Robustness Study of an LS-DYNA Occupant Simulation Model at DaimlerChrysler Commercial Vehicles Using LS-OPT

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Abstract

The robustness properties of crash simulation models are emerging as an important criterion in today's simulation driven vehicle development process. We consider it relevant to any study of highly non-linear crash problems to obtain measures for the repeatability and reliability of both experimental and numerical tests.
In 2003, we conducted a robustness study of a structural front impact model (*JAPAN LS-DYNA Users Conference 2003)* using the Meta-Model concept of LS-OPT. This study seemed to indicate that there is an inherent, residual randomness in crash problems.
In the present paper, we present a new robustness study of a frontal sled test occupant model with a 50th percentile FTSS dummy.

Our goals were:

- Determine variations of typical occupant safety responses such as HIC, chest intrusion, and others due to uncertainties in the experimental setup, including dummy position, airbag mass flow, and acceleration.
- Separate deterministic and residual, random variations of responses using the Meta-Model technique.
- Get a feeling for random variations inherent in occupant studies.
- Evaluate the generality of these robustness results through a convergence study varying the number of simulation experiments and variables for the Meta-Model.

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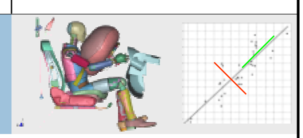
Outline



- Overview
- Purpose of this study
- Meta-Modeling theory: separation of deterministic and random variation
- Sled test occupant model and design variables
- Different Meta-Modeling setups for the sled test model
- Robustness results
- Convergence studies
- Conclusions / Outlook / Questions

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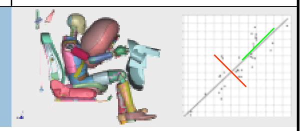
Overview



- Joint analysis by DYNAmore and DaimlerChrysler Commercial Vehicles.
- Based on a sled test occupant model using LS-DYNA.
- Based on new Meta-Model features of LS-OPT by Dr. Roux (LSTC) in connection with development of LS-OPT.
- 10 and 7 uncertainty design variables were considered
- From 30 to 120 simulation results were used for each Meta-Model

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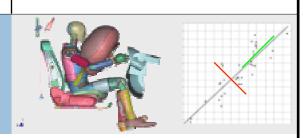
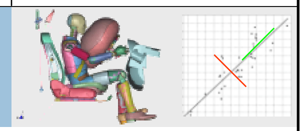
Purpose of this Study



- Determine robustness of a sled test occupant model in LS-DYNA
- Separate random and deterministic variation of intrusions.
- Get a better feel for accuracy of our predictions.
- Get a better feel for repeatability of tests.
- Conduct a convergence study of residuals and stochastic contributions
- Compare the residuals obtained through Meta-Modeling with the variations triggered by purely numerical parameters in LS-DYNA

Meta-Modeling as Projection onto a Predictable Space



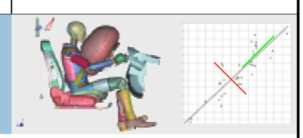
$$y = \eta(\mathbf{x})$$

- y: Scalar response variable
- η: LS-DYNA
- $\mathbf{x}$: Vector of design variables

$$\eta(\mathbf{x}) = f(\mathbf{x}) + r(\mathbf{x}) = P\eta(\mathbf{x}) + Q\eta(\mathbf{x})$$

- f: Meta-model
- r: Residual
- P: Projection onto predictable space
- Q: Projection onto residual space

Meta-Model Characteristics



$$f(\mathbf{x}) = \sum_{\alpha=1}^{n} a_\alpha \varphi_\alpha(\mathbf{x}) = a_\alpha \varphi_\alpha = \mathbf{a}^T \varphi(\mathbf{x})$$

- a_α: *n* coefficients
- φ_α: *n* basis functions, e.g. linear or quadratic

$$[\mathbf{x}_i] = \mathbf{X} = [\mathbf{x}_1\ \mathbf{x}_2 \ldots \mathbf{x}_m]$$

- $\mathbf{x}_i$: *m* experimental points, e.g. D-optimality criterion

$$\Phi = [\Phi_{i\alpha}] = [\varphi_\alpha(\mathbf{x}_i)]$$

- Φ: $m \times n$ basis function matrix

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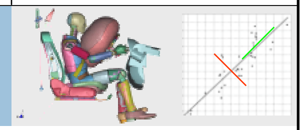
Fit Meta-Model to Experiments



$$\mathbf{y}^T = [y_1\, y_2 \ldots y_m] \qquad \mathbf{r}^T = [r_1\, r_2 \ldots r_m] = \mathbf{y}^T - \mathbf{a}^T \Phi^T = \mathbf{y}^T - \mathbf{f}^T$$

