.398, 336.3	2.398, 349.3		
t3 , m3	2.510, 340.5	2.510, 293.4	2.510, 329.1	2.510, 348.6		
t4, m4	2.399, 292.6	2.399, 269.7	2.399, 310.9	2.399, 336.4		
t5, m5	2.721, 180.5	2.721, 300.6	2.721, 333.8	2.721, 291.8		
t6, m6	2.721, 275.2	2.721, 180.1	2.721, 255.5	2.721, 328.2		
t10, m10	2.162, 298.5	2.162, 180.2	2.162, 283.5	2.162, 246.5		
t11, m11	2.927, 330.2	3.600, 299.2	2.667, 350.0	3.040, 308.1		
t12, m12	2.948, 330.3	3.257, 330.0	3.350, 267.1	2.499, 223.1		
t64, m64	1.010, 190.6	1.010, 180.1	1.010, 218.6	1.027, 183.8		
t73, m73	1.593, 345.5	1.593, 349.8	1.593, 270.3	1.593, 182.3		
N1_disp	725.5	723.1	722.6	724.4	Kriging	
RMS	9.22	8.00	9.22	9.27		
N2_disp	722.3	725.7	723.1	724.7	Kriging	
RMS	8.77	7.72	8.83	8.99		
Stage1_pulse	6.818	6.03	6.598	5.869	Linear	
RMS	0.0646	0.0624	0.105	0.122		
Stage2_pulse	20.3	21.09	21.03	21.09	Linear	
RMS	0.377	0.378	0.432	0.532		
HIC	1.148e+05	7.93e+04	9.56e+04	1.089e+05	Kriging	
RMS	2.76e+05	7.09e+05	2.83e+05	2.86e+05		
scl_mass	0.8006	0.8001	0.8006	0.8051		
scl_disp	0.9984	0.9991	0.997	0.9994		
scl_stage1_pulse	0.9019	0.7976	0.8728	0.7763		
scl_stage2_pulse	0.9577	0.9947	0.9918	0.9946		

min *mass (11 parts, 22 variables)*
s.t. *displacement ≤ 1*
stage1_pulse ≤ 1
stage2_pulse ≤ 1



Design Parts (Thickness variables)

