BETA

SIMULATION SOLUTIONS

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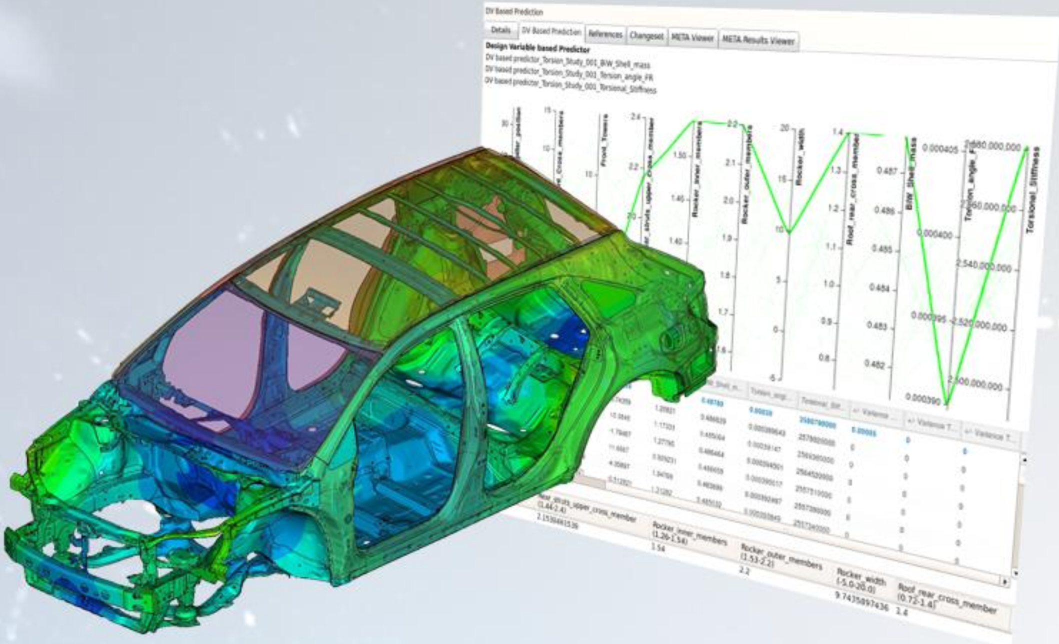

White paper

Simulation enabling technologies

Employing Machine Learning for torsional stiffness and angle prediction

Torsional stiffness and torsional angle are among the most important key values in a vehicle's Body in White (BiW) development. Using a trained Machine Learning model the identification of these values can be predicted in a fraction of the time needed for re-designing and running again the analysis.

Introduction

Torsional stiffness and torsional angle are among the most important key values in a vehicle's Body in White (BiW) development. These two values describe the rigidity of the vehicle's body, determine its behavior concerning comfort and handling, and provide the basis on which the suspension components are designed.

During the development of a BiW, multiple modifications may occur in its design such as, changes in thickness and geometry of parts, or changes in the position of connections. Identifying the effect of such modifications requires time spend for CAD redesign, simulation model pre-processing, analysis, and results evaluation. This time-consuming process may be required multiple times during product development.

To speed up this process, Machine Learning prediction models can be trained. These models can be used to predict in a fraction of the time how modifications would affect torsional stiffness and angle.

In this case, such Machine Learning models are trained and used for torsional stiffness and angle predictions.

BiW Torsion/Bending loadcase

A BiW model is prepared for a static analysis with three loadsteps: Torsion, Bending, and Adjusted bending (Bending with modified Force vectors).(Fig.1)

