Automotive Closures Optimization employing Machine Learning.

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Abstract

In the lifetime of a vehicle, ease of use and quality of appearance is as important a goal as the longevity of the vehicle: engineers do not only need to manufacture a car whose various mechanisms will remain functional without defects after continuous use, but they must also ensure that the users will be able to operate it comfortably.

This study aims to optimize the design and manufacturing of the tailgate component of a vehicle on two fronts: manufacturing quality and user comfort. The optimization process involves the modification of the gas lifter components positions in each design iteration in order to perform Multi-Body Dynamic simulations followed by Structural analyses. The goal is to find an optimal design that maintains the deformations of the tailgate component at reduced levels resulting in optimum external appearance regarding panel gaps, as well as comfortable user operation.

Machine Learning predictive models (also referred to as predictors) are employed to accelerate the product design and evaluation process. Engineers can explore various what-if scenarios and extract the necessary key responses for each modification applied to the vehicle, to estimate its improved performance and usability, without sacrificing the design time. At the same time Machine Learning predictors are employed in Optimization studies, replacing the FE (Finite Element) Solver, in order to reach the optimum design in an automated and faster way, thus, improving the product development time.

In this study three optimization approaches are presented, utilizing machine learning methods that predict simulation results for two different analyses. Compared to the established "Direct" optimization method (design updates, FE analysis, post processing), the Machine Learning assisted Optimization methods significantly reduced the optimization time while maintaining similar levels of accuracy. This allowed for more optimizations studies resulting in reduced product development time and increased product performance.

1. Problem Description

As technology advances, automotive design and manufacturing becomes more and more challenging. The requirements for emissions and efficiency are stricter and the market necessitates excellent quality. For such reasons, the design and manufacturing of automotive closures (tailgate, hood) becomes more and more complex. The gas lifter components, mechanisms responsible for the opening and closing of the closures, could cause undesired deformations that not only affect the durability and performance of the structure but also reduce the appearance quality.

A common solution for this issue involves increasing the thickness of the sheet metal panels to reduce the deformations. However, this increases the weight of the structure, leading to more manufacturing and running costs, while limiting the usability of the closures.

In continuation of the study by J. Shin and A. Paraschoudis [1], an automated optimization process has been suggested that combines Structural and Multi-Body Dynamics analyses and Machine Learning solutions. This work aims to reduce panel deformations on the tailgate closure, maintain comfortable use and evade the common solution of increasing the sheet metal thickness to avoid deformations. To accelerate the optimization processes, three approaches employing the Machine Learning capabilities of ANSA [2], an advanced multidisciplinary CAE pre-processing tool, have been investigated.

2. Finite Element Modelling, Load-case set up

A finite element model of a vehicle's tailgate was created (Figure 1). The load-case set up was performed using an automated process and, initially, involved the definition of the kinematic bodies and the connectivity joints, components necessary for the Multi-body Dynamic (MBD) analysis. Following, the loading and boundary conditions were defined. These were the force applied by the gas lifters on the tailgate mounting points, and the handling force in a user specified location, representing the required user effort to open/close the tailgate, calculated through differential equations (Figure 2).