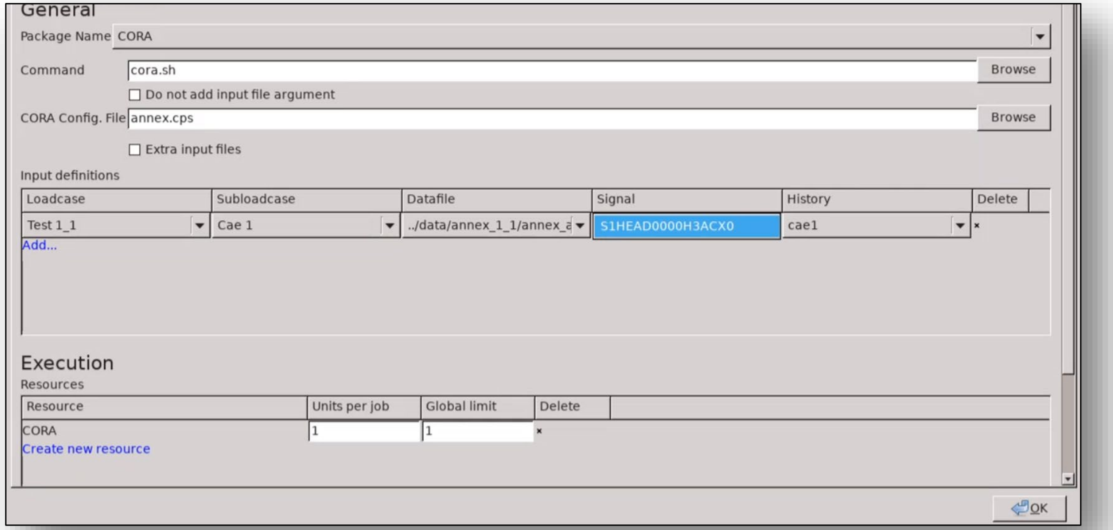


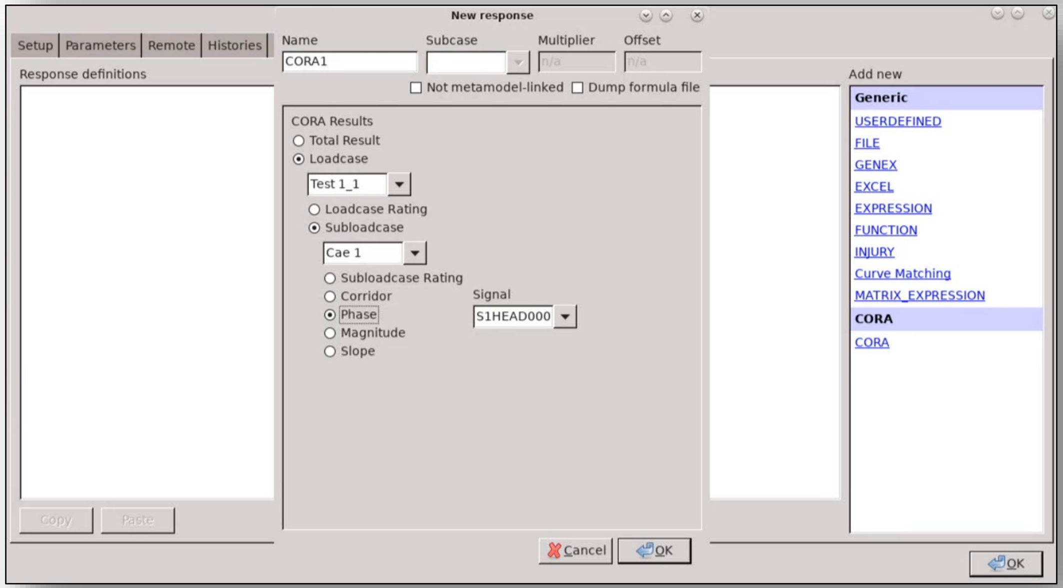
Continuous Part Material Variables

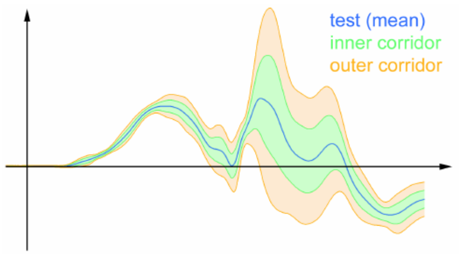
Metamodel built using 800 points
RMS error evaluated using 1200 test points

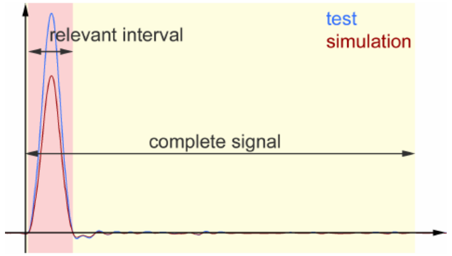
CORA Interface for ISO Rating of Dummies & Barriers

- Multiple ratings – for each signal, rating specific to a load case and injury criterion (e.g. head, neck etc.), global rating
- Rating is a weighted sum of measures from different approaches







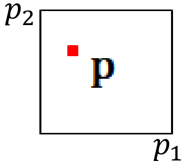


Ref: Gehre, C., Gades, H. and Wernicke, P., 2009. Objective rating of signals using test and simulation responses. In *Proceedings: International Technical Conference on the Enhanced Safety of Vehicles* (Vol. 2009). National Highway Traffic Safety Administration.

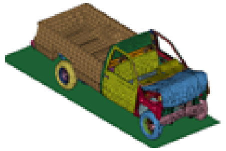
R2022 R2 Development & Outlook

Reduced Order Modeling: History/Multiresponse/Multihistory

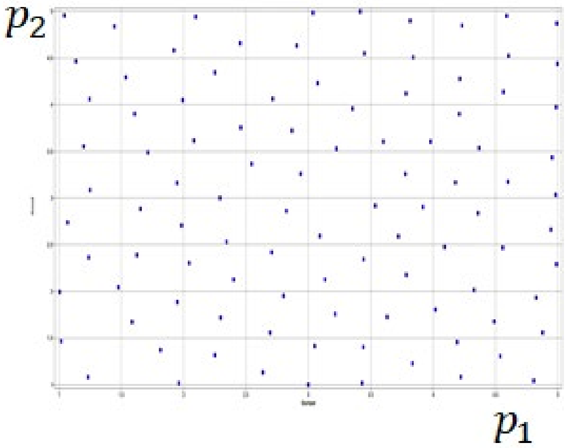
- Express the data as POD/PCA expansion
- Identify the important features
- Building metamodels for the important coefficients
- Predicting the coefficients



