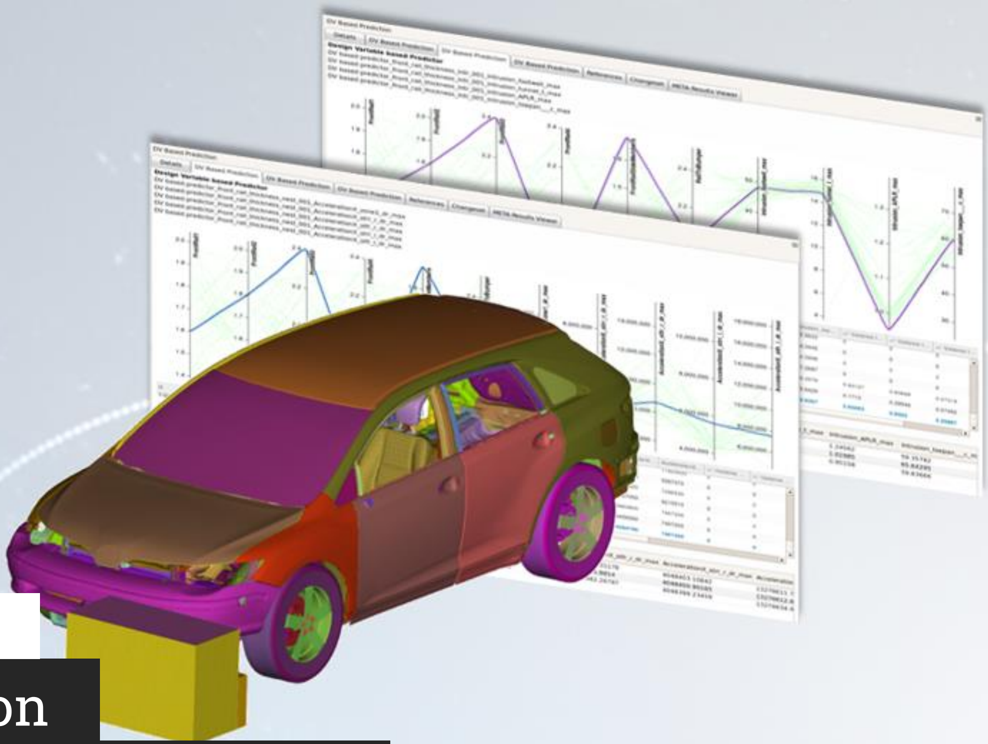
BETA
SIMULATION SOLUTIONS

physics on screen



White paper

Simulation enabling technologies

Employing Machine Learning for front crash responses prediction

Front crash is one of the most common finite element analyses during vehicle development. The Machine Learning functionality implemented in KOMVOS can be trained to predict the behavior of theoretical designs in a front crash, without running the full FE analysis. This enables the performance of multiple “what-if” studies without requiring the otherwise additional design and solver run time.

Introduction

One of the most common finite element analyses in vehicle development is the front crash simulation (Figure 1). This test is important as it simulates a very probable and dangerous real case scenario. In such an impact, the vehicle's structural parts that absorb most of the impact energy are the front rails (Figure 2).

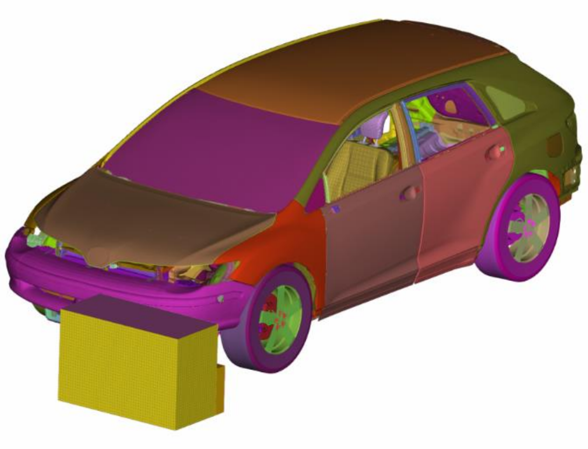


Figure 1: RH Front crash

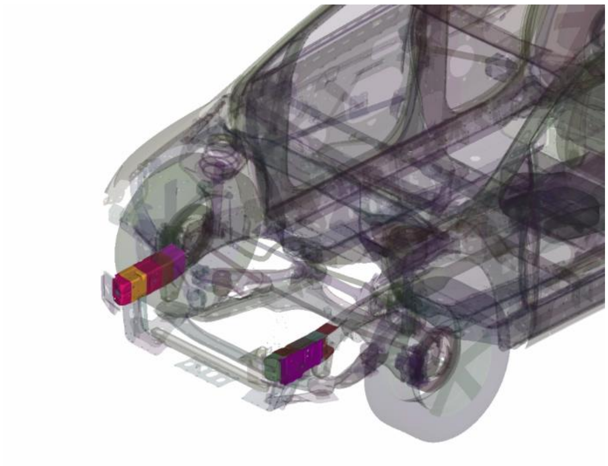


Figure 2: Vehicles' front rails

The thickness of the front rails plays a significant role on the general behavior of the vehicle in the front crash case. To investigate the effect of the thickness, a Design of Experiments (DOE) analysis is set up using the ANSA optimization tool with design variables defined to modify thickness values.

These experiments and their responses are used to build a dataset that will train Machine Learning predictive models. Then, by employing the Machine Learning functionality, implemented in KOMVOS, we can predict the behavior and key values such as maximum intrusions or accelerations, without the need to run the full FE analysis. This enables the investigation of multiple "what-if" studies eliminating further analysis and design time.

Model Parameterization

For this study, six parameters that modify the thickness of front rails' specific parts have been defined. These parts were then split into symmetrical segments for which parameters were created.

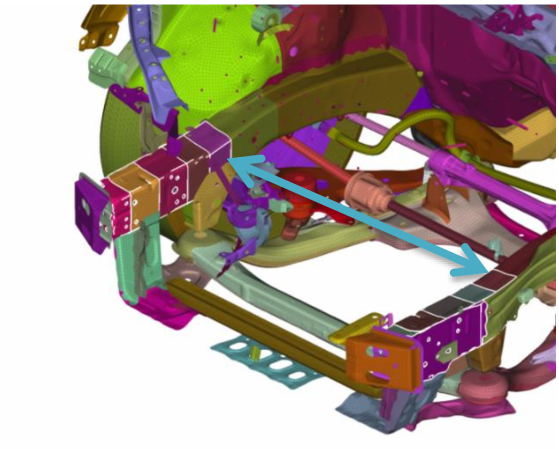


Figure 1: Symmetrical parts with thickness parameters

For each one of these thickness parameters, design variables with specific bounds were defined to create an Optimization task with six design variables (Figure 4).

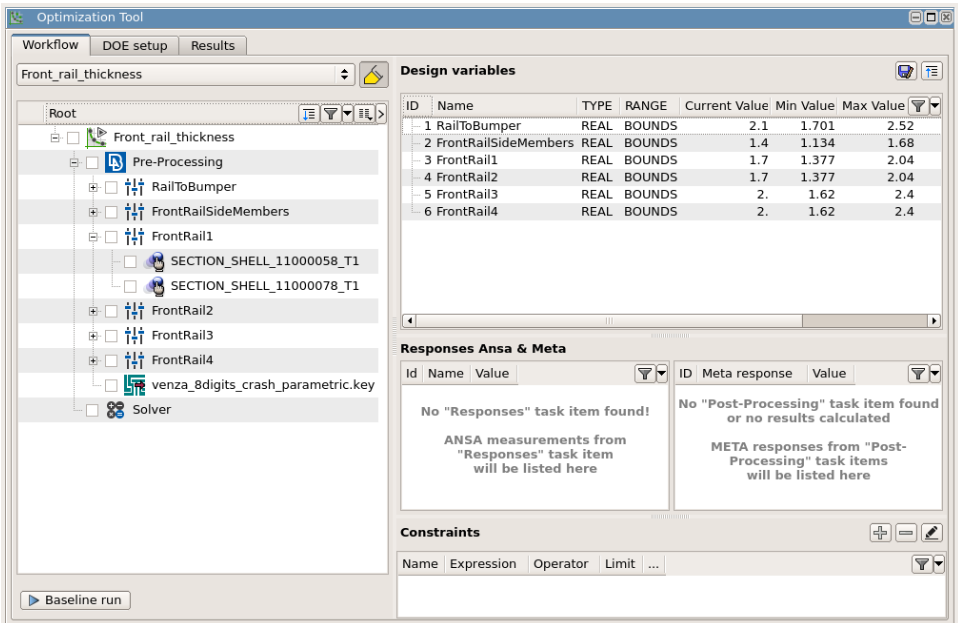


Figure 2: The Optimization task

Dataset creation

Pre-Processing

Through the Optimization tool's workflow, several experiments were produced to form the Machine Learning dataset using the Uniform Latin Hypercube DOE algorithms. 60experiments were created each with different values in the design variables, forming a dataset with sufficient spread in the design space (Figure 5).

