BETA SIMULATION SOLUTIONS

physics on screen

White paper

Simulation enabling technologies

Occupant Safety Prediction

One of the most common finite element analyses in vehicle development is designed to study the passengers' safety during a front crash using a sled test. Machine Learning functionality can predict the model's behavior and key values such as injury criteria or body parts' accelerations, without the need of running the full FE analysis. Thus, multiple "what if" studies can be performed without the expense in analysis and design time.

1. Introduction

One of the most common finite element analyses in vehicle development is the study passengers' safety during a front crash using a sled test (**Figure 1**). This study simulates the interaction between the passenger and the vehicle during such an accident and the actual consequences on the human body.

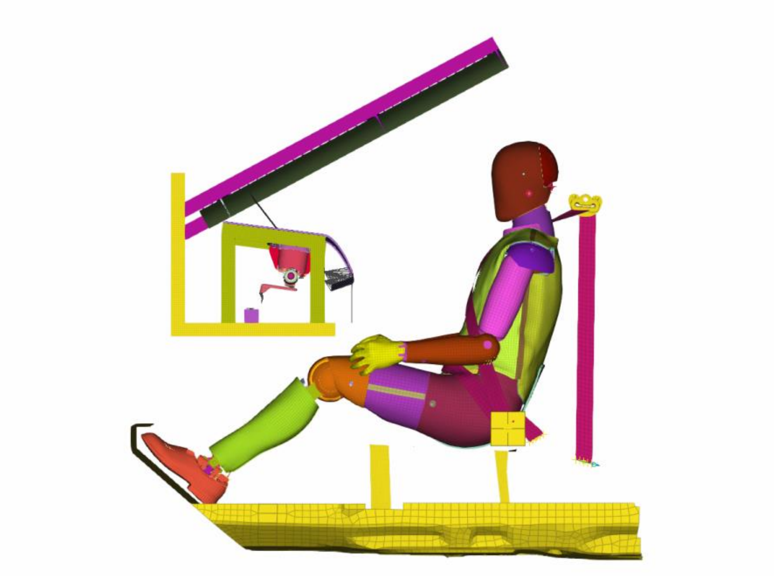


Figure 1 Sled test configuration

The test case involves a sled test with a restraint system (including an airbag and seatbelt) and the occupant represented by the THOR-50M Anthropomorphic Test Device (ATD). (**Figure 2**). The simulation of the vehicle-human interaction during such an accident and its actual consequences on the human body are used to train Machine Learning models and predict the occupant's safety.

The study focuses on the effect of the various restraint systems' parameters on the occupant's injury criteria. Design variables were defined to control crucial characteristics of the airbag and the restraint system that affects the ATD's kinematics, to investigate the effects of seatbelt and airbag's parameters on occupant's injury criteria (e.g HIC_15/36, BRIC, upper body parts' acceleration and load absorption etc.). A Design of Experiments (DOE) provided us with the dataset that Machine Learning can utilize.

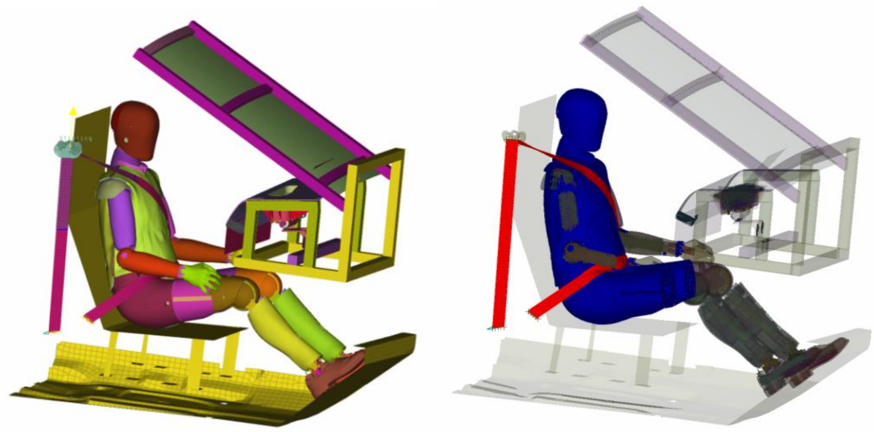


Figure 2 Restraint system and dummy’s parameters

The trained Machine Learning models can predict the FE model's behavior and key values, such as maximum accelerations or deformations, without the need to run the full FE analysis. This capability enables multiple "what if" studies, saving time and resources in analysis and design processes. Additionally, such trained predictive models are used for optimization purposes as response surface models, increasing the optimization speed and achieving improved designs faster.

2. Model Parameterization

Four parameters were defined on the FE model to control a) the seatbelt’s slipring position along the Z-axis (**Figure 3**), b) the friction coefficient between the seatbelt and the dummy, c) the airbag’s venting trigger time and d) the seatbelt’s sensor trigger time.

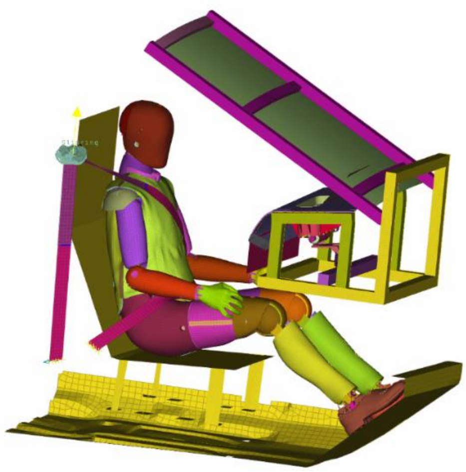


Figure 3 The slipring’s position parameter

An Optimization Task (**Figure 4**) was created using ANSA's Optimization Tool with design variables for each of the previously created parameters. Specific bounds and values' type were assigned to these design variables to permit the correct fluctuation of the design parameters' values.

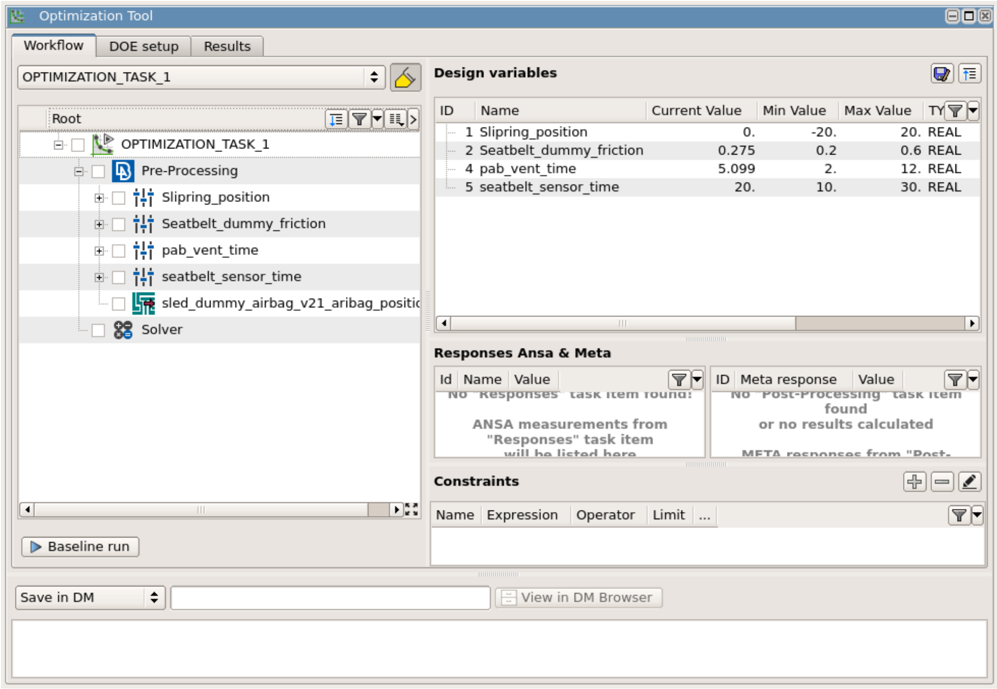


Figure 4 Optimization task

3. Dataset creation

3.1. Pre-Processing

To create the dataset that was used for training the Machine Learning models, a Design of Experiments (DOE) was defined using the Optimization tool (**Figure 5**). The “Uniform Latin Hypercube” DOE Algorithm was selected to generate 25 experiments in total. The algorithm’s nature drives the equal distribution of the experiments’ values within the design space that is defined by the design variables’ bounds. For every experiment, different values were calculated for each design variable, providing a good coverage of the available space.