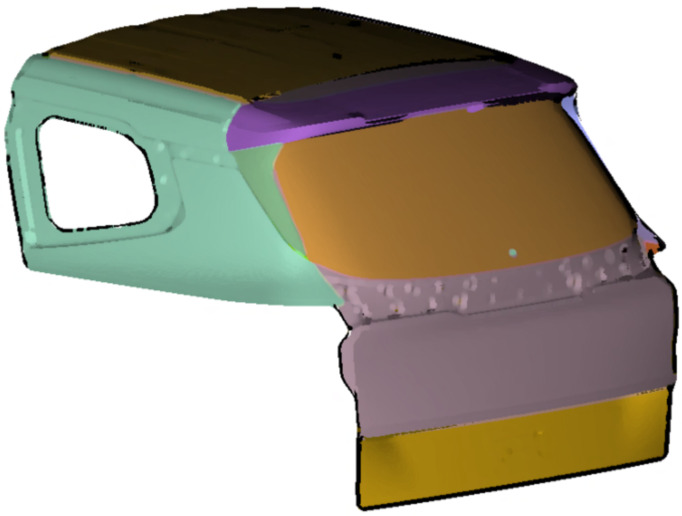

Figure 1: Finite Elements model of Tailgate

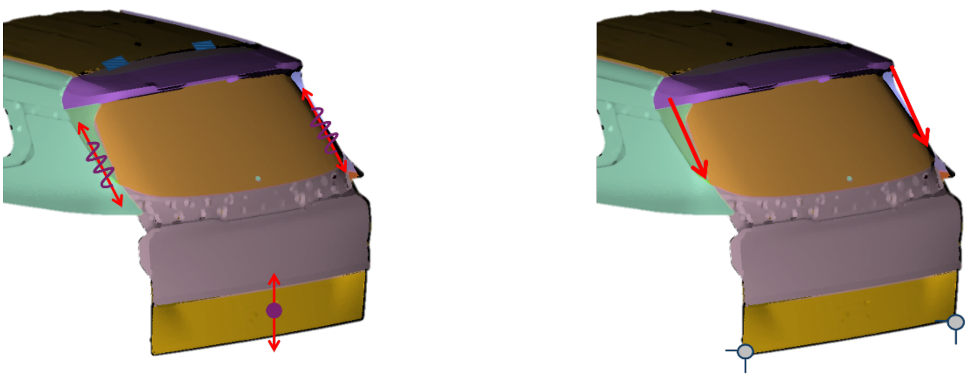

Figure 2: a) Multi-Body Dynamics and b) Structural load-case

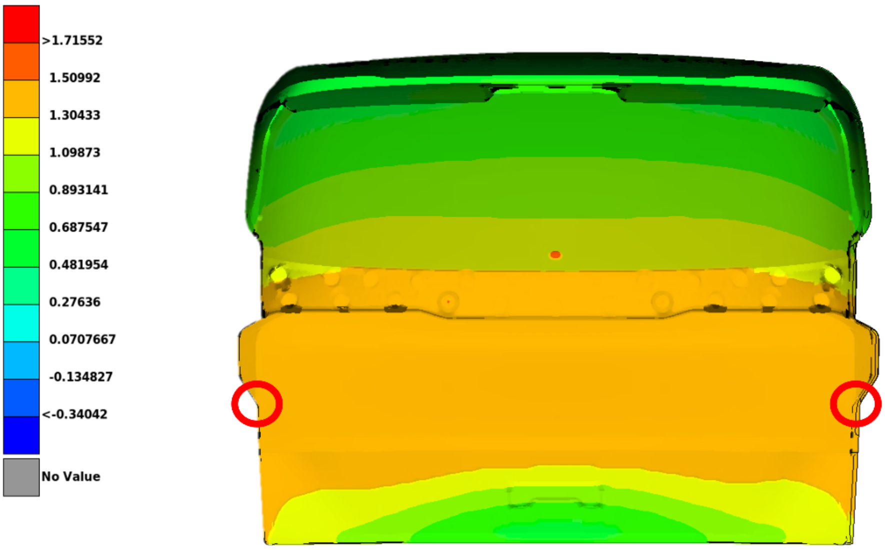

Figure 3: Tailgate closures deformation

The deformation results of the entire tailgate were obtained from the structural analysis (Figure 3). Regarding the MDB analysis, for every angle of the tailgate, a static equilibrium simulation is executed. For each angle, the handling force required is calculated through the previously defined differential equations. This process was performed once for opening and once for closing as the gas lifter characteristics are different for each scenario. The result of this analysis was two curves plotting the handling force per angle for the opening and closing of the tailgate.

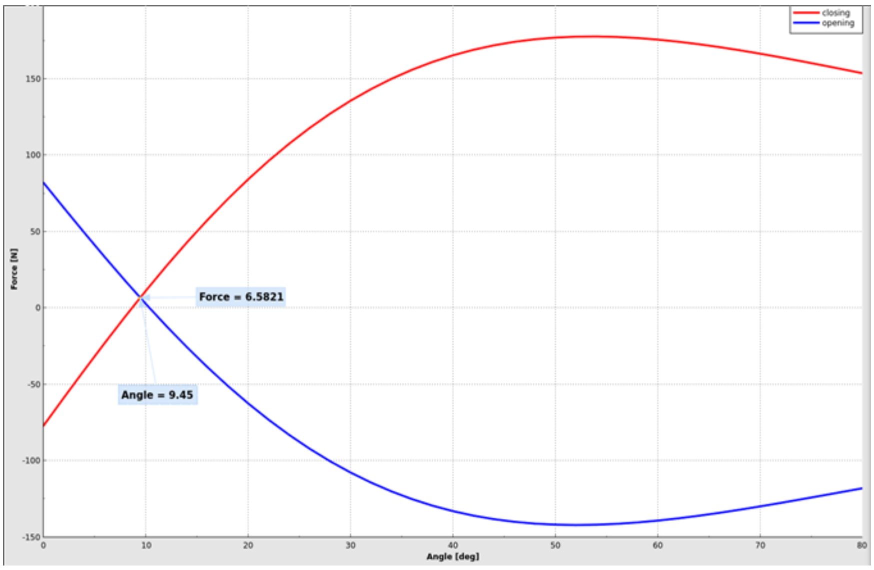

Figure 4: Handling Force vs Tailgate Angle during Opening/Closing

3. Parametrization - DOE

Five design variables were defined for this parametric model, in order to be optimized; one that controlled the value of the preload Force (F1) applied by the gas-lifter mechanism to the structure and four that modified the X and Z components of the gas-lifter attachment points (S1 and S2).

From the structural analysis, two responses were extracted (through post-processing) that calculated the deformations on the specified measuring points on the critical locations of the tailgate panel (Nodal_dx_1, Nodal_dx_2).

According to the specifications of the manufacturer, in order to maintain comfortable use, the user effort should be minimized when the angle of the tailgate is within a specific range. The design of the structure is to be optimized for ease of use in both opening and closing scenarios at the same time. Thus, from the MBD analysis, two responses were extracted that corresponded to the coordinates of the intersection point of the two curves (Force, Angle). For the Force response, in specific, the absolute value of the y-coordinate was used, as this response would participate as the objective of the optimization study.

