Beyond Simulation: AI's Role in Future Crash Studies

Srikant Adya[1], Celalettin Karadogan[2], Shyam S. Vasu[2], Nikolay Lazarov[2], Martin Husek[1], André Haufe[2]

[1] Ansys Inc., part of Synopsys Inc.
[2] DYNAmore GmbH, part of Synopsys Inc.

1 Abstract

Artificial Intelligence (AI) and Machine Learning (ML) are increasingly transforming Computer-Aided Engineering (CAE) workflows by enabling faster design iterations and reducing computational costs. Ansys SimAI is a deep learning-based surrogate modelling platform designed to replicate complex physics-based simulations with significantly reduced runtimes. This paper presents the application of Ansys SimAI's design exploration and validation capabilities in modelling an automotive side impact scenario using high-fidelity physics-based data generated from LS-DYNA simulations.

The study begins with the development of an AI model trained on a dataset where the pole impact position and door beam configurations are systematically varied. The trained model demonstrates strong predictive capabilities, accurately capturing vehicle deformation patterns and curves of pole force progress across a range of input configurations. In a second case, a separate model is trained using simulations with fixed pole and door beam settings, but varying rocker panel reinforcements. Again, the AI model shows excellent generalization, accurately predicting results for unseen reinforcement geometries.

To expand the model's applicability, both datasets are combined to train a comprehensive surrogate capable of simultaneously accounting for variations in pole position, door beam configuration, and rocker reinforcement design. This integrated model successfully predicts the deformed shape and force-time histories for new design combinations within the training space, showcasing SimAI's ability to generalize across a multi-dimensional design space.

Such tools have the potential to assist designers in orienting themselves within the design space, facilitating the identification of enhanced alternatives and the pursuit of optimal solutions. However, it appears that the design of new geometries may become the bottleneck this time, given the rapid advancements in AI-based validation tools. At this point, it seems that the AI-based geometry exploration functionality implemented in SimAI is proving to be a practical tool that can be used to generate completely new geometries based on the manually created ones. In our further study, we used the geometries already available for the rocker reinforcement to train the AI-based geometry exploration tool and have it generate new geometries, which can then be quickly tested in crash scenarios using the previously trained SimAI model.

The results demonstrate that expensive and time-consuming LS-DYNA simulations can be leveraged effectively to build AI models that dramatically reduce the time required for design exploration. In addition, Ansys SimAI models are valuable tools for continuous engineering development because they can be trained further with new data, allowing for iterative improvement and adaptability. With SimAI in the loop, we envisage CAE workflows to shift from simulation-driven design to AI-augmented autonomous engineering exploration. Instead of engineers manually setting up, running, and interpreting simulations as discrete tasks, workflows will evolve into continuous, data-driven cycles where geometry generation, simulation, validation, and optimization converge into an intelligent closed loop.

2 Introduction

Artificial intelligence (AI) and machine learning (ML) have become transformative forces in technical design, particularly in computer-aided engineering (CAE) workflows, where the computational requirements for high-precision simulations remain a major hurdle. One such challenge is the accurate modelling of automotive crash scenarios which require complex physics solvers such as LS-Dyna and involve significant resource investments. These simulations are critical to ensuring vehicle safety and structural performance, but their runtime and data intensity can slow down design cycles and limit exploratory agility in multi-parameter spaces.

To accelerate this process without compromising accuracy, recent developments have turned to deep learning-based surrogate modelling. Conventional alternatives—including response surface models [1], reduced modelling [2], and kriging interpolation [3]—have helped reduce computational effort but are often unable to capture nonlinear responses across high-dimensional input spaces. In contrast, graph neural networks (GNNs) offer a powerful approach that can encode spatial and topological relationships