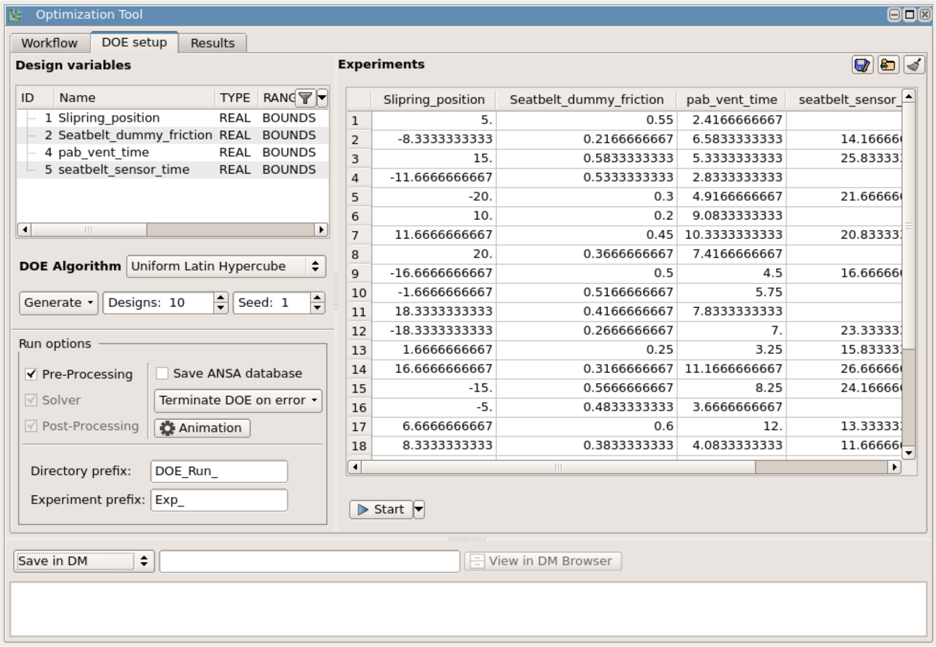


Figure 5 Design of Experiments table

Once the DOE process was properly defined the FE model LSDYNA analysis run with the values of each of the 25 experiments in a completely automated procedure. The created data were saved in a DM container system with specific structure and hierarchy.

The tree structure created in the DM by this process consists of a main Simulation model top that contains two other entities, the DOE Studies and the Parametric Structure. The DOE Studies include the created experiments as Simulation runs, each containing the experiment’s information, results and design variables’ details. The Parametric Structure contains all the information concerning the parameterization of the Simulation model.

3.2. Post Processing

The post processing (**Figure 6**) was done massively for all experiments using a session file, which was read by META during the automated run of the DOE process. All necessary data that would be needed for the Machine Learning actions including results, curves, pictures, videos and the important key values were extracted and saved in the DM.

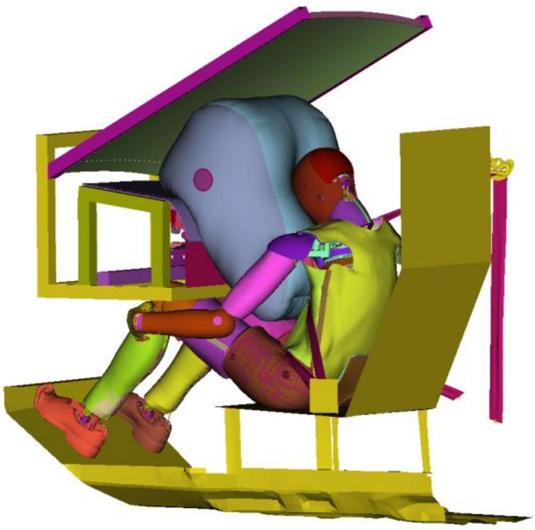


Figure 6 FE analysis results regarding airbag-passenger interaction

The information gathered during the post processing was automatically added as separate Report items under each Simulation Run (**Figure 7**, **Figure 8**).
In these Report items, all of the requested key values can be found regarding occupant's injury criteria and upper body parts' accelerations and deformations. These key values were used as responses for the training of the Machine Learning models.

	A	B	C	D	E
1		KeyValue			
2	BRIC	0.55779			
3	HIC_15	110.107			
4	HIC_36	161.535			
5	head_acceleration_res	38.8967			
6	left_clavicle_inboard_load_cell_res	1.51241			
7	thorax_ll_rib_def_res	55.3904			
8	thorax_lr_rib_def_res	17.8638			
9	thorax_ul_rib_def_res	66.2301			
10	thorax_ur_rib_def_res	41.3391			
11	upper_neck_nij	0.38959			

Figure 7 Key Values of Simulation Runs.

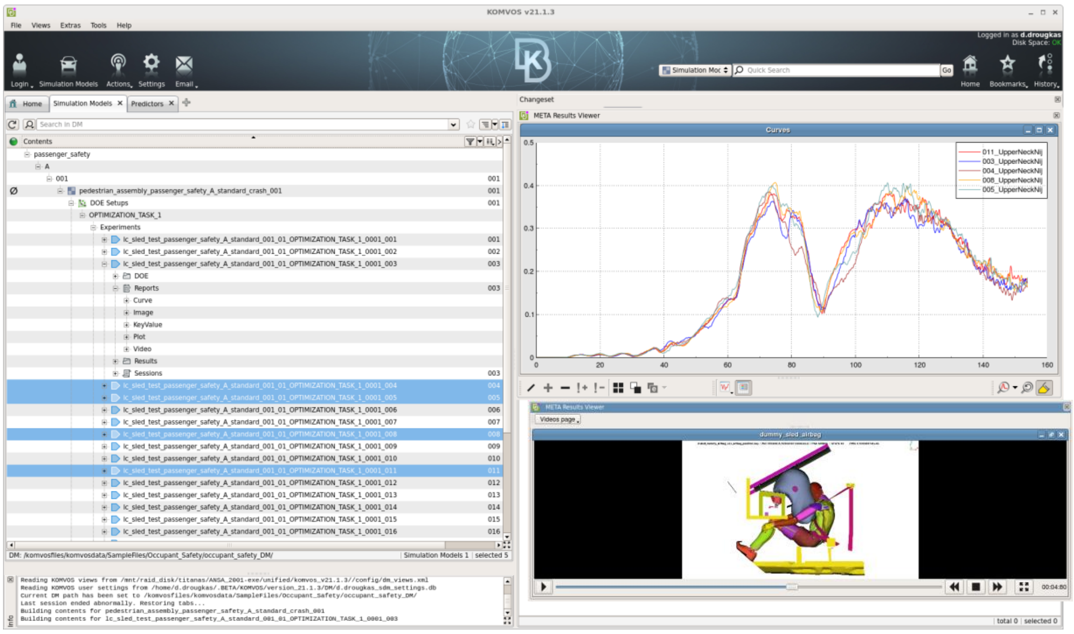


Figure 8 Simulation Run reports in KOMVOS

4. Machine Learning Training

The 'Design Variable based' Machine Learning was selected as the training method in KOMVOS, using the 25 available Simulation Runs to train a group of predictive models in order to generate predictions for the above-mentioned key values. Different groups of predictors (**Figure 9**) are defined for the different categories of responses, listing each predictor that corresponds to a single key value. Using a predictor entity, provides the direct prediction of the respective key value, based on any configuration of design variables' values. Thus, the prediction of a model's response can be done much faster than the actual FE analysis, leading to a significant decrease in the computational time.