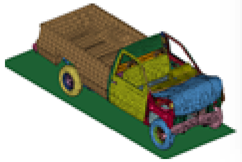
New Sample ($\mathbf{p}$)

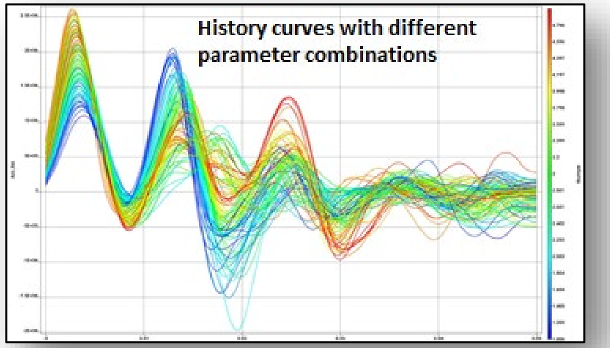


Sampling



LS-DYNA





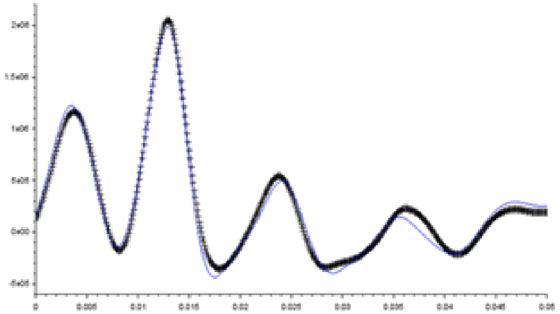
Reduced order modeling

PCA + metamodel

ROM

$$S(\mathbf{p}) = \sum_{j=1}^{MS} \hat{\alpha}_j(\mathbf{p}) \mathbf{V}_j$$

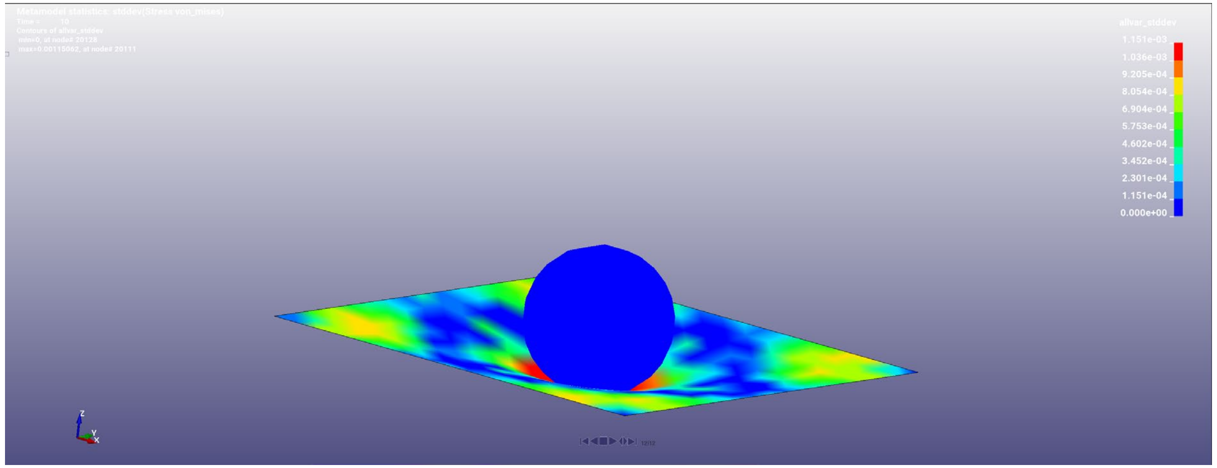
Inexpensive ROM Computation



- Applicable to approximation of histories, multiresponses & multihistories
- Parameter identification
- DynaStats spatial approximation
- Multifidelity optimization/reliability assessment with ROM as low fidelity model

