

NEXT LEVEL ENGINEERING

MACHINE LEARNING IN CAE – STEPS TOWARDS INTELLIGENCE



22.05.2019
Gagan Saket

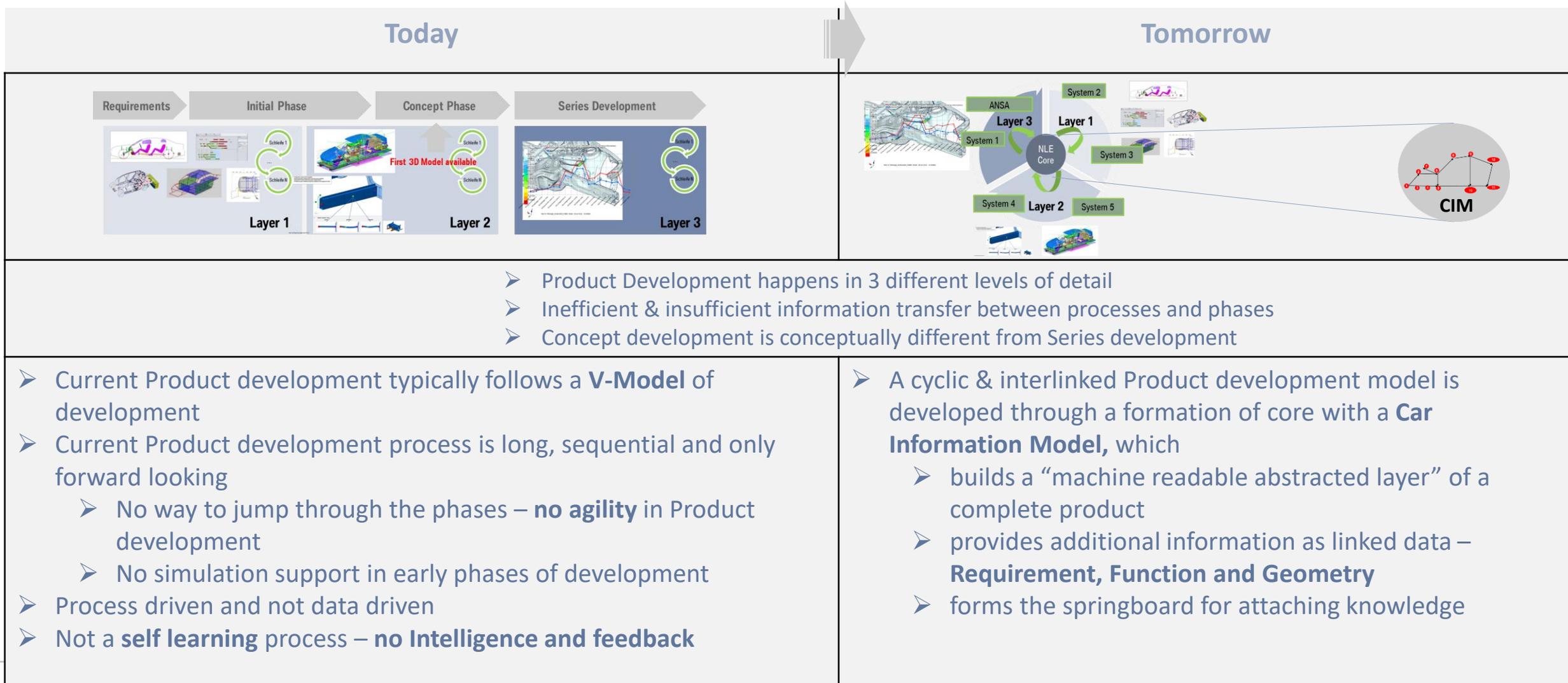
**BMW
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THE NEXT
100 YEARS 

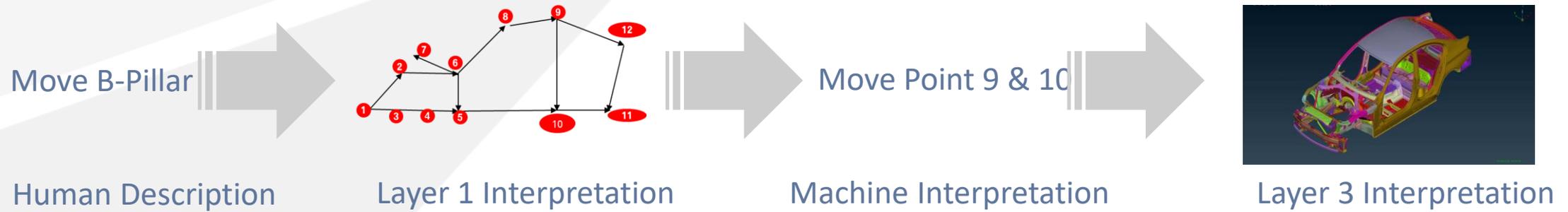


QUICK OVERVIEW.