in structural models, making them particularly well suited for applications involving geometry-dependent physics, such as crash dynamics [5-7].
Ansys SimAI is a GNN-based surrogate modelling platform specifically designed to accelerate design exploration in CAE environments [8]. SimAI is physics- and mesh-agnostic and leverages existing simulation data to train models that can quickly evaluate new geometric configurations with acceptable engineering accuracy. This allows researchers and engineers to bypass resource-intensive simulations and perform comparative studies between different design alternatives in a fraction of the time. Recent developments at SimAI now make it possible to generate new geometries by using existing designs to train the AI model. The AI-based geometry exploration tool is capable of generating new geometries in the meta-space defined by the features of the geometries provided.
The study examines the performance of SimAI using a case study for side impact tests in the automotive sector. First, the GNN-based model is trained using LS-DYNA simulations with different pole positions and door beam geometries. The model demonstrates strong predictive capabilities and accurately reproduces the deformation patterns of the vehicle and the evolution of pole force. A second scenario examines the model's ability to generalize to different reinforcement configurations of the rocker panel under impact conditions with fixed pole position. Both models show excellent potential for extrapolation to previously unknown geometries. To improve applicability, these data sets are integrated to create a unified surrogate model that can respond to simultaneous variations in the point of impact on the pole, the door beam structures, and the reinforcement design. This composite model provides reliable predictions, confirming the usefulness of SimAI as a design acceleration tool for high-dimensional parameter spaces. Compared to the traditional approach where new DOEs had to be generated to incorporate each of these design variables, this GNN-based model significantly reduces the number of simulations required to assess the interplay between the design variables. Furthermore, the reliance on manually defined design variables can be reduced by creating new designs using an AI-based geometry exploration tool. Although these AI-generated shapes result from interpolation of existing geometries, they often exhibit more organic and natural characteristics compared to conventional parametric variations. This approach enables exploration of entirely new design possibilities within the meta-space of geometric features present in the available designs but not yet explored.
Section 2 of this paper describes the data creation and training process in detail. The use of the AI-based geometry exploration functionality is also presented here. Section 3 presents and discusses the results of all test cases and evaluates the prediction accuracy, generalization ability, and runtime improvements. These sections ultimately show that SimAI is more than just a computational shortcut—it is a platform that enables scalable and iterative design optimization based on legacy and newly generated simulation data.

3 Materials and Methods

This study is a proof of concept to demonstrate how SimAI can be used to accelerate the design optimization phase. This approach makes it possible to evaluate a range of car parts to identify potential improvements in a fraction of the time that would normally be required. Here, SimAI not only predicts the complete simulation result in a few minutes but also helps to generate design alternatives using its geometry exploration tool.
Once accurate simulation results have been generated using LS-Dyna from various design alternatives, a SimAI model can be trained using data from all concurrent design optimization studies. Implementing the SimAI model should accelerate the evaluation of new alternatives, at least in quantitative terms. This approach reduces the time required to test each individual alternative, and SimAI's AI-based geometry exploration tool supports the generation of new geometries based on existing ones, which can drastically shorten the design phase or achieve a near-optimal design level within the same timeframe.

3.1 Design Variations

The FE model used for this study is the openly available “Toyota Camry (CCSA V5a) 2012 FE-Model” [9]. The model is modified to become a side impact scenario against a pole. The details of the model are shown in Figure 1a. The first study focuses on the contribution of the door beams in a side impact, varying also the position of the pole from the center of the front door to the center of the rear door. For this purpose, eight different pole positions are selected evenly and the beams in the front and rear doors are alternately removed or attached. This study is visualized in Figure 1b. The second study examines the influence of the cross-sections of the rocker in-lays without changing the position of the pole and can be seen in Figure 1c.
As highlighted in Figure 1, each variation study comprises four test cases that are not used during training and serve exclusively to test the predictive quality of the SimAI model. Each of these studies could be used to train its own SimAI model, which would only be useful for that specific study. Our goal