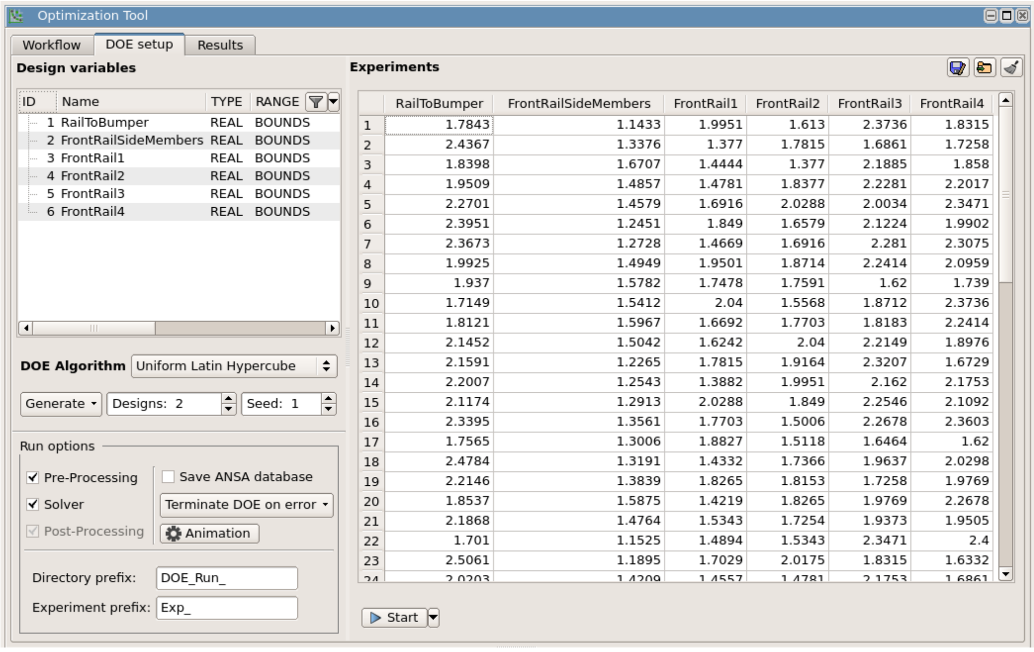


Figure 3: Design of Experiments table

The DOE process created the 60 designs and run the analysis for each. The created data were then saved in a DM container system with a specific structure and hierarchy. The DM system can be handled through ANSA or KOMVOS.

The created structure consists of a main Simulation model at the top of the tree structure and contains the DOE studies and the Parametric Structure. The DOE Studies contain the created experiments as Simulation runs, each including the experiment's information, results, and design variable details. The Parametric structure holds all the information relating to the parameterization of the Simulation model.

Post Processing

Post processing was also performed for all experiments using a session file, to extract curves, pictures, videos, and the important key values required for the Machine Learning procedures.

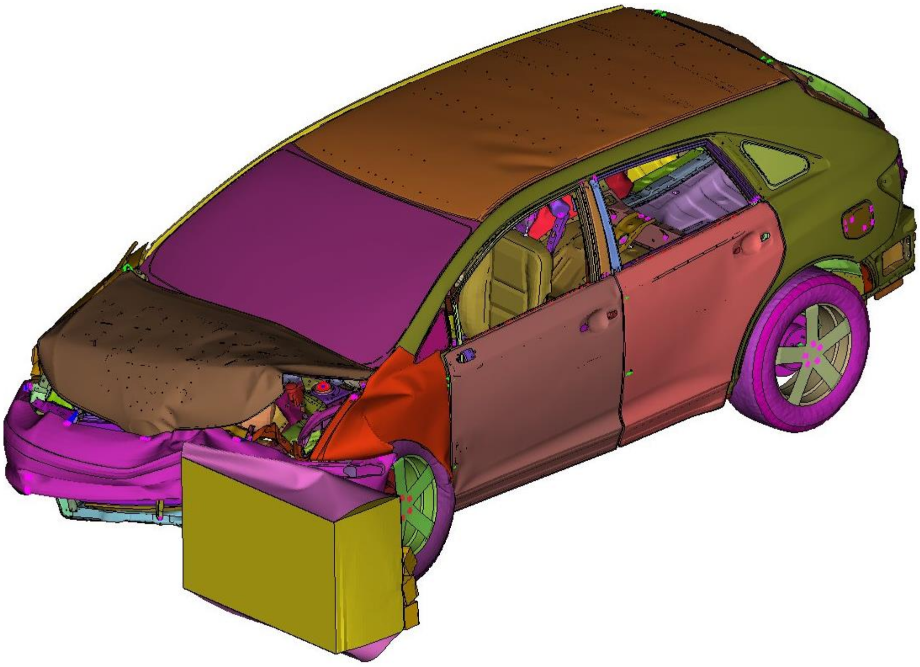


Figure 4: FE Crash analysis results

The post processing findings were automatically added as report items in each simulation run (Figures 7, 8).
Each of the Simulation runs contains key values for the selected accelerations and intrusions at various points on the vehicle. These key values can be used as responses to train the Machine Learning models.

KeyValues

	A	B	C	D	E	F
1		001	002	010	020	025
2	RH_EAP_Displacement_0.14	-208.3216705322266	-212.1101989746094	-208.1366271972656	-208.9314880371094	-210.2083282470703
3	inner_side_member_max_pl_strain	0.002547349315136671	0.01236706413328648	0.003053518943488598	0.004796065855771303	0.008063674904406071
4	rear_cross_tube_max_pl_strain	0.0001529157452750951	0.003293070942163467	0.003377452725544572	0.001557440380565822	0.004227188415825367
5	rear_side_patch_max_pl_strain	0.04367338865995407	0.01190080959349871	0	0	0.000605840003117919
6						

Figure 5: Key values of simulation runs

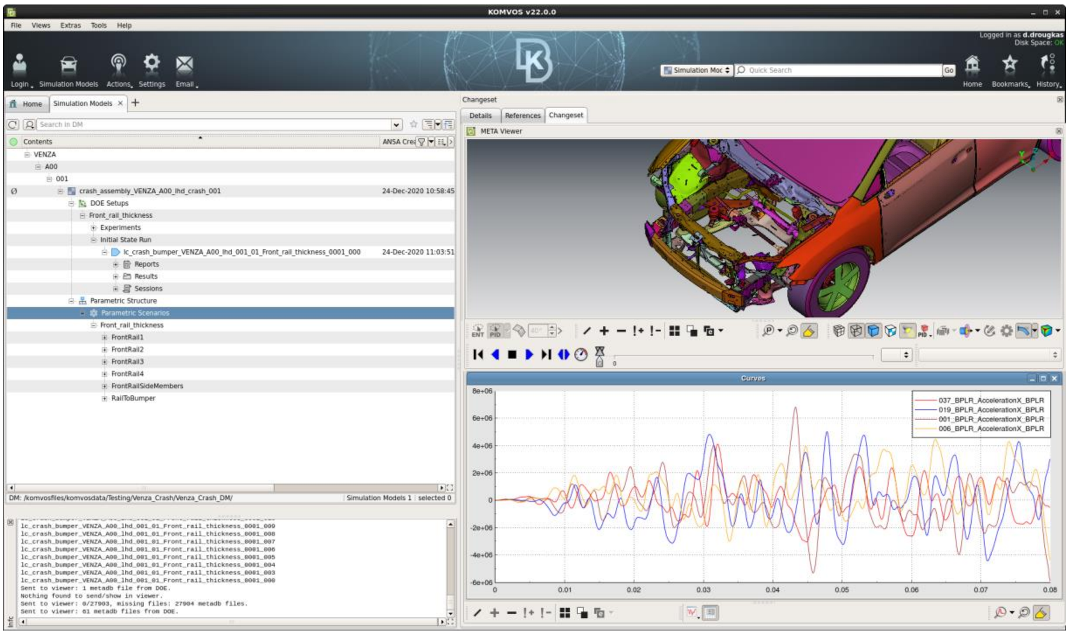


Figure 6: Simulation run reports in KOMVOS

Machine Learning Training

Using the design variable-based Machine Learning option (ML Train), and the 60 available simulation runs, a group of predictive models was trained to calculate the maximum intrusion at specified measurement points of the vehicle (A pillar base, footwell, toepan, and tunnel). Similarly a group was also trained to predict the maximum acceleration on the driver's seat fixation points (Figure 9). The predictor entities calculate these specific key values based on any design variables values, avoiding the use of solver runs and thus eliminating the time needed to run the solution.

Figure 7: Intrusion measurement (left), Acceleration measurement (right)

Each predictor contained report charts showing performance and sensitivity of design variables. The charts in Figures 10 and 11 depict the design variables that have the largest effect on the response values. This chart is essential to reach to a better performing design.

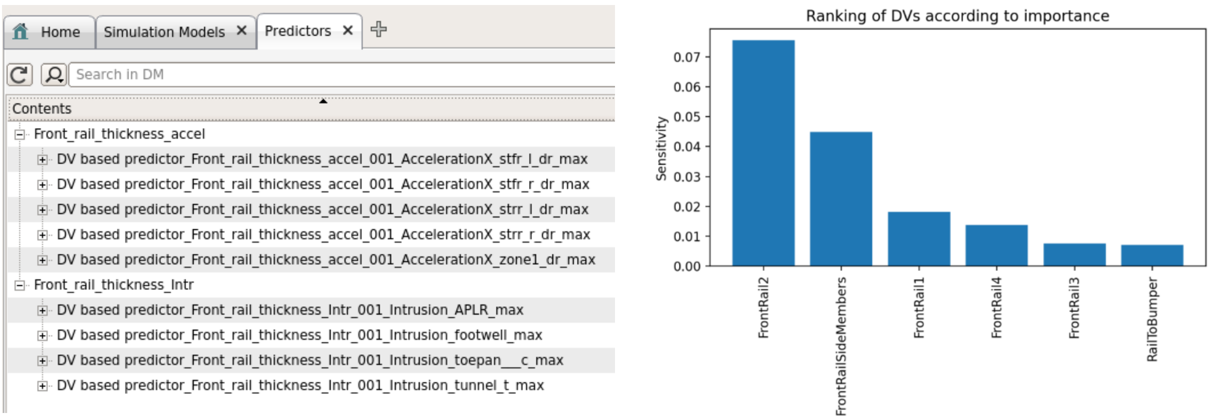


Figure 8: Predictive models and DV Sensitivity chart for A-pillar intrusion predictor