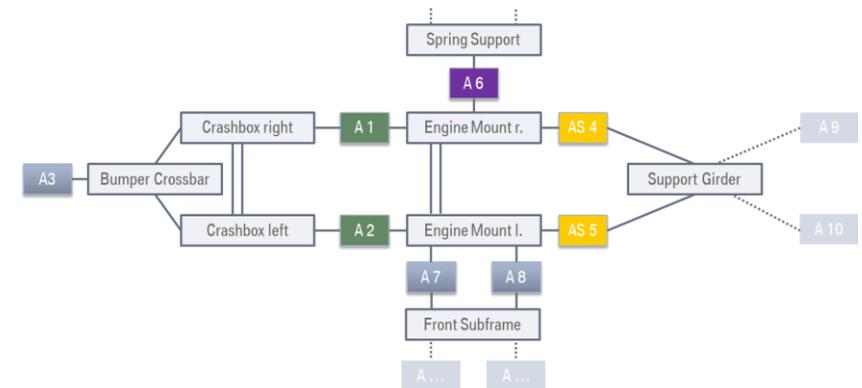
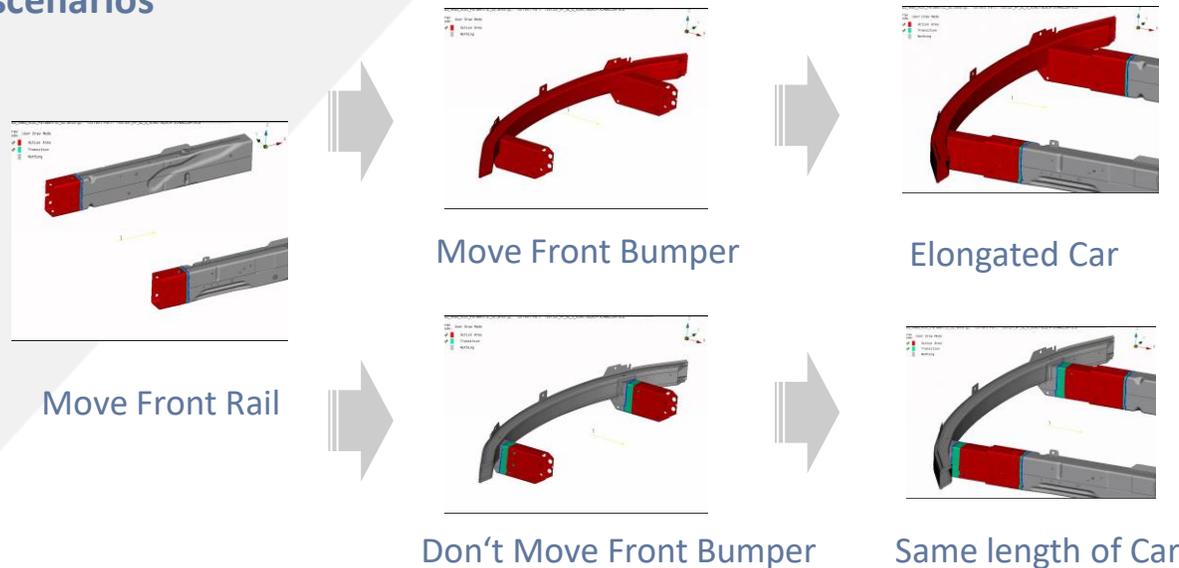
DATA VIEW - FROM TODAY TO TOMORROW.



