

Meta Modeling and Multi Objective Optimization

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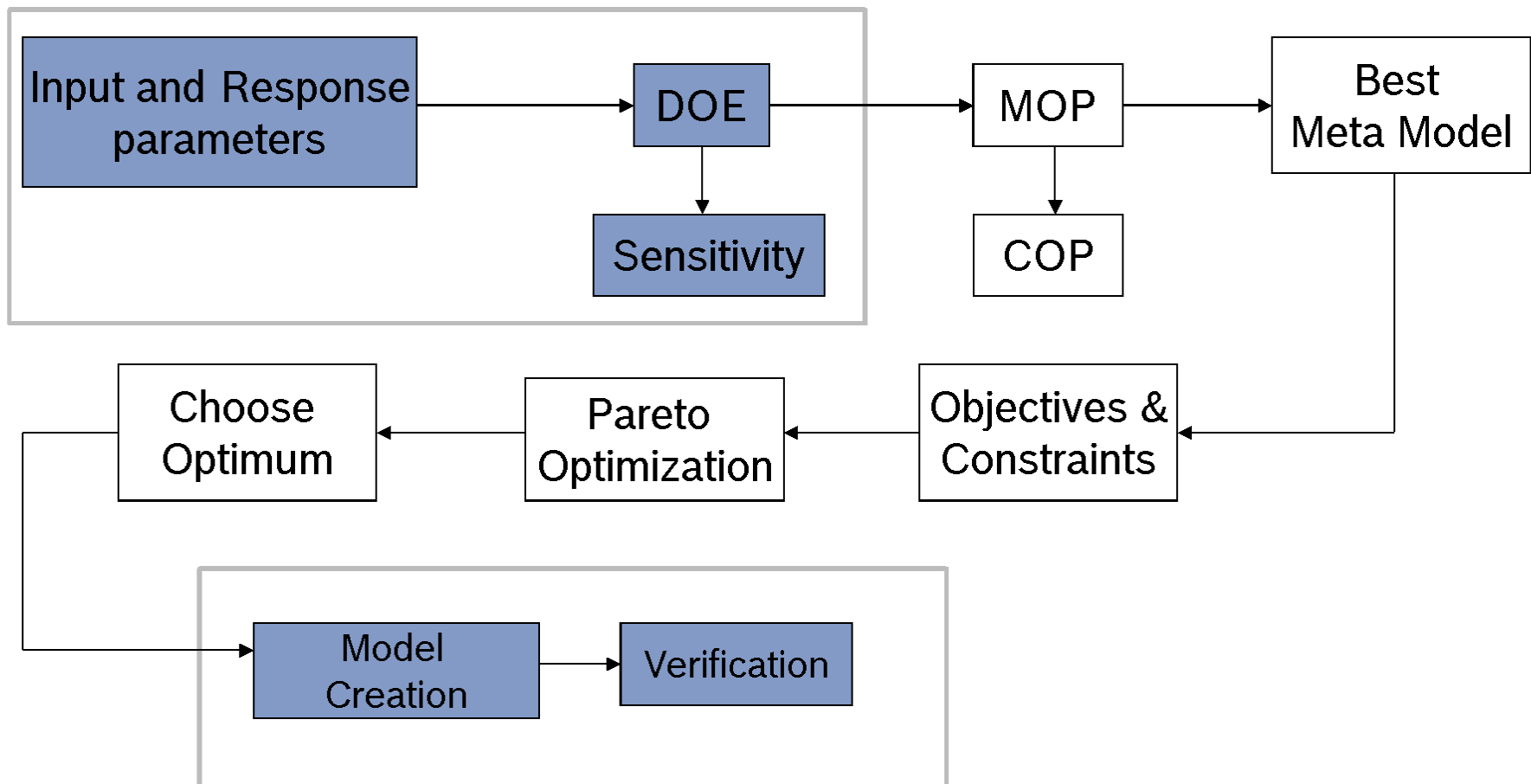
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Meta-Modeling and Multi Objective Optimization

Optimization Process Overview



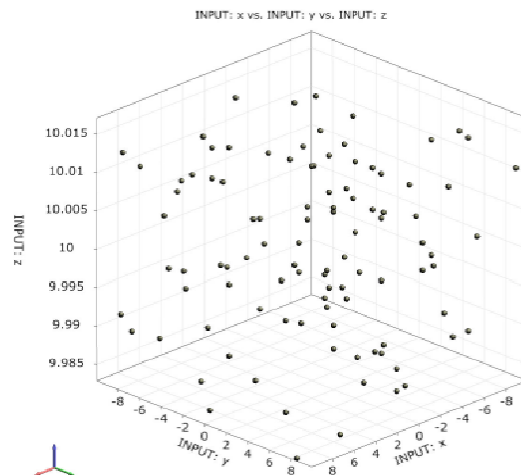
Meta-Modeling and Multi Objective Optimization