Enhancements to ROM Methodology

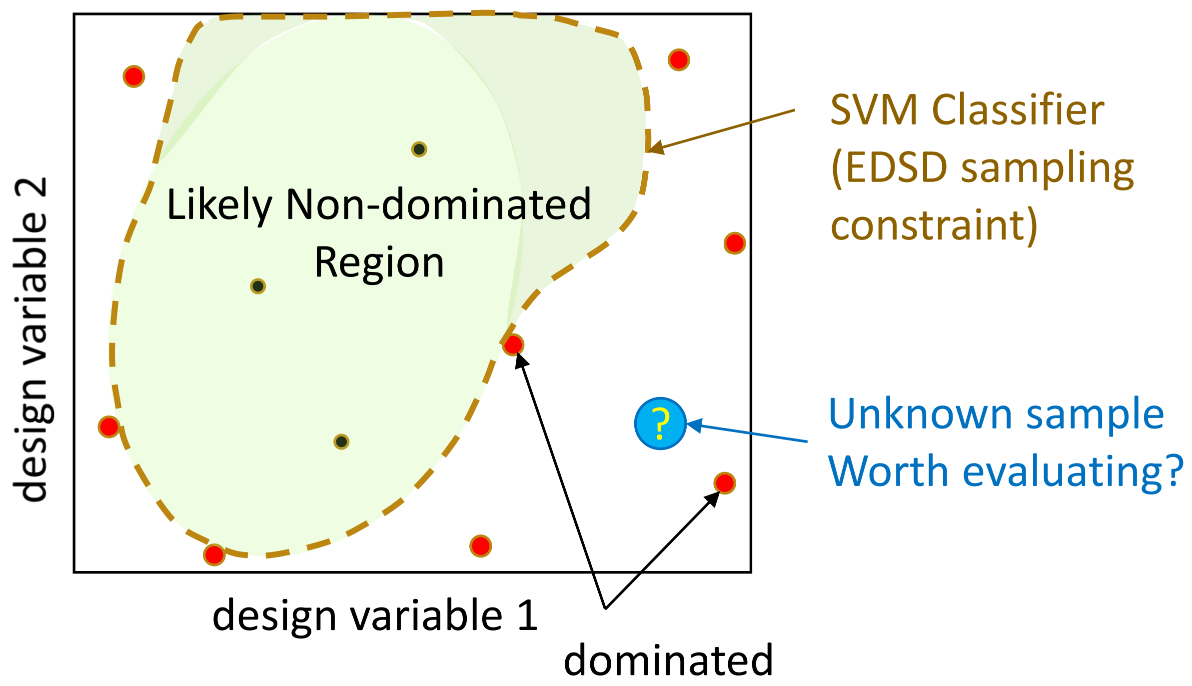
- Accuracy for nonlinear problems could be improved



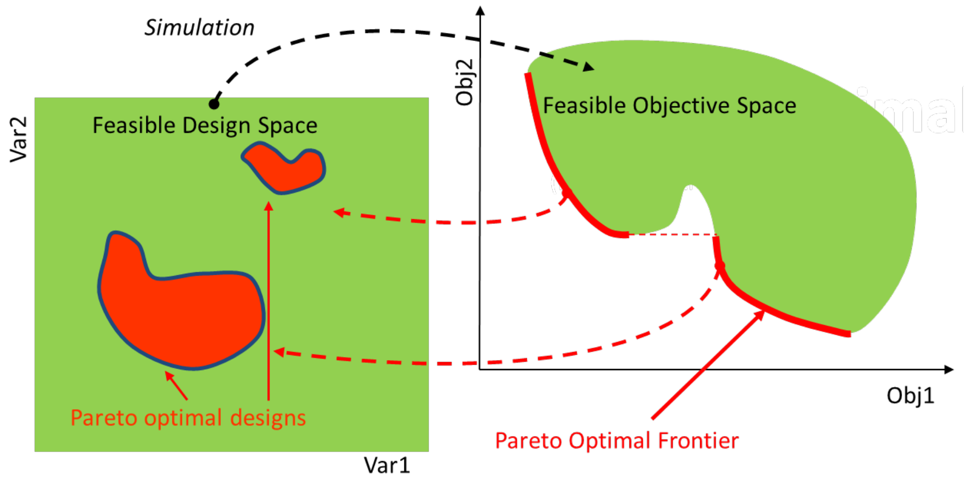
- A methodology involving the partitioning of space to treat nonlinear regions separately being considered.
- Use of Deep Neural Networks will be explored as well in the future.