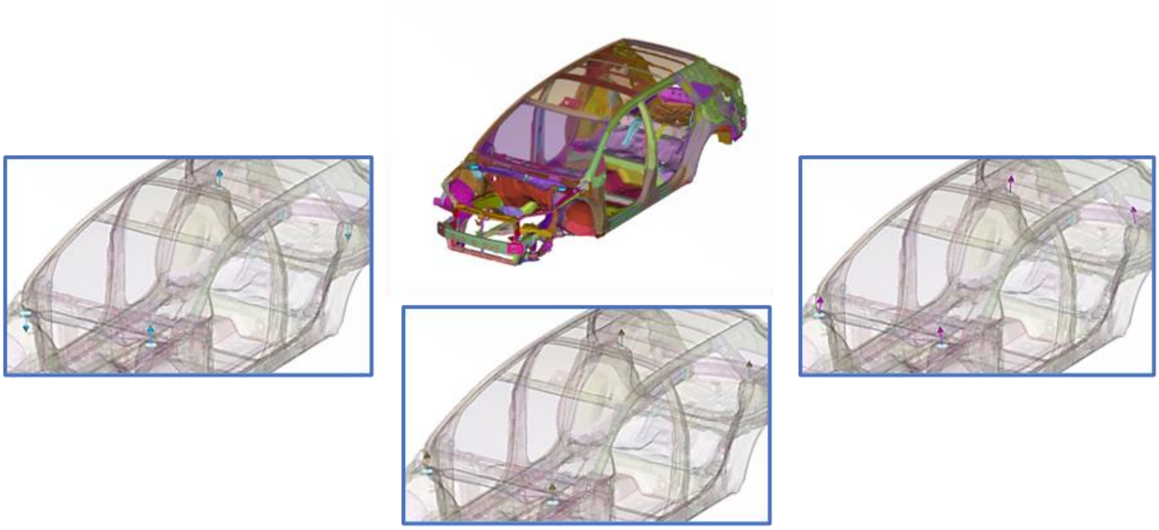

Fig. 1 BiW. Torsion, Bending, Adjusted Bending.

The outcome of these three load cases are the values of Torsional stiffness, Torsional angle, Torque, and displacements at critical areas. These values will be used to train the prediction models.

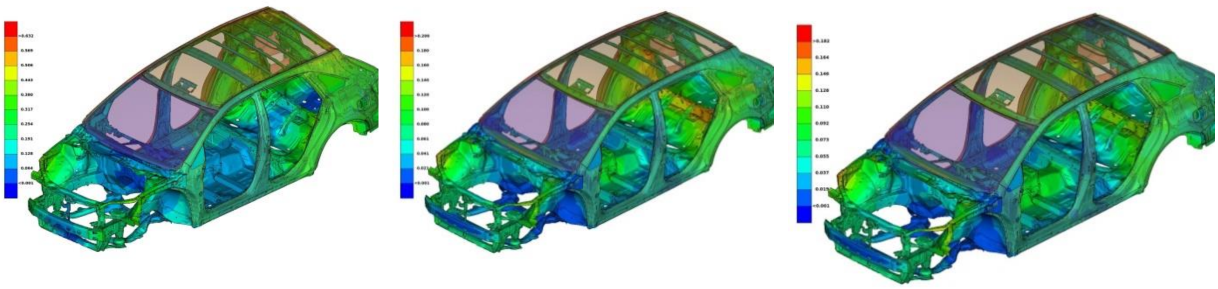

Fig. 2 Results of static analysis for three loadcases. a)Torsion. b)Bending, c)Adjusted Bending

Parameterization

To create machine learning predictive models, a training process is necessary. During this process, the ML algorithms are provided with the “knowledge” of the vehicle’s behavior when some parameters are modified. This Dataset is created using ANSA’s mesh morphing capabilities along with the Optimization tool.
The morphing functionality allows for the creation of parameters that modify the geometry and properties of the ready-to-run BiW.
Four parameters are defined to modify the model’s geometry (Fig.3):

a. position of the b-pillars and middle cross members(roof and floor)
b. position of the front strut towers
c. width of the rockers
d. position of the front inner cross members