4. Optimization Setup

A workflow for the optimization process was defined in the Optimization tool of ANSA. The goal of the optimization process was to minimize the deformations and the absolute value of the handling force, while the angle remains constrained according to specifications from the manufacturer (x1, x2). The optimization algorithm used was NSGA-II/ DE / IDEA, an algorithm suitable for multi-objective optimizations [3]. The selected algorithm is a combination of three well-known optimization algorithms from literature: 1) NSGA-II, a multi-objective optimization, which allows for diversity among the solutions of each optimization iteration by sorting them into fronts in two different stages with the non-dominated sorting and crowding distance criteria, 2) Differential Evolution, an optimization algorithm responsible for the generation of the design population of each iteration, able to search very large areas of the design space for possible solutions, and 3) IDEA, an algorithm responsible for handling design constraints, which drives the optimization process to the region of infeasible designs (where optimal solutions have been observed to lie in constrained optimization studies) by maintaining a percentage of infeasible solutions into the design population.

The parameters of the selected optimization algorithm are listed in Table 1. Multiple parameter configurations were tested; the selected one was found to allow for better design space exploration and avoid excessive diversity among the solutions of each population.

Table 1: Optimization Study Parameters

Crossover factor	0.8
Initial Population size	10
Mutation factor	0.7
Mutation factor range	0.2
Proportion of infeasible designs (IDEA)	0.2
Convergence Tolerance	0.0001
Objective1	Minimize deformations: Nodal_dx_1, Nodal_dx_2
Objective 2	Minimize Force
Constraints	x1<Tailgate Angle<x2

Initially, a Design of Experiments (DOE) process created 20 designs using the Optimal Latin Hypercube sampling algorithm. For each of these experiments, the MBD and structural analyses ran, and the 4 responses were extracted.

A direct optimization study was also conducted in order to better evaluate the benefits of introducing Machine Learning functionalities in the optimization process.

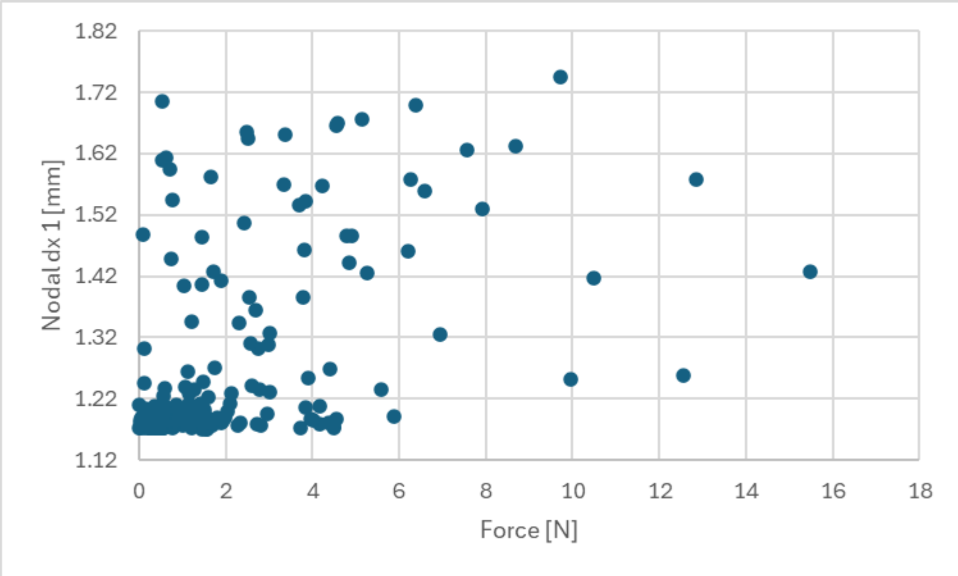

Figure 5: Direct Optimization results

The optimization converged to a pareto front of optimums after 190 iterations (Figure 5). The overall time required for the direct optimization required around 157.5 hours, consisting of the processes listed in Table 2.

Table 2: Required time for Direct Optimization approach

Sub-process	**Required time**
20 DOE study Experiment Runs	~ 14 hours
Direct Optimization (190 runs)	~ 143 hours
Total	~ 157.5 hours

5. Machine Learning

Machine learning was utilized in order to speed up the optimization process. Specifically, a response surface model (RSM) was trained utilizing various regression machine learning algorithms, and was able to predict the simulation results, avoiding the need to run the FE analyses.

The initial DOE study of 20 experiments was used as training dataset for Machine Learning predictive models, also referred to as predictors or RSMs, that were able to predict the selected simulation results (key value responses, curves, field results) of new theoretical experiments (by giving new input Design Variable values) much faster than the two FE solvers.

The automated process that takes place during the Machine Learning training considers the use of multiple candidate ML algorithms, to be fitted upon the training data. For each of those algorithms, hyperparameter tuning is performed and then, each is tested internally against some experiments of the provided training dataset. This provides the error estimation for the generalization capabilities of each candidate predictor. The candidate with the least Mean Absolute Error (MAE) exhibited during the internal testing is the one provided as the final ML model. [4]

The time required for the training of an ML predictor varies according to the complexity of the results (1D Key Value responses, 2D curves, and full 3D field results), the training dataset size and the number of the selected output responses that the ML predictor will be trained upon. In this work, the training time for ML models, with DOE studies of 20 experiments as training data, that predicted the respective output is presented in Table 3.

Table 3: Machine Learning Training time per predicted result for 20 experiments

Trained ML predictor output	**ML training time**
Key Value: Force, Angle, Nodal deformations	~ 1.5 minutes
Curves: Opening and Closing Force-Angle curves	~ 2.5 minutes

Accompanying the trained ML model are various Key Performance Indicators (KPIs) that showcase its performance, accuracy and the dependence of the estimated responses to the input parameters (design variables). The primary metrics for evaluating the accuracy of the trained ML models in this study were Mean Absolute Error (MAE) of the predictive model, from the internal testing process during the training, and Predictive Power Score (PPS) an early indicator of the suitability of the dataset to train an accurate ML model that takes values between zero and a hundred percent (0-100%).