Along with predictors trained with key values, 2D and 3D results predictions were also trained using the existing results from the dataset. A predictor for Displacements was trained for 3D results and a predictor group was trained for various 2D results like Kinetic energy, Total energy and accelerations curves of several nodes of the ATD (head, sternum etc.)

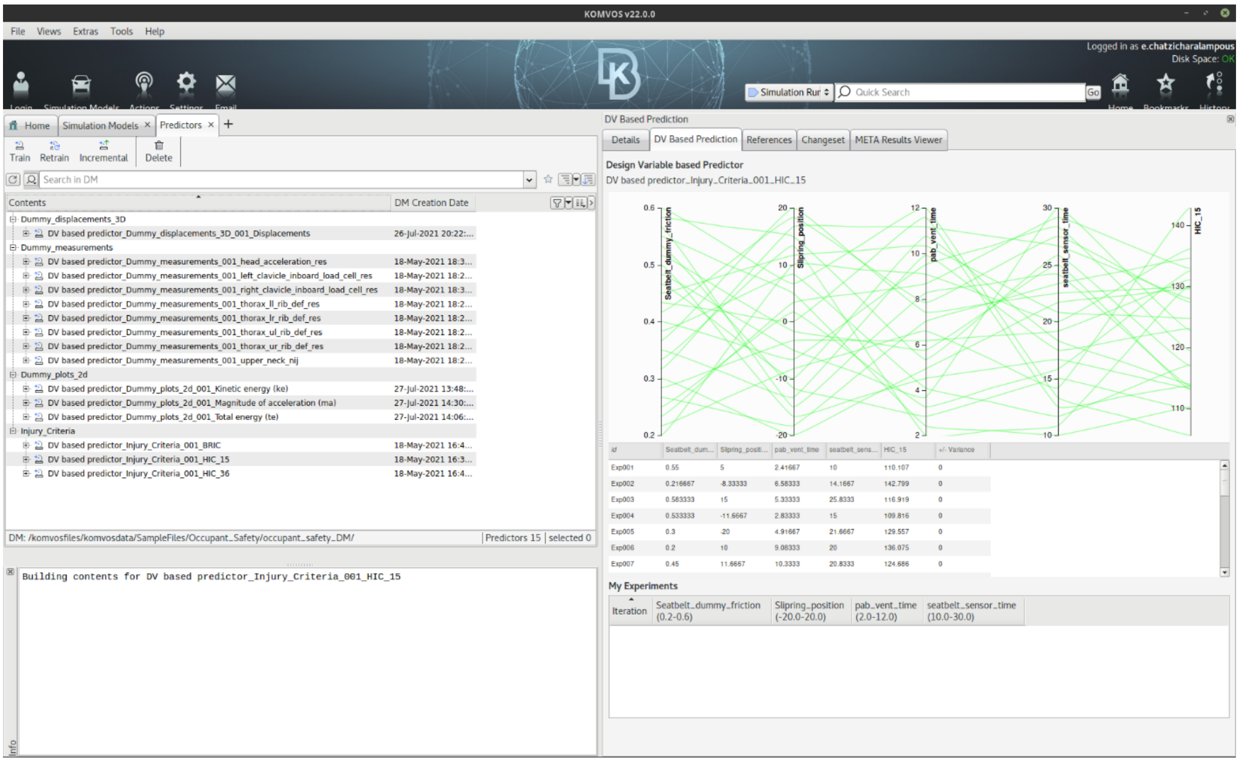


Figure 9 Groups of predictive models

Each predictor contained report charts evaluating its accuracy based on test data, along with charts about the performance and sensitivities of the design variables. The following charts (**Figure 10**, **Figure 11**) list the design variables in order of greater influence regarding two of the responses. This chart is considered essential in the search for a better performing design as it highlights the design variables that will affect the behavior the most, should they be modified.

Figure 10 Sensitivity chart for HIC_15

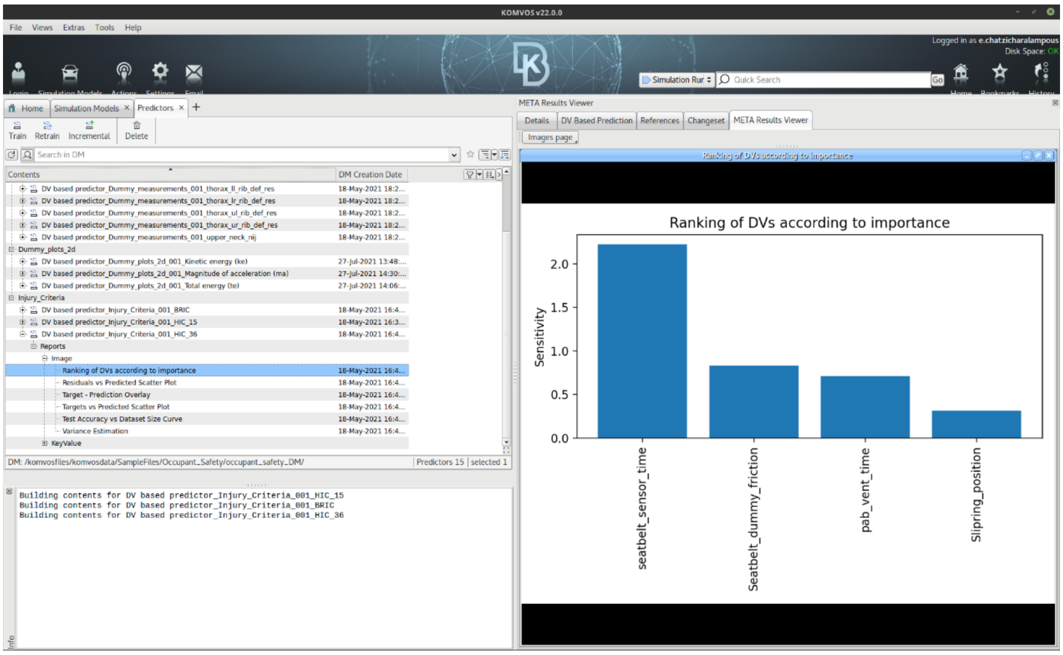


Figure 11 Sensitivity chart for HIC_36

5. Machine Learning Prediction

The HIC_15, HIC_36 and BRIC injury criteria were selected as the main responses for identifying the best experiment among the 25 simulation runs. This was the basis for creating a new ‘what if’ scenario. For this purpose, the parallel coordinates chart was used to visualize the design variables and key values of all runs simultaneously and distinguish the better performing experiments according to their key values. (**Figure 12**, **Figure 13**).

