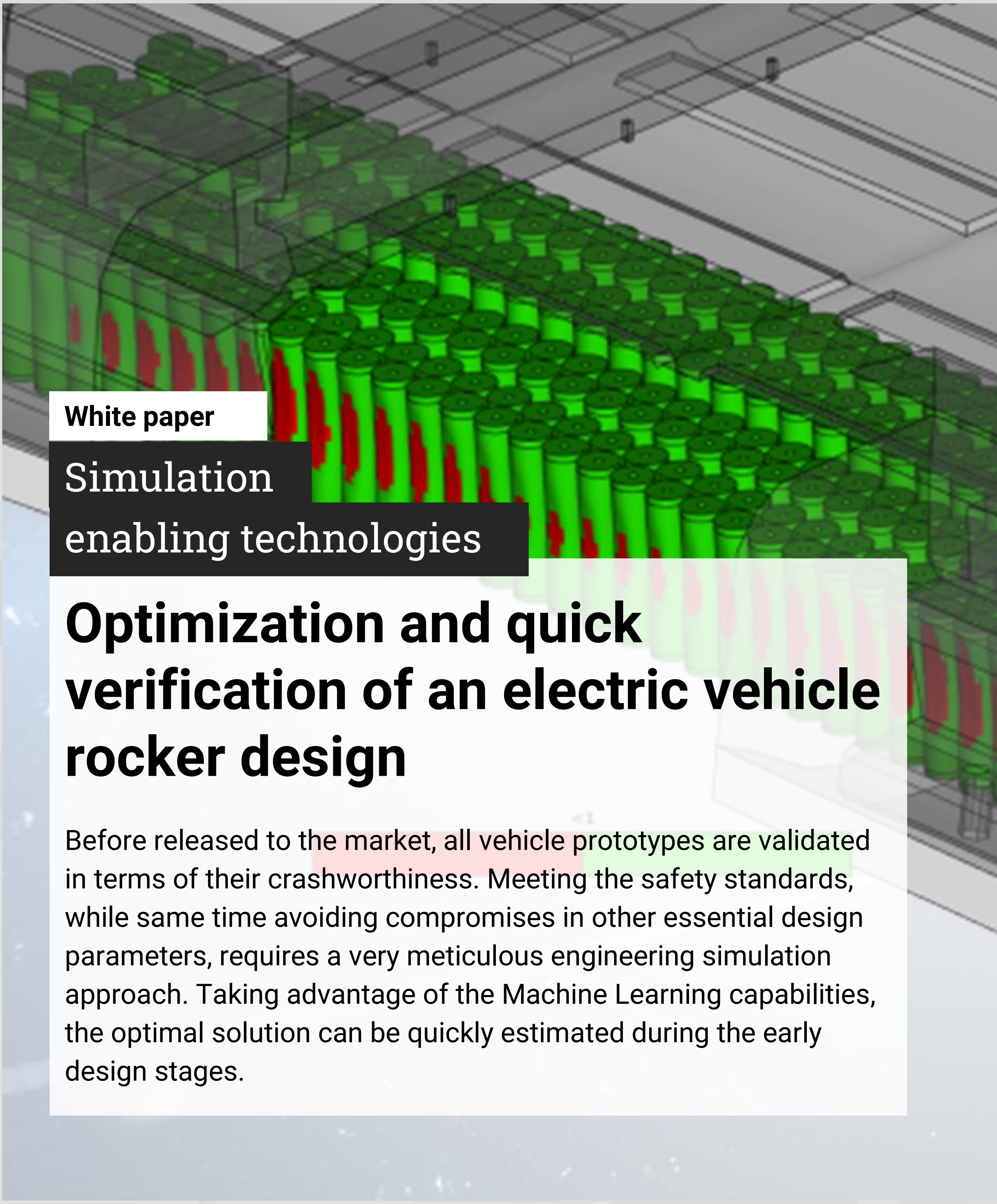
BETA SIMULATION SOLUTIONS

physics on screen



White paper

Simulation enabling technologies

Optimization and quick verification of an electric vehicle rocker design

Before released to the market, all vehicle prototypes are validated in terms of their crashworthiness. Meeting the safety standards, while same time avoiding compromises in other essential design parameters, requires a very meticulous engineering simulation approach. Taking advantage of the Machine Learning capabilities, the optimal solution can be quickly estimated during the early design stages.