Result vector

Residual vector

Prediction vector

$$\mathbf{a} = \left(\Phi^T \Phi\right)^{-1} \Phi^T \mathbf{y} \quad \text{minimizes} \quad \mathbf{r}^T \mathbf{r}$$

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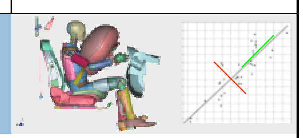
Extract Residual Using the Meta-Modeling Technique



$$\mathbf{f} = \mathbf{A}\mathbf{y} \quad \text{with} \quad \boxed{\mathbf{A} = \Phi\left(\Phi^T \Phi\right)^{-1} \Phi^T}, \quad \mathbf{A} = \mathbf{A}^T, \quad \mathbf{A}\mathbf{A} = \mathbf{A}$$

Predictability Projection Matrix

$$\mathbf{r} = \mathbf{B}\mathbf{y} \quad \text{with} \quad \mathbf{B} = \mathbf{I} - \mathbf{A}, \quad \mathbf{B} = \mathbf{B}^T, \quad \mathbf{B}\mathbf{B} = \mathbf{B}, \quad \mathbf{A}\mathbf{B} = \mathbf{0}$$

Residual Projection Matrix

Solution Decomposition

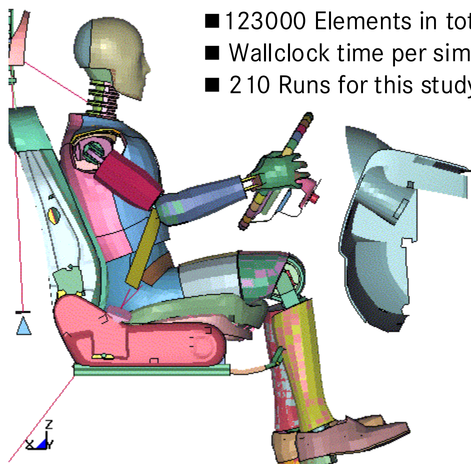
$$\mathbf{y} = \mathbf{A}\mathbf{y} + \mathbf{B}\mathbf{y} = \mathbf{f} + \mathbf{r} \quad \text{with} \quad \mathbf{f}^T \mathbf{r} = 0$$

Predictable by meta-model

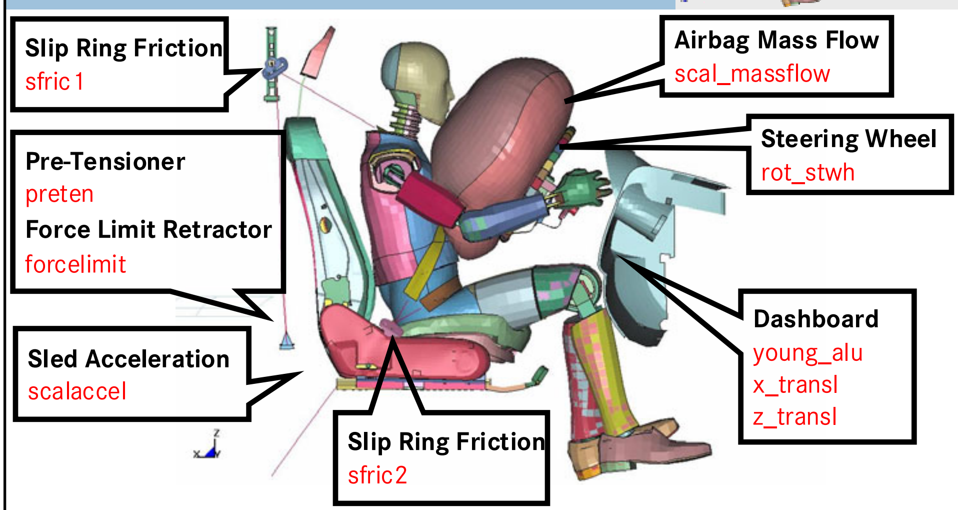
Residual

Occupant Simulation Model

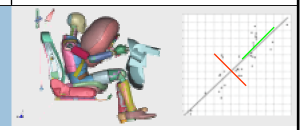
- Sled test model for validation of occupant simulation
- 123000 Elements in total (Beams/Shells/Solids)
- Wallclock time per simulation: 9.5 hours on 16 cpus
- 210 Runs for this study