is to show that a SimAI model overarching multiple studies can be useful for all of them at the same time.
After performing the LS-Dyna simulations, the input files for training SimAI, can be generated from the LS-Dyna results files, such as the d3plot and binout, using the functions available in the Ansys Data Processing Framework (DPF). Each generated instance contains the input for SimAI as well as the expected output for SimAI's supervised training. In the context of crash events, all deformation states considered in a crash simulation are treated as separate instances. Instances are saved in VTK file format using the DPF functionality coming from the pyDPF library. Each instance comprises the initial geometry of the vehicle and the initial geometry of the relevant environment in the form of an FE mesh. This mesh is always used as input. In addition, the file can also contain distributed values as fields that are mapped to the mesh entities, such as the displacements that reflect the deformation state, the strains and stresses, the change in thickness, or any other field that can be mapped on to the mesh, can be made available to SimAI. The user can define these fields as either inputs or outputs during the configuration of the SimAI model. If scalar values are required to describe the instance, such as the time of the corresponding deformation state or the initial speed of the car (if this is a parameter that varies across instances), these are provided in a separate JSON file linked to the geometry file. The creation of the directory structure with directories representing instances and containing a VTK-format file for geometry and a JSON file with the values of additional input features is performed automatically by the DPF functionality and is directly adopted by the SimAI platform. The generated database is sent to SimAI, where a quick check of all content is performed to ensure that everything can be processed during training. The next step is to configure the training, categorizing the provided content as input or output. Distributed field variables can be classified as output and are predicted by the SimAI model. The SimAI platform can also be configured to perform basic calculations of some derived values based on these fields. In this case, these are calculated automatically and made available during the deployment of the model. Defining the analysis volume is the next configuration step. The volume should be defined so that the future geometries used to generate a prediction are within its boundaries. The final step is to start training. Here, the user can choose between a debug run and intensive training with a specific time limit. Further training of an already trained model is possible at any time, either based on existing dataset or even based on newly added data points.
In this study, we used the displacement field and contact force between the pole and the vehicle as results from the model. To illustrate the flexibility in combining the data sets, we used 20 time-steps for the first dataset and 25 time-steps for the second dataset for the same side impact problem, which was calculated for 100 milliseconds. Since the geometry is accurately predicted, the intrusion value, which is an important criterion for crash safety, can be derived from the predicted displacement field and therefore does not necessarily have to be provided as a curve to be predicted, which would also be an option. . The model was trained for the most precise accuracy setting which took three days to converge. After completing the training, SimAI generated sample forecasts on the platform so that the results could be quickly reviewed. In addition, a report is automatically generated that summarizes the results of the test scenarios and is a good source of information on the quality of the trained SimAI model. Based on this, new training can be started, or the model can be used for predictions.
Deploying the SimAI model is very simple, as only the inputs for the SimAI platform need to be provided. If no field variables are used as inputs, a VTK-format file with the ability to store field information is not strictly necessary, so the geometry could even be provided in STL format. In our case, a prediction took about 5 seconds. The prediction of an entire crash with 25 time steps therefore takes about two minutes. The prediction results can be downloaded for further calculations or evaluations. The point values of the output curves to be predicted are also calculated, so that these are also readily available after the prediction. A trained SimAI model can be used to calculate responses for geometry or parameter variations that are relevant for improving the crash performance of the vehicle. Time interpolation is also flexible and can be used to predict results with high time density or only a few important time points. The variation of component geometries is also possible regardless of mesh size and connectivity, but a suitable mesh size should be used to achieve predictions with reasonable spatial density.
The legacy rocker inlay geometries, which were used as design alternatives and to train the SimAI, were also used for AI-based geometry exploration. For this purpose, the geometry exploration tool of the SimAI was trained with these 24 inlay geometries, which are shown in Fig. 1c. The trained AI model learned the features and physical constraints inherent in these geometries. The meta-space in which such features are linked to coordinates is also referred to as latent space. We selected three of the existing geometries and had SimAI generate seven new geometries, shown in Fig. 2, in the latent space that are close to these, with analogous features but are completely new geometries. The number of new geometries was limited here to demonstrate the available possibilities within the limited space available

for this technical paper. However, exploring the entire latent space with all potential geometric alternatives opens up the possibility of extremely rapid qualitative design optimization.