Introduction

Before released to the market, all vehicle prototypes are validated in terms of their crashworthiness. Meeting the safety standards, while same time avoiding compromises in other essential design parameters, requires a very meticulous engineering simulation approach during product design. These processes become even more complicated, and time-consuming, with electric vehicles, such as Lithium-ion battery-powered cars. In many cases to accomplish the safety aims during product design, while also meeting time limitations and deadlines, sophisticated simulation tools need to be employed. Such tools are those that enable optimization studies and that take advantage of Machine Learning capabilities.

In this study, an optimization and a quick verification of an electric vehicle rocker design were performed with the aid of an Optimization tool and Machine Learning methods.

Through this Optimization tool, several Design Experiments have been created and then, by training a Machine Learning model (referred to as a "Predictor"), the optimal design parameters were approached for the given objective and constraints. Since during the designing stages, the geometry can be often modified, the proposed approach saves a considerable amount of time, as it avoids repeating the complete ML Optimization process or solving each updated model individually. To accomplish this, Transfer Learning methods were utilized to employ the already trained ML predictive model to verify and optimize the updated geometry. This way, an optimized design for the updated model can be calculated, avoiding re-training an updated Predictor and producing new data sets. The use of this already trained Predictor extends also to the field of a quick verification of the newly updated designs. The several design modifications were quickly tested without needing to solve the model again. To further reduce simulation time and modeling effort, a macroscopic battery model was used. This way, the ML Predictor was able to also consider the electromagnetic phenomena related to damaged batteries without increasing the solution time of the side-crash simulation.

All in all, using the Machine Learning-based Optimization tool and the Transfer Learning related functionality, an already trained predictive model was able to verify any updated designs and estimate an optimized vehicle model with updated components without having to re-run the complete optimization and solution processes.

1. Optimization method and model description

The current study focuses on the crash simulation of a Li-ion battery-powered EV module platform which is imposed to a side collision with a rigid pillar at 60 km/h. For the battery modeling of the li-ion batteries located inside the platform, the macroscopic battery model "BatMac" based on the equivalent Randles circuit was used [1]. For the investigation of an internal battery short, LS-DYNA provides a keyword that triggers the short when the criteria defined inside the function are met [2]. In the current case, the shorting conditions are based on the stress values applied to each cell. When the stress exceeds a particular value, an internal battery short occurs [3].