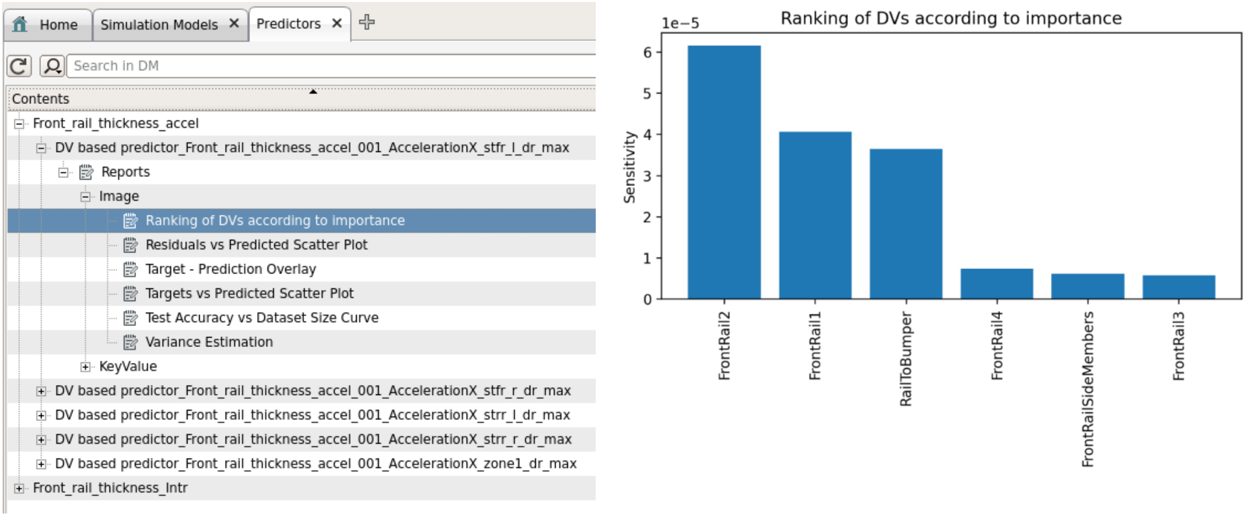
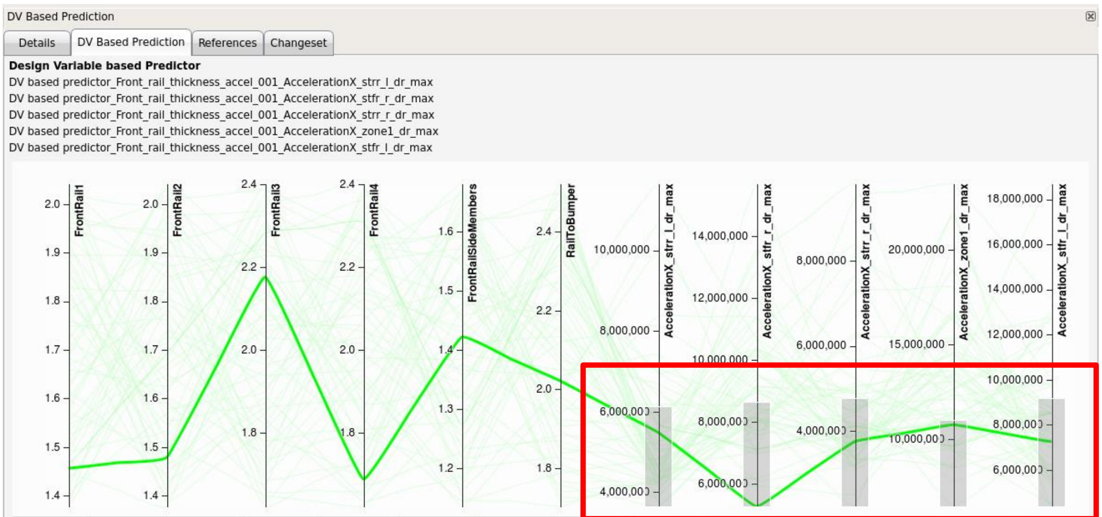


Figure 9 Predictive models and DV Sensitivity chart for Acceleration at seat fixation

Machine Learning Prediction

Utilizing the parallel coordinate chart, it was possible to filter and identify the experiments with the lowest maximum acceleration values and respective intrusion values at all the measurement points (Figure 12, 13).



id	FrontRail1	FrontRail2	FrontRail3	FrontRail4	FrontRailSide...	RailToBumper	AccelerationX...	AccelerationX...	AccelerationX...	AccelerationX...	AccelerationX...	+/- Variance ...	+/- Variance ...
Exp007	1.4669	1.6916	2.281	2.3075	1.2728	2.3673	5677530	7100850	4101600	9623000	8497940	0	0
Exp024	1.4557	1.4781	2.1753	1.6861	1.4209	2.0203	5463780	5250030	3740270	10737700	7231880	0	0

Figure 10: Identification of lowest RH EAP Displacement experiment

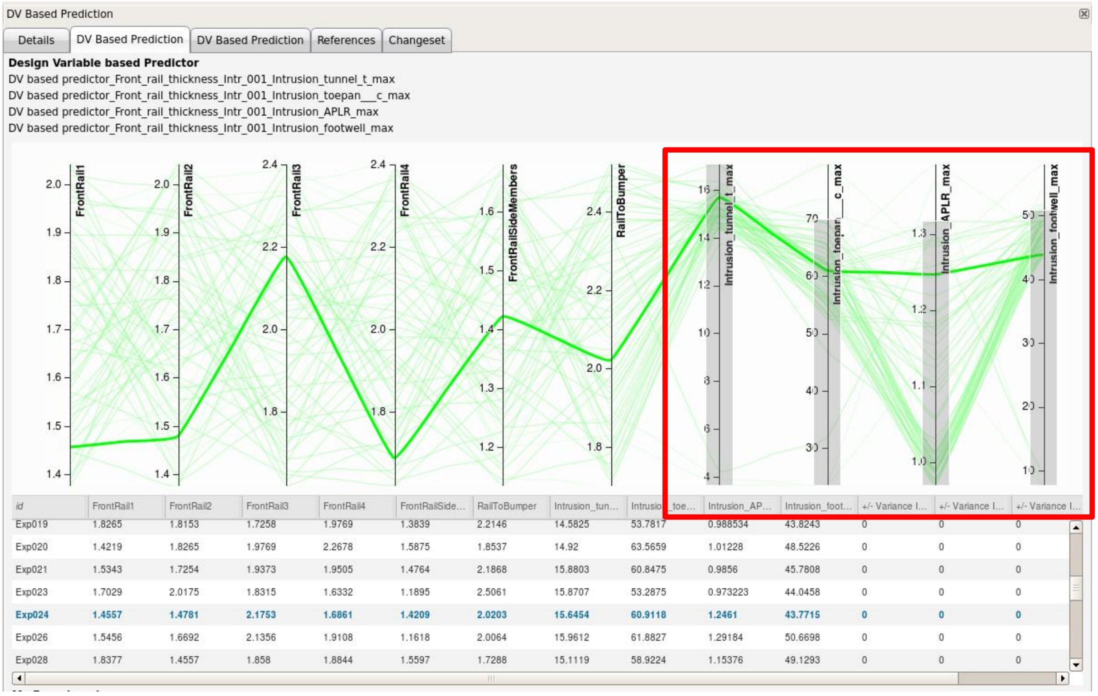


Figure 11: Identification of lowest maximum plastic strain experiment

As expected, experiments with lower acceleration measurements had higher intrusion values at the areas of interest. The design variables of the identified experiment (24) were used as initial values to define "what-if" scenarios.

Based on the information of the importance maps of each predictor (Figures 14-17), it was clear that the design variables FrontRail2, FrontRail3 and FrontRail4 are affecting the intrusions and accelerations the most.