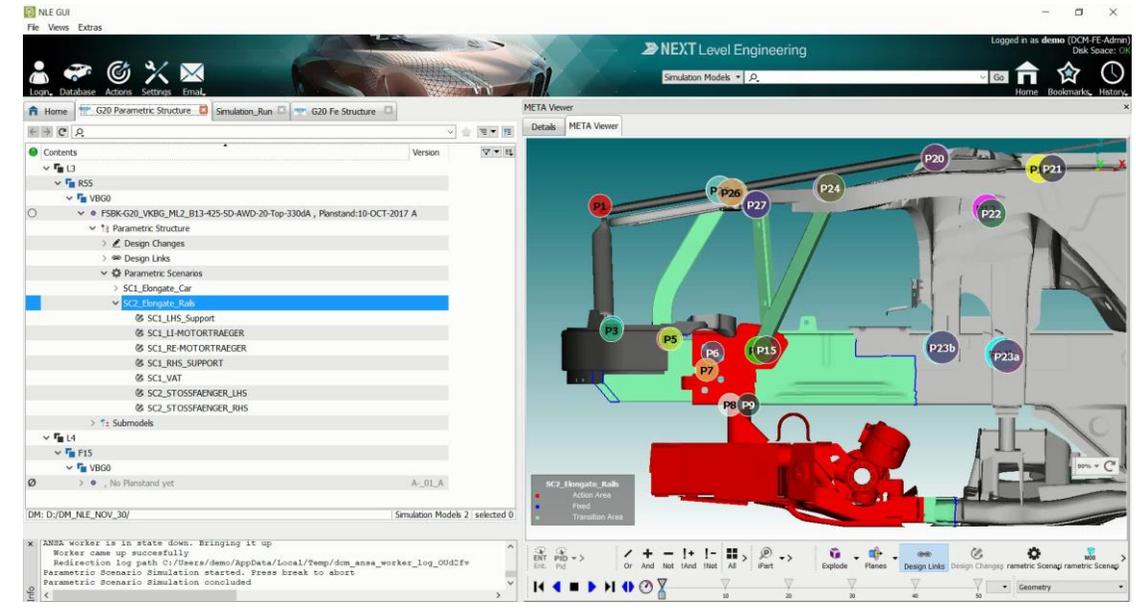
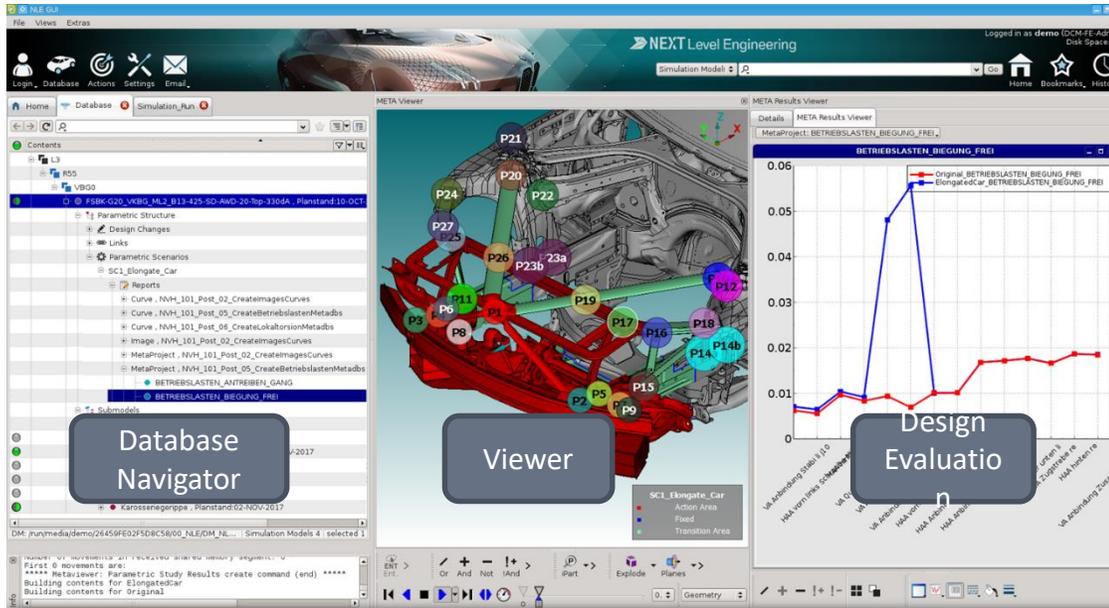
QUICK OVERVIEW. FROM HUMAN DESCRIPTION TO MACHINE DESCRIPTION.



A complex geometry change **“Move B-Pillar”** has been translated into a simple machine understandable language **“Move Points 9 & 10”** through the implementation of **Car Information Model (CIM)**. Even complex changes could be modeled through scenarios



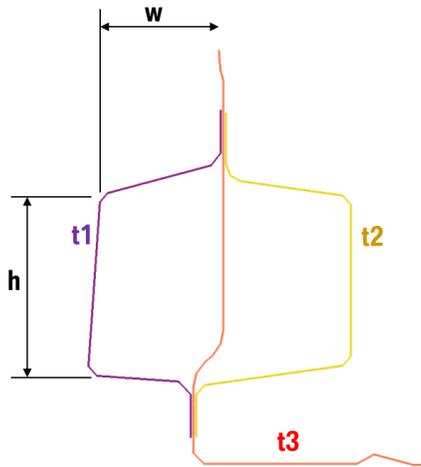
QUICK OVERVIEW. THE PARAMETRIC CAE DESIGN FRAMEWORK (PCD).