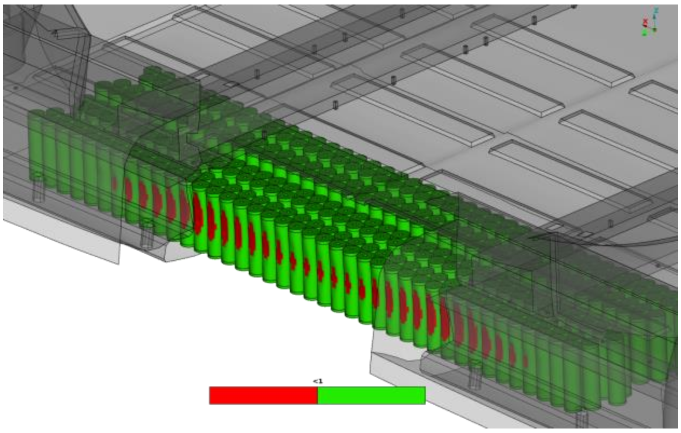


Figure 1: Affected batteries during the Side-crash event

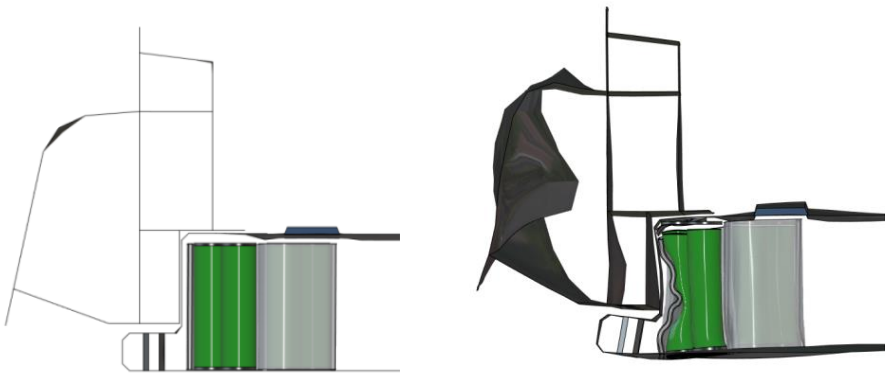


Figure 2: EV Rocker Cross-Section before and after the crash event

Regarding the optimization workflow, a set of pre- and post-processing functionalities were used, accelerating the optimization process of an electric car platform design, using the embedded Machine Learning Optimization tool [4]. Specifically, the process consists of setting up an Optimization Task which embeds the Design of Experiment method to produce several DOE studies. The design parameters whose value varies from study to study, are referred to as Design Variables, and the dependent critical results as Responses. Based on these datasets, an ML Predictor is trained using the Response Surface Model. Then, the objective and constraints of the Optimization Study are defined, and finally, by utilizing the predictive model of the Predictor, the Optimizer returns the optimal solution. In the studied optimization scenario, the objective is to minimize the number of damaged batteries without increasing the rocker's mass, and hence, the corresponding values were assigned as Responses. The defined Design Variables are the rocker plates' thickness and location variation along the y-axis.

2. Predictive model and optimization results

The values of the design variables are obtained by the Uniform Latin Hypercube DOE generation algorithm. For each iteration, the generated experiments with the different DV values are solved and post-processed as assigned in the Optimization Task workflow. This way, a file repository occurs, containing all the necessary data to train a predictor. In this case, 100 DOEs were solved.

To evaluate the quality of this dataset, information can be retrieved from the Correlation Matrix (**Figure 3**) and the Pair Plot of the DVs versus the Responses (**Figure 4**), as well as the Power Predictive score. In the following matrix, the correlation is described through a factor that fluctuates between -1 and 1. Values close to 0 mean that there is not any relationship between the DVs and responses, and values closer to 1 and -1 mean that there is a strong correlation. In this case, it is highlighted that the mass is mainly affected by thicknesses 1 and 2 and the number of damaged cells is affected mostly by Plate Location and Thickness 2. The positive and negative signs imply that the variables are proportional and reversely proportional, respectively. Considering the Pair Plots, each DV's values are depicted versus the corresponding response value. In the plots where patterns are noted e.g. in thickness 1 vs mass or Plate Location vs Num. of damaged cells, it is safe to assume that there is a linear correlation between those variables.