Scanning Design Space

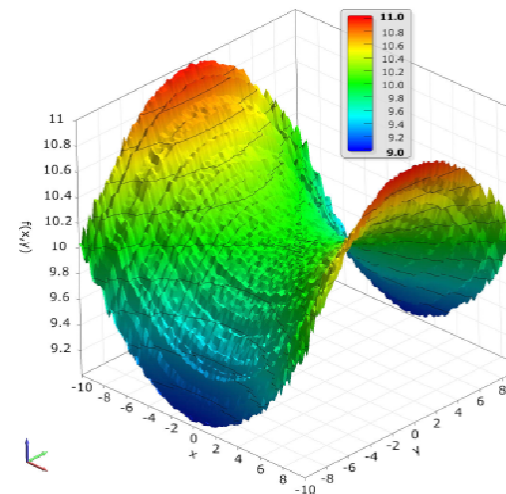
Inputs

$$\left. \begin{matrix} X_1 \\ X_2 \\ \vdots \\ X_k \end{matrix} \right\}$$

Design of experiments



Design evaluation



Outputs

$$\left. \begin{matrix} Y_1 \\ Y_2 \\ \vdots \\ Y_m \end{matrix} \right\}$$

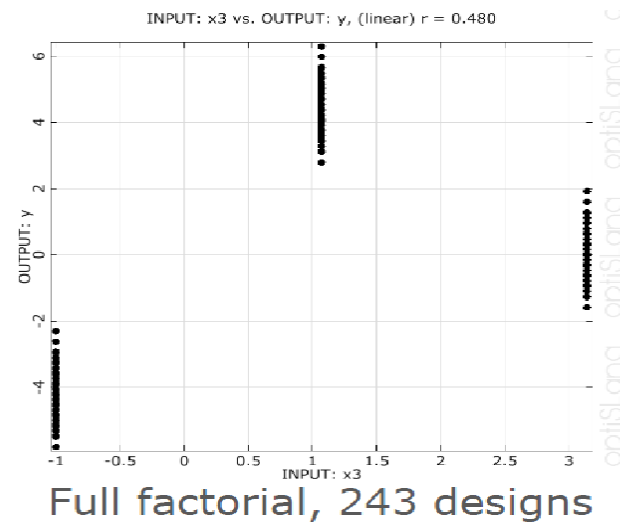
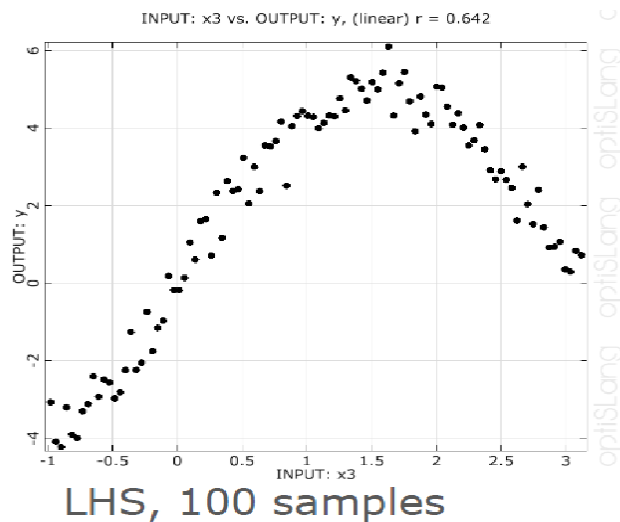
- Output variability and input sensitivities
- Input parameter significance and multivariate dependencies
- Minimum number of designs should cover the input space optimally and avoid clustering
- For each design/sample the outputs are calculated/measured

Source: Dynardo

Meta-Modeling and Multi Objective Optimization

Stochastic Sampling: Why?

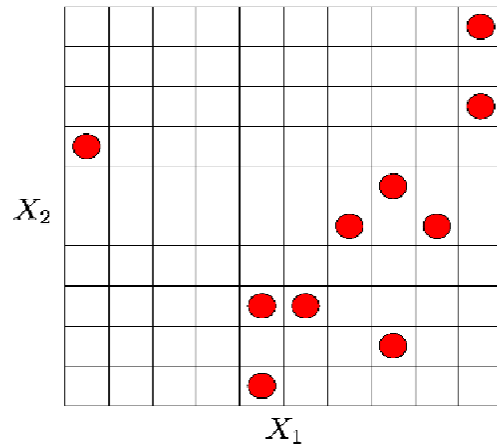
- Deterministic designs use maximum 3 levels for each variable
- LHS has for each variable N levels
- If we reduced the variable space by removing unimportant variables, deterministic designs lose the information of these variables, but with LHS this is not the case
- Example: 4 minor and 1 major important input variables:



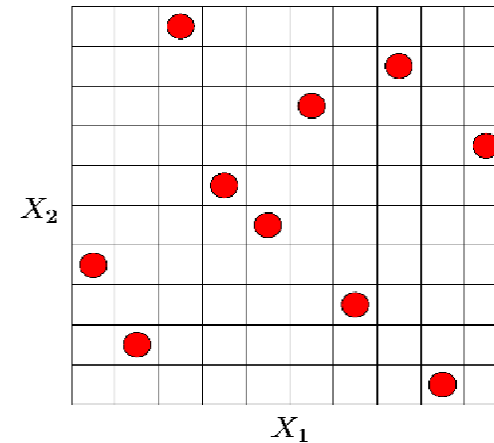
Source: Dynardo

Latin Hypercube Sampling

Standard Monte Carlo Simulation



Latin Hypercube Sampling



- Improved Monte Carlo Simulation
- Cumulative distribution function is subdivided into N classes with same probability
- Reduced number of required samples for statistical estimates
- Reduced unwanted input correlations
- Add optimal samples to an existing set of LHS samples (ALHS)