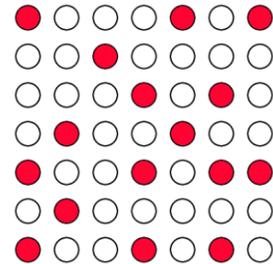
PCD Framework

- can understand the CIM logic and can display & change the contents in CIM – including the linking of geometry & function (focus of our discussion in this presentation)
- can generate complex Scenarios for complex topological change in a car concept
 - These scenarios could be run, to automatically generate many variants with different combinations of parameters defined in the scenarios

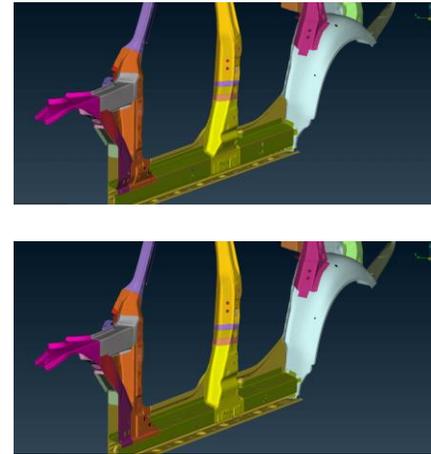
USE CASE : ROCKER PANEL VS GLOBAL FUNCTION TORSIONAL STIFFNESS. GENERATION OF INPUT DATA.



- Parameters:
- Thickness
 - Height
 - Width



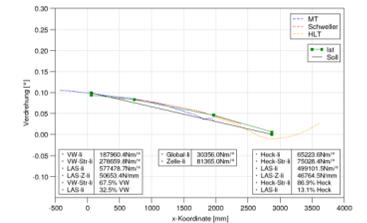
Generation of 100 different combinations so as to cover a wide spectrum



Generating 100 variants with the chosen 100 combinations using PCD Framework



Solver



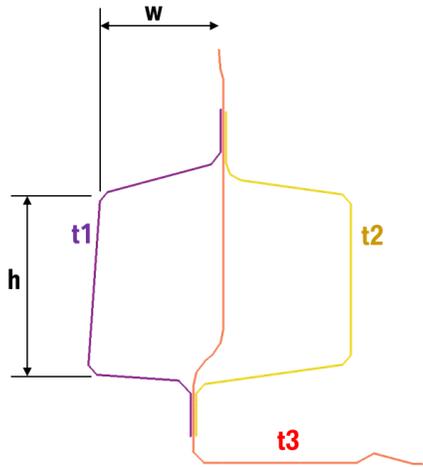
Solving & Post-Processing of the 100 generated variants conventionally for Global torsional stiffness

USE CASE : ROCKER PANEL VS GLOBAL FUNCTION TORSIONAL STIFFNESS. WHY GENERATE NEW CONCEPT VARIANTS?

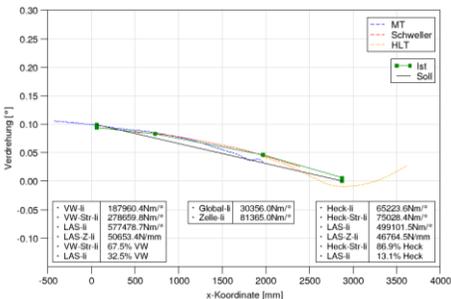
- A Machine Learning (ML) model is as good as the data set used to test and validate the result.
- Although there are many variants available for use in a typical database of an OEM but,
 - They are mostly in a form of unstructured and unlabeled data that needs a lot of work to make it usable for ML model. It is sometimes faster to create new data than to use existing data
 - Most of the time, there are not enough variance* in the concept.

*) We can get hundred variants from existing data banks, but may not get 100 different Rocker Panel concept in those variants

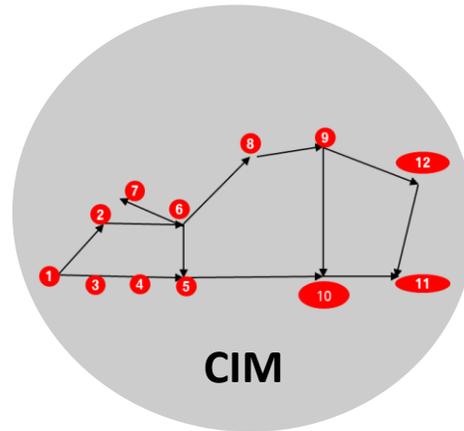
USE CASE : ROCKER PANEL VS GLOBAL FUNCTION TORSIONAL STIFFNESS. TRAINING A NEURAL NETWORK.