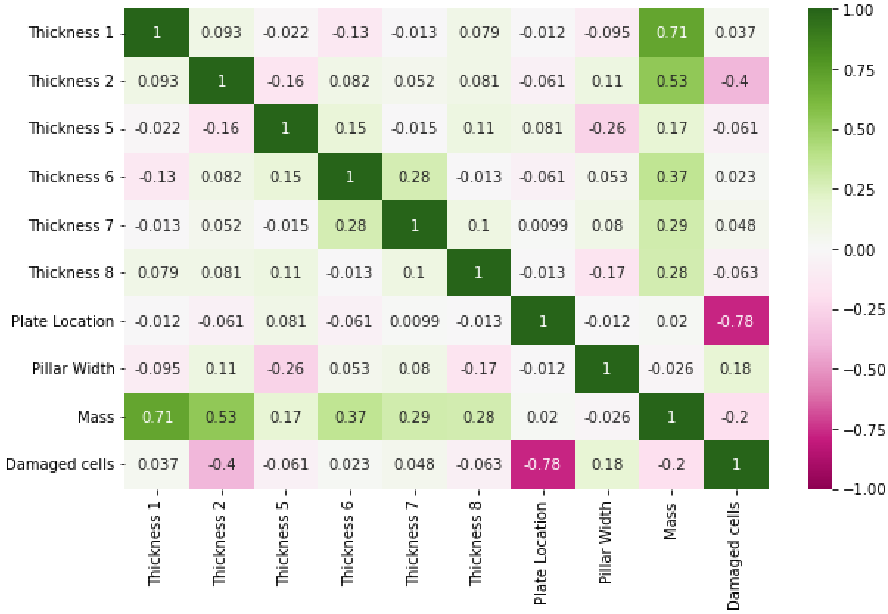


Figure 3: Correlation Matrix

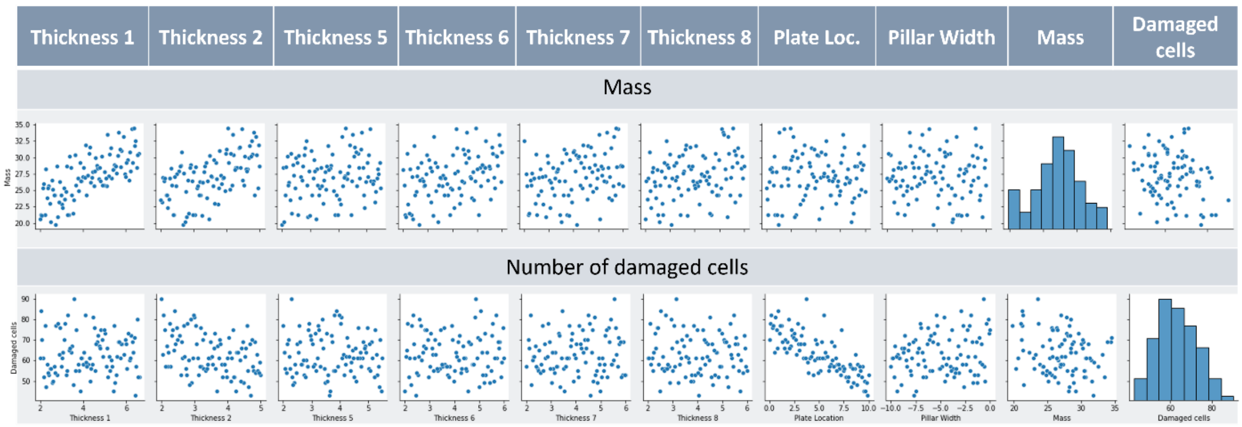


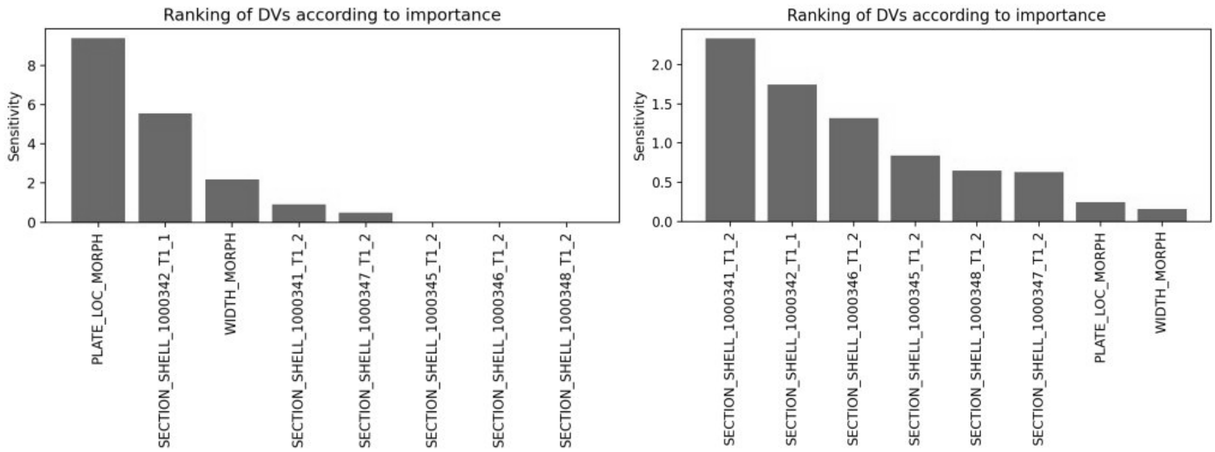
Figure 4: Pair Plots of the Responses vs. DVs

Lastly, the predictive power score (PPS) is an asymmetric, data-type-agnostic score that can detect linear or non-linear relationships between two columns. The score takes values between 0 (which means no predictive power) and 1 (which means perfect predictive power). For the Mass, the PPS is 0.98 whilst for the Number of Damaged Cells is 0.64.