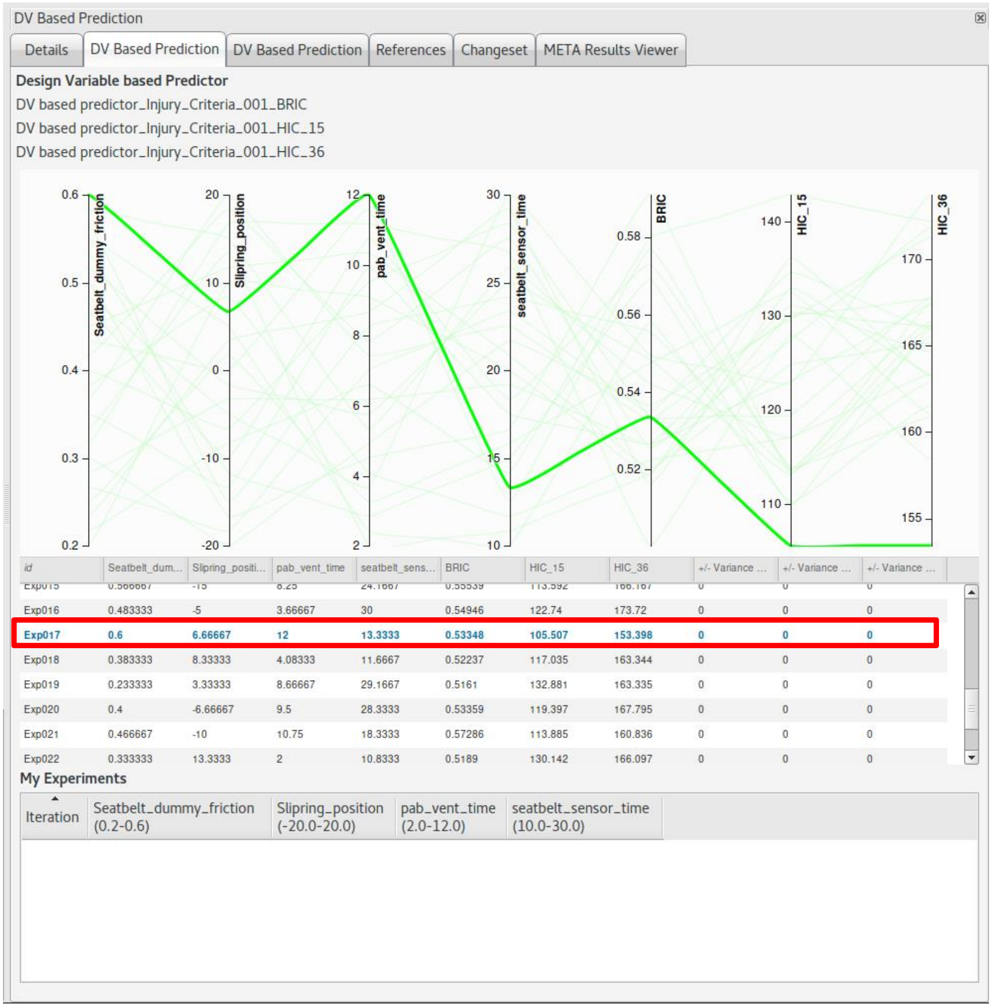


Figure 12 Experiment’s identification with the lowest HIC_15 value

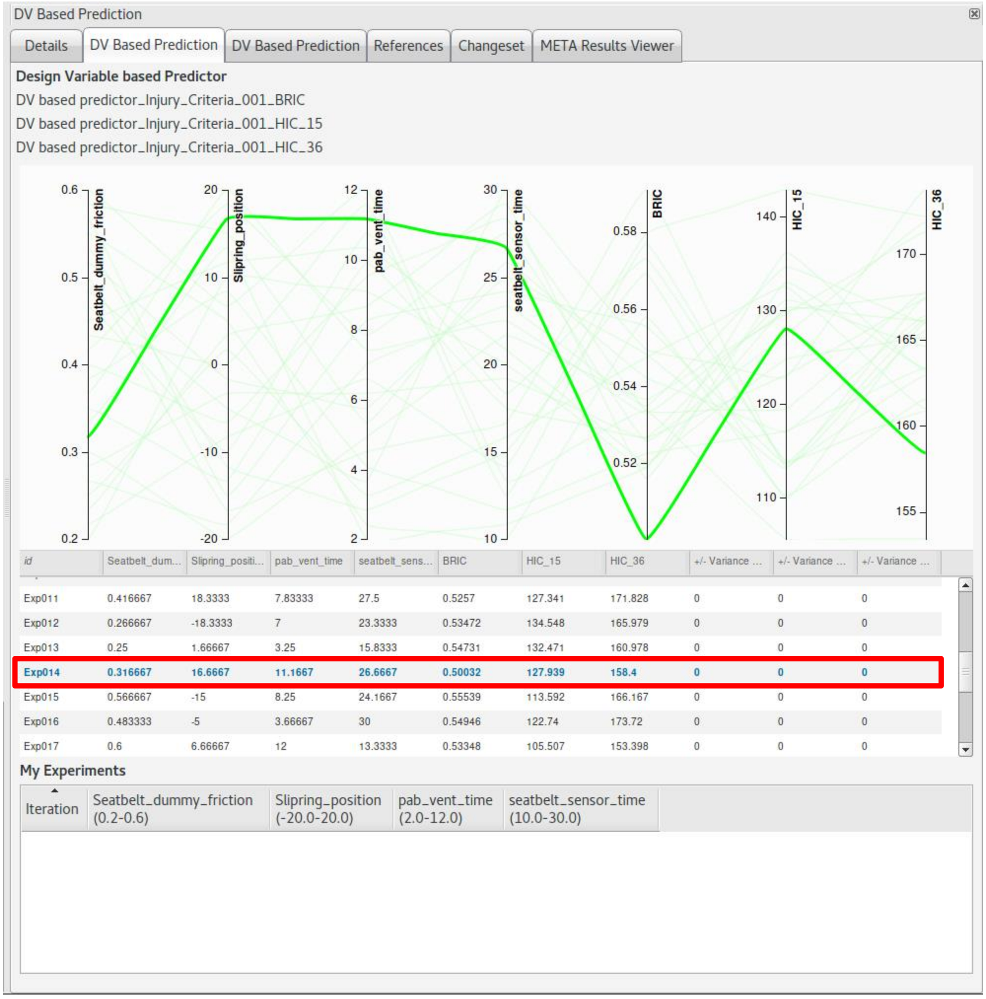


Figure 13 Experiment's identification with the lowest BRIC value

The simulation run 17 resulted in the lowest values of both HIC_15 and HIC_36, while the BRIC criterion was also kept low. The values of the rest of the responses were also checked for this experiment whether they lied within the lower values' ranges. Therefore, the design variables of the identified experiment (Exp017) were used as initial values in order to define a new "what if" scenario.

Based on the information provided by the importance maps, each predictor was affected by a different design variable the most. Thus, it was decided to primarily try reducing the HIC and BRIC criteria that are affected mainly by the dummy-seatbelt friction, the seatbelt sensor time and the slipring's position (**Figure 14**, **Figure 15**).