In this study, 3 different approaches were investigated. In each case, an optimization study was defined utilizing the Machine Learning predictor as RSM and optimal solution were obtained.

5.1. 1st Approach

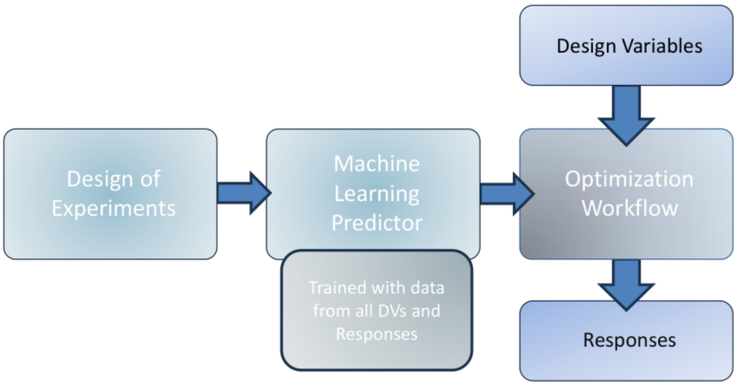

Figure 6: 1st Machine Learning Optimization Workflow

With the initial DOE study of 20 experiments, a Predictor was trained for the 4 Key Value responses (Nodal deformations, Force and Angle). From the KPIs, it was shown that the predictor could achieve good predictive accuracy for the deformation responses. However, the accuracy of the force and angle predictions required improvement.

Table 4: Accuracy Metrics of the Initial RSM, trained with a DOE of 20 experiments

	Test error: MAE	**Predictive Power Score**
Force	5.6598	9.59%
Angle	1.2032	66.79%
Nodal dx 1	0.0044	96.43%
Nodal dx 2	0.0045	96.21%

Using a Smart Sampling process, 40 new experiments were generated, solved and added in the training dataset. The predictor was retrained using the additional data and the predictive accuracy was re-evaluated. Although the errors were reduced, the performance could be improved further.

Since this predictor was going to be used in an optimization study, the goal was to achieve good accuracy around the region of the design space close to the optimal solutions. Thus, this improved predictor was used in a preliminary optimization study in order to identify the optimal region.

This preliminary optimization run identified an area of interest, narrowing the design space.

A new DOE study was created with 20 new experiments around the optimal solution of the preliminary optimization study. The new experiments were added to the training dataset and the predictor was retrained. The KPIs for the improved RSM are presented in Table 5.

Table 5: Accuracy Metrics of the Improved RSM, trained with 80 experiments

	Test error: MAE	**Predictive Power Score**
Force	3.2826	40.48%
Angle	0.7535	79.54%
Nodal dx 1	0.0037	97.62%
Nodal dx 2	0.0039	97.45%

It is worth mentioning that the values that appear in Tables 4 to 7 correspond to the error estimation of the predictor throughout the whole design space.

In the following tables (Tables 6, 7), the same accuracy metrics are presented for every 20 more experiments added in the training dataset for the predictors:

Table 6: KPIs for Force and Angle response predictions for every 20 more experiments included in the training

	Force		**Angle**	
DOE No	**Test error: MAE**	**PPS**	**Test error: MAE**	**PPS**
20	5.6598	9.59%	1.2032	66.79%
40	5.7662	16.93%	0.9056	75.67%
60	3.9107	22.82%	1.0441	76.50%
80	3.2826	40.48	0.7535	79.54%

Table 7: KPIs for Deformation response predictions for every 20 more experiments included in the training

	Nodal dx 1		**Nodal dx 2**	
DOE No	**Test error: MAE**	**PPS**	**Test error: MAE**	**PPS**
20	0.0044	96.43%	0.0045	96.21%
40	0.0048	96.41%	0.0049	96.16%
60	0.0048	96.94%	0.0049	96.74%
80	0.0037	97.62%	0.0039	97.45%

A new optimization study was defined, utilizing the final improved predictor. The result of this optimization study was a Pareto front of 8 experiments that were validated, and the validated optimal result can be found in Table 8.