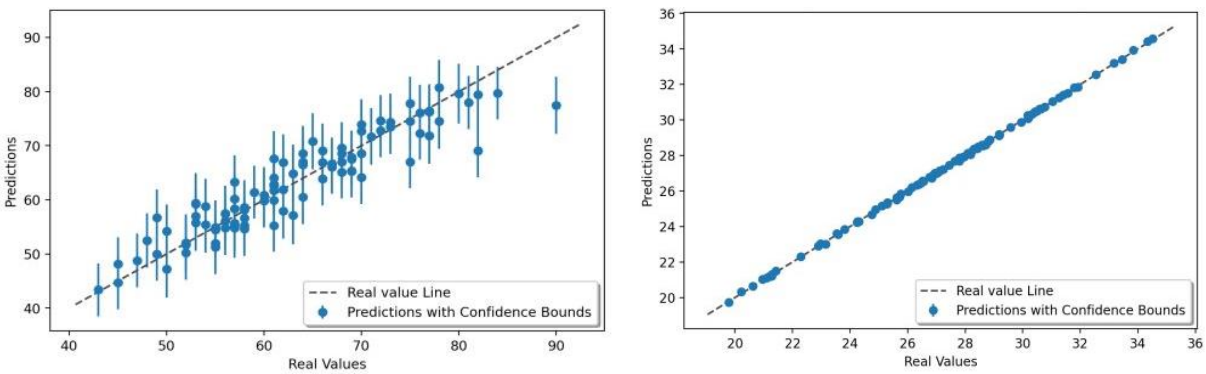
The occurring calculated predictive model calculates the relationship between the Design Variables and the Responses using a Regression method. Once the predictor is trained, graphs are reported giving information about the quality of the Predictor (**Figure 5**).

The following bar charts (**Figure 5.a**) sort the design variables according to their importance in the optimization process. As shown, the number of damaged cells is mostly affected by the plate location, whilst the mass mostly depends on the thickness of plate 1. Then, from the variance estimation graph (**Figure 5.b**), the predictions with their confidence bounds are indicated. The Minimum Average Error of Variance and the Accuracy are also calculated where the first equals to the minimum error of the confidence bounds for each prediction and the second is the percentage of the configuration bounds that correctly include the ground truth value. Afterwards, from the next graph (**Figure 5.c**) the relationship between the size of the training dataset and the accuracy is depicted, highlighting that predicting the mass accurately requires far less DOEs in comparison with the number of damaged cells. The last graph indicates the deviation between the target and the predictions by overlaying their values (**Figure 5.d**).

Number of Damaged Cells **Mass**

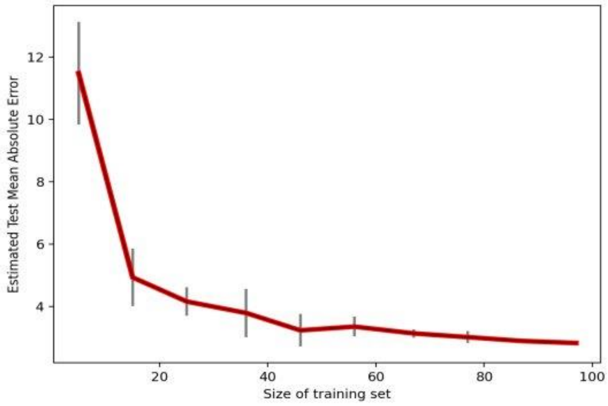


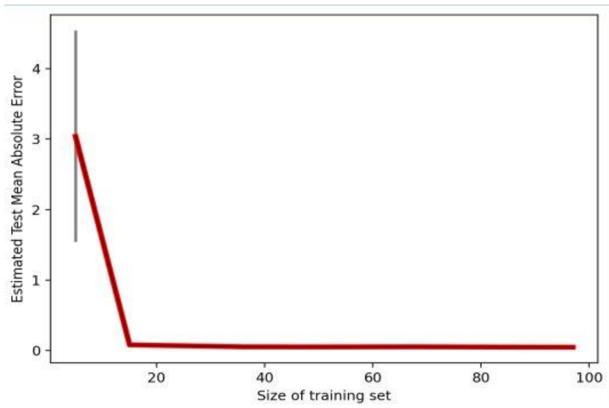
(5.a) Ranking of DVs Importance regarding the number of damaged cells