Source: Dynardo

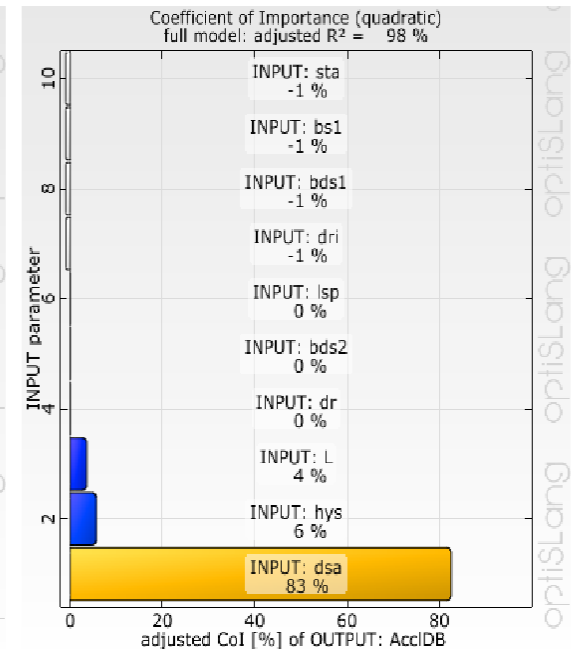
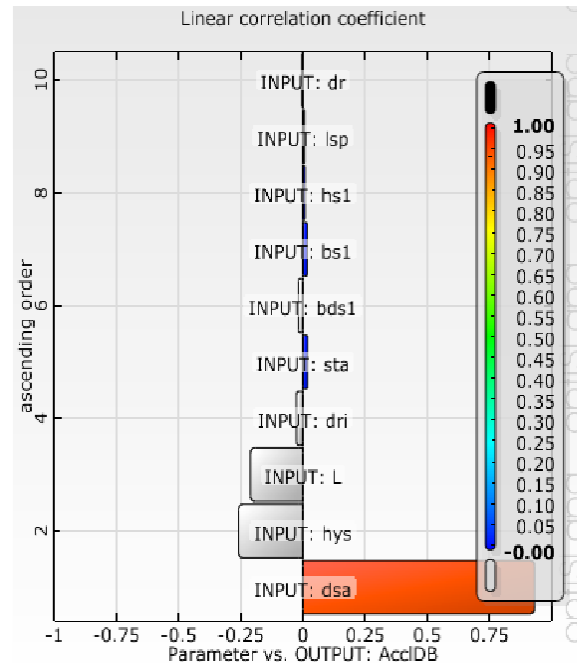
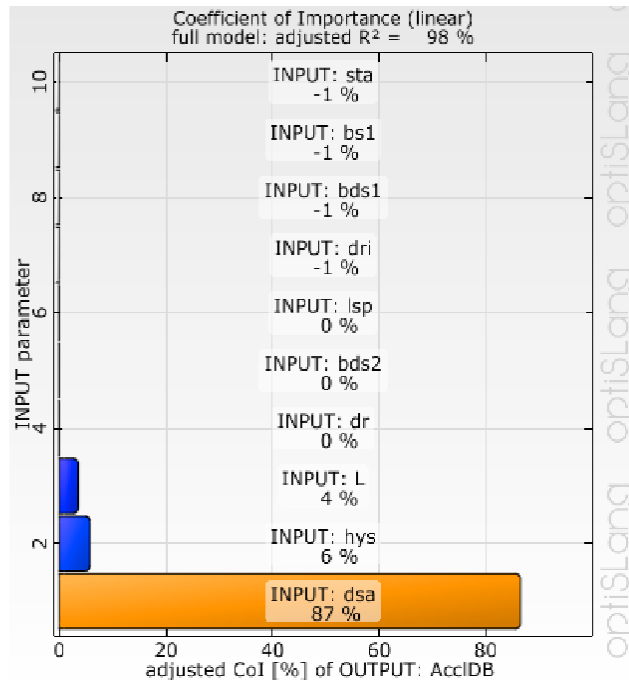
DOE: Sensitivity Study

- DOE helps for following
 - To find out the effect of the input parameter variation over the output responses and to rank the important parameters with respect to the output.
 - It is the base data to generate meta models, which are helpful to minimize the actual sample runs and minimize overall optimization lead time.
- Procedure for DOE is to generate LHS (Latin Hypercube) sample and run for the DOE analysis
- Sensitivity co-efficient are calculated during DOE run and important parameters are identified.

Parameter	Range
dr	20 to 27.5 mm
dri	...
L

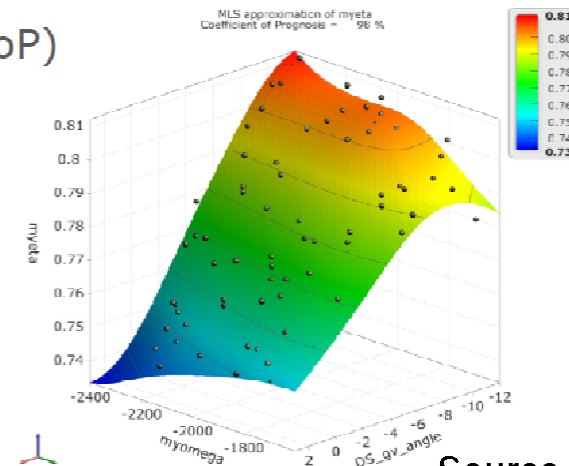
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Sensitivity based on Linear correlation coefficient



Meta-model of Optimal Prognosis (MOP)

- Approximation of solver output by fast surrogate model
- Reduction of input space to get best compromise between available information (samples) and model representation (number of input variables)
- Advanced filter technology to obtain candidates of optimal subspace (significance and CoI filters)
- Determination of most appropriate approximation model (polynomials with linear or quadratic basis, MLS, ..., Box-Cox)
- Assessment of approximation quality (CoP)
- **MOP solves three important tasks:**
 - Best variable subspace
 - Best meta-model
 - Determination of prediction quality

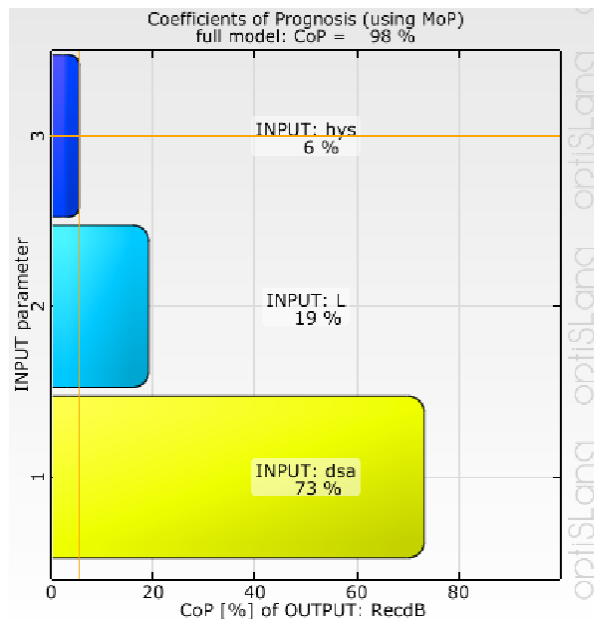


Source: Dynardo

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COP: Example

→ The COP value for the meta models are good and these models can be used for further optimization



protocol.txt

Response: RecdB

iteration	meta model	no. parameter	CoDadj	CoP
1	Partially Quadratic Regression Important variables: L, dsa, hys	3	0.9925	0.9904
2	Linear Regression Important variables: L, dsa, hys	3	0.9820	0.9806
3	Linear Regression Important variables: L, dsa, hys	3	0.9820	0.9806
4	Linear Regression Important variables: L, dsa, hys	3	0.9820	0.9806
5	Linear Regression Important variables: L, dsa, hys	3	0.9820	0.9806

Model of optimized prognosis

response name	metamodel	no. parameter	CoD adj.	CoP
Acc1DB	Quadratic (no mixed) Regression	3	0.9893	0.9882
RecdB	Linear Regression	3	0.9820	0.9806
Mass	Linear Regression	2	0.9937	0.9935