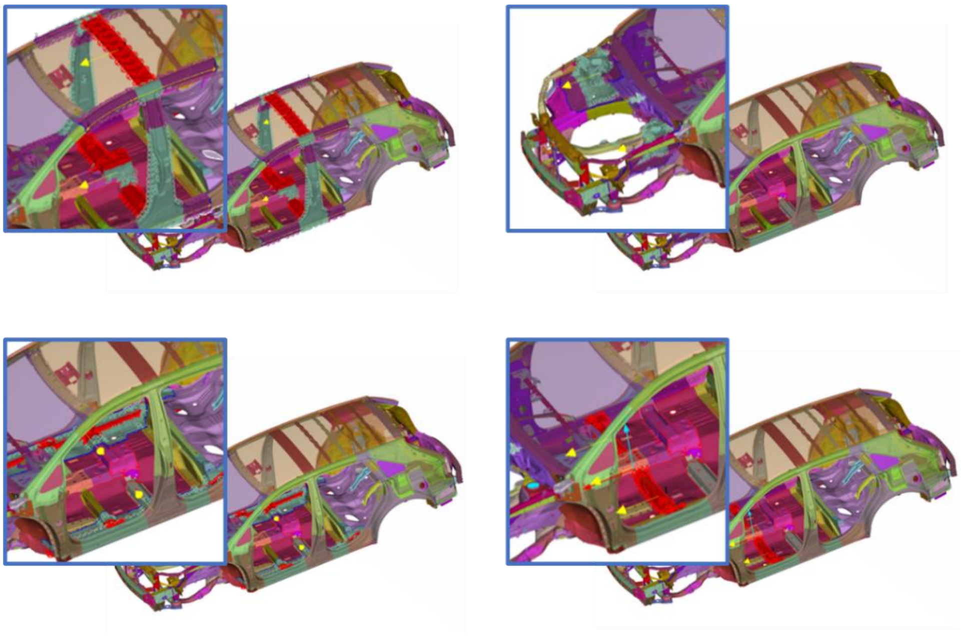

Fig. 3 Geometry modifying parameters

Except from the morphing parameters, additional thickness modification parameters are defined for some critical structural parts of the BiW (Fig.4):

a. Thickness of Rocker inner members
b. Thickness of Rocker outer members
c. Thickness of rear roof cross member
d. Thickness of rear strut towers reinforcement cross member

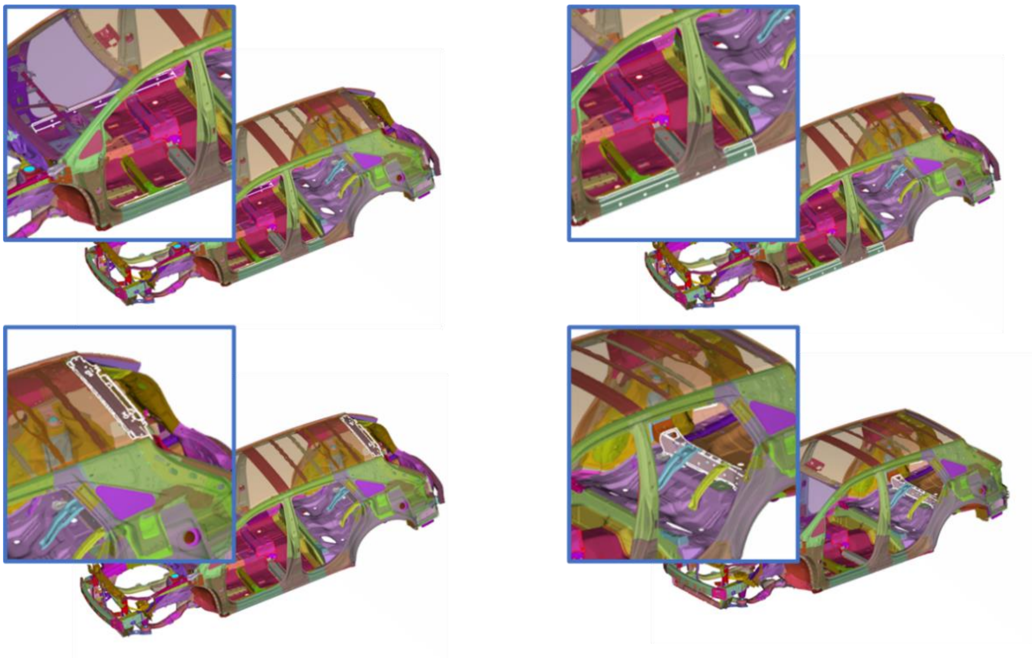

Fig. 4 Thickness change parameters

The total of 8 parameters is added in the ANSA Optimization Tool as design variables with specific types and bounds. The workflow of the Optimization Tool contains the design variables, connections application, a response measurement of the BiW mass, the FE model output item, and a solver item.