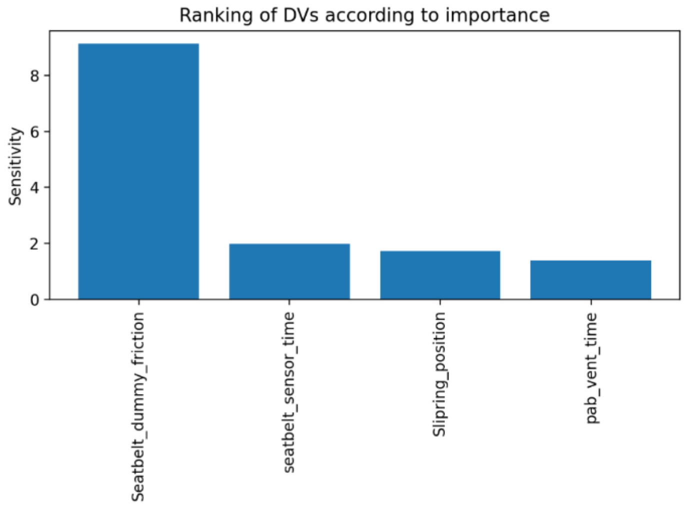


Figure 14 HIC_15 DV importance map

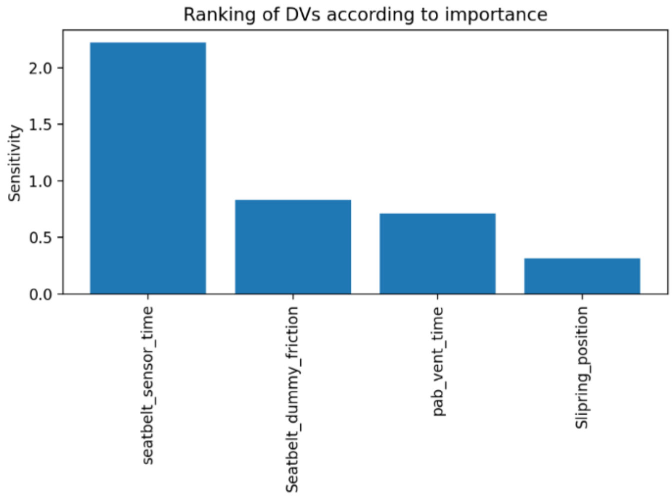


Figure 15 HIC_36 DV importance map

With this information, we could filter which design variables should be tuned in order to give improved responses' values. So, new theoretical values were given to those variables to create several 'what if' scenarios. The final target was to distinguish one theoretical experiment that would achieve a trade-off among improved values for the HIC and BRIC criteria while keeping the other measurements on safe levels.

The “My Experiments” table of the grouped parallel coordinates chart was utilized, to perform the ‘what if’ scenarios. Predictions for the new experiments were ran directly from this area, so the new key values were listed in the table and also added to the chart (**Figure 16**).

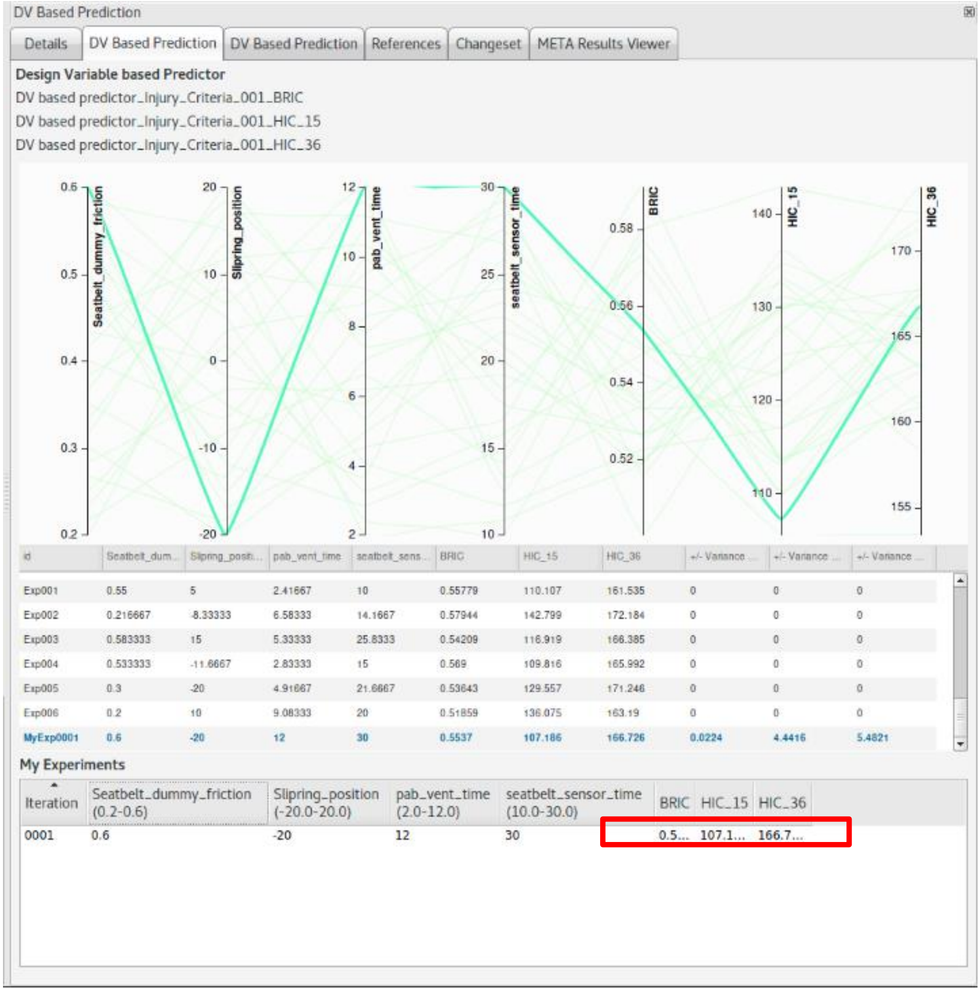


Figure 16 HIC & BRIC prediction for theoretical experiment 0001

The first theoretical experiment resulted in higher HIC_36 values, so there was room for further improvement. Further decrease of the seatbelt sensor time (**Figure 17**) led to further decrease of both the HIC criteria, while the BRIC criterion remained within a logically low range.