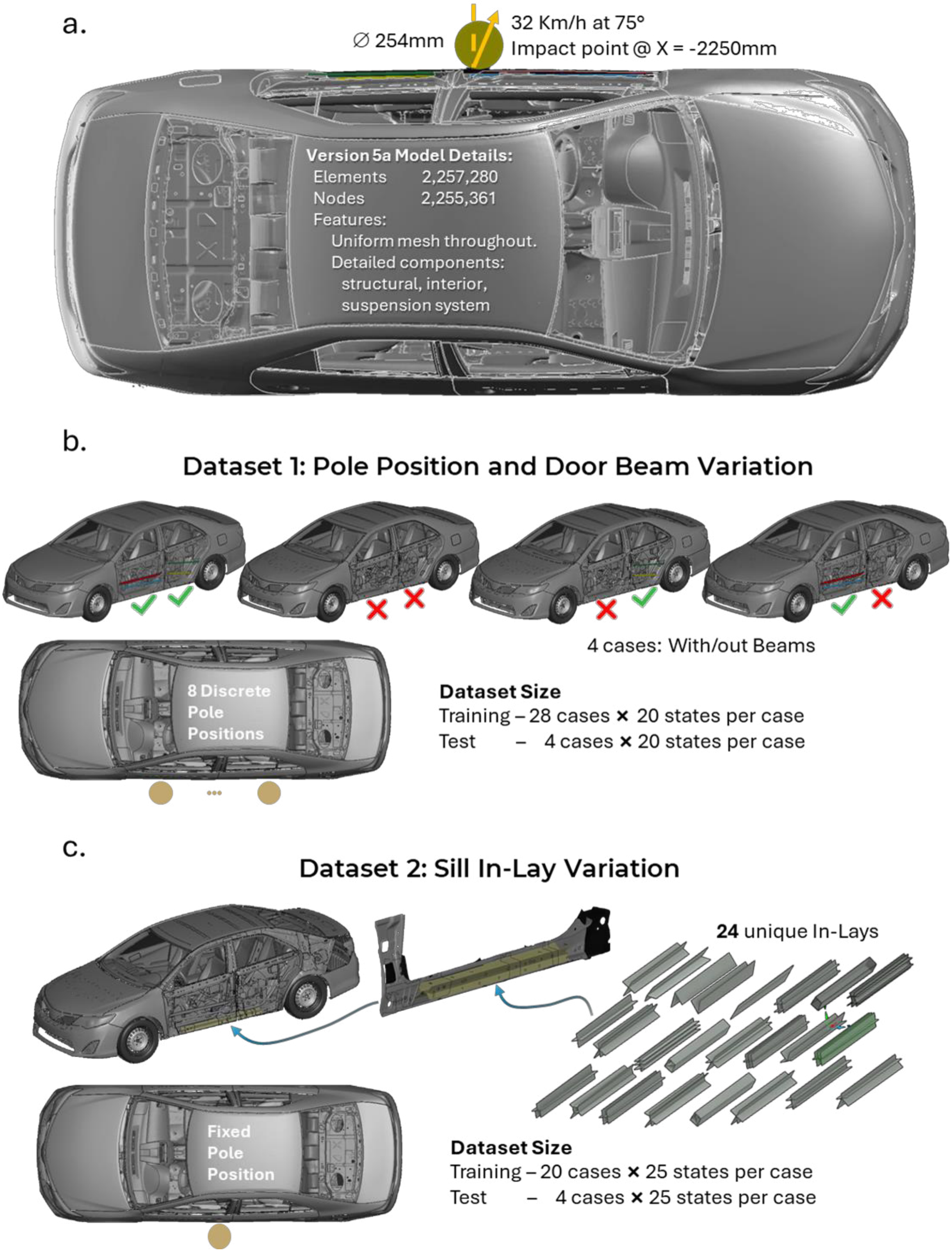


Fig.1: a. "Toyota Camry (CCSA V5a) 2012 FE-Model" [9] modified for pole impact, b. Pole position and door beam variations, c. Rocker in-lay variations.