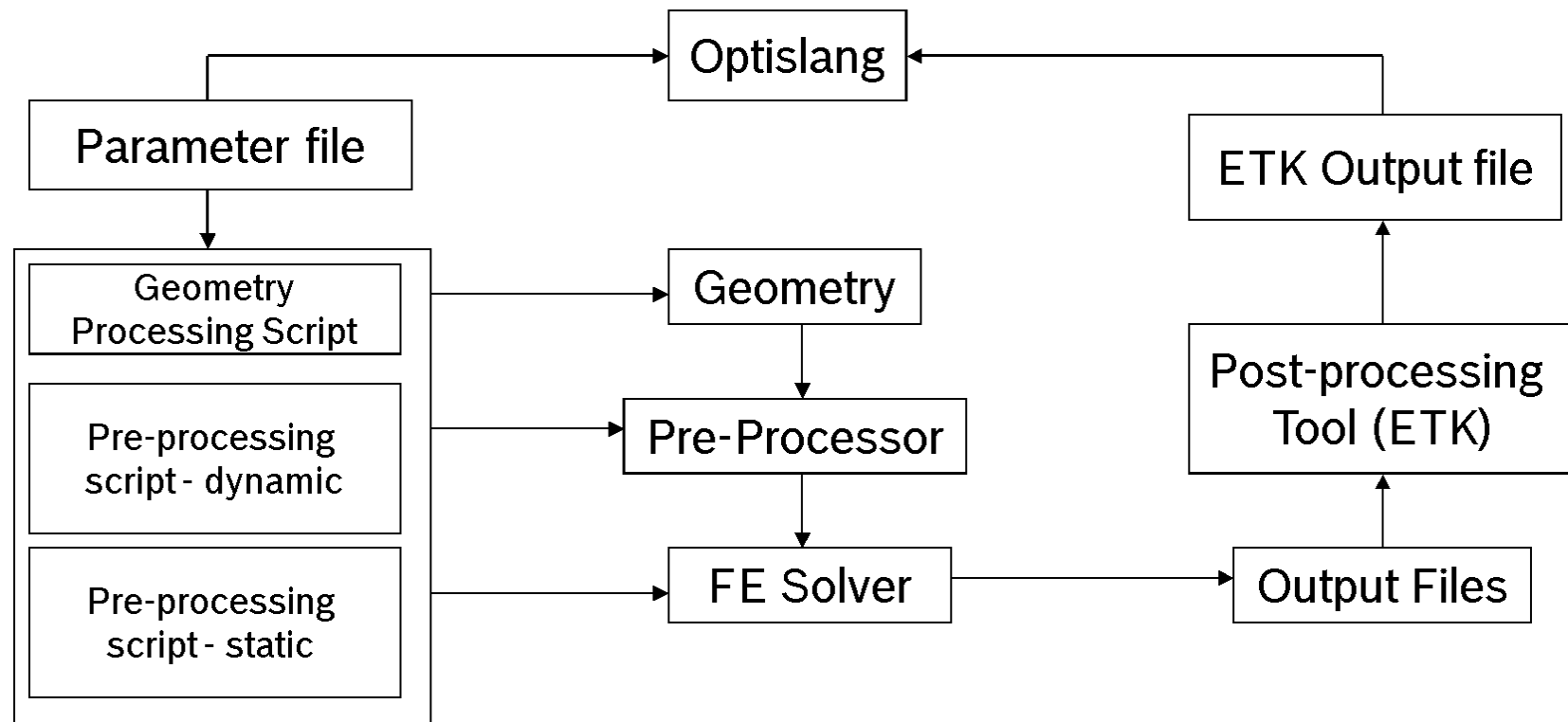
Relative frequency of importance

dr: 0 %
L: 100 %
dri: 0 %
dsa: 100 %
bds1: 0 %
bds2: 0 %
bs1: 0 %
hs1: 0 %
hys: 67 %
sta: 0 %
lsp: 0 %

Source: Dynardo

Meta-Modeling and Multi Objective Optimization

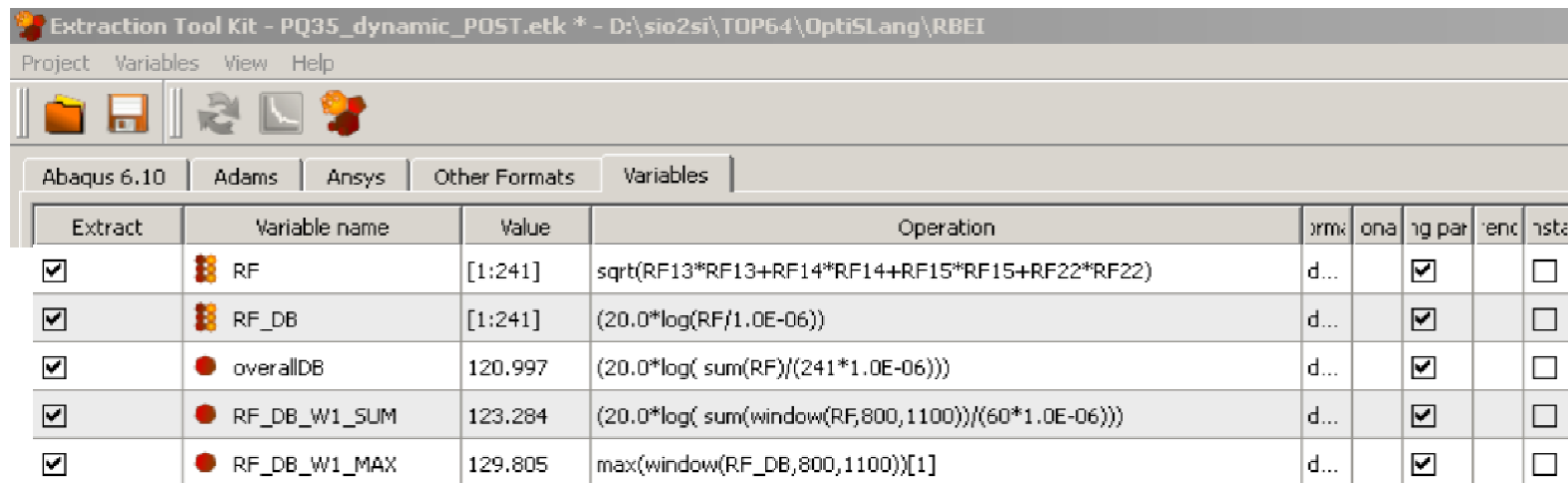
Generic Data Processing for MOO



Meta-Modeling and Multi Objective Optimization

ETK (Extraction Tool Kit)