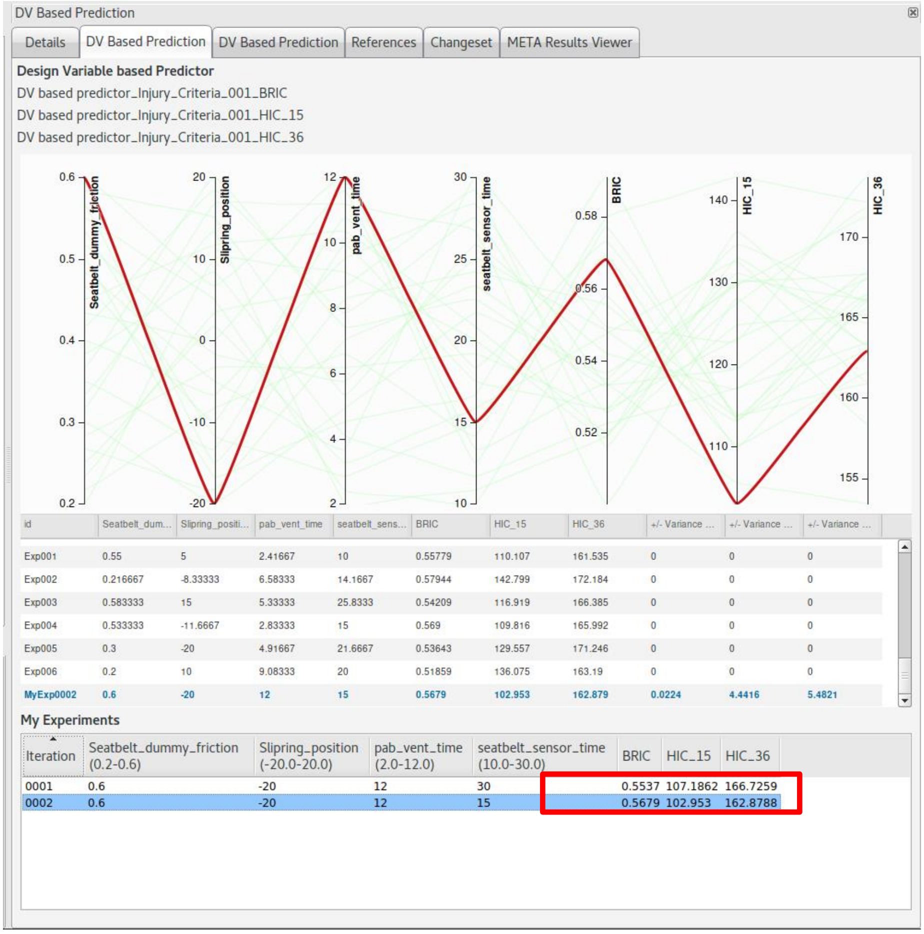


Figure 17 HIC_36 & HIC_15 predictions for theoretical experiment 0002

Such "what if" scenarios were conducted in order to quickly get the various injury criteria and intrusion responses without running the full analysis. Similar to single key value responses, displacements and 2D results were predicted, to enrich the design exploration.

6. Optimization

The created predictors were used in an Optimization study, in order to find the optimum design concerning injury criteria. The predictors were used as response surface models, speeding up the optimization progress by quickly predicting the desired responses. The objective of this problem was to minimize the HIC15 value. For this optimization setup, the Simulated Annealing optimization algorithm was selected and the BRIC and HIC 36 were constrained to specific limits (**Figure 18**).

Results

Name	Value
Name	**Minimize_HIC15**
Iteration	**001**
Algorithm	**Simulated Annealing**
Method	**RSM**
DOE	
DV	
Seatbelt_dummy_friction	
Initial Value	0.6
Max Value	0.6
Min Value	0.2
Slipring_position	
Initial Value	6.6666666667
Max Value	20
Min Value	-20
pab_vent_time	
Initial Value	12.
Max Value	12
Min Value	2
seatbelt_sensor_time	
Initial Value	13.3333333333
Max Value	30
Min Value	10
Optimization	
Constraints	
Constraint_1	HIC_36 < 170
Constraint_2	BRIC < 0.58
Objectives	
Objective_1	HIC_15 Minimize

Figure 18 Optimization set up

The optimization ran for a few minutes since the prediction for the injury criteria for each iteration took a few seconds. After 500 iterations (**Figure 19**) the optimum design was obtained and succeeded in reducing the HIC 15 response while the HIC 36 and BRIC responses were constrained to acceptable low limits.

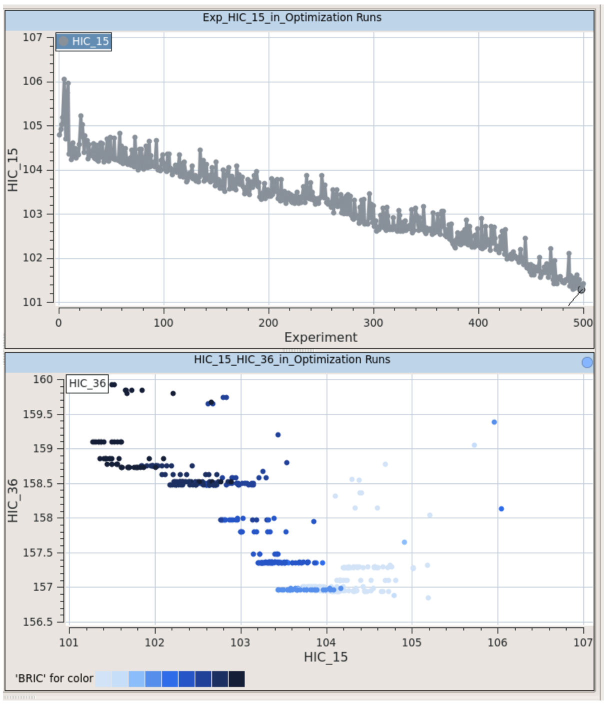


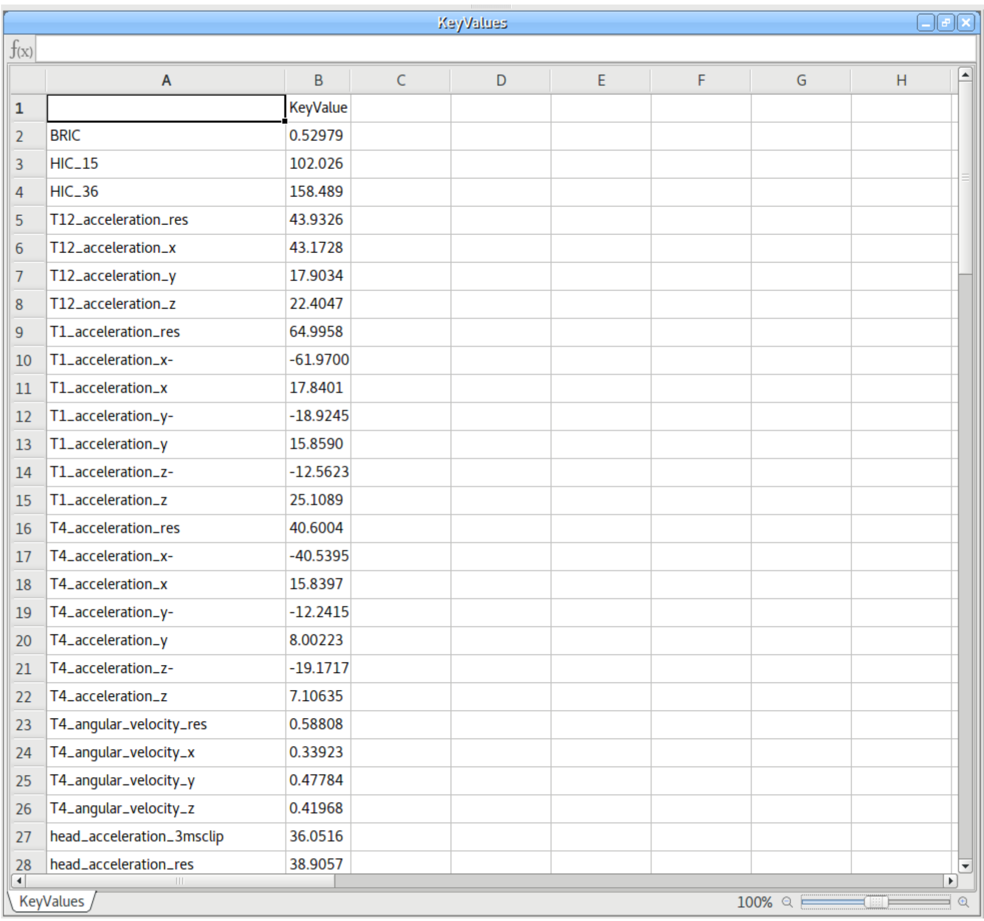
Figure 19 Optimization results

	Initial	Optimum
HIC 15	132.365	101.541
HIC 36	165.047	159.096
BRIC	0.534	0.5674

Table 1 Optimum design predicted injury criteria

7. Validation

An LSYDYNA FE Analysis ran for the design variables of the optimum design. The experiment and its FE results and respective post processing reports were added in the DM as a validation simulation run (**Figure 20**).