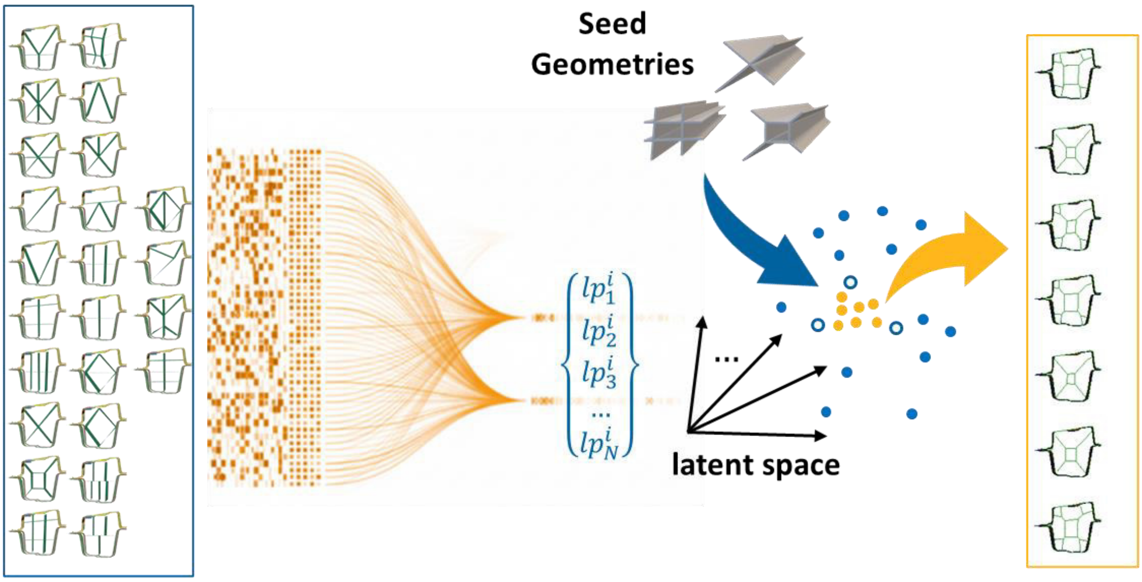


Fig.2: Schematic representation of SimAI's geometric concept exploration tool for generating new geometries based on existing ones.

4 Results and Discussion

With the trained SimAI model, one can now predict crash results for new geometries. Test geometries that were left out during training are the readily available candidates for this purpose. This is a necessary step to ensure that the trained SimAI model has been generalized across the available sample space and is ready to make reliable predictions for completely new "un-seen" geometries. Although comparisons with the LS-Dyna results were performed for all eight test geometries, due to space limitations, only the comparison results for a few test geometries from datasets 1 and 2 are shown below. To demonstrate the further applicability of the SimAI model, we manually generated a completely new geometry that represents a mixture of variations from both datasets. In addition, the seven inlay designs generated using SimAI's AI-based geometry exploration tool are used for demonstration purposes.

4.1 Testing of SimAI model on eight test cases not used during the training

The report generated immediately after completion of the SimAI training contains valuable information about the quality of the training. One piece of information concerns the quality of the prediction of the curves provided during training. In our case, this is the contact force between the pole and the vehicle. Each state, i.e., each exported time step, has a value calculated by LS-Dyna and a prediction value calculated by SimAI. Fig. 3 provides a comparison of all these values from all unused and therefore unknown test cases, shown as red dots, and for the values from some of the training cases, shown as green dots. A point that is very close to the 45° line, "0% error", means an accurate prediction by SimAI. Fig. 3 shows that 96% of all predictions for unknown test geometries are within the relative error range of 10%. Figure 4 shows the force-time curves for all eight test cases. The light curves in the background of these graphs are all force-time responses from the complete data sets. It is clear from this background information that the SimAI predictions are very similar to the LS Dyna results in most cases, compared to the responses originating from that system. SimAI allows further training when new LS-Dyna simulation results are available. This will improve the model generalization, especially for cases where SimAI predictions and LS-Dyna simulation results differ considerably.