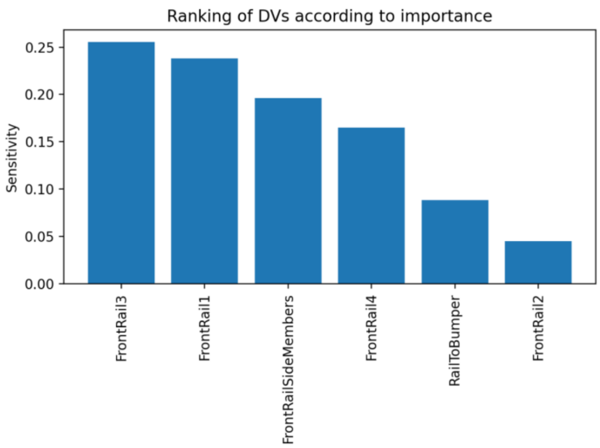


Figure 12: Tunnel intrusion DV importance map

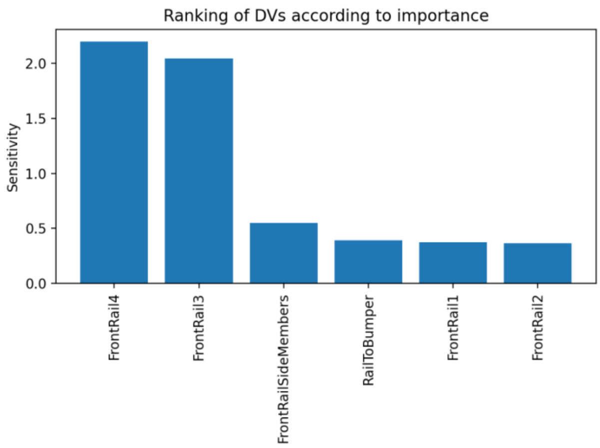


Figure 13: Toepan intrusion DV importance map

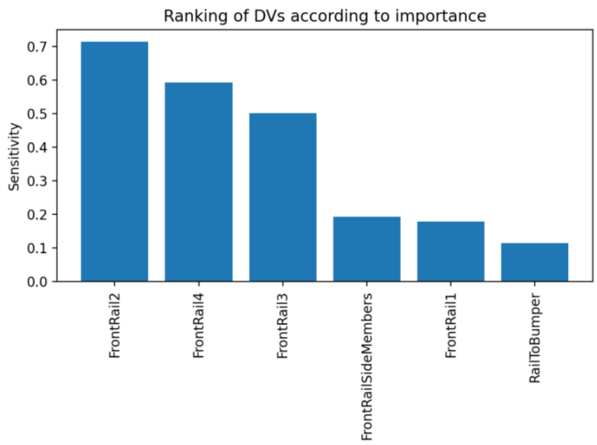


Figure 14: Footwell intrusion DV importance map

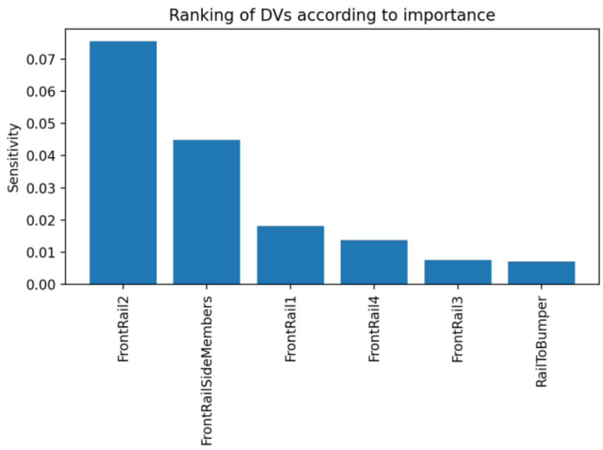


Figure 15: A Pillar intrusion DV importance map

With this information, we could filter design variable values and then apply theoretical values to create more “what-if scenarios” .The target was to identify design variable values and achieve a tradeoff between low acceleration values and low intrusion values.

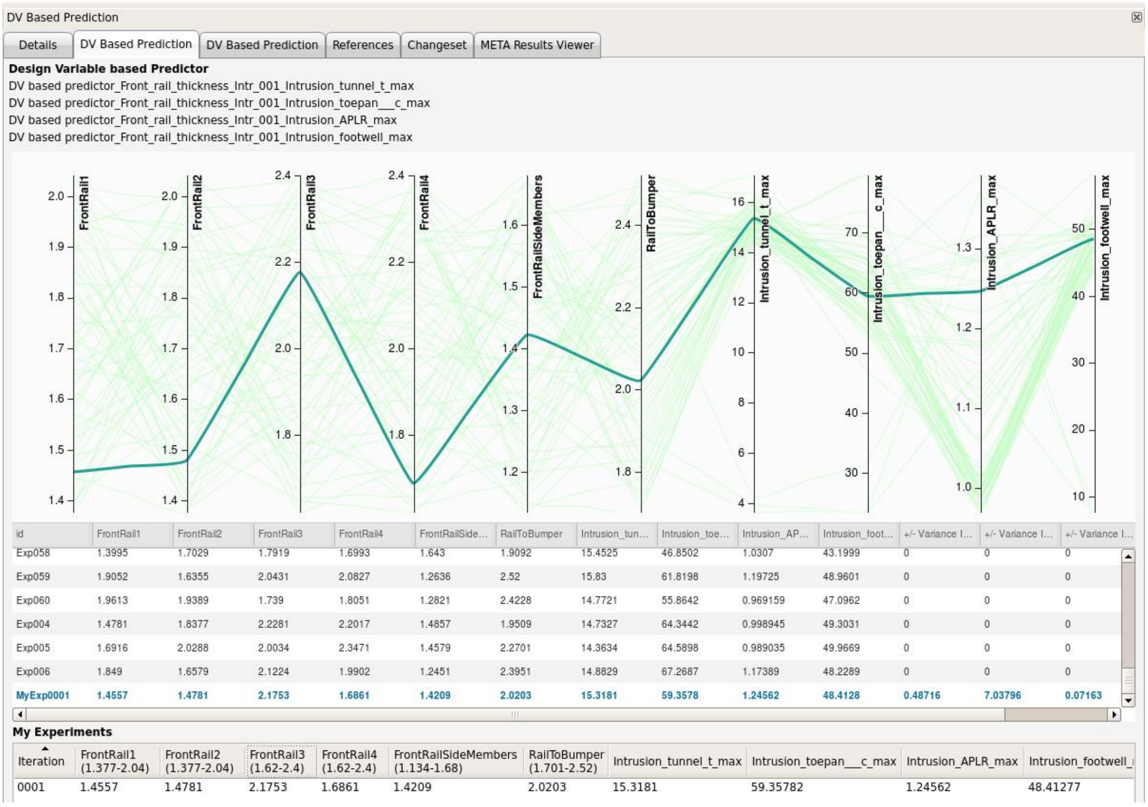
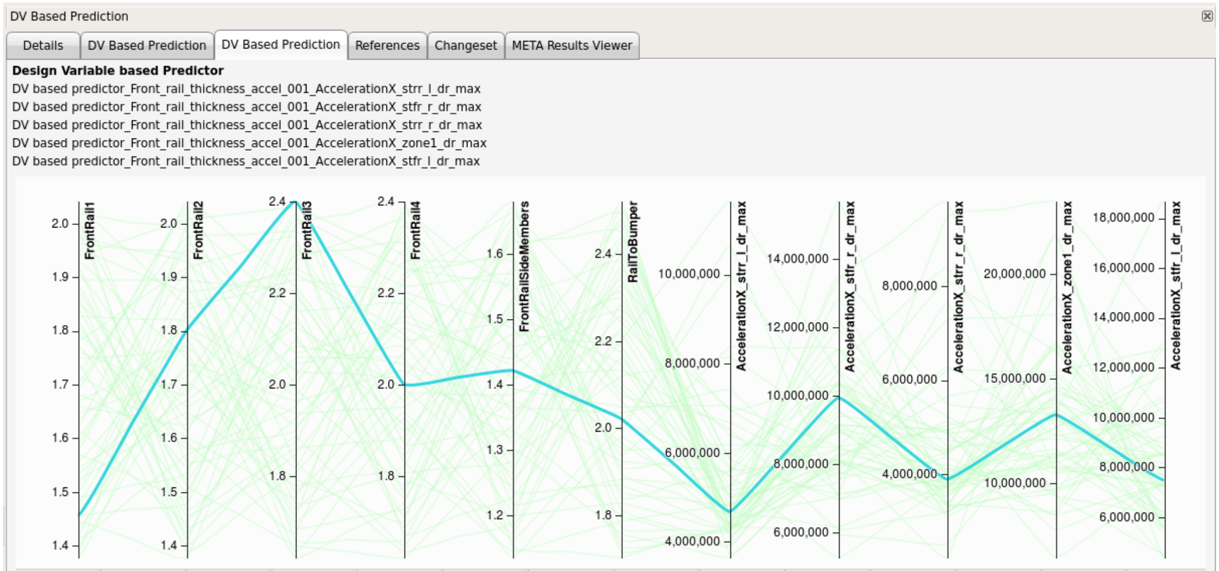


Figure 16: Intrusions for experiment 24

Utilizing the “My Experiments” list of the parallel coordinates chart it was possible to specify design variable values for each design variable and predict the respective key values for intrusions and accelerations. The goal was to try some design variable values and identify a combination that would improve intrusion values without affecting accelerations too much. Experiment 0001 in the “My Experiments” list was the experiment 24, added for comparison (Figure 18).



id	FrontRail1	FrontRail2	FrontRail3	FrontRail4	FrontRailSide...	RailToBumper	AccelerationX...	AccelerationX...	AccelerationX...	AccelerationX...	AccelerationX...	+/- Variance ...	+/- Variance ...
Exp058	1.3995	1.7029	1.7919	1.6993	1.643	1.9092	5975610	10130400	3861820	10953800	9661570	0	0
Exp059	1.9052	1.6355	2.0431	2.0827	1.2636	2.52	3722420	8288410	3874840	12283500	8133130	0	0
Exp060	1.9613	1.9389	1.739	1.8051	1.2821	2.4228	5866710	6957430	4350210	8490650	11925400	0	0
Exp004	1.4781	1.8377	2.2281	2.2017	1.4857	1.9509	6170520	8466670	3651500	11043600	5597370	0	0
Exp005	1.6916	2.0288	2.0034	2.3471	1.4579	2.2701	6963620	7689900	5104640	10680200	7296530	0	0
Exp006	1.849	1.6579	2.1224	1.9902	1.2451	2.3951	5007050	8393240	4181680	9865140	9210510	0	0
MyExp0001	1.4557	1.8	2.4	2	1.4209	2.0203	4664930	9922380	3882780	13247900	7467200	0	0

My Experiments

Iteration	FrontRail1 (1.377-2.04)	FrontRail2 (1.377-2.04)	FrontRail3 (1.62-2.4)	FrontRail4 (1.62-2.4)	FrontRailSideMembe (1.134-1.68)	RailToBumper (1.701-2.52)	AccelerationX_strr_l_dr_max	AccelerationX_stfr_r_dr_ma	AccelerationX_strr_r_dr_max	AccelerationX_zo
0001	1.4557	1.4781	2.1753	1.6861	1.4209	2.0203	4664925.74995	10235887.4581	3882779.62601	12923988.36307
0002	1.4557	1.8	2.4	2.2	1.4209	2.0203	4664925.74996	9962107.11152	3882779.62504	13270769.91017