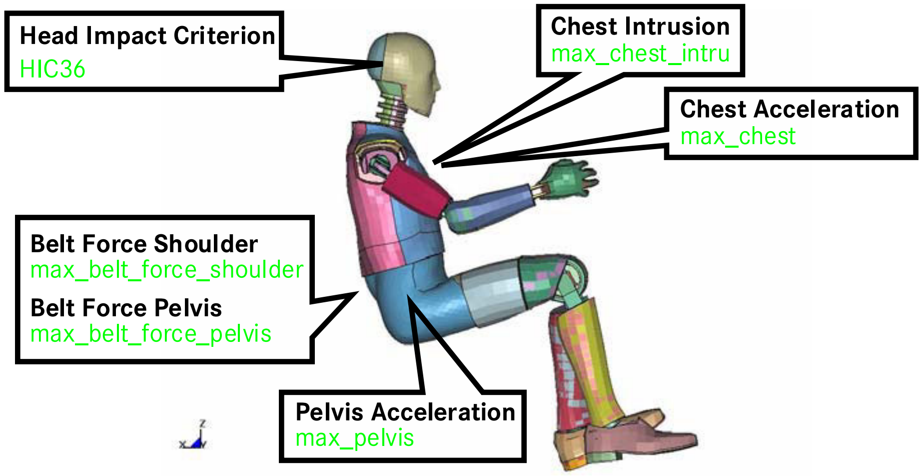


Uncertainty Design Variables

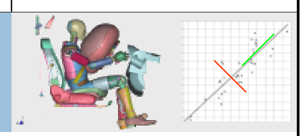


Responses: Standard Dummy Evaluations

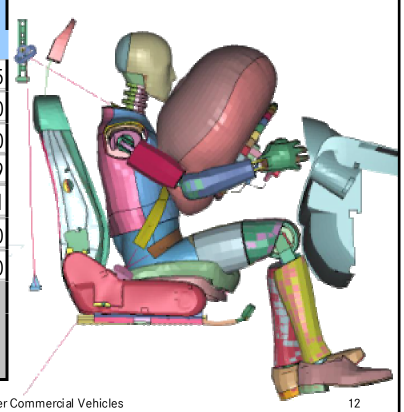




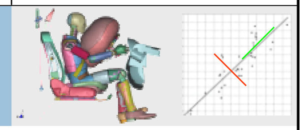
Experimental Setup of the Robustness Studies (1)



		Setup 1			Setup 2		
		Range for Response Surface		Standard Deviation for Meta-Model	Range for Response Surface		Standard Deviation for Meta-Model
Variable	Nominal Value	Min	Max		Min	Max	
scalaccel	1,00	0,95	1,05	0,03	0,90	1,10	0,05
sfric1	1,00	0,50	1,50	0,25	0,00	2,00	0,50
sfric2	1,00	0,50	1,50	0,25	0,00	2,00	0,50
preten	1,00	0,91	1,09	0,04	0,82	1,18	0,09
forcelimit	1,00	0,89	1,11	0,06	0,78	1,22	0,11
rot_stwh	-1,00	-1,10	-0,90	0,05	-1,19	-0,81	0,10
transl_x	0,00	-1,00	1,00	0,50	-2,00	2,00	1,00
transl_z	0,00	-1,00	1,00	0,50			
scalmassflow	1,00	0,90	1,10	0,05			
young_alu	1,00	0,90	1,10	0,05			