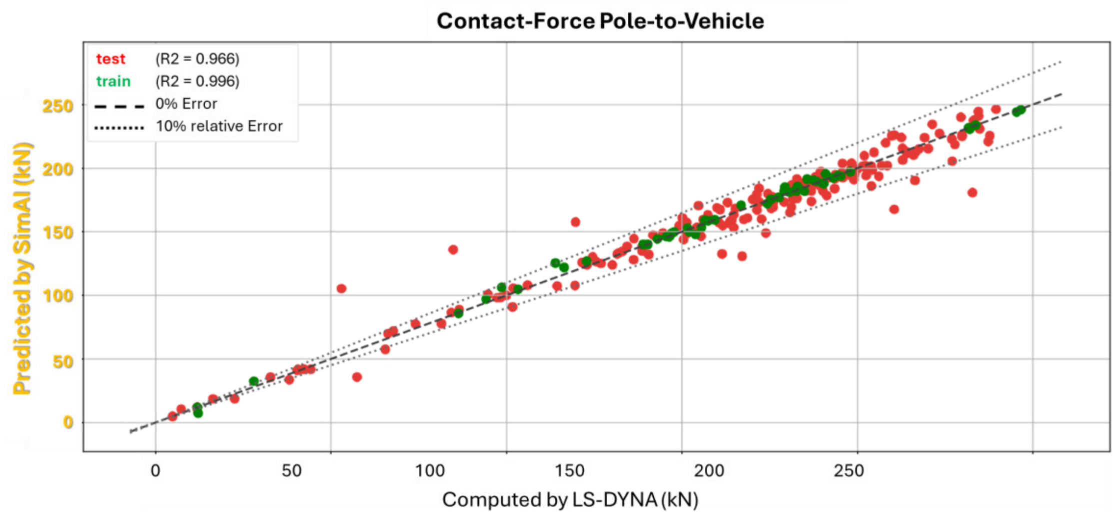
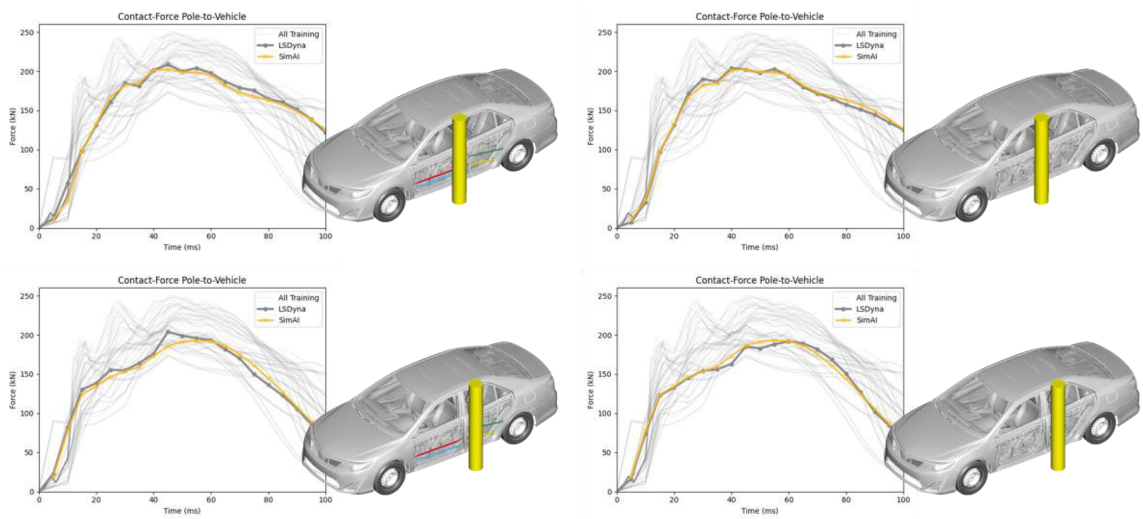
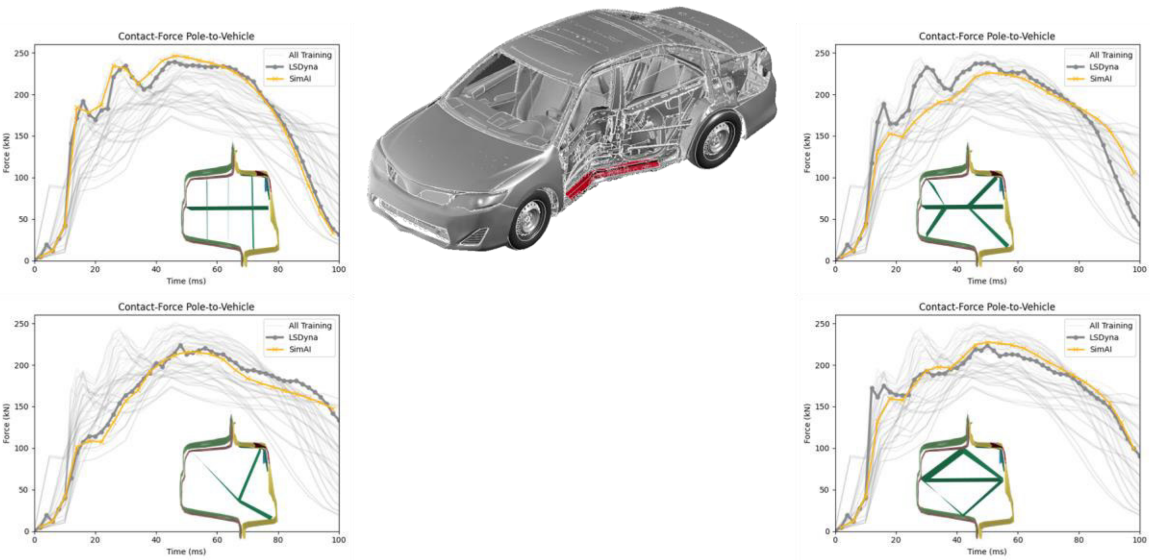