- Import of ABAQUS, ANSYS, Adams and Edyson result files
- GUI- and Batch modus
- Visualisation as xy-Plots (field and history data)
- Manipulation of results by mathematical functions and own macros
- Export of scalar, vector and signal data to OptiSLang-Problemfile (*.pro), ASCII (*.out), Excel (*.xml)
- Usage for optimization and analysis



Extract	Variable name	Value	Operation	orm	ona	lg par	enc	rst
<input checked="" type="checkbox"/>	RF	[1:241]	$\sqrt{\text{RF13} \cdot \text{RF13} + \text{RF14} \cdot \text{RF14} + \text{RF15} \cdot \text{RF15} + \text{RF22} \cdot \text{RF22}}$	d...		<input checked="" type="checkbox"/>		<input type="checkbox"/>
<input checked="" type="checkbox"/>	RF_DB	[1:241]	$(20.0 \cdot \log(\text{RF} / 1.0\text{E-}06))$	d...		<input checked="" type="checkbox"/>		<input type="checkbox"/>
<input checked="" type="checkbox"/>	overallDB	120.997	$(20.0 \cdot \log(\text{sum}(\text{RF}) / (241 \cdot 1.0\text{E-}06)))$	d...		<input checked="" type="checkbox"/>		<input type="checkbox"/>
<input checked="" type="checkbox"/>	RF_DB_W1_SUM	123.284	$(20.0 \cdot \log(\text{sum}(\text{window}(\text{RF}, 800, 1100)) / (60 \cdot 1.0\text{E-}06)))$	d...		<input checked="" type="checkbox"/>		<input type="checkbox"/>
<input checked="" type="checkbox"/>	RF_DB_W1_MAX	129.805	$\max(\text{window}(\text{RF_DB}, 800, 1100))[1]$	d...		<input checked="" type="checkbox"/>		<input type="checkbox"/>

Source: Mr. Schirmacher Roland (CR/ARH2)

CASE STUDY

Optimization Problem

- Design Variable:
 - Height and thickness of 8 ribs.
- Response Variables:
 - V.mises stress at 8 ribs
 - 1st bending frequency
 - Total reaction force at mounting points.
- Objectives:
 - Minimizing overall dB target 1 < 120 dB (800-1100Hz)
 - Minimizing overall dB target 2 < 116 dB (1100-2000Hz)
 - Stresses at the ribs < 50 MPa
- Constraints:
 - First bending > 150 Hz
- Optimization method:
 - Pareto-Optimization

Parameter	Range
R1_H	0.5 to 20 mm
R1_W	0.5 to 3.5 mm
R2_H	0.5 to 20 mm
R2_W	0.5 to 3.5 mm
R3_H	0.5 to 20 mm
R3_W	0.5 to 3.5 mm
R4_H	0.5 to 20 mm
R4_W	0.5 to 3.5 mm
R5_H	0.5 to 20 mm
R5_W	0.5 to 3.5 mm
R6_H	0.5 to 20 mm
R6_W	0.5 to 3.5 mm
R7_H	0.5 to 20 mm
R7_W	0.5 to 3.5 mm
R8_H	0.5 to 20 mm
R8_W	0.5 to 3.5 mm

Definition of steps and output

→ Static analysis

- Static perturbation step using two load cases
- Output of displacements and v.Mises stress as field output
- Extraction of maximum v.Mises stresses at ribs, mounting points and inner part by ETK

→ Dynamic analysis

- Modal perturbation step up to 4 kHz
- Steady State Dynamics (modal) step from 800 Hz to 2000 Hz
- Tabular modal damping between 0.02 and 0.05
- Output of reaction forces at mounting points as history output
- Extraction and conversion of reaction forces at mounting points and shaft by ETK

Meta-Modeling and Multi Objective Optimization

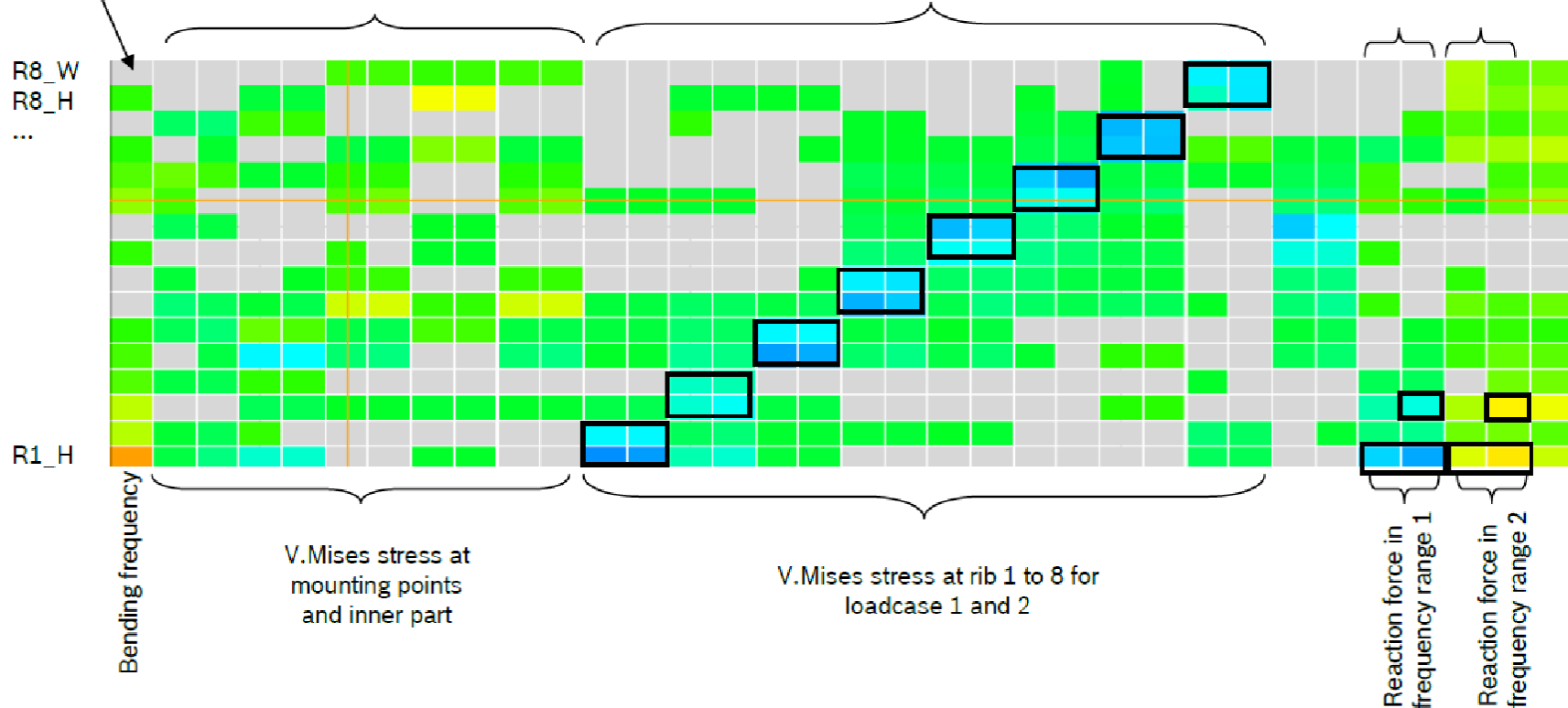
Correlation matrix of training data (1/2)