Figure 17: Accelerations prediction for theoretical experiment 0002

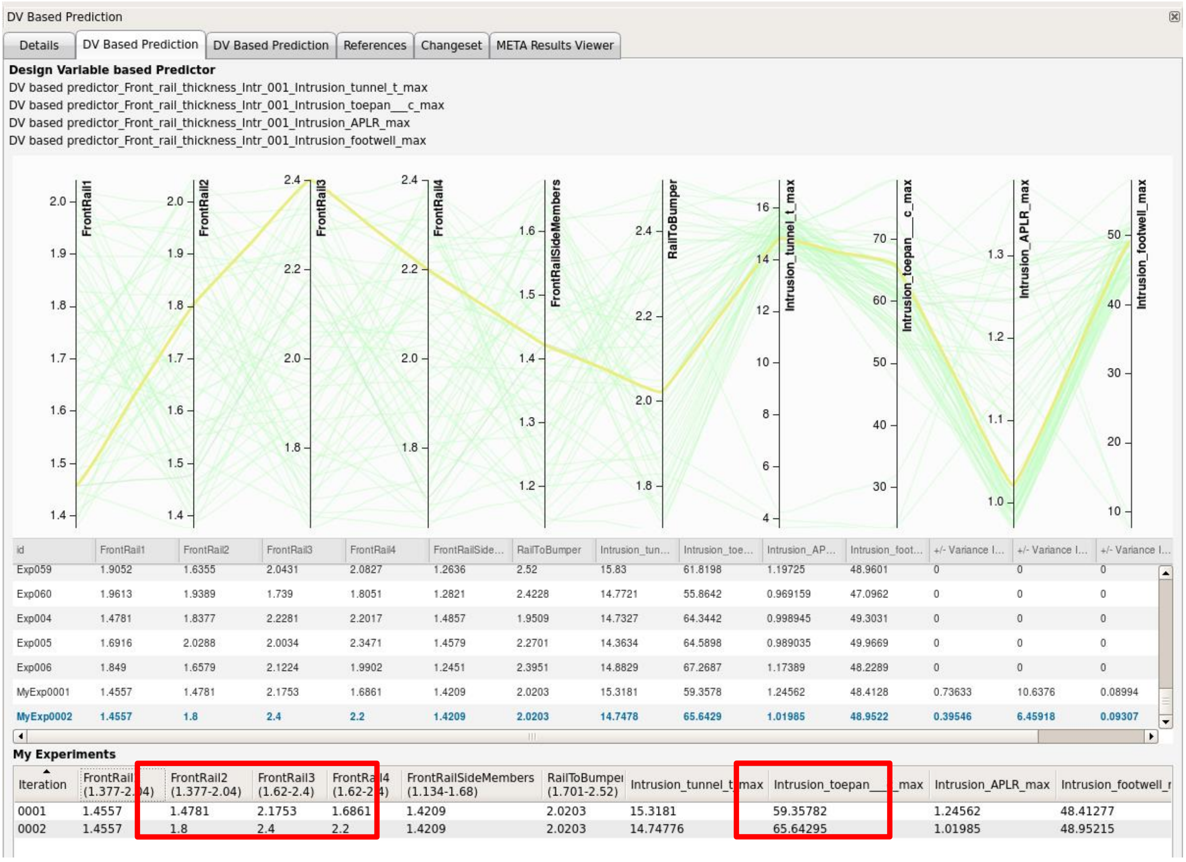


Figure 18: Intrusions prediction for theoretical experiment 0002

After modifying the design variable values based on the importance maps (Figures 14-17), the predictions for accelerations were acceptable (Figure 19) however intrusion for toepan area was increased (Figure 20). A new what-if scenario was created, adding different values in my experiments list, to create new predictions.

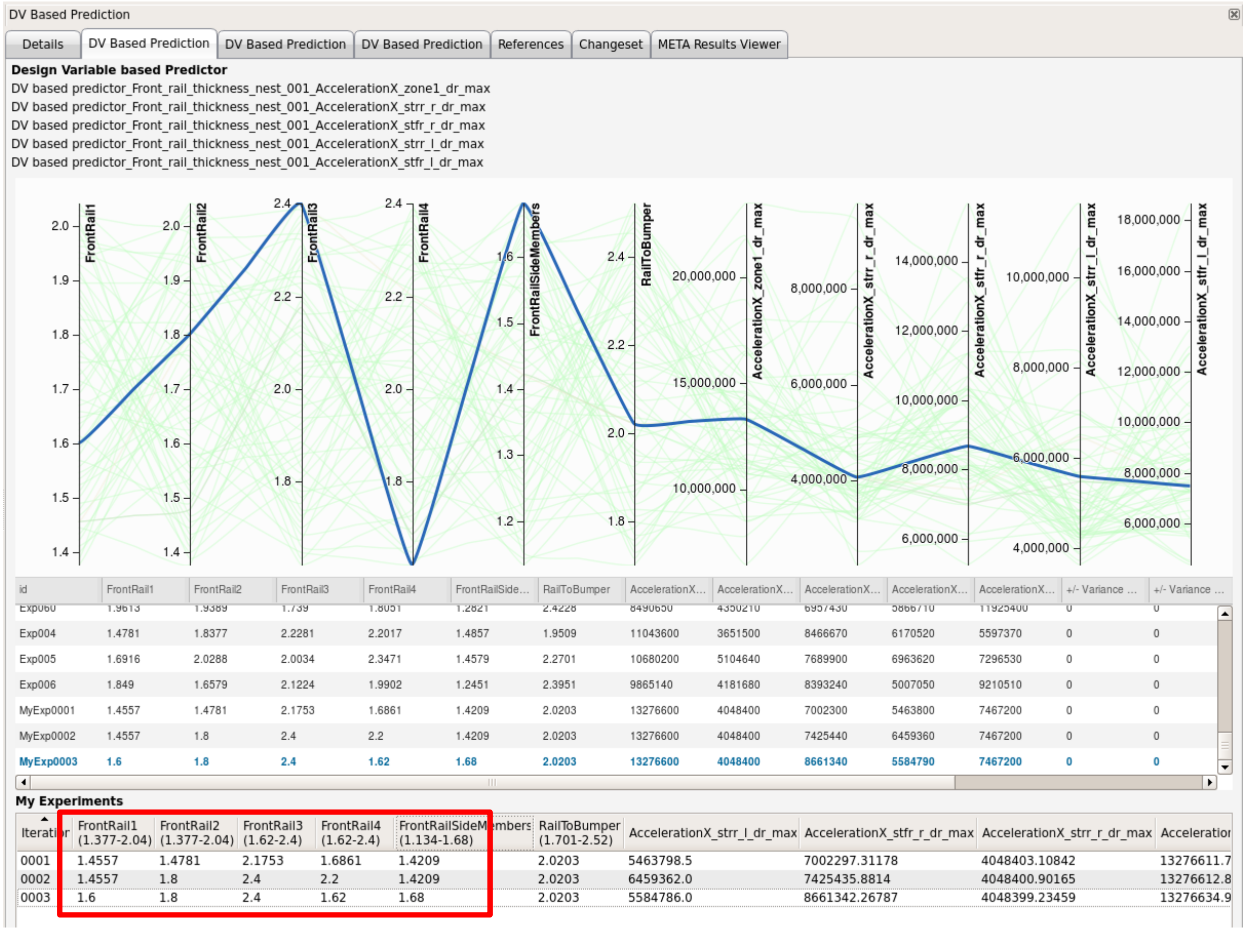


Figure 19: Accelerations prediction for theoretical experiment 0003

For the second “what-if” scenario, the predicted acceleration values were similar to the original accelerations of experiment 24 (Figure 21). However intrusions were decreased for all measured areas, which was the goal of this analysis (Figure 22).

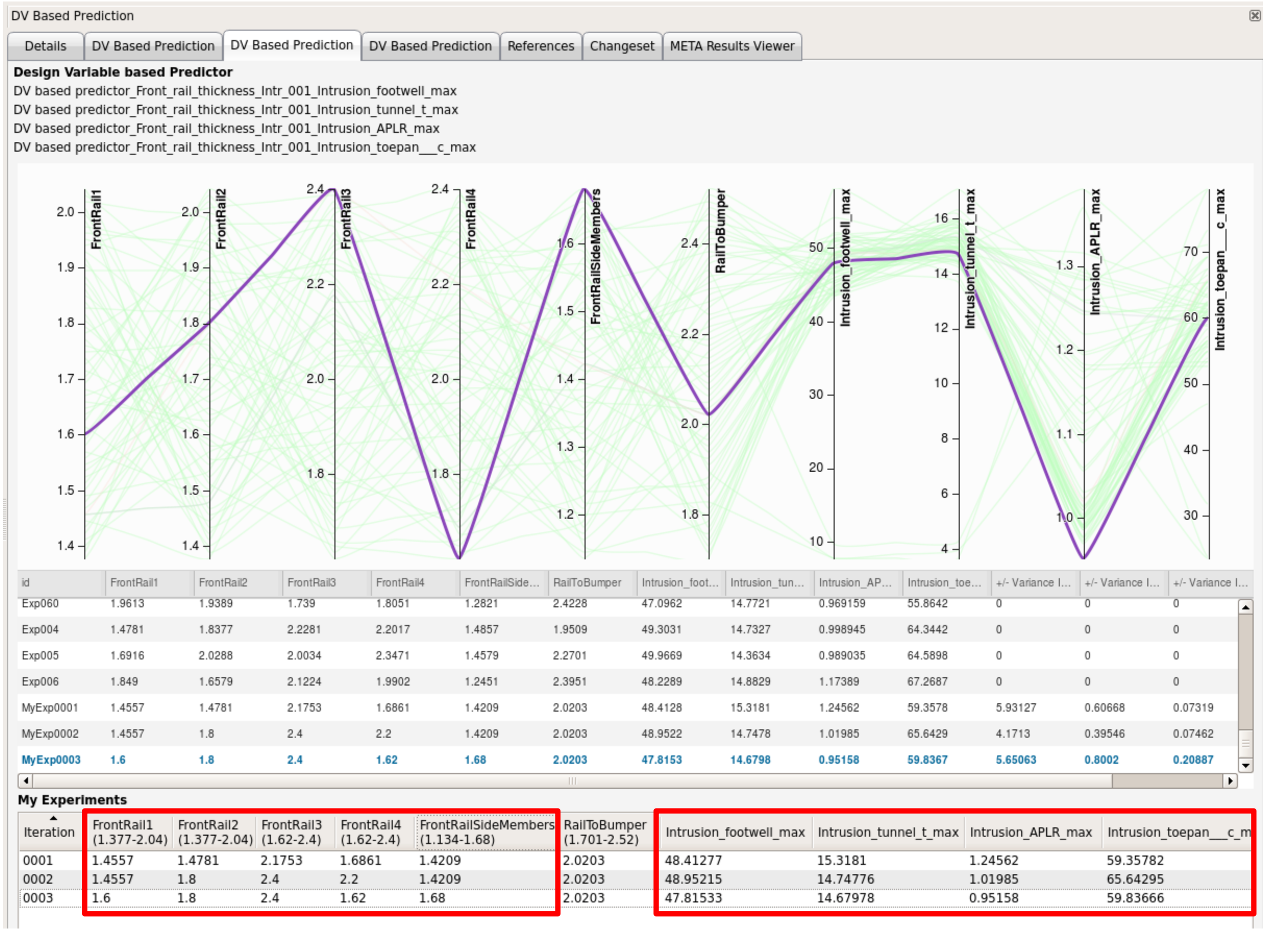


Figure 20: Intrusions prediction for theoretical experiment 0003

This “what-if” scenario was a good candidate and was added in the DM through an automated process, starting from this prediction. ANSA was automatically deployed and the selected design variable values were applied on the original model. The analysis was done and the new Simulation run was added in the DM.