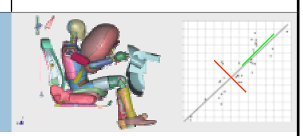


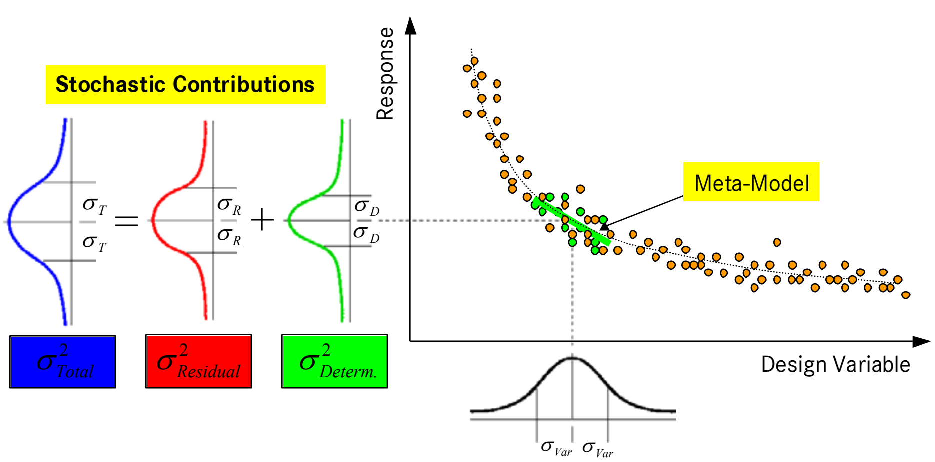
Experimental Setup of the Robustness Studies (2)



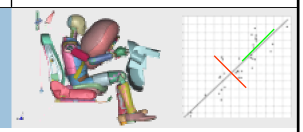
Name of Robustness Study	Number of Experiments	Experiment Selection	Design Variables and Ranges	Response Surface
L1-30	30	*D-optimal for linear response surface*	setup 1	linear
L1-60	60		setup 1	linear
L1-90	90		setup 1	linear
L1-120	120		setup 1	linear
L2-30	30		setup 2	linear
L2-60	60		setup 2	linear
Q1-90	90		setup 1	quadratic
Q1-120	120		setup 1	quadratic
Q2-60	60		setup 2	quadratic
Pure Noise	30	random	numerical parameters only (number of cpus, soft constraint, etc.)	none

Meta-Modeling and Stochastic Contributions

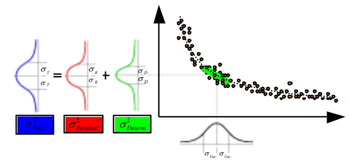




Stochastic Contribution Results for 30 Experiments (Linear Meta-Model)



Design Variable	Standard Deviation of Design Variable	Standard Deviation Contribution HIC36	max_chest_intru	max_b_f_shoulder	max_bf_pelvis	max_chest	max_pelvis
scalaccel	2,5%	3,1%	1,5%	0,1%	2,3%	1,9%	2,9%
sfric1	25,0%	1,3%	0,6%	4,1%	1,8%	0,7%	0,7%
sfric2	25,0%	0,5%	0,6%	0,1%	3,7%	0,1%	0,1%
preten	4,4%	0,0%	0,5%	0,0%	1,1%	0,3%	0,2%
forcelimit	5,6%	1,3%	0,4%	4,4%	0,6%	1,4%	0,2%
rot_stwh	4,8%	0,5%	0,1%	0,1%	0,0%	0,1%	0,1%
transl_x	50,0%	0,1%	0,1%	0,7%	4,5%	0,5%	0,8%
transl_z	50,0%	1,2%	1,0%	0,3%	1,6%	0,2%	0,9%
scalmassflow	5,0%	1,8%	1,8%	0,6%	2,2%	0,6%	0,9%
young_alu	5,0%	0,3%	0,3%	0,0%	0,5%	0,1%	0,1%
all variables		4,3%	2,8%	6,1%	7,2%	2,6%	3,4%
residuals		4,7%	1,9%	1,8%	6,0%	3,5%	2,3%
Total		**6,4%**	**3,4%**	**6,3%**	**9,4%**	**4,3%**	**4,1%**



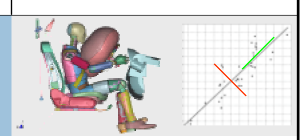
Contribution of Variation of design variables to variation of results.

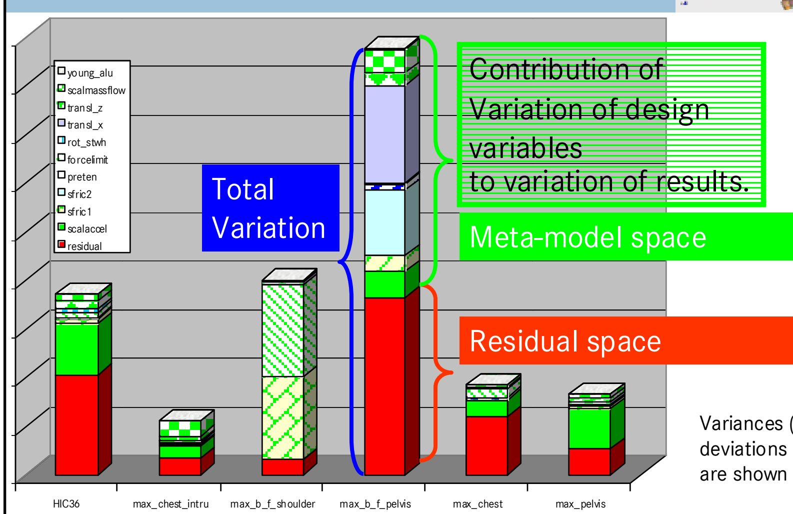
Meta-model space

Residual space

Total Variation

Stochastic Contribution Plot for 30 Runs (Linear Meta-Model)