R1_H has the biggest influence of the bending frequency; high R1_H means high frequency.

no clear correlation to the v.Mises stress at the mounting points and inner part

v.Mises stress at the ribs are mostly influenced by the geometry of each rib; there are mostly no global effects between the ribs. High Rx_H and Rx_W mean low v.Mises stresses.

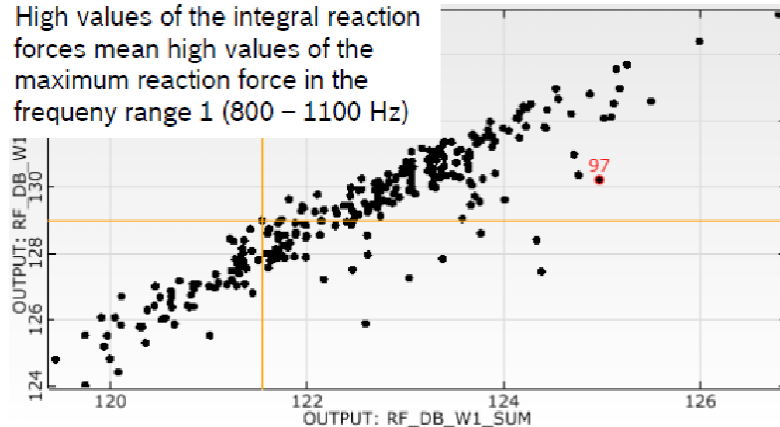
R1_H, R1_W and R3_H have the biggest influence on the reaction forces in both frequency ranges, but with positiv / negative correlation coefficient.



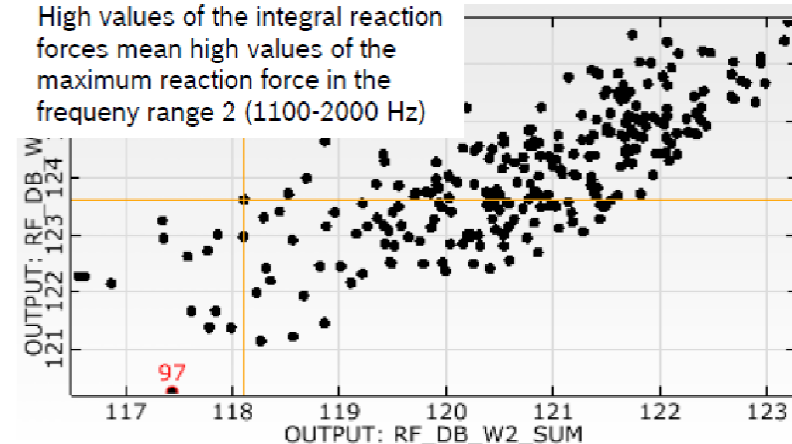
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Correlation matrix of training data (2/2)

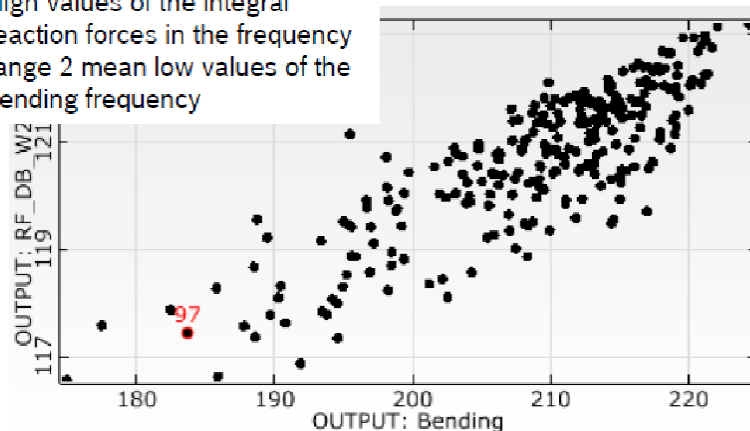
High values of the integral reaction forces mean high values of the maximum reaction force in the frequency range 1 (800 – 1100 Hz)



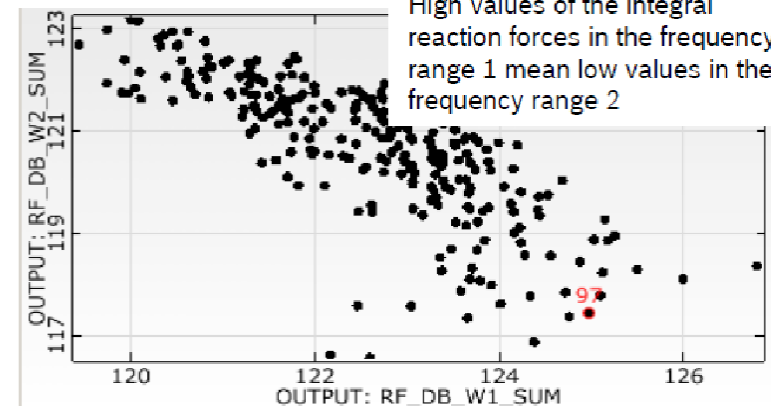
High values of the integral reaction forces mean high values of the maximum reaction force in the frequency range 2 (1100-2000 Hz)