Pareto-Optimality Based Classifier for Multi-Objective Optimization

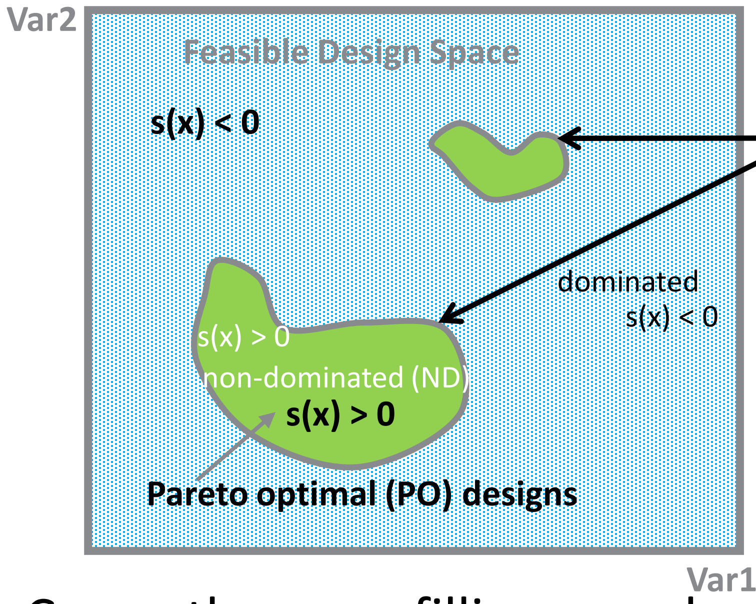
- Current metamodel-based MOO limited to sequential sampling
- No adaptive sampling



- A new classifier type for dominated vs non-dominated.
- Classifier used as a sampling and/or design constraint for MOO.
- Adaptive: avoid sample evaluation in "known" non-optimal regions.



Adaptive Multi-objective Optimization Method (AEMOO)



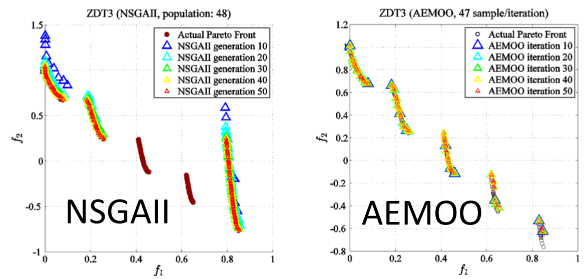
Approximate boundary instead of objective function value

Boundary separates dominated and Non-dominated design space

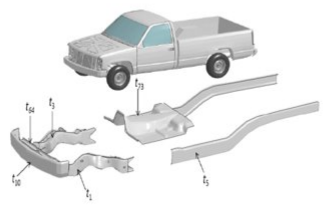
- Currently space-filling samples selected within predicted ND domain (or relaxed)
- Approximation of the classifier boundary allows definition of an adaptive sampling region

Basudhar A, inventor; Livermore Software Tech Corp, assignee. Multi-objective design optimization using adaptive classification. United States patent US 9,852,235. 2017 Dec 26. Chinese Patent 2021.

30 variable ZDT3 Example:

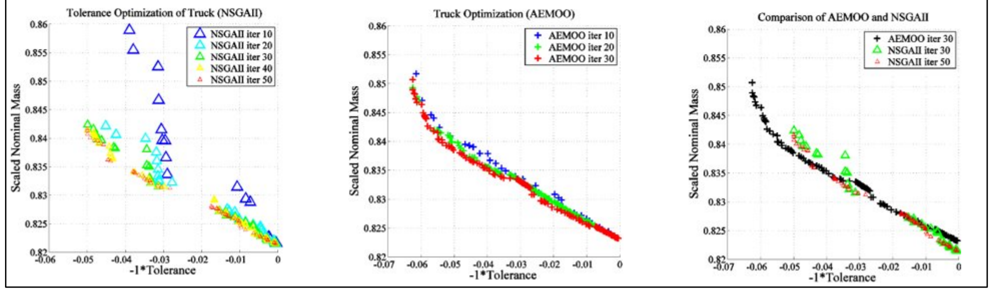


Truck Tolerance Example (7 var):



Objectives:
1. Minimize Mass
2. Maximize Tolerance (robust)