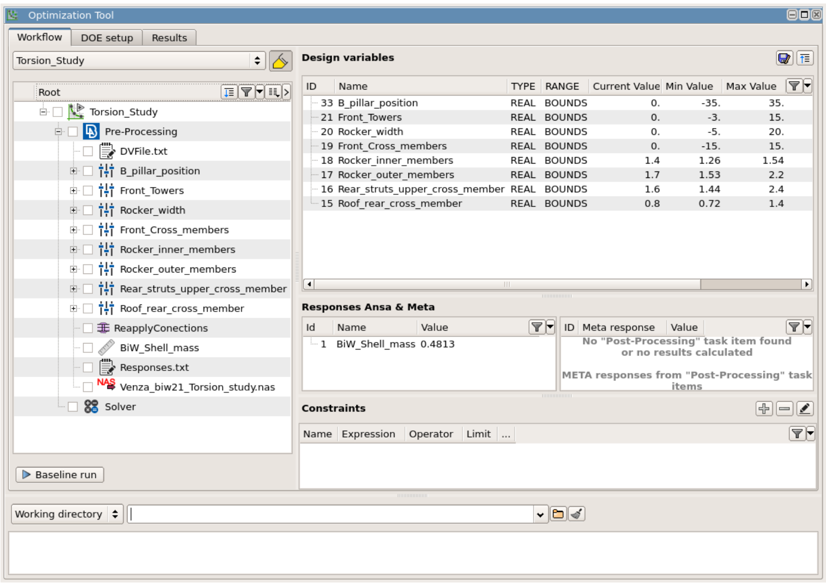

Fig. 5 Optimization tool Workflow

Dataset creation

The Optimization tool workflow is employed to produce the several experiments that form the dataset. This is possible using the Uniform Latin Hypercube out of the available Design Of Experiments (DOE) algorithms. 40 experiments are created each with different values in the design variables, forming a dataset with sufficient spread in the design space (Fig.6).

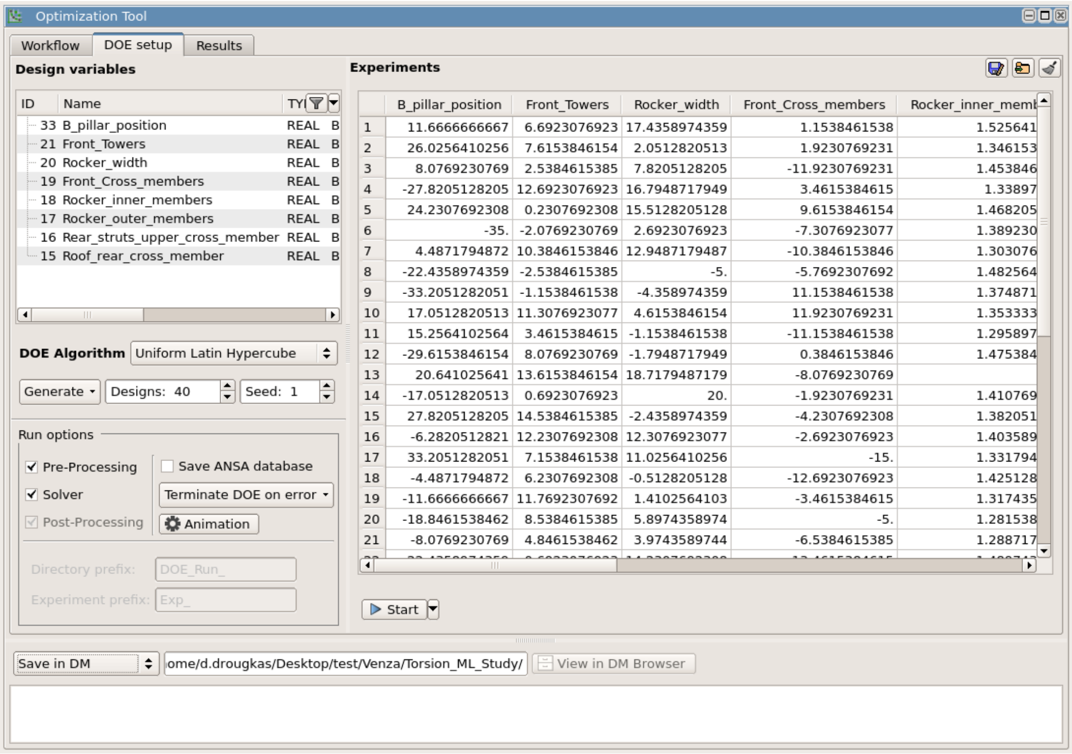

Fig. 6 Design Of Experiments table

The DOE process creates the 40 designs and run the analysis for each one of these. The created data are saved in a DM container system with a specific structure and Hierarchy. The DM system can be handled through ANSA or KOMVOS.