High values of the integral reaction forces in the frequency range 2 mean low values of the bending frequency



High values of the integral reaction forces in the frequency range 1 mean low values in the frequency range 2



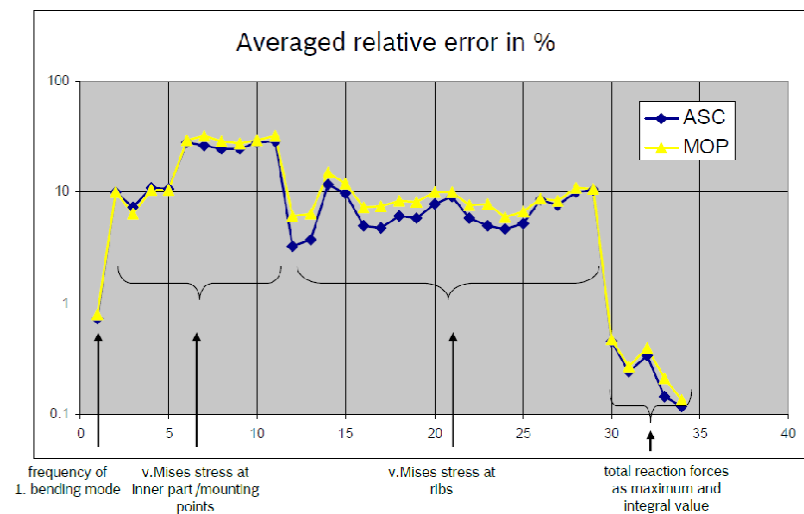
DOE: Observations

- The sensitive parameters are identified for different output variables.
 - R1, R2, R3, R4 ribs are mainly influencing the overall dB
- All the rib dimensions are directly related to the stress increase. So if the dimensions of the ribs reduced the respective stress increases.
- It is also observed that the overall dB in the 800-1100Hz requirements are in contradiction with the overall dB requirement in the 1100-2000Hz range.
- To meet the contradicting requirements Pareto-optimization needs to be used.
- Due to limitations in time, s/w and h/w, meta models are preferred to speed up the optimization process.

Meta-Modeling and Multi Objective Optimization

Meta model

- These meta models have been tested and the accuracy of the meta model is shown in the below graph as % error.
- From the graph it is inferred that meta models are good for studying the dynamic behavior and the static stress at the ribs.

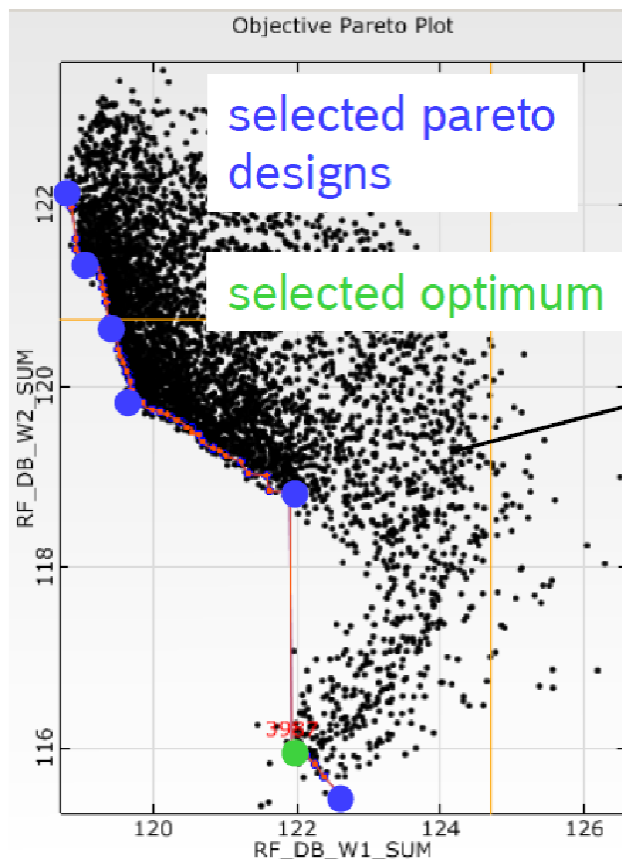


ASCMO: Tool from Bosch-ETAS

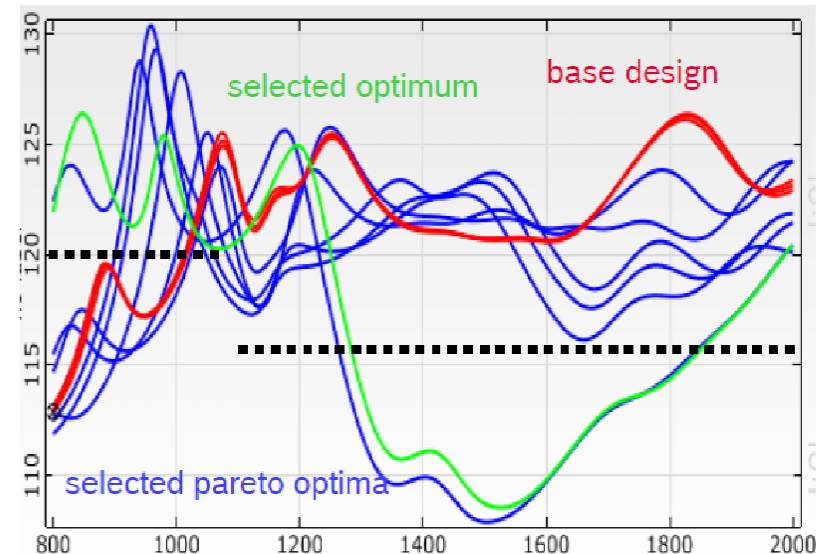
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Optimization results (1/2)

results based on ASCMO-analysis



results based on FE-analysis



→ No design fulfills the dynamic targets of max. 120 dB (800-1100 Hz) and max. 116 dB (1100-2000 Hz).