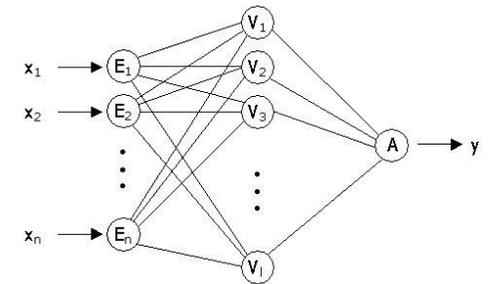
100 Variants representing different Concepts through different combination of parameters (t1,t2,...,tn,h,w)



100 Key Function values for all the variants (global torsional stiffness in this case)

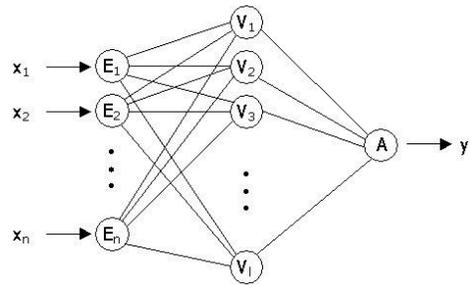


Linked Function and Geometry: in form of parameter combination as input for Machine Learning model



Training & validation of a Neural Network through the data set generated

USE CASE : ROCKER PANEL VS GLOBAL FUNCTION TORSIONAL STIFFNESS. WHAT WE GOT? – INTERPRETING THE NEURAL NETWORK.

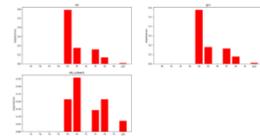


Trained Neural Network



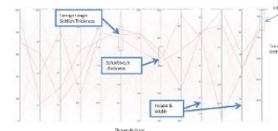
Correlation Plots

plots the correlation of each geometry parameter ($t_1, t_2, \dots, t_n, h, w$) w.r.t function or to each other.



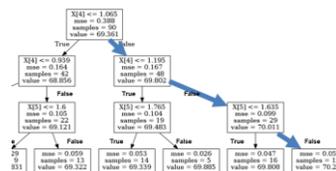
Importance Diagram

plots histograms with all geometry parameter ($t_1, t_2, \dots, t_n, h, w$) in X-axis w.r.t to importance in Y-axis .