The structure created by this process, consists of a main Simulation model at the top of the tree structure, the DOE Studies, and the Parametric Structure. The DOE Studies contain the created experiments such as Simulation runs, each containing the experiment's information, results and design variable details. The Parametric Structure contains all the information concerning the parameterization of the Simulation model.

The post-processing is preformed collectively for all experiments using a session file, to extract curves, pictures, videos, and the important key values needed for the machine learning actions. The findings are added as report items in each simulation run (Fig.7).

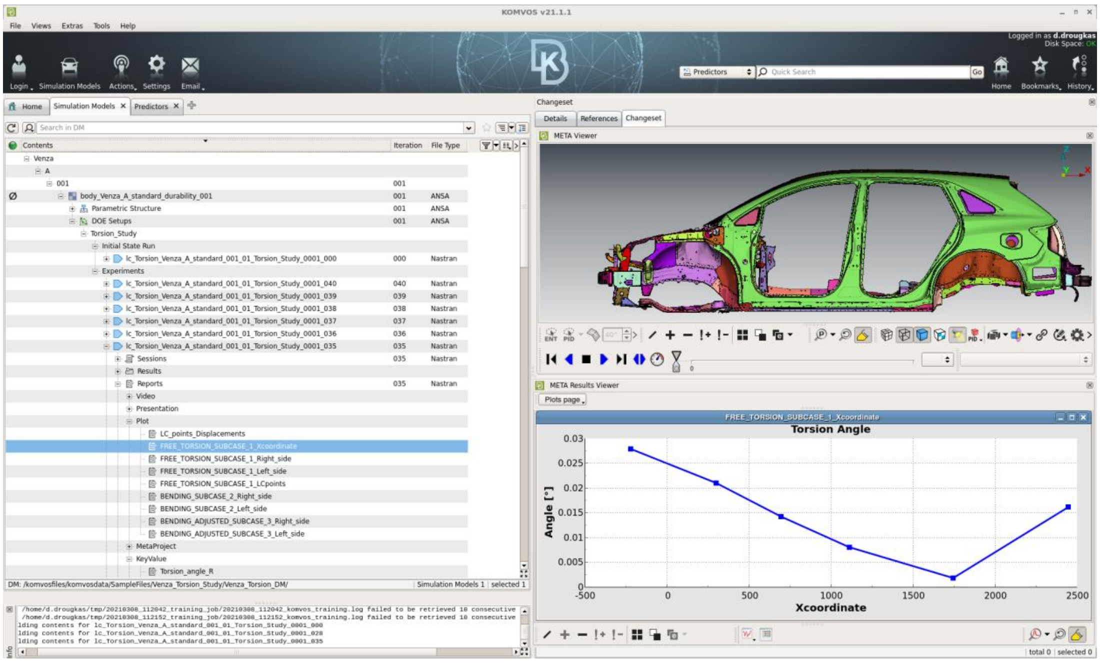

Fig. 7 Simulation Runs and Reports.

Each of the simulation run contains key values extracted to train a predictive model (Fig.8). This way, the dataset of 40 simulation runs with the design variable details and the key value responses was complete.

KeyValues

	A	B	C
1		KeyValue	
2	BENDING_ADJUSTED_Disp_z_LCP_FR_RH	0.1075158715248108	
3	BENDING_Disp_z_LCP_R_LH	0.1820486485958099	
4	BiW_Shell_mass	0.4824362094876641	
5	Torsion_angle_FR	0.0004036704053776553	
6	Torsion_angle_R	0.000645341189723709	
7	Torsional_Stiffness	2499391181.118733	
8	Torsional_Stiffness_FR	3053642032.139968	
9	Torsional_Stiffness_R	1945140330.097499	

Fig. 8 Key Values of Simulation Runs.

Machine Learning Training

Using the Design Variable-based Machine Learning option, and the 40 available simulation runs, a group of predictive models is trained to predict Torsional Stiffness, Torsion angle FR (front and rear) and the BiW weight (tn). A second group is trained to predict the displacements on two important points of the BiW, for the two bending loadcases (Fig.10).