Variances (standard deviations squared) are shown

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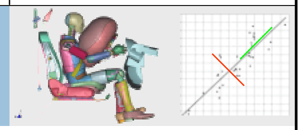
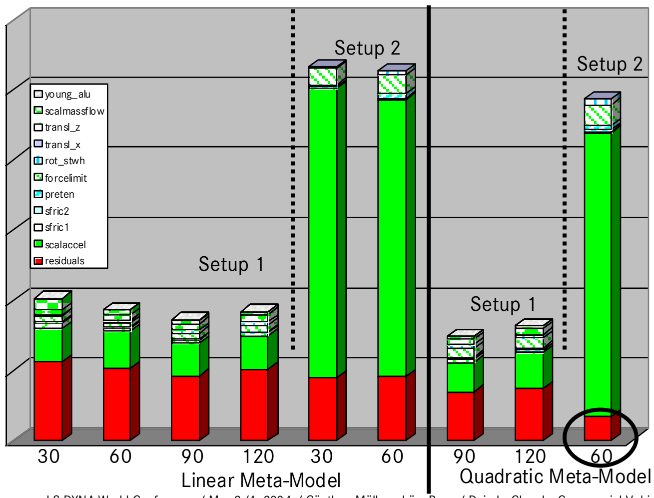
Convergence Study of Stochastic Contributions and Residual for HIC36





Good agreement of residual for different meta-models.

Small oversampling for Q2-60 => small residual.

Good agreement of stochastic contributions within experimental setup.

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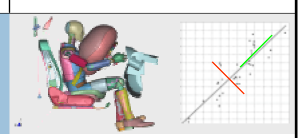
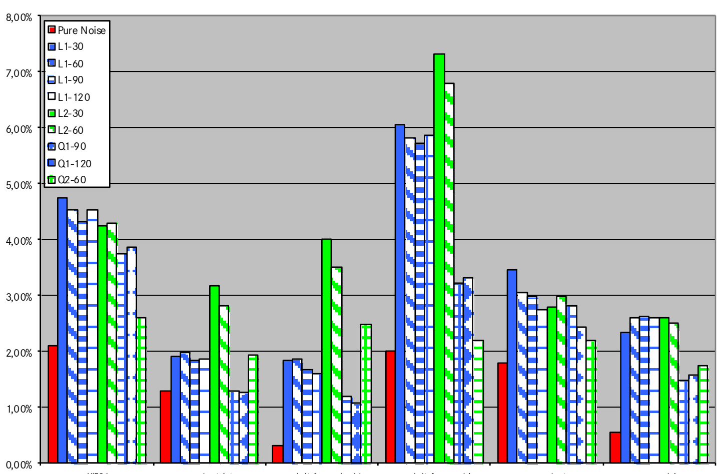
Convergence Study of Residual and Comparison to „Pure Noise“ Residual





Good agreement of residual for different meta-models.

Residual is always smaller for quadratic response surface

„Pure Noise“ residual is smaller than meta-model residual; same order of magnitude

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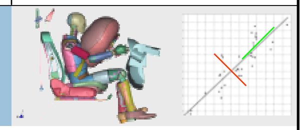
Conclusions



- Meta-Modeling was used to separate predictable effects from random and noise effects
- We obtained a good feel for the accuracy of our results.
- Random variation of occupant results was quantified.
- Total variation of occupant results was quantified.
- Residual variation was compared to "pure noise" variation

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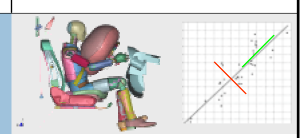
Outlook / Open Questions



- This method shows great promise to be used in all stages of the vehicle development process to test for robustness of crash relevant components.
- Is the variation we found inherent in the physics of the problem, or in finite element modeling? Difficult to say, unless we conduct a statistically significant number of identical hardware tests.