Constraints:
1. Intrusion
2. Stage 1 pulse
3. Stage 2 pulse

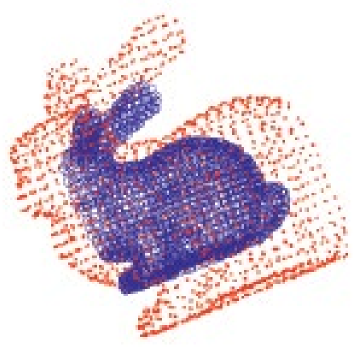


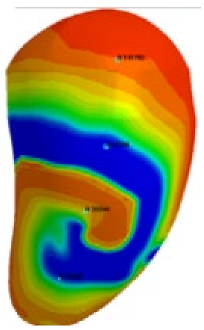
- Next Steps (Ongoing):
  - Acceleration of solution using non-domination rank optimization
  - Prevention of local solution due to classification error

Ansys

Point Set Registration

- **Parametric Shape Optimization Using Image Point Set Matching** (e.g. medical MRI data)
  - Modify shape of parametrized LS-DYNA model.
  - Rigid point set registration for each shape parameter set. (Started; currently on hold)





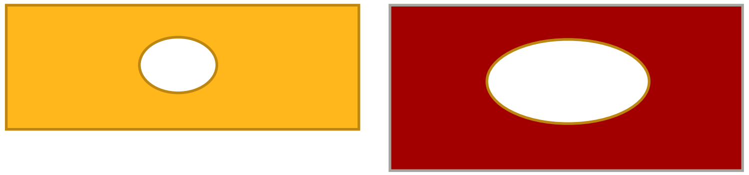
- Mode Tracking using MAC based on eigenvectors of modal analysis

$$\max_j \frac{\{\varphi_0\}^H\{\varphi_j\}\{\varphi_j\}^H\{\varphi_0\}}{\{\varphi_0\}^H\{\varphi_0\}\{\varphi_j\}^H\{\varphi_j\}} = \max_j MAC_j$$

Reference mode

Compared mode

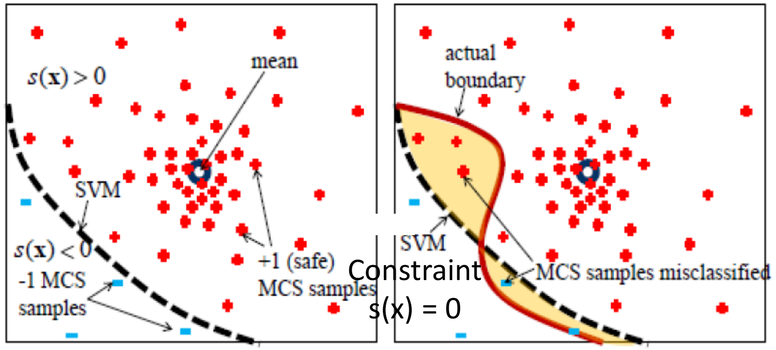
- **Mode Tracking with Varying Geometries** - Node sets and eigenvectors not comparable



- Spatial Mapping
  - Part specific (substructure) mapping
  - Non-rigid point set registration
- MAC for mapped designs

Other Developments

- Considering metamodel/classifier error in reliability estimate



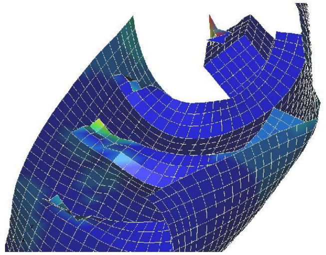
Basudhar, A. and Missoum, S., 2013. Reliability assessment using probabilistic support vector machines. *International Journal of Reliability and Safety*, *7*(2), pp.156-173.

- Adaptive methods for reliability assessment

- Metamodel formulae
  - Currently available for polynomials/RBF
  - Extend to FFNN, SVR, Kriging

- Parallel Efficient Global Optimization

- Sequential DynaStats (extend to iterative analysis)
  - Statistics based on samples from each iteration
  - Statistics based on accumulated samples



Concluding Remarks

- A major change is the transition of LS-OPT to the **licensed LS-OPT Pro** product under the 3-tier Process Integration and Design Optimization lineup of Ansys (Pro/Premium/Enterprise).
- First version of LS-OPT Pro 2022 R1 in Jan. Old versions can be used, but no new development there.
- A major change in 2022 R1 is the **integration of LS-OPT Extractor to LS-Reader**. This will help in keeping all LS-DYNA responses up to date and automatically incorporate any correction or improvement.
- Metamodel of Optimal Prognosis (MOP) was added to automatically select the best suited metamodel type.
- Developments have been made for calibration – CORA & element interpolation for DIC
- Reduced Order Modeling is being implemented. A new adaptive MOO method is also being implemented.

Ansys