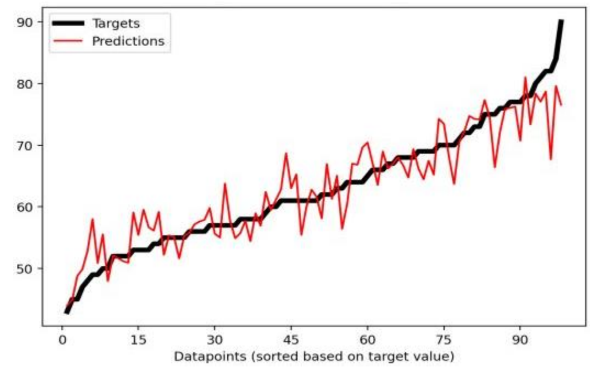
(5.b) Variance Estimation Graphs

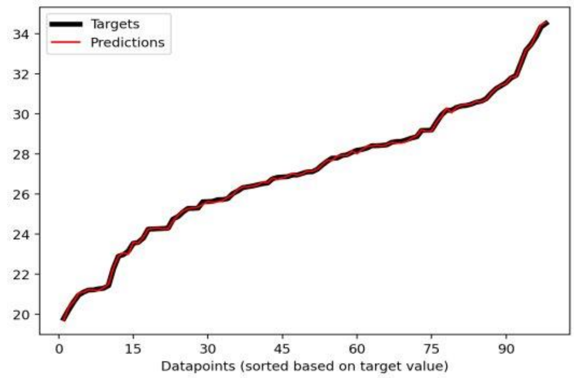
Number of Damaged Cells | **Mass**





(5.c) Dataset Size vs. Accuracy





(5.d) Target vs. Predictions values

Figure 5: KPI plots

Finally, using the Differential Evolution method, the Optimization Study is run resulting in the optimal solution. As shown below (**Figure 6**), all the studies explored by the Optimizer do not exceed the Mass constraint of 36 kg. The optimal solution is the last study which suggests that the predicted mass is at 24.5 kg whilst the predicted damaged batteries are 37.