Validation

The theoretical experiment created from a “what-if” scenario, was added in the DM along with the analysis results as a validation simulation run. A post processing session automatically extracted the respective reports and key values. Key values are directly compared in KOMVOS.

	A	B
1		KeyValue
2	AccelerationX_stfr_l_dr_max	7552044.5
3	AccelerationX_stfr_r_dr_max	7318835.5
4	AccelerationX_strr_l_dr_max	4885381
5	AccelerationX_strr_r_dr_max	3553885.75
6	AccelerationX_zone1_dr_max	14815225
7	Intrusion_APLR_max	0.9896778512334095
8	Intrusion_footwell_max	42.13635738088976
9	Intrusion_toepan___c_max	57.06002163175026
10	Intrusion_tunnel_t_max	14.58201699254755
11	Predicted AccelerationX_stfr_l_dr_max from Front_rail_thickness_nest	7467200.74991
12	Predicted AccelerationX_stfr_r_dr_max from Front_rail_thickness_nest	8661342.26787
13	Predicted AccelerationX_strr_l_dr_max from Front_rail_thickness_nest	5584786.0
14	Predicted AccelerationX_strr_r_dr_max from Front_rail_thickness_nest	4048399.23459
15	Predicted AccelerationX_zone1_dr_max from Front_rail_thickness_nest	13276634.98879
16	Predicted Intrusion_APLR_max from Front_rail_thickness_Intr	0.95158
17	Predicted Intrusion_footwell_max from Front_rail_thickness_Intr	47.81533
18	Predicted Intrusion_toepan___c_max from Front_rail_thickness_Intr	59.83666
19	Predicted Intrusion_tunnel_t_max from Front_rail_thickness_Intr	14.67978
20		

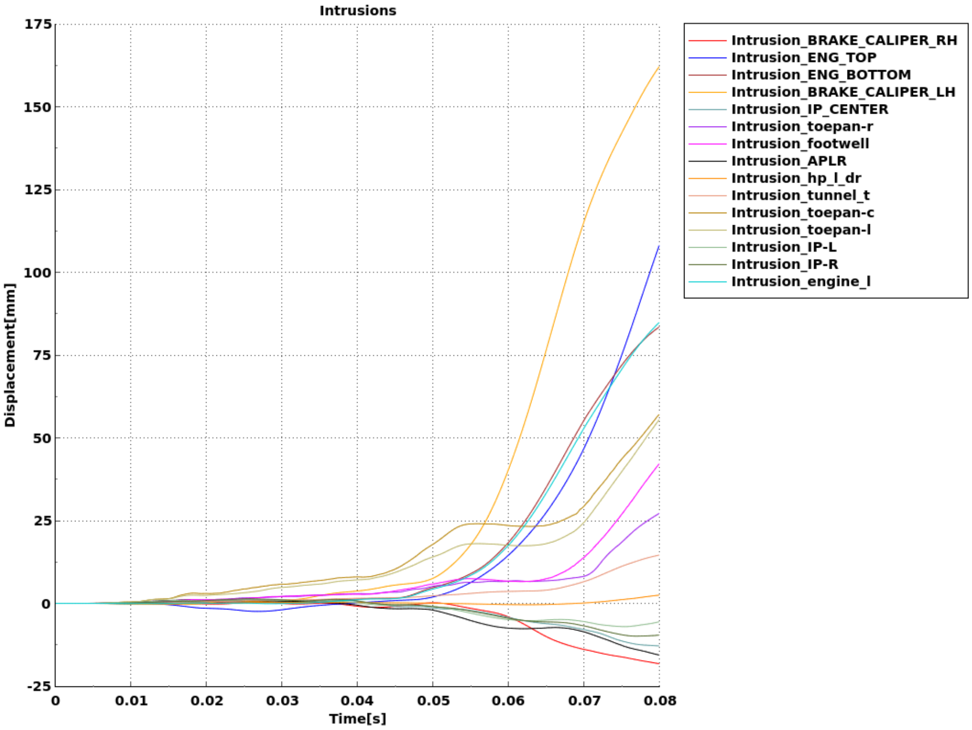
Figure 21: Predicted and Analysis KeyValues of validation Simulation Run

	Analysis result	Prediction	Error (%)
Intrusion A pillar (mm)	0.9896778	0.95158	3.9%
Intrusion footwell (mm)	42.13635	47.81533	12.6%
Intrusion toepan c (mm)	57.060	59.8366	4.7%
Intrusion tunnel (mm)	14.58201	14.67978	0.9%
Acceleration Seat front left (mm/s^2)	7552044.5	7467200.749	1.1%
Acceleration Seat front right (mm/s^2)	7318835.5	8661342.267	16.8%
Acceleration Seat rear left (mm/s^2)	4885381	5584786	13.3%
Acceleration Seat rear right (mm/s^2)	3553885.75	4048399.234	13.0%
Acceleration zone 1 (mm/s^2)	14815225	13276634.988	10.9%

Table 1: Validation of predictions

The predictions for intrusion values at all points of measurement had relatively small error and all predictions were within the Mean Absolute Error of the predictor (MAE) given in the predictor's reports and within the confidence bounds of each prediction.

Figure 24 shows the intrusions for all measuring points for the initial model (top) and the validation model.



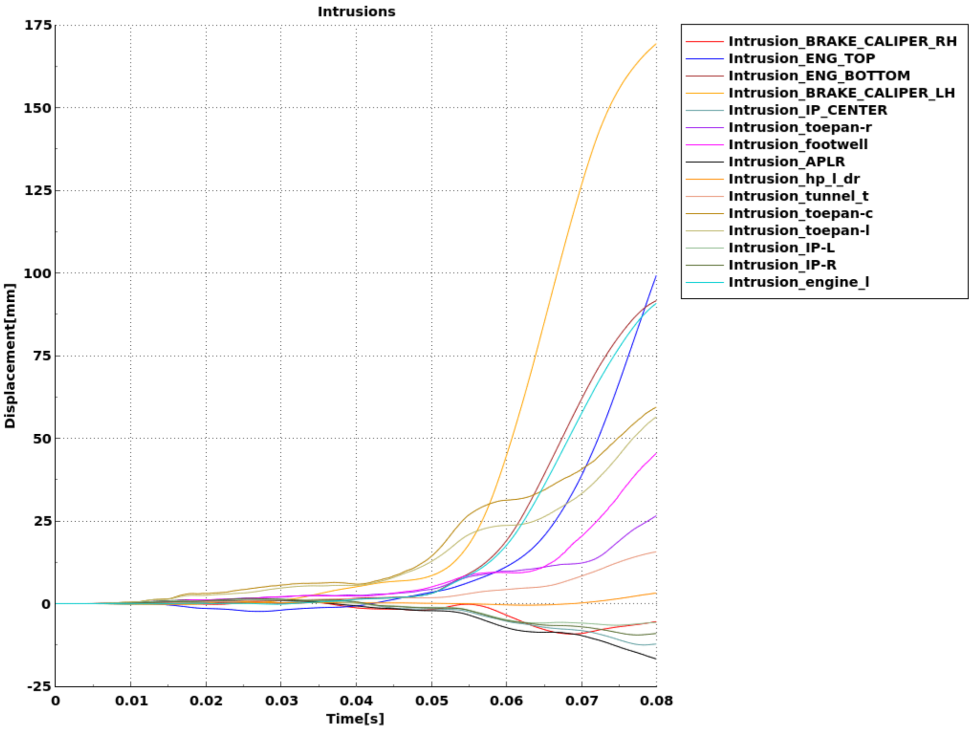


Figure 22: Initial model intrusions (top), Validation model intrusions (bottom)

3D Results

To predict 3D field scalar results, new predictors were trained, using 20 of the available experiments. For 3D results the prediction was made on the displacements and plastic strain (3 through thickness integration points (3ips)), for all the time steps providing an animation of the entire process. The prediction was done automatically after selecting values for the design variables and was visible in the embedded results viewer. The 3d field results prediction achieved almost identical to the validation FE analysis result (Figure 25, 26)