	KeyValue
BRIC	0.52979
HIC_15	102.026
HIC_36	158.489
T12_acceleration_res	43.9326
T12_acceleration_x	43.1728
T12_acceleration_y	17.9034
T12_acceleration_z	22.4047
T1_acceleration_res	64.9958
T1_acceleration_x-	-61.9700
T1_acceleration_x	17.8401
T1_acceleration_y-	-18.9245
T1_acceleration_y	15.8590
T1_acceleration_z-	-12.5623
T1_acceleration_z	25.1089
T4_acceleration_res	40.6004
T4_acceleration_x-	-40.5395
T4_acceleration_x	15.8397
T4_acceleration_y-	-12.2415
T4_acceleration_y	8.00223
T4_acceleration_z-	-19.1717
T4_acceleration_z	7.10635
T4_angular_velocity_res	0.58808
T4_angular_velocity_x	0.33923
T4_angular_velocity_y	0.47784
T4_angular_velocity_z	0.41968
head_acceleration_3msclip	36.0516
head_acceleration_res	38.9057

Figure 20 Predicted key values of the validating Simulation Run

The predictions for the HIC_15, HIC_16 and BRIC values gave a relatively small error, while all predictions remained within the Mean absolute Error of the Predictor (MAE) given in the predictor’s reports and within the confidence bounds of each prediction.

	Analysis result	**Prediction**	**Error**
HIC_15	102.026	101.541	0.47%
HIC_36	158.489	159.096	0.38%
BRIC	0.5297	0.5674	6.87%
Dummy measurements			
Head acceleration $(\mathbf{mm})$	38.905	38.5627	0.88%
Left clavicle inboard load cell$(\mathbf{kN})$	1.3762	1.3916	1.11%

Right clavicle inboard cell $(\mathbf{kN})$	1.204	1.26	4.54%
Upper neck nij	0.3988	0.4022	0.84%
Thorax rib LL $(\mathbf{mm})$	59.148	58.401	1.27%
Thorax rib LR $(\mathbf{mm})$	17.603	17.126	2.74%
Thorax rib UL $(\mathbf{mm})$	65.597	66.321	1.09%
Thorax rib UR $(\mathbf{mm})$	43.722	43.421	0.69%

Table 2 Validation of predictions

	Initial	**Optimum**	**Reduction**
HIC 15	132.365	102.026	22.92%
HIC 36	165.047	158.489	3.97%
BRIC	0.534	0.5297	0.8%

Table 3 FE Analysis Optimum results

8. 3D Results

Displacements and other scalar values of theoretical experiments were predicted simply by selecting values for the design variables. The prediction was realized for all time steps of the sled test simulation, so an animation of the entire process was available in the embedded META Results Viewer. The accuracy of the predicted 3d field results was quite high since they had a small deviation in comparison to the computed results of the FE validation model (**Figure 21**).

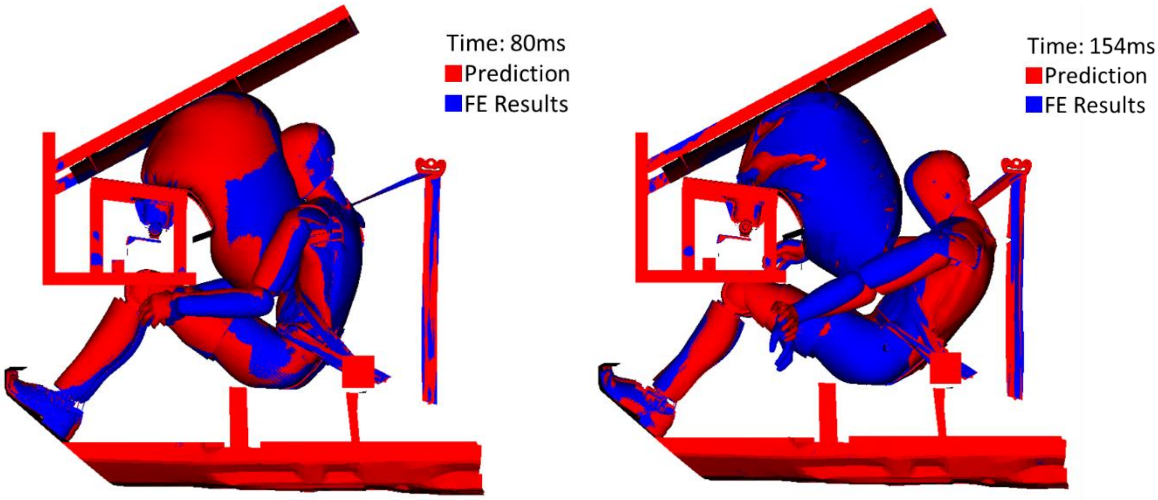


Figure 21 Overlay of FE & prediction displacements results in 2 different times

The pictures above show an overly between the predicted displacements as computed by the ML algorithm and the respective FE analysis results. It can be seen that the predicted values are close to the ones from original FE model, a clear indication that the predictor was subjected to a satisfactory training and provided accurate results.

9. 2D Results

2D history curve results such as acceleration magnitude of different body parts, kinetic and total energy, forces etc., were also predicted for all states. The design variables of the validating optimum experiment were used in order to predict various 2D curves that were also validated with the respective plots of the original FE model (**Figure 22, Figure 2, Figure**).