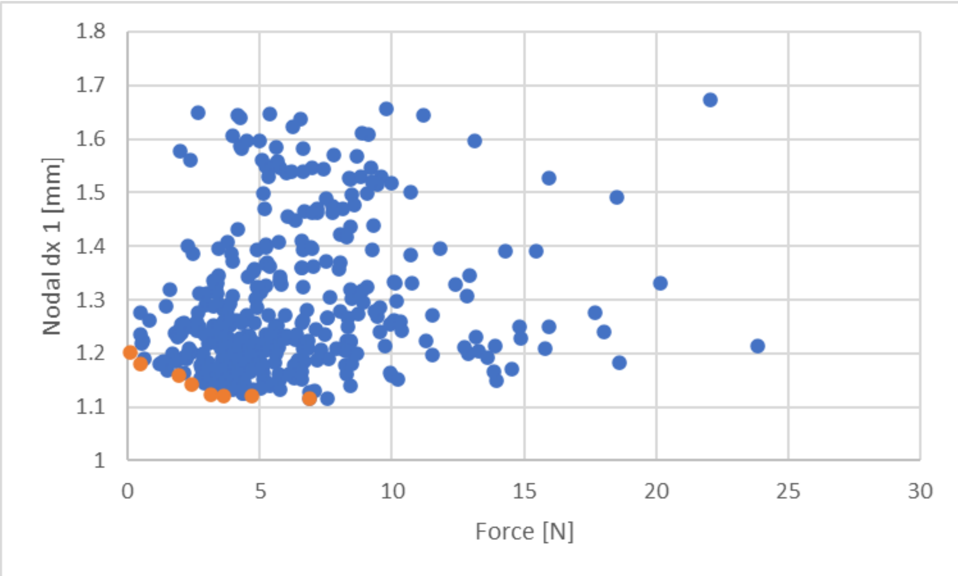

Figure 7: ML 1st Approach: Predicted Optimization Results

Table 8: ML 1st Approach: Validated Optimal Result

	F1	S1_X	S1_Z	S2_X	S2_Z	Nodal dx1	Nodal dx2	Angle	Force
Initial	600	3388.346	963.711	3218	1203	1.4573	1.4155	9.4499	6.5821
Optimized	404.939	3392.924	969.289	3219.425	1201.798	0.5519	0.5189	19.017	0.7731

The overall time required for the 1st approach is around 63 hours, consisting of the processes as defined in Table 9.

Table 9: Required time for 1st ML Optimization

Sub-process	Required time
80 DOE study Experiment Runs for the ML training	~ 55 hours
Initial RSM Optimization	23 minutes
Final RSM Optimization (390 runs)	39 minutes
8 Validation Runs	~ 6 hours
Total	~ 63 hours

5.2. 2nd Approach

After evaluating the results from the 1st approach, we deduced that for each of the Simulation Runs analyses of the original “Direct” optimization, most of the computational time is used for the Structural FE analysis. Additionally, based on the performance of the ML predictors trained during the 1st approach, with a small dataset of only 20 experiments, it is possible to achieve very good predictive accuracy for the deformation responses but not for the MBD responses. Evidently, additional data are required in order to achieve significant reduction in the error estimation for the Force and Angle responses, related to the Multi-Body Dynamics solution.

Based on these observations, a hybrid solution was developed that used an ML predictor to substitute the Structural solution but ran the MBD analysis normally. This approach overcame the lower accuracy of the predictions for the MBD responses when smaller training datasets are used and still accelerated the optimization study by employing an ML model to substitute the Structural solution, at the cost of increasing the complexity of the setup for the Optimization process.

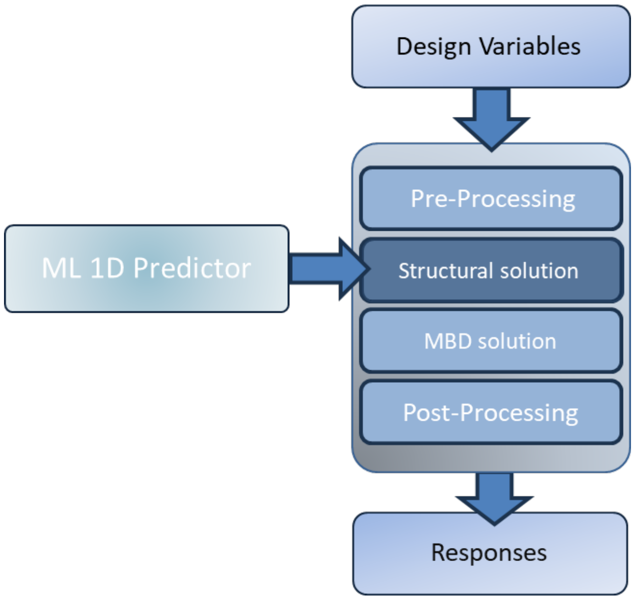

Figure 8: 2nd Machine Learning Optimization Workflow

For this 2nd approach, with the initial DOE of 20 experiments, an ML predictor was trained on the two deformation responses. This predictor replaced the analysis responsible for the Structural solution while the rest of the workflow remained the same. An Optimization study ran and resulted in a pareto front of 4 experiments (Figure 9).