Each predictor contains report charts showing the performance and sensitivity of the design variables. The chart in Fig.10 demonstrates the design variables with the bigger effect on the response values. The predictor entities forecast the key values based on any design variables values, avoiding the use of solver, and thus saving time.

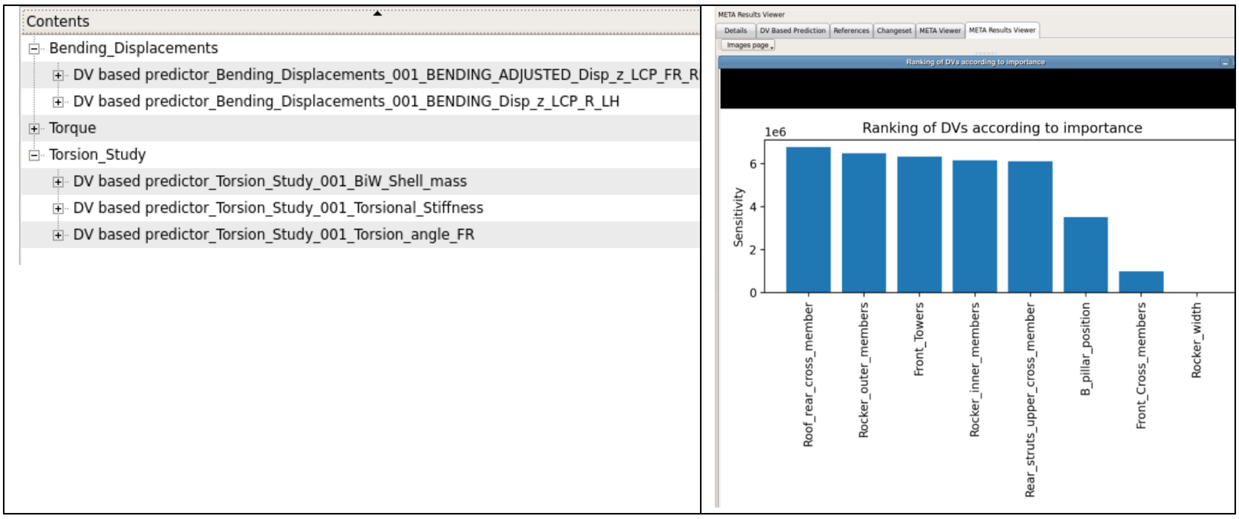

Fig. 9 Predictive models and DV Sensitivity chart.

Machine Learning Prediction

Utilizing the parallel coordinate chart it is possible to identify the experiment with the highest Torsional stiffness (Fig.10). Same time, predictions for torsion angle and BiW mass are also available.