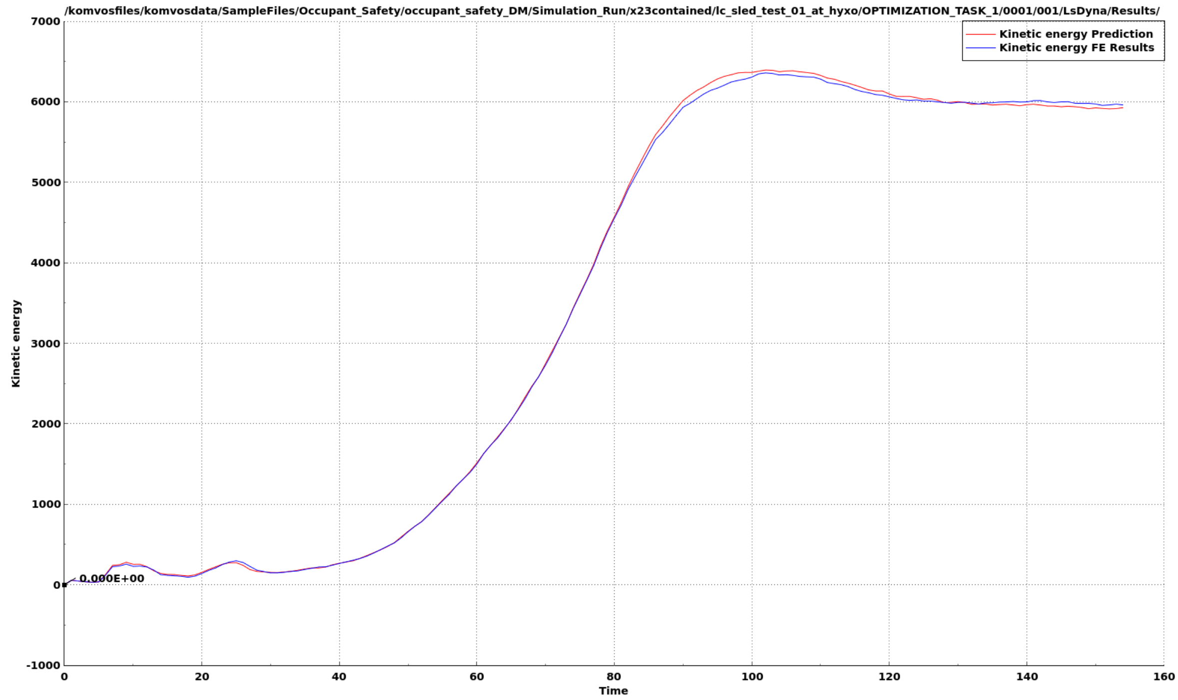


Figure 22 Kinetic Energy results of the FE model vs prediction model

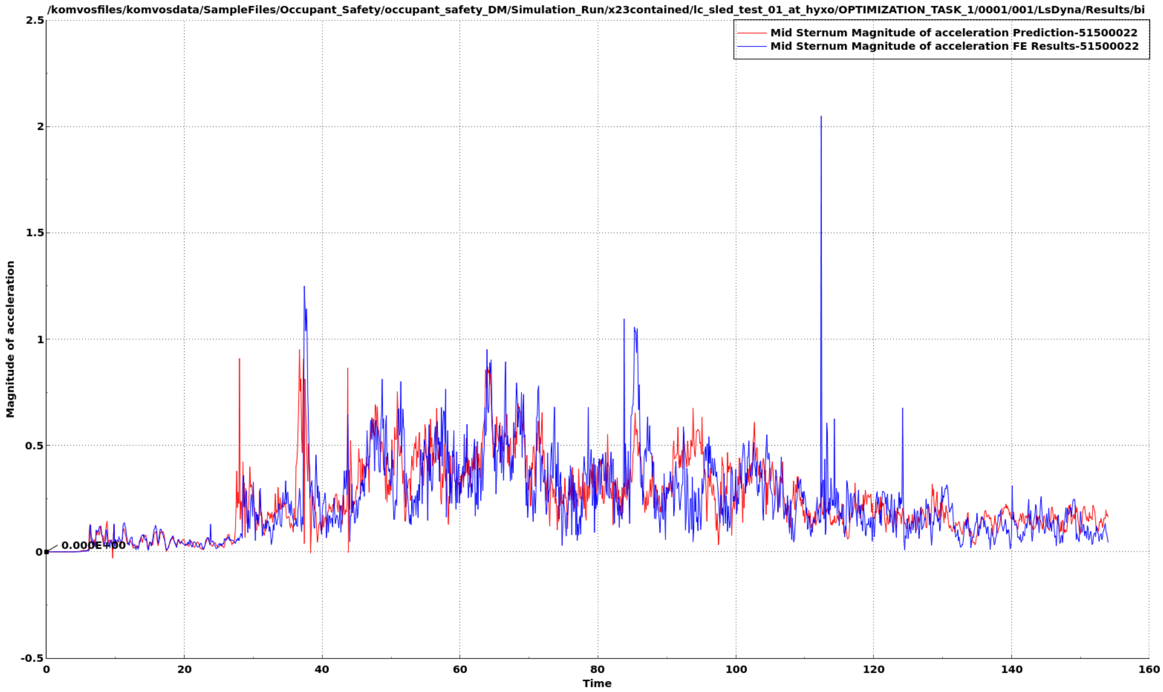


Figure 233 Middle sternum results of the FE model vs prediction model

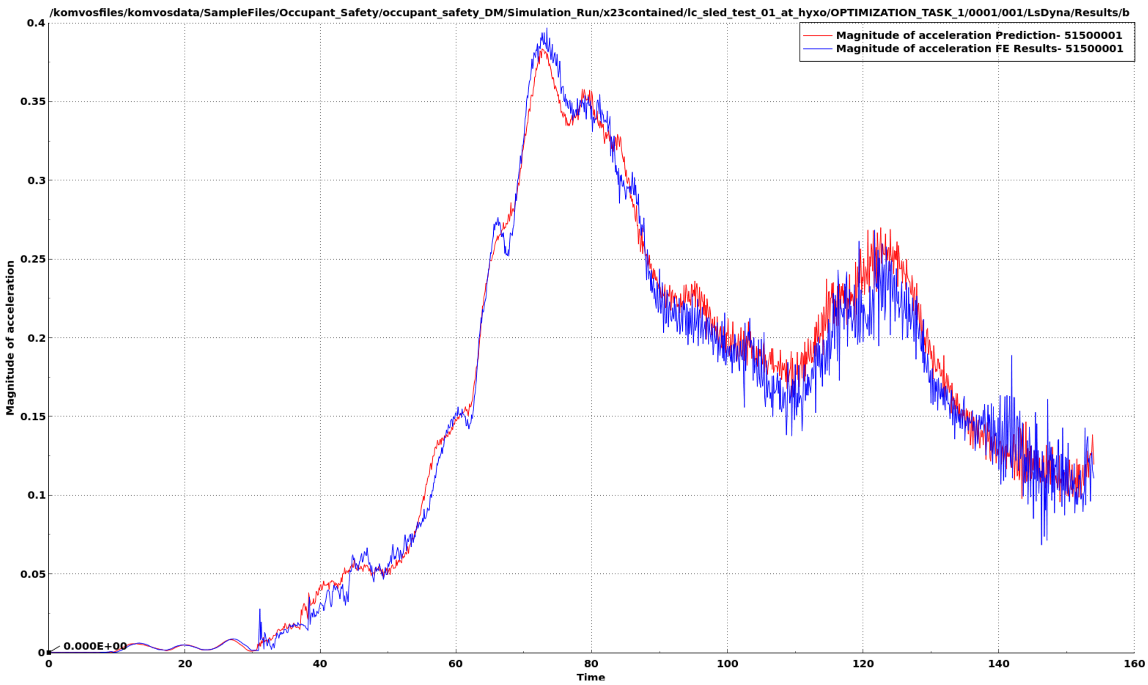


Figure 4 Head acceleration results of the FE model vs prediction model

10. Conclusion

In this study, predictive models were created using the Machine Learning tool of KOMVOS, to predict values based on injury criteria and various other dummy body measurements during a sled test that included an occupant, a seatbelt and an airbag. A DOE study was set using ANSA's Optimization Tool to get the initial training dataset. The study included 25 experiments that were solved with the LS-DYNA FE solver. All data was then added in a DM system that can be manipulated through KOMVOS, where the training of the predictive models would take place.

Utilizing the prediction's parallel coordinates chart and design variable sensitivity plots, it was possible to come up with different exploratory 'what if' scenarios and apply the respective design variable values to predict the specified key values in seconds. An Optimization study was ran using the trained predictor as a response surface, quickly resulting in finding the optimum design. An FE Analysis was run for the optimum design to validate the occupant criteria predictions.

In addition, predictors were trained to predict 2D plots and 3D field scalar results that were also validated against the respective results of the FE Analysis.

The Machine Learning functionality implemented in KOMVOS offers prediction capabilities of high accuracy for CAE "what if" studies. Combined with the Optimization tool of ANSA and the post processing capabilities of META, KOMVOS provides powerful tools including capabilities to create a dataset, train Machine Learning algorithms, create predictive models, and run optimization studies in a fraction of the actual FE solution time. Results overview and comparison of the Simulation runs, DOE Studies, predictions of results for theoretical runs and creation of new experiments through the KOMVOS interface allows for an efficient design exploration.

11. Literature

[1] Fokylidis.T.,Tzolas.N:"Performing DOE Studies in Occupant Protection Using BETA CAE Tools", CAASE20, June 16-18

[2] Ljungqvist.C., Wass.C., Tzolas.N., Appelgren.P.: "Occupant Injury Criteria, a Complete Solution for the Evaluation of Occupant and Structural, Simulation and Physical Test Results in META", 5th LS-DYNA International Conference & Users Meeting, June 10-12.

[3] ANSA v23.0.x User Guide June 2022

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Headquarters
Platz 4
CH-6039 Root D4,
Switzerland
+41 415453650

Email: ansa@beta-cae.com
URL: www.beta-cae.com

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