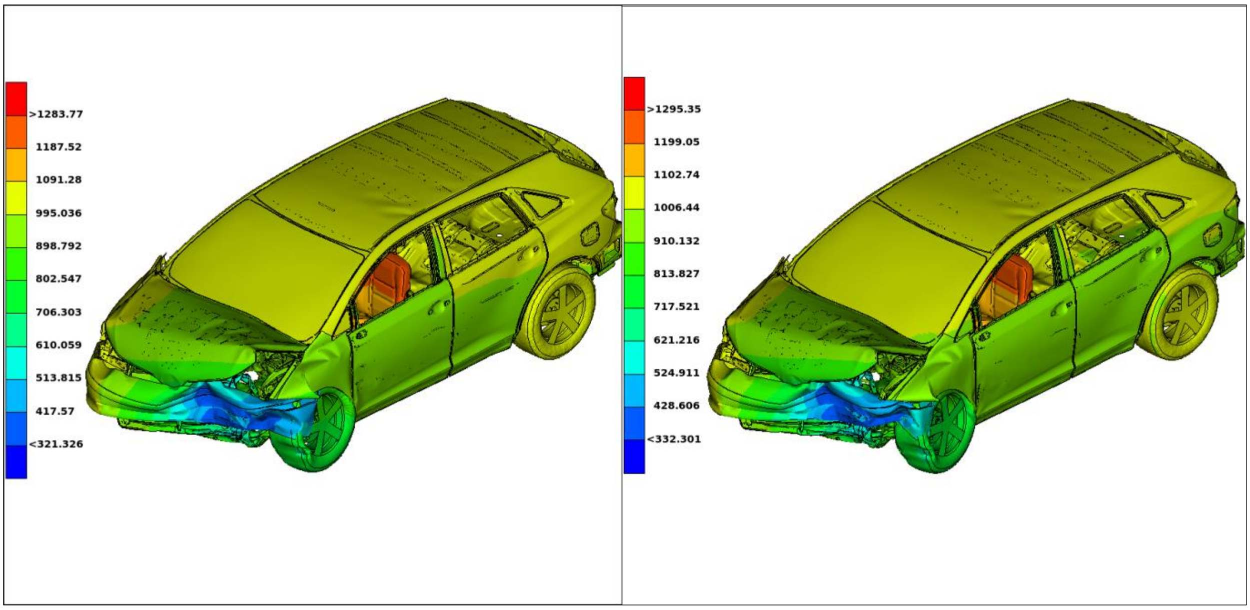


Figure 23: Displacements FE Results (left), Prediction (right)

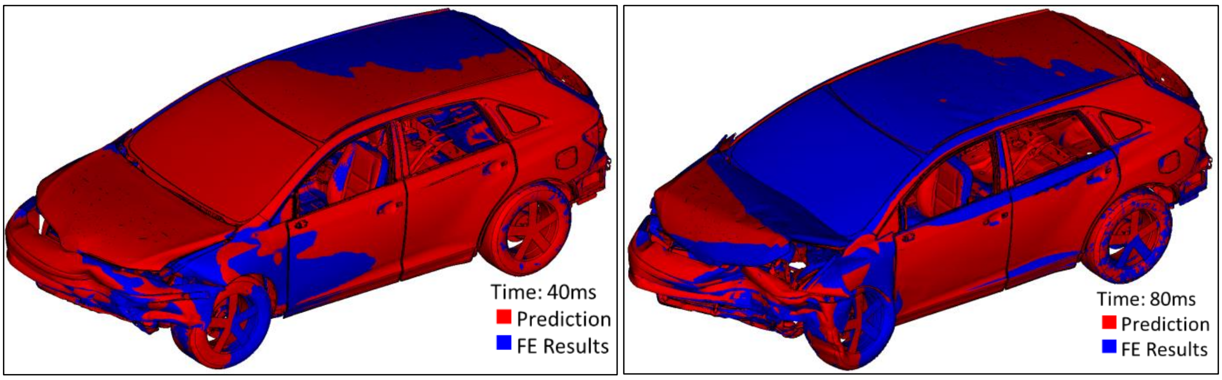


Figure 24: Displacements overlay at 40ms and 80ms

The following pictures show predictions of plastic strain values (ip1) compared with the respective FE Analysis results. The ML algorithm managed to predict plastic strain values providing very similar to the FE Analysis results.

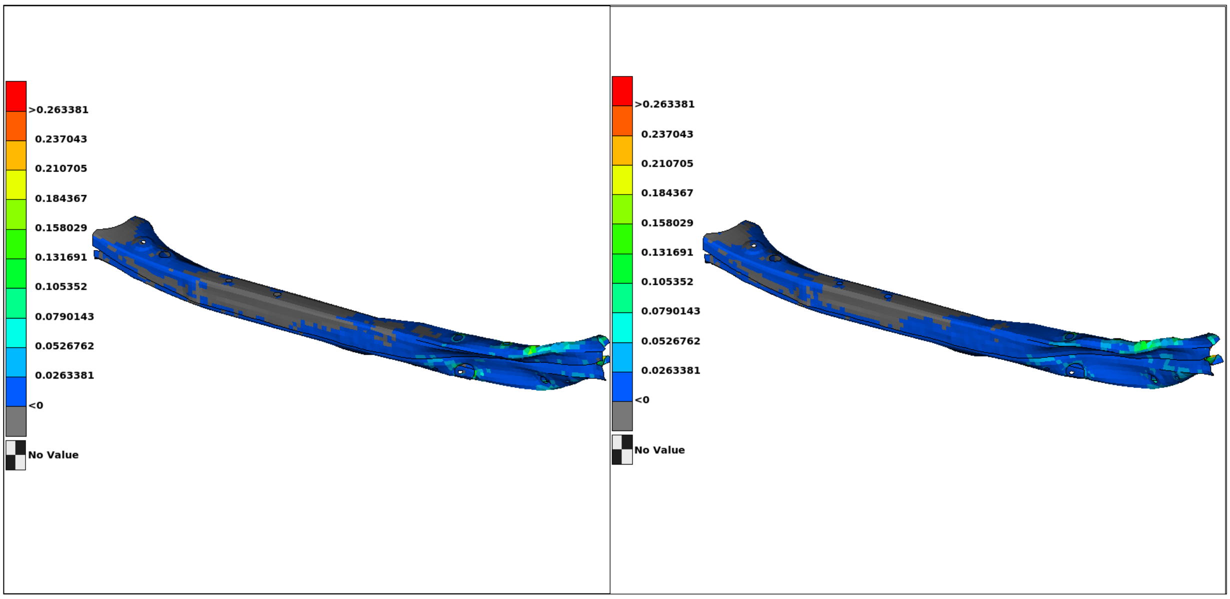


Figure 25 Front Sub-frame Plastic strain ip1 FE Results (left), Prediction (right)

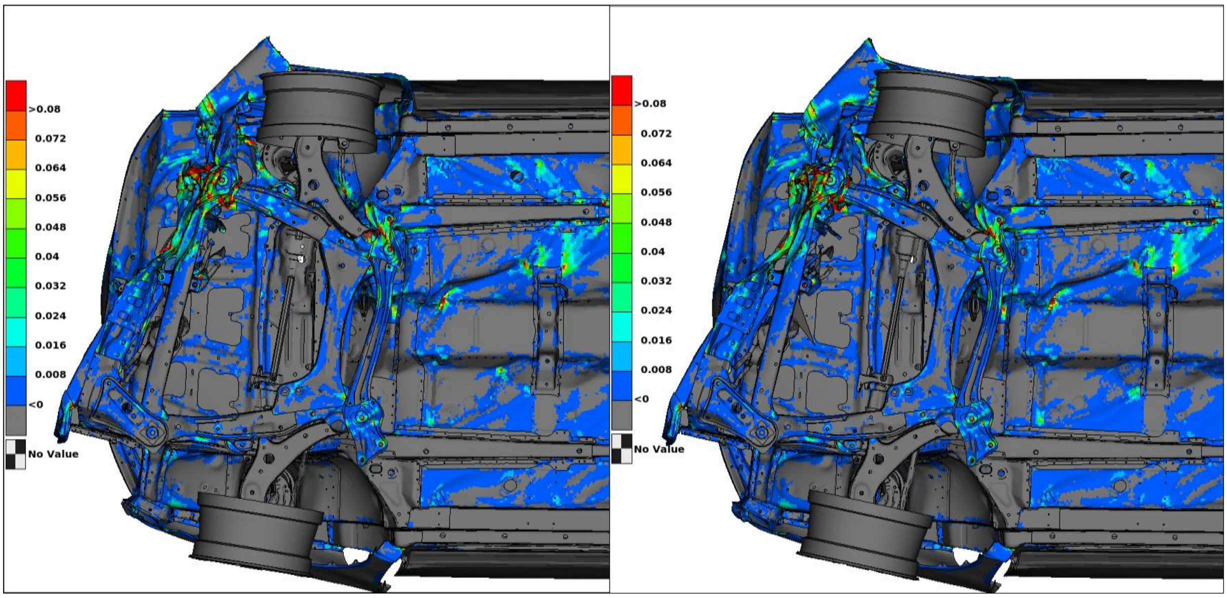


Figure 26 Plastic strain ip1 FE Results (left), Prediction (right)

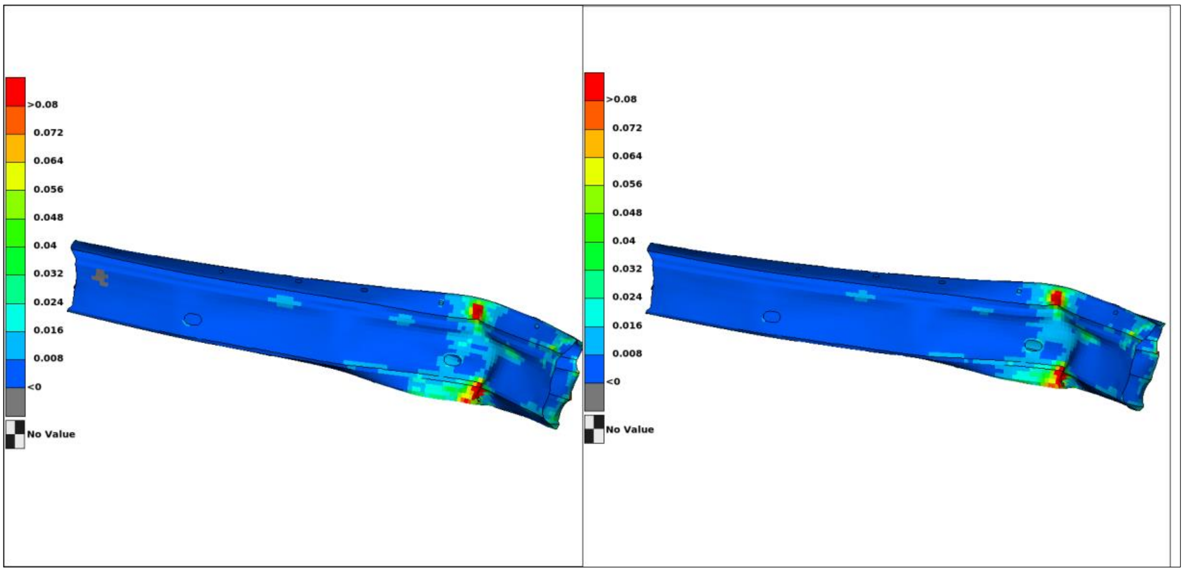


Figure 27 Front-bumper bar Plastic strain ip1 FE Results (left), Prediction (right)

2D Results

To predict 2D curve/plot entities, new predictors were trained, using 20 of the available experiments. For the scenario mentioned and validated above (Table 1), the predictions for some of the available curves are presented in Figures 30-32.