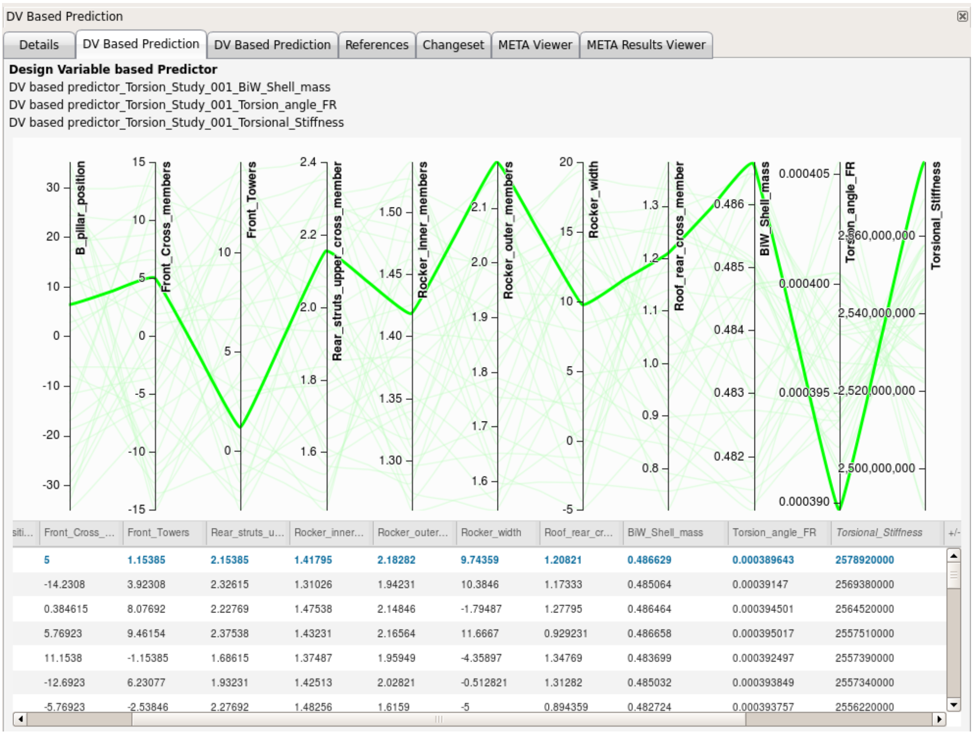

Fig. 10 Identification of highest stiffness experiment

The design variables of this experiment are used as initial values to define a “what if” scenario. Based on the information of the importance map, the values for the first four design variables are modified, targeting to increase the torsional stiffness (Fig.11). The design variable values tested, are within the range of values for the initial simulation model.

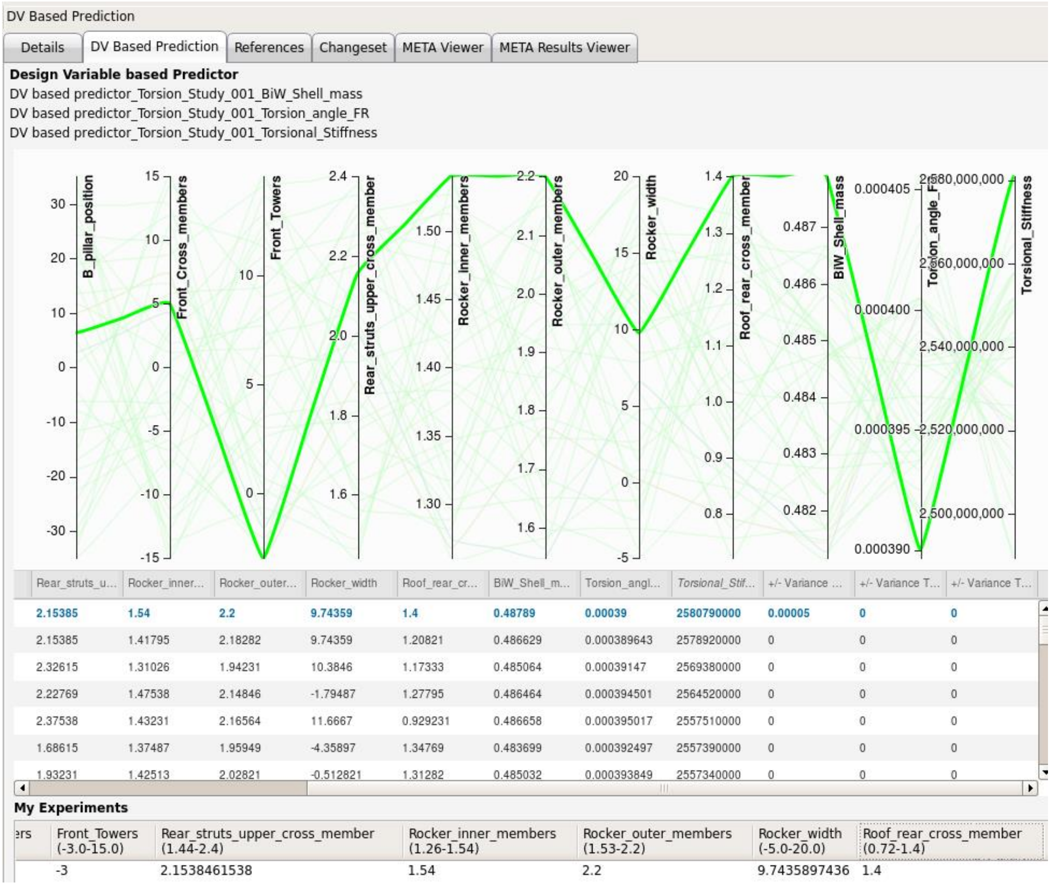

Fig. 11 Prediction of Key Values for “what if” scenario

After a few attempts, the predicted Torsional stiffness becomes higher than in all other experiments. Same time, prediction for mass demonstrated a small increase as well, while the torsional angle an expected small decrease.