Fig.3: Comparison of contact forces predicted by SimAI and calculated by LS-Dyna.



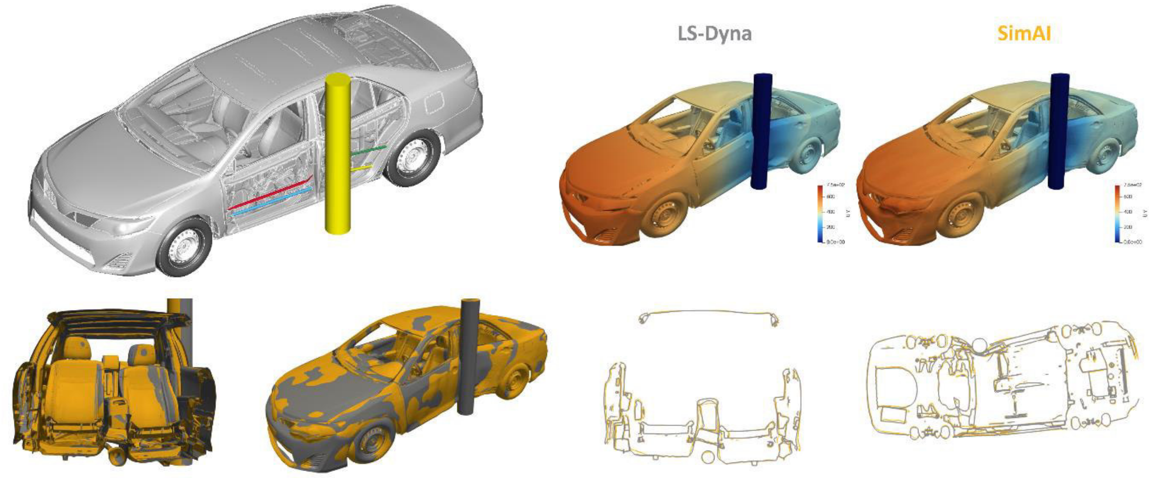
a.



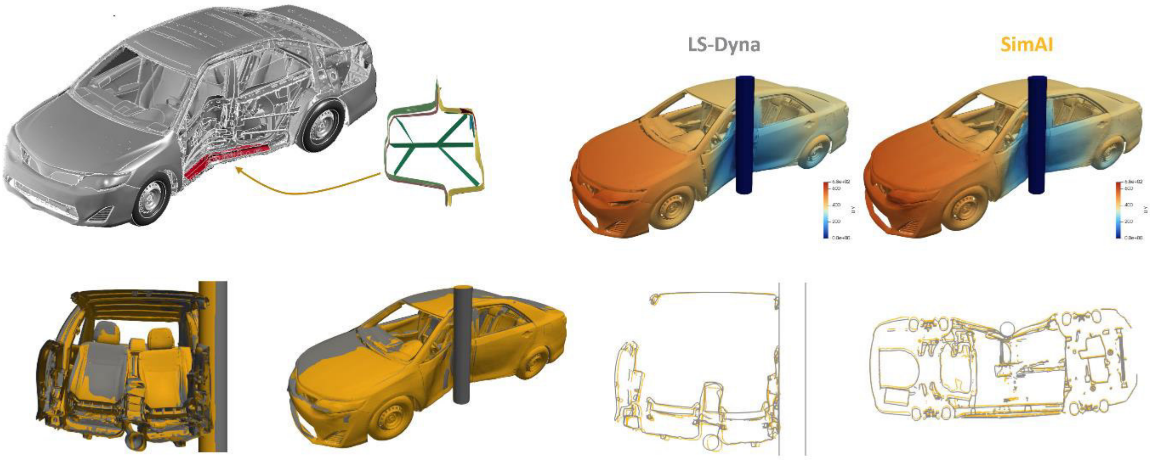
b.