Morphology Diagram

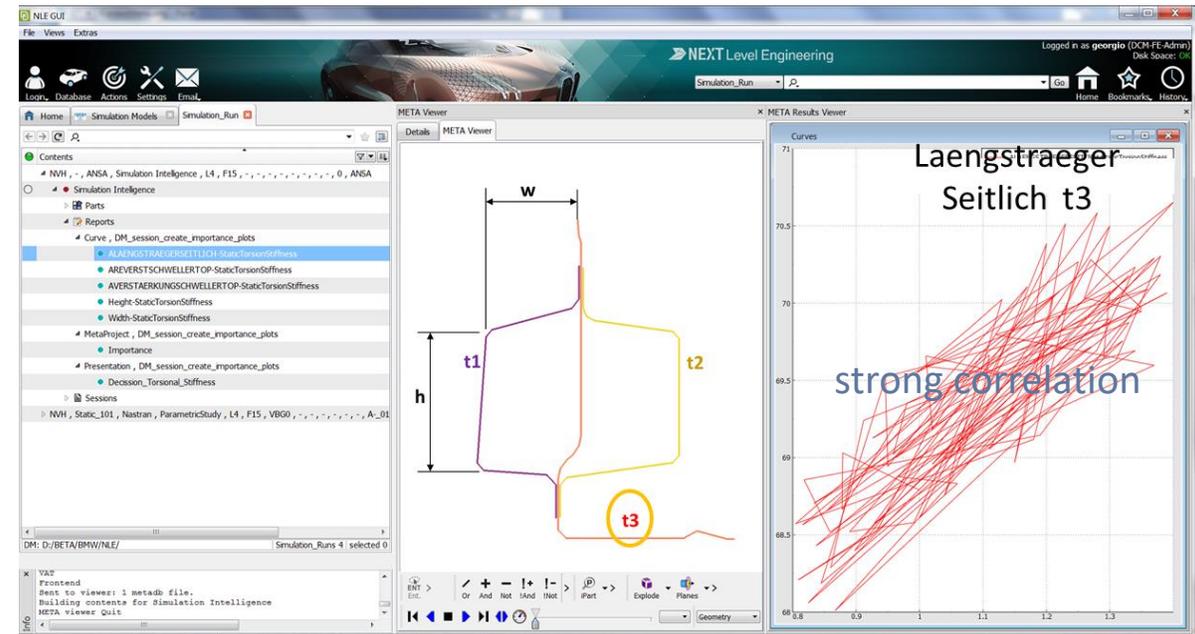
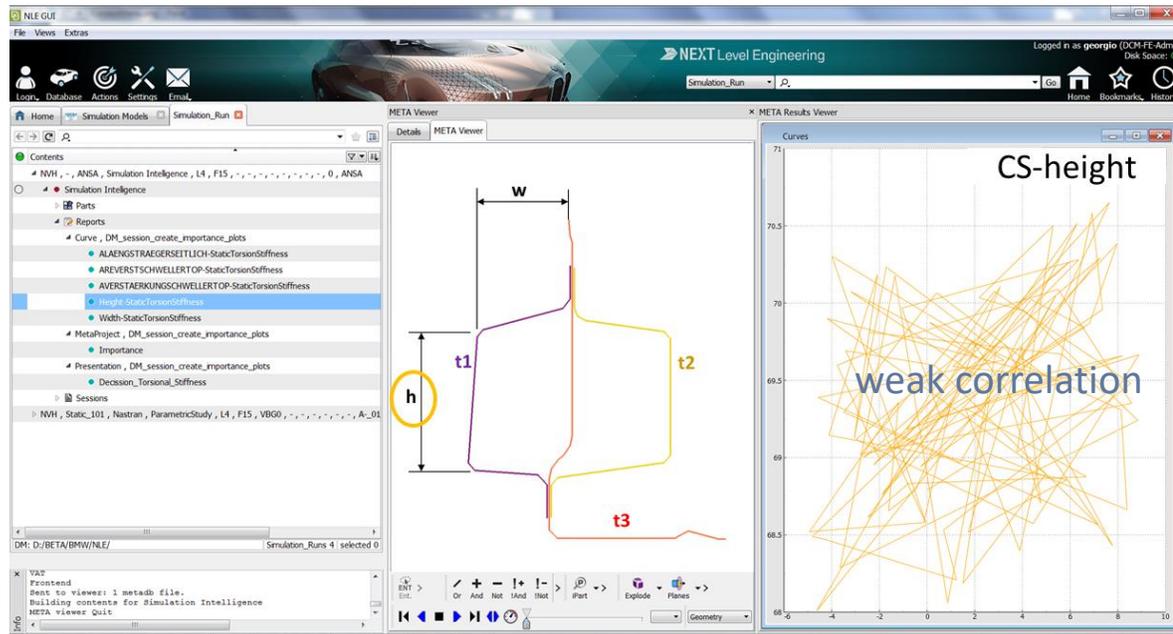
plots all possible combinations of geometry parameter & function seen by the Neural Network.



Decision Tree

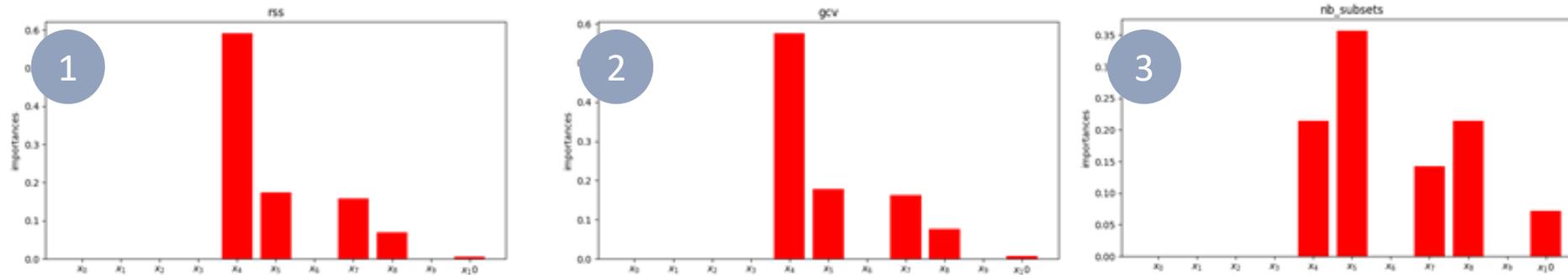
w.r.t to starting value of a chosen parameter, plots all the possible combinations in the form of decision tree

USE CASE : ROCKER PANEL VS GLOBAL FUNCTION TORSIONAL STIFFNESS. INTERPRETING THE NEURAL NETWORK – CORRELATION PLOT.