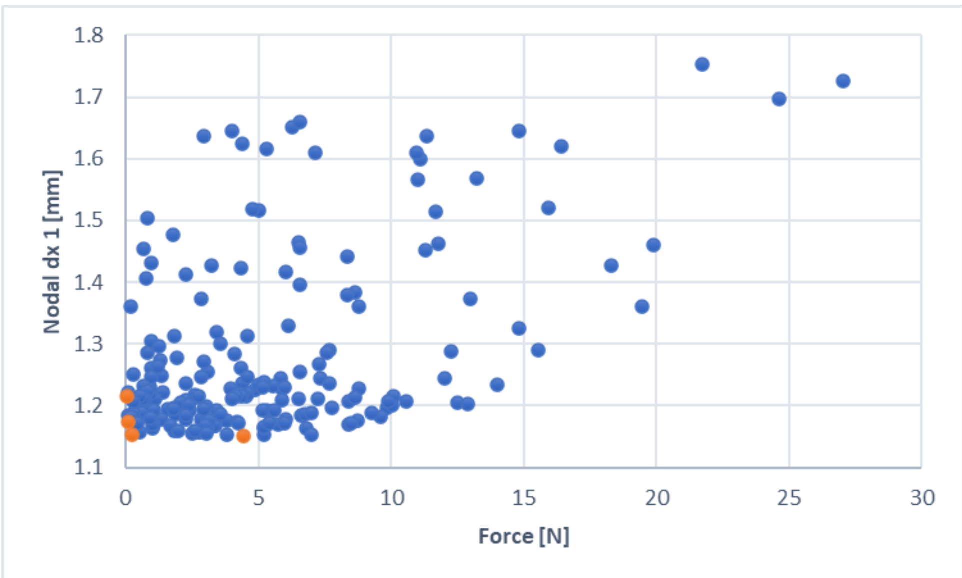

Figure 9: ML 2nd Approach: Predicted Optimization Results

Table 10: ML 2nd Approach: Validated Optimal Result

	F1	S1_X	S1_Z	S2_X	S2_Z	Nodal dx1	Nodal dx2	Angle	Force
Initial	600	3388.346	963.711	3218	1203	1.4573	1.4155	9.4499	6.5821
Optimized	402.153	3392.580	969.119	3221.417	1201.767	1.1522	1.1709	19.645	0.2402

The overall time required for this 2nd approach was 18.5 hours. The time required for each individual process appears in Table 11.

Table 11: Required time for 2nd ML Optimization

Sub-process	Time required
20 DOE Runs for the ML training	~ 14 hours
Optimization Study (200 runs)	~ 100 minutes
4 Validation Runs	~ 2.5 hours
Total	~ 18.5 hours

5.3. 3rd Approach

Further improvement could be achieved utilizing the additional capability of Data driven or Design Variable based ML methods that is to train ML models to predict simple key value responses, 2D curve results as well as full field results.

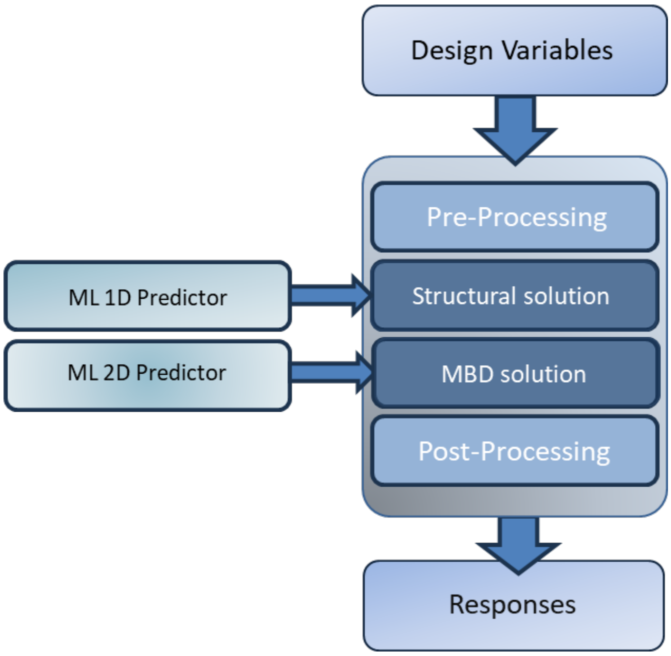

Figure 10: 3rd Machine Learning Optimization Workflow

The results from the MBD analysis were primarily two Force –Angle curves (Figure 4) from which we extracted the values of the intersection point between the two. This suggested that a ML model could be integrated into the workflow (replacing the MBD analysis) that would be able to predict the Force-Angle curves. Then, the predicted curves would be automatically post-processed in order to calculate the Force and Angle responses from their intersection point.

Using the original DOE of 20 experiments an ML predictor was trained to predict the Opening and Closing Force-Angle curves of the MBD analysis. The KPI's of this predictor showed very good accuracy predicting both curves (Figure 11), with the Closing curve showing almost no mean absolute error Figure 12).

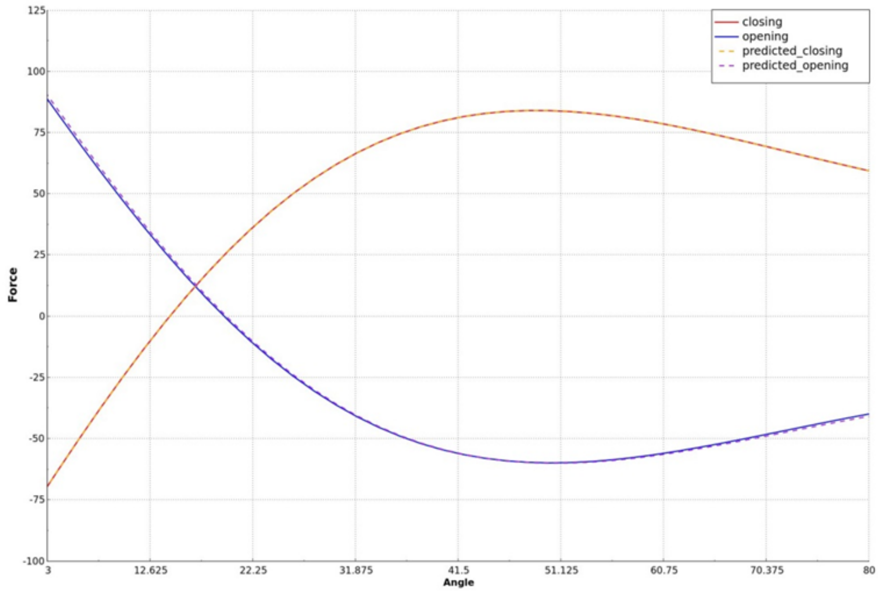

Figure 11: Real and Predicted Opening/Closing Force-Angle curves

Table 12: KPIs of Key Value Deformation and Curve predictions

ML Predictor Output	Predictor Test MAE
Nodal dx 1	0.0045
Nodal dx 2	0.0046
Opening Force-Angle curve	1.1448
Closing Force-Angle curve	1.6360E-06

At the same time, a predictor was trained to predict the key value deformation responses (similar to the 2nd approach) and both predictors replaced the Structural and MBD analyses in the workflow, respectively. The Optimization study ran and resulted in a pareto front of 4 experiments (Figure 12).