Meta-Modeling and Multi Objective Optimization

Meta model Runs

Meta Models					
S.No.	Name	Algorithm	Start population	Best Design	Total runs
6	Pareto Optimization 1	EA	1000	3987	5608
2	Pareto Optimization 2	EA	1000	3498	4400
3	Pareto Optimization 3	PSO	1000	9340	10000
4	Pareto Optimization 4	EA	1000	1216	1284
5	Pareto Optimization 5	EA	1000	212	788
6	Nature inspired Optimization 1	EA	1000	1051	1284
7	Nature inspired Optimization 1	EA	1000	424	680
8	Nature inspired Optimization 1	EA	1000	592	788

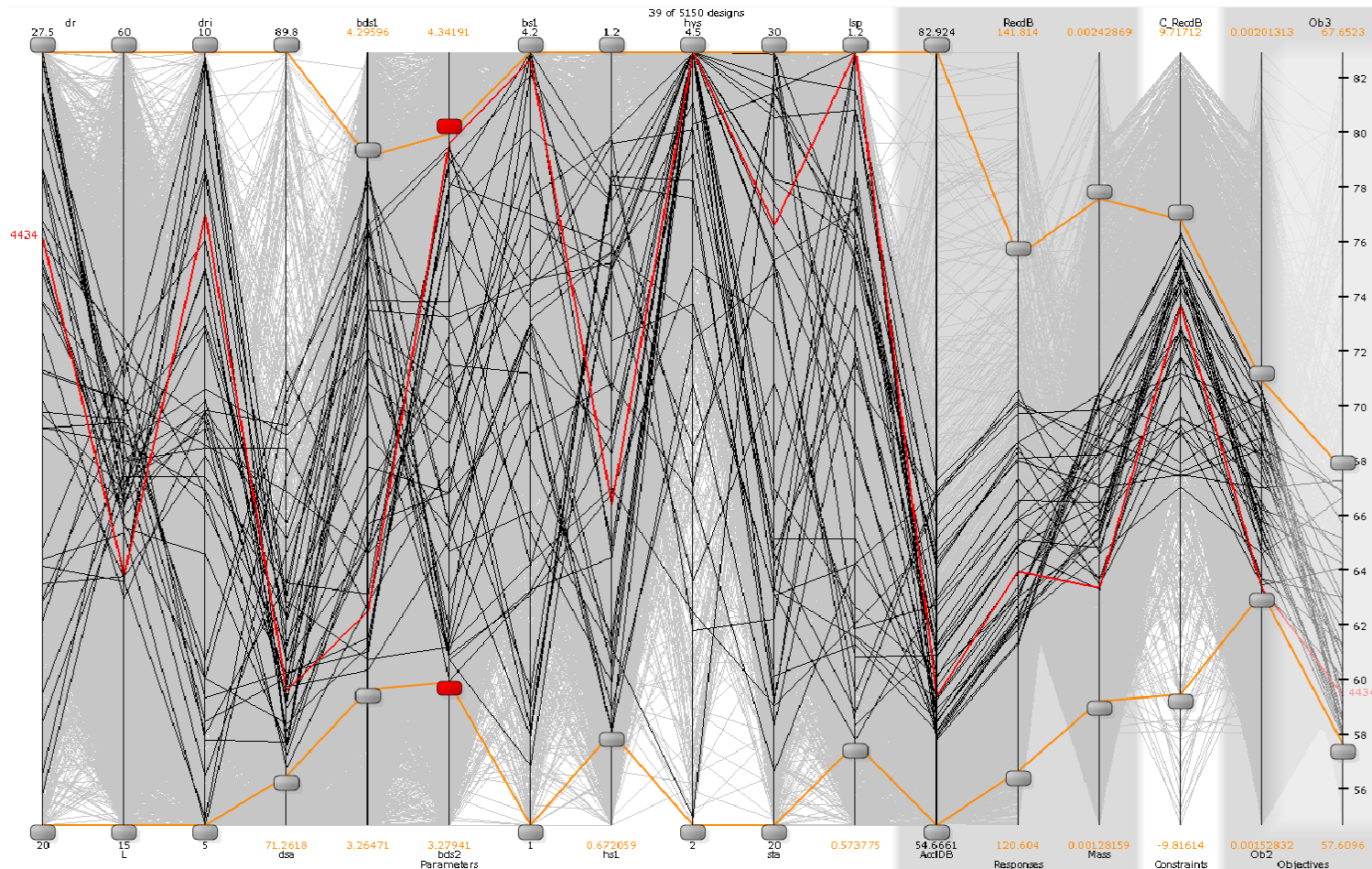
Overall dB Reduction			
Base	V1	V2	V3
122.4	117.6	117.9	115.3

Verification Results Comparison

		Reaction dB		Acceleration dB		Mass in kg	
		Meta	CAE	Meta	CAE	Meta	CAE
Load1 case	BASE	-	137.5	-	67.7	-	1.56
	V1	125	125	56.5	57.2	1.55	1.59
	V2	119.4	119.4	54.7	55.1	2.38	2.44
	V3	128.9	128.9	59.8	61.5	1	1.08
	V4	-	126.1	-	56.6	1.56	1.6
	V5	-	121.2	-	54.7	2.45	2.51
	V6	-	126.4	-	56.8	1.5	1.57
Load2 case	BASE	-	108.6	-	62	-	1.56
	V1	-	105.5	-	57.7	1.55	1.59
	V2	-	101.8	-	55.1	2.38	2.44
	V3	-	107.2	-	59.4	1	1.08
	V4	104.8	104.8	57.5	56.9	1.56	1.6
	V5	101.4	101.1	55.6	54.7	2.45	2.51
	V6	105	105	57.6	57.1	1.5	1.57

Meta-Modeling and Multi Objective Optimization

Design Selection: Multi-Objective



Summary

- Meta model has been created based form the DOE samples
- Process to create meta models is established and it has been tested for different projects.
- Best meta models are obtained based on COP and accuracy of the models are evaluated on the output response.
- Meta models are used for multi-objective optimization and Different optimizations procedures have been tried with meta models.
- Optimized designs derived from the meta models are verified using the actual models and found in good match.
- Generic data processing scheme for the entire process is standardized.

Thank You!

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