Plots the correlation of each geometry parameter ($t_1, t_2, \dots, t_n, h, w$) w.r.t function or to each

USE CASE : ROCKER PANEL VS GLOBAL FUNCTION TORSIONAL STIFFNESS. INTERPRETING THE NEURAL NETWORK – IMPORTANCE DIAGRAM.

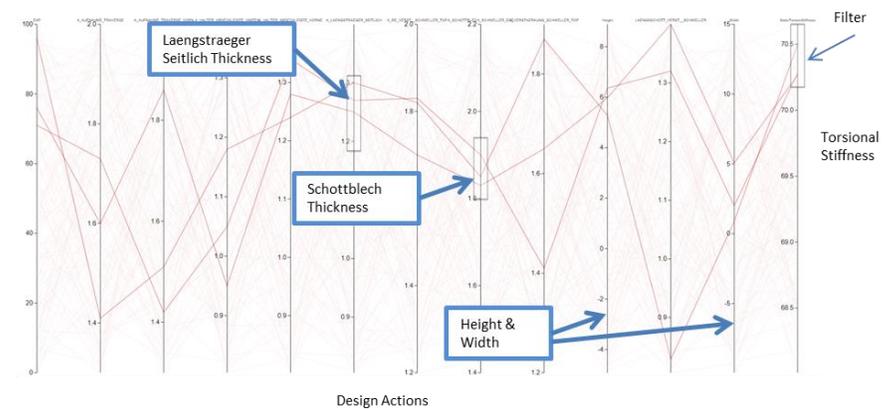
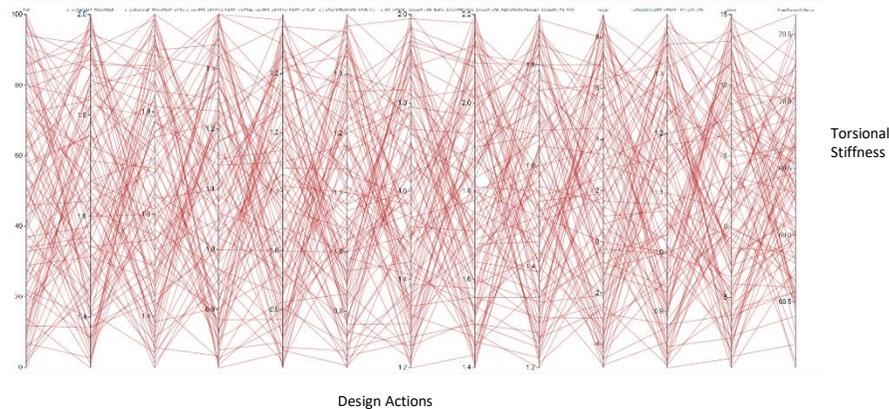


Plots histograms with all geometry parameter ($t_1, t_2, \dots, t_n, h, w$) in X-axis w.r.t to importance in

The difference between the 3 diagrams lies in 3 different algorithms to compute the importance.

1. RSS = Residual sum of squares
2. GCV = Generalized cross validation
3. nb_subsets = Number of subsets of MARS model terms

USE CASE : ROCKER PANEL VS GLOBAL FUNCTION TORSIONAL STIFFNESS. INTERPRETING THE NEURAL NETWORK – MORPHOLOGY DIAGRAM.



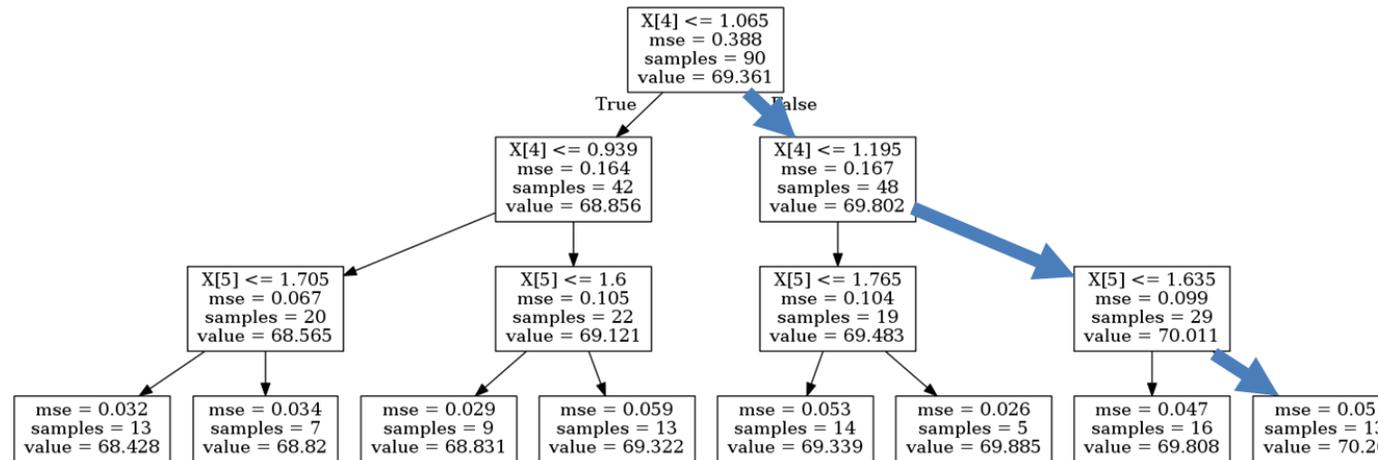
Plots all possible combinations of geometry parameter & function seen by the Neural