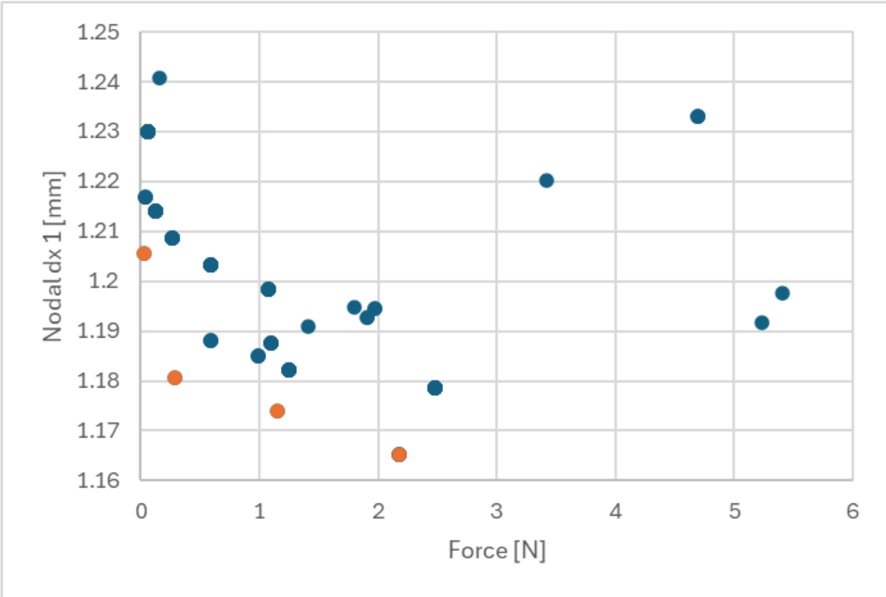

Figure 12: ML 3rd Approach: Predicted Optimization Results

Table 13: ML 3rd Approach: Validated Optimal Result

	F1	S1_X	S1_Z	S2_X	S2_Z	Nodal dx1	Nodal dx2	Angle	Force
Initial	600	3388.346	963.711	3218	1203	1.4573	1.4155	9.4499	6.5821
Optimized	412.598	3392.672	965.396	3215.966	1202.498	1.1869	1.1572	18.5308	0.4326

With this approach, the overall time required was around 17.5 hours. The individual sub-processes and their required time are listed in Table 14.

Table 14: Required time for 3rd ML Optimization

Sub-process	Time required
20 DOE Runs	~ 14 hours

ML Optimization (120 runs)	~ 47 minutes
4 Validation Runs	~ 2.5 hours
Total	~ 17.5 hours

6. Results Validation

The validation of each of the Machine Learning applications was based on two methods: 1) the overall time required to reach an optimal solution, and 2) the achieved predictive accuracy, based on the size of the training dataset.

6.1. Time Required for the Optimum

Table 15: compares the optimal design found with each approach against the initial design, as well as the time required to reach it.

Table 15: Comparison of Optima of each approach against the initial design

Optimal Design	F1	S1_X	S1_Z	S2_X	S2_Z	Nodal dx1	Nodal dx2	Angle	Force	Time hours
Initial Reference	600	3388.346	963.711	3218	1203	1.4573	1.4155	9.4499	6.5821	-
Direct Optimal	400.304	3391.47	967.006	3219.88	1201.45	1.172	1.143	17.8722	0.009097	**157.5**
Approach 1	404.939	3392.924	969.289	3219.425	1201.799	0.5519	0.5189	19.017	0.7731	**63**
Approach 2	402.153	3392.580	969.119	3221.417	1201.767	1.1522	1.1224	19.592	0.2402	**18.5**
Approach 3	412.597	3392.672	965.395	3215.965	1202.498	1.1868	1.1571	18.531	0.4326	**17.5**

Based on Table 15, all four techniques were able to reach an optimal solution. However, employing Machine Learning models in the optimization task provided a significant reduction to the overall time required.

6.2. Accuracy of Machine Learning techniques

In order to evaluate the accuracy of the three ML techniques, 8 designs close to the optimal solutions were created and solved. Then, each of the ML models was used in order to predict the responses of those designs. The MAE metrics for the predictions of each case were compared. For each case, a simple predictor trained with the original DOE of 20 experiments was also used for reference in the comparison.