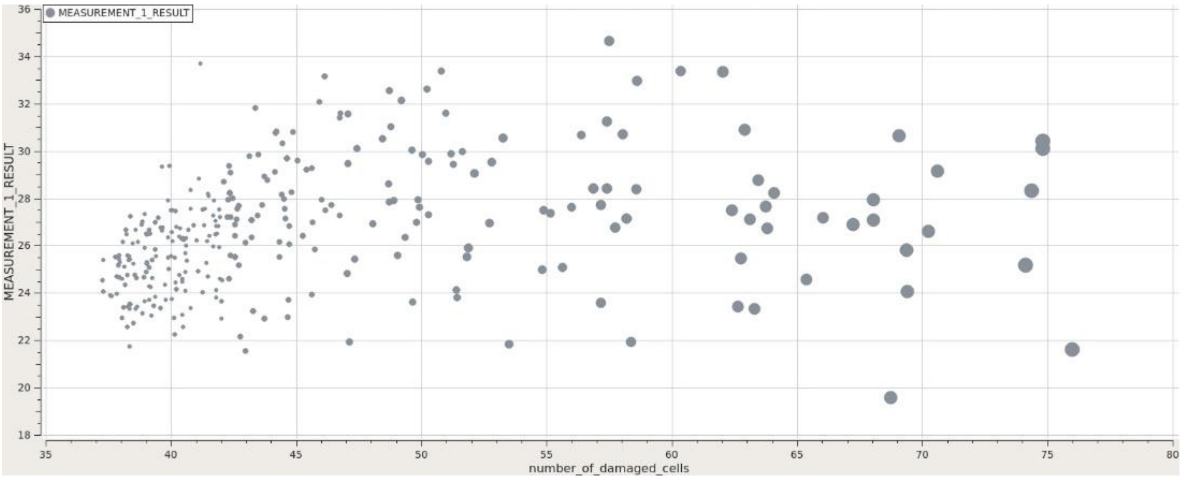


Figure 6: Optimization Studies: Mass vs Number of Damaged Cells

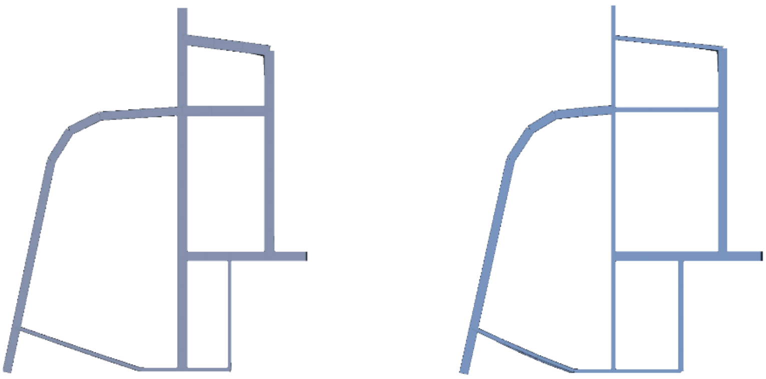


Figure 7: Left: Initial rocker design, Right: Optimal rocker design

Moreover, the optimized model is normally solved to validate the optimization estimations, while also to evaluate the optimization results in overall.

Response	Initial Model	Predicted Optimal	Validated Model
Mass [kg]	37.56	24.57	24.39
Num. of damaged cells	68	37	46

Table 1: Evaluation of Optimization Results

3. Quick verification of the modified EV model

The predictive model trained previously can be used in cases where the initial model has been slightly modified on areas affected by the design variables (**Figure 8**) and they have a relatively high similarity factor among the parameters of the baseline model. The response values can be quickly predicted without requiring solving the model. So, this way, the changes in the geometry can be quickly evaluated. Again, the results were validated, highlighting that the change in the plate's thickness will worsen the crash behavior of the vehicle. This way, the designers can save a significant amount of time during the early design stages, as they are prevented from following the wrong design direction without requiring solving numerous design scenarios.

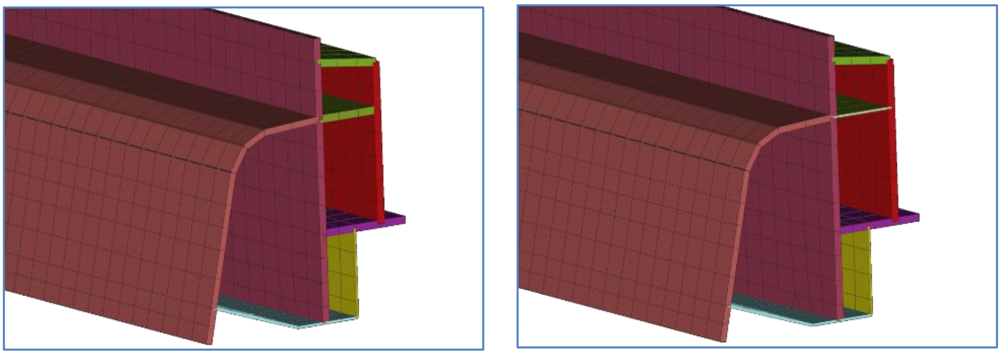


Figure 8: (a) Left: Initial rocker design, (b) Right: Modified rocker design

Response	Initial Model	Predicted	Real Modified
Mass [kg]	37.56	35.8	35.82
Num. of damaged cells	68	72	73

Table 2: Evaluation of Quick Verification Results

4. Conclusions

To conclude, the ML Optimization process discussed in this study introduces a semi-automated way: (a) to produce the required data to train an ML Predictor, (b) to estimate the optimal design of an EV using the trained Predictor and (c) to quickly evaluate potential relatively small modifications to the Baseline Model without demanding training a new predictive model. Lastly, the embedded plotting functionalities facilitate the visualization of the ML-related results, allowing the inspection of the quality of the training dataset, the Predictor accuracy, as well as to evaluate the whole Optimization process.

5. References

[1] Pierre L'Eplattenier, Inaki Caldichoury, "BatMac: A battery Macro Model to simulate a Full Battery in an Electric or Hybrid Car Crash using LS-DYNA", 12th European LS-DYNA Conference, 2019

[2] LS-DYNA, "EM Theory Manual – Electromagnetism and Linear Algebra in LS-DYNA", August 2012

[3] Sarah Bateau-Meyer, Pierre L'Eplattenier, Jie Deng, Min Zhu, Chulheung Bae, Theodore Miller, "Randles Circuit Parameters Set Up for Battery Simulations in LS-DYNA" 15th International LS-DYNA Users Conference, June 2018

[4] BETA CAE Systems, "Optimization with ANSA / META", 2022

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

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

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

© 2024 BETA CAE Systems International AG • Features subject to change without notice • All trademarks are property of their respective owners.

BETA
SIMULATION SOLUTIONS

physics on screen