Shows all the combination analyzed and reflects the domain of knowledge of Neural Network

Shows a typical use of the Diagram in which the choice is narrowed down by restricting one or more values of Parameters and/or Function.

The result is all possible combination possible within the constraints

USE CASE : ROCKER PANEL VS GLOBAL FUNCTION TORSIONAL STIFFNESS. INTERPRETING THE NEURAL NETWORK – DECISION TREE.



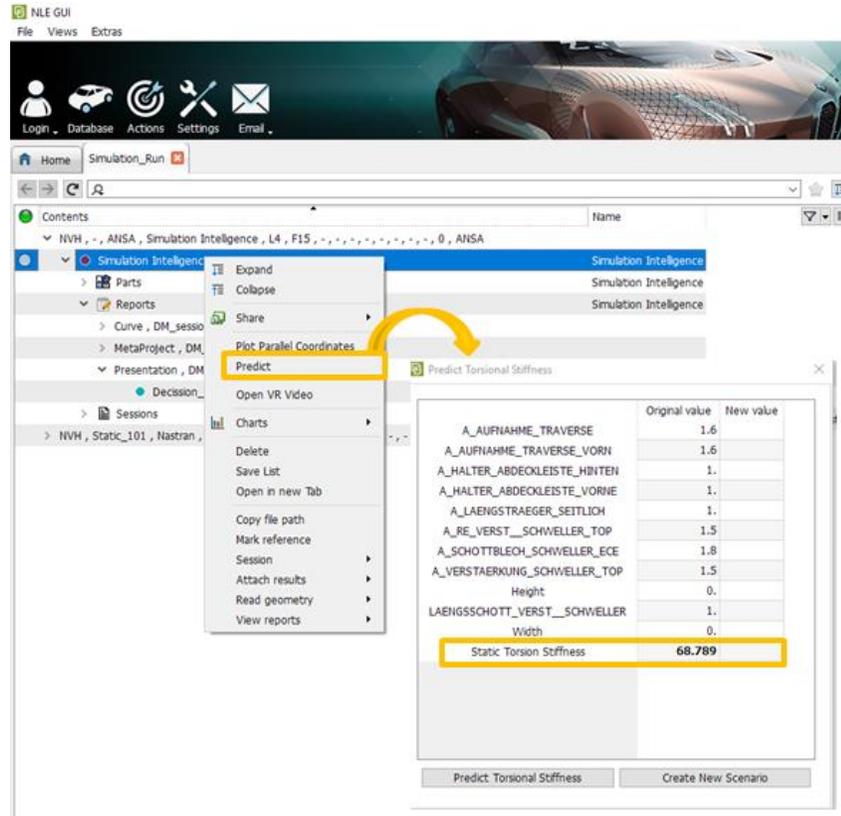
w.r.t to starting value of a chosen parameter, plots all the possible combinations in the form of

- The parameter with the highest importance is identified through importance diagram
- This variable is placed at the top of the tree and fed a decision condition of type True or False.
- Depending on True or False of the fed condition, two separate branches lead to another decision condition with the most important parameter among remaining parameters
- This process can continue to any depth till the desired parameter is reached, where the possible values of the desired parameter could be read

CONCLUSION.

- ML could be effectively used as an additional assistance tool for concept development
- ML has an advantage over traditional Optimization tool:
 - the method is self learning and reusable
 - can handle multiple constraints in parallel
 - can give multiple optimized solutions for a desired constraint or a function value

OUTLOOK.



- Extending the scope of ML to Prediction
- Adding prediction utility in the PCD Framework

Thank You