Table 16: Validation experiments of Machine Learning predictors

#	F1	S1_X	S1_Z	S2_X	S2_Z	Nodal dx1	Nodal dx2	Angle	Force
1	428.4052	3392.742	957.4489	3217.545	1198.933	1.2333713	1.2025122	16.869503	0.455137871
2	409.0520	3392.967	956.4480	3217.22	1201.975	1.2101646	1.1806173	19.945623	4.423322739
3	400.8373	3392.837	959.2616	3218.973	1201.444	1.1909393	1.1619131	20.547092	3.061858805
4	414.0651	3392.620	967.2282	3217.410	1203.017	1.1828664	1.1530121	18.578679	1.199505038
5	400.8373	3392.749	967.8110	3217.224	1201.595	1.1639063	1.1349768	19.268696	1.494776419
6	400.8373	3392.749	967.9720	3219.146	1202.876	1.1633213	1.1343131	20.037557	1.336624624
7	404.9396	3392.924	969.2892	3219.425	1201.798	0.5519236	0.5188905	19.017102	0.773087997
8	400.8373	3392.854	969.2786	3218.973	1204.167	0.5476908	0.5149033	20.419674	2.630435475

For the Force and Angle responses it is worth mentioning that the 2nd ML approach did not utilize ML models for the calculation of the same responses, since it utilized the actual FE MBD solution, so it was omitted from this comparison.

Table 17: Force: Real vs Predicted values

#	Real	RSM (DOE 20)	Approach 1: Improved RSM (DOE 80)	Approach 3: 2D curve predictions (DOE 20)
1	0.45513787	5.991	0.0869	0.807993
2	4.42332274	7.4515	0.49630001	4.38157

3	3.0618588	7.2184	1.94260001	2.87836
4	1.19950504	6.5221	2.40639997	0.472762
5	1.49477642	5.4829	3.13529992	2.35065
6	1.33662462	6.7234	3.60520005	0.632673
7	0.773088	6.0494	4.67269993	1.62517
8	2.63043548	7.1434	6.87919998	1.8843
MAE	**-**	**4.65091888**	**2.33486121**	**0.55786155**

Table 18: Angle: Real vs Predicted Values

#	**Real**	**RSM (DOE 20)**	**Approach 1: Improved RSM (DOE 80)**	**Approach 3: 2D curve predictions (DOE 20)**
1	16.8695039	14.9817	17.3377991	16.7894
2	19.9456231	16.3626	19.4507008	19.9347
3	20.5470928	16.6374	19.7054996	20.4929
4	18.5786794	16.2052	18.0501995	18.3915
5	19.2686966	16.2352	18.6249008	19.0372
6	20.0375571	16.7828	19.1676006	19.844
7	19.0171029	16.3606	19.1604996	18.7902
8	20.419675	17.045	20.0632992	20.1993

MAE		**3.00917886**	**0.54335193**	**0.15059136**

For the Deformation responses, the 2nd and 3rd approach utilize the same ML model trained with the original DOE of 20 experiments. Thus, the comparison is between the original RSM trained with a DOE of 20 runs and the Improved RSM (trained with 80 experiments) of Approach 1.

Table 19: Deformations: Real vs Predicted values

#	Nodal dx1	RSM (DOE 20)	Approach 1: Improved RSM (DOE 80)	Nodal dx2	RSM (DOE 20)	Approach 1: Improved RSM (DOE 80)
1	1.23337138	1.2339	1.2318	1.20251226	1.2025	1.2009
2	1.21016467	1.2116	1.2092	1.18061733	1.1814	1.1793
3	1.19093931	1.19	1.1874	1.16191316	1.1603	1.1579
4	1.18286645	1.1753	1.1725	1.15301216	1.1447	1.1417
5	1.16390634	1.1549	1.1519	1.13497686	1.1252	1.1219
6	1.16332138	1.1543	1.1513	1.13431311	1.1245	1.1211
7	0.55192363	1.153	1.15	0.5188905	1.123	1.1197
8	0.54769081	1.1482	1.1451	0.51490331	1.1184	1.1148
MAE		**0.15376037**	**0.15449438**		**0.15473955**	**0.15565638**

From the above comparisons, it can be observed that to accurately predict the Force and Angle Key Value responses, more data-points are required to be solved and used in the ML training, compared to the size of the training dataset for a predictor that can accurately predict the 2D curves. The difference in the achieved accuracy can be attributed to the relationship between the input design variables and the output responses (Force-Angle curves, Force/Angle key value responses). In the case of the 2D predictor, the relationship between the input and output is simple. In the case of the key value responses, an additional layer of complexity is introduced in the input-output relationship as the responses are calculated on the intersection point of the two curves (an arbitrary point on the MBD curves) while the Force response is the absolute value of the y-coordinate of said intersection point.

Regarding the MAE of the deformation predictions, it is observed that when we use a larger training dataset for the creation of the ML predictor, the MAE increases slightly. However, the observed increase in error is minimal and, thus, the MAE can be considered the same before and after the improvement.

Additionally, the calculated MAE for the Force and Angle responses of the Improved RSM of the first approach is even lower on the Validation runs, than previously estimated from the predictor's KPIs, also validating the improved accuracy of the RSM specifically in the region of the design space where the optimal solutions lie.

7. Conclusion

In this study, an automated process on the Optimization of Automotive closures using Machine Learning techniques was presented. Three different approaches were investigated and validated. The results of this work suggest that employing ML methods to create Response surface models allows for accelerated optimization studies with controllable accuracy. Additionally, simple key value responses, curves or full field results can be predicted with acceptable accuracy in the process of design exploration and testing of "What-if" scenarios, avoiding the time-consuming FE Analyses.

8. References

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