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

Validation

The theoretical experiment created from a “what if” scenario, is added in the DM along with the analysis results. A post-processing session automatically extracts the respective reports and key values.

	Analysis result	Prediction	Error (%)
Torsional Stiffness (N*mm/deg)	2598228073.489	2580792945.789	0.673298
Torsion angle FR (deg)	0.00038611	0.00039	1.00244
Displacement S2(mm)	0.178688	0.17896	0.1521
Displacement S3(mm)	0.104689	0.10469	0.00096
BiW weight(tn)	0.48788	0.48789	0.00205

Table 1 Validation of predictions

Finally, a visual comparison between the created design and the initial model is automatically created in KOMVOS presenting the geometrical differences between the two (Fig.12).

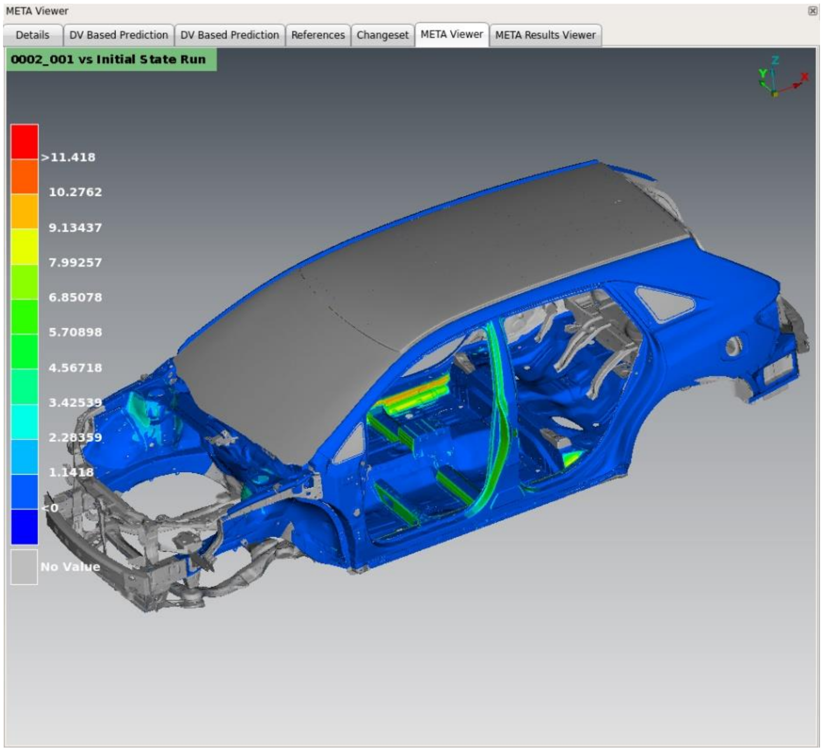

Fig. 12 Initial vs Created model geometrical differences.

Conclusion

In this study, a predictive model is defined, using the Machine Learning tool, to predict the torsional stiffness of a BiW. The initial training dataset was created using the ANSA Optimization tool and the training and creation of the predictor was performed in KOMVOS.

Utilizing the prediction parallel coordinate's chart and design variable sensitivity, it was possible to apply design variable values and predict the torsional stiffness of a theoretical model 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.

The machine learning functionality implemented in KOMVOS offers high accuracy prediction capabilities for CAE "what if" studies. Combined with the Optimization tool of ANSA and the post-processing capabilities of META, KOMVOS provides powerful tools with the capabilities to create a dataset, train Machine Learning algorithms and create predictive models. Simulation runs results overview and comparison, prediction of results for theoretical runs, and creation of new experiments are also possible through the KOMVOS interface.

About BETA CAE Systems International AG
BETA is a simulation solutions provider, dedicated to the development of state-of-the-art software systems for CAE. For almost 30 years, we have been developing tools and delivering services for the front-runners in numerous sectors by listening to their needs and taking up even the most demanding challenges. For more information on BETA CAE systems, our products, and our services, visit www.beta-cae.com

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