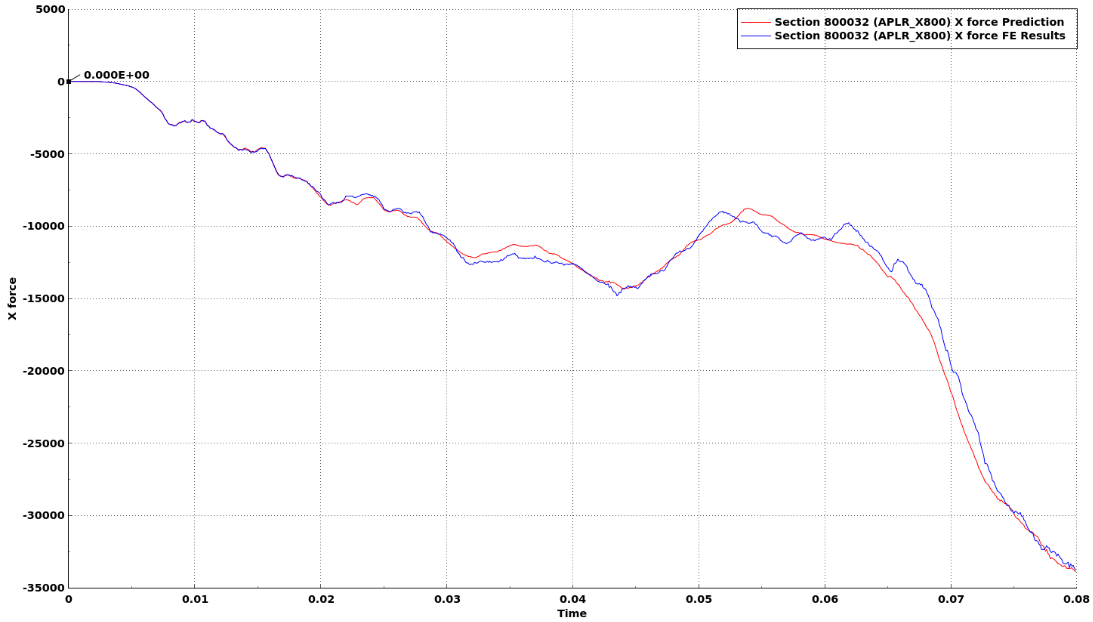


Figure 28 A-Pillar section force Fe Results (blue) vs Prediction (red) plot

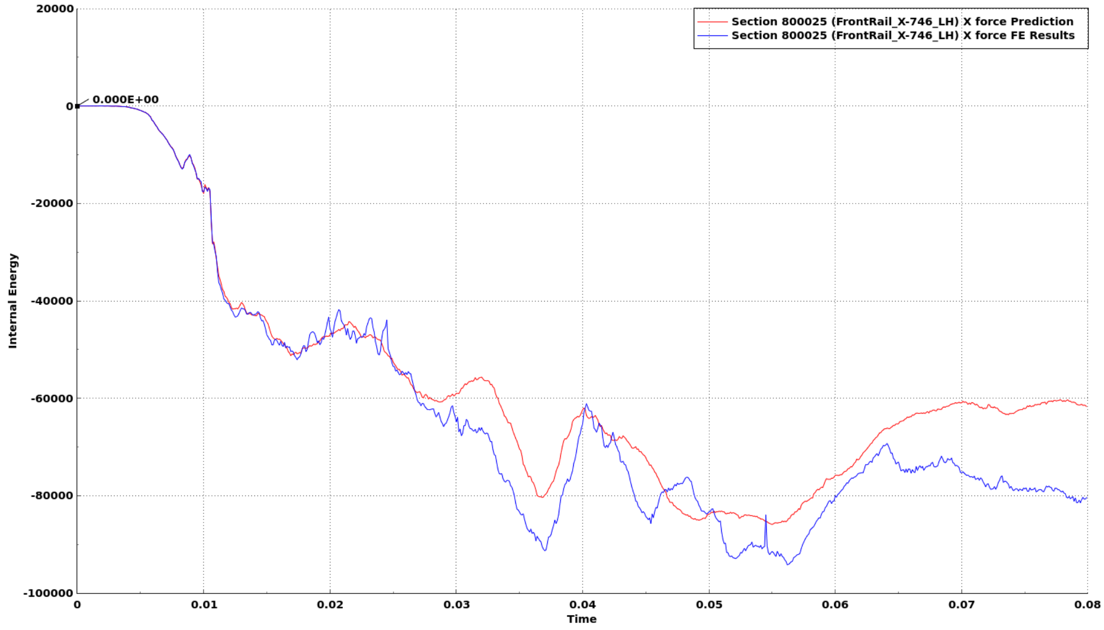


Figure 29 Left hand side Front Rail Section force FE Results (blue) vs Prediction (red)

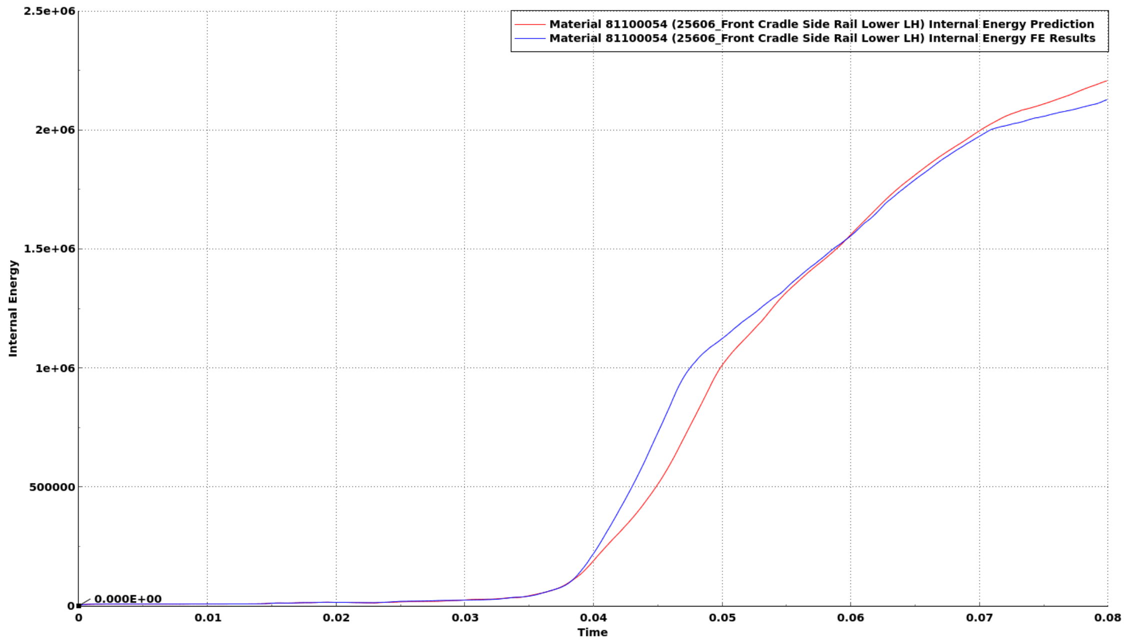


Figure 30Material Internal Energy FE Results (blue) vs Prediction (red)

Conclusion

In this study, predictive models were defined using the Machine Learning tool of KOMVOS, to predict the intrusion displacements and the accelerations at specific locations of the vehicle. The initial training dataset was created using the ANSA Optimization tool that produced the 60 experiments to run the FE analysis. The data was then added in a DM system while the training and creation of the predictive models was performed in KOMVOS.

Utilizing the predict window's parallel coordinates chart and the design variable sensitivity maps; it was possible to apply design variable values exploratory and predict the max intrusions and accelerations in seconds. A selected design variable value configuration was used to create a new simulation run and save it in the Data Management system for validation of the predictions. The training and prediction times per results are listed in Table 2.

Result	**Training time**	**Prediction time**
Key Value	3~4 minutes	10-12 seconds
2D	30~40 minutes	2~3 minutes
3D	1~1.5 hours	5~7minutes

Table 2 Machine learning training and prediction time per result.

2d plots and 3d field scalar predictors were also created based on 20 of the existing experiments. The selected design variable values were also used to predict 2D and 3D results, and the predictions were validated against the FE result.
Validation results show good accuracy between predictions and FE results for all types (key values, 2d and 3D results), considering the number of experiments and design variables.

The Machine Learning functionality implemented in KOMVOS offers high prediction accuracy for "what-if" studies saving significant time over the FE analysis. Combined with the Optimization tool of ANSA and post processing capabilities of META, KOMVOS provides powerful tools to create a dataset, train Machine Learning algorithms, and create predictive models.

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

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

BETA SIMULATION SOLUTIONS

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