Fig.4: Prediction of force-time responses for new geometries. Responses for test cases with variations a.) in pole position and door beam configuration, b. Responses for test cases with variations in the geometries of the rocker in-lay profiles.

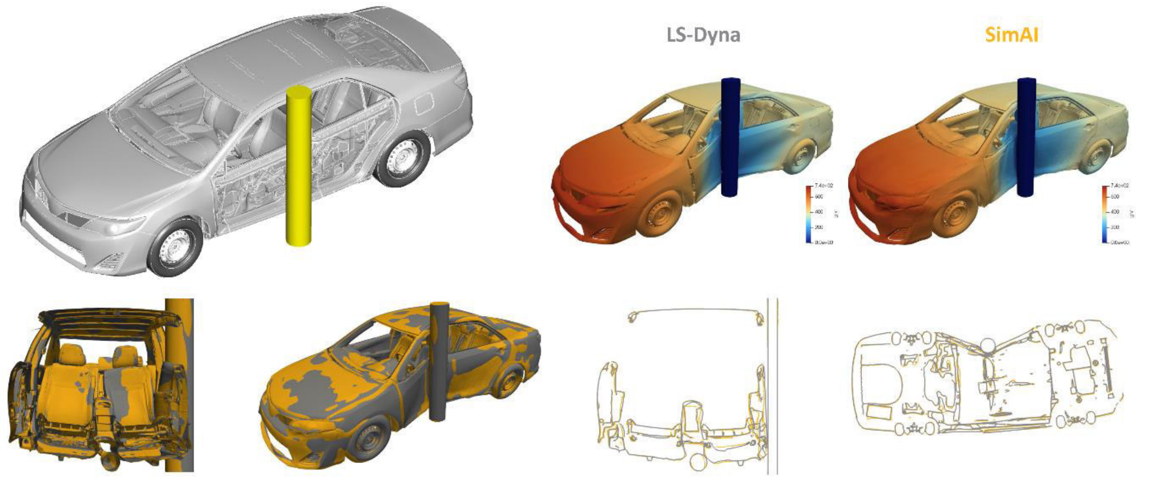
From these eight new geometries, we selected the three cases corresponding to bottom-left in Fig. 4a, top-right in Fig. 4b and top-right in Fig. 4a to further illustrate the quality of the deformation predictions made by SimAI. Due to space limitations, we present only these three cases here, the first two of which provide the worst predictions in terms of force-time responses, while the third appears to be the best prediction. These deformation predictions are shown in Figures 5a, 5b and 5c, respectively. It can be seen from the overlayed images that the SimAI predictions match well with the Solver output. Since the results are predicted as displacements for the entire car body as a transient response, the intrusions can be easily calculated from the SimAI prediction results, as is also done from the simulation results.



a.



b.



c.

Fig.5: Prediction of deformation responses for selected geometries with correspondence: a. Bottom-left in Figure 4a, b. Top-right in Figure 4b and c. Top-right in Figure 4a.

4.2 Testing SimAI model on a new case

Having been trained using both data sets, including the cross-combination of pole position with door beams and rocker in-lay profile variants, the SimAI model should also be able to predict mixed variants from both optimization studies. Such a completely new design is created by retaining only one beam in the front and rear doors (this is not available in the database prior to training) and selecting one of the unused rocker inlay profiles. The predicted displacements and force-time behavior are shown in Figure 6 with the same color coding as above. The predicted force-time response captures the peak values and also the general trend as simulated by LS-Dyna. The displacements are accurate enough for a prediction that takes only two minutes and are fully usable for evaluating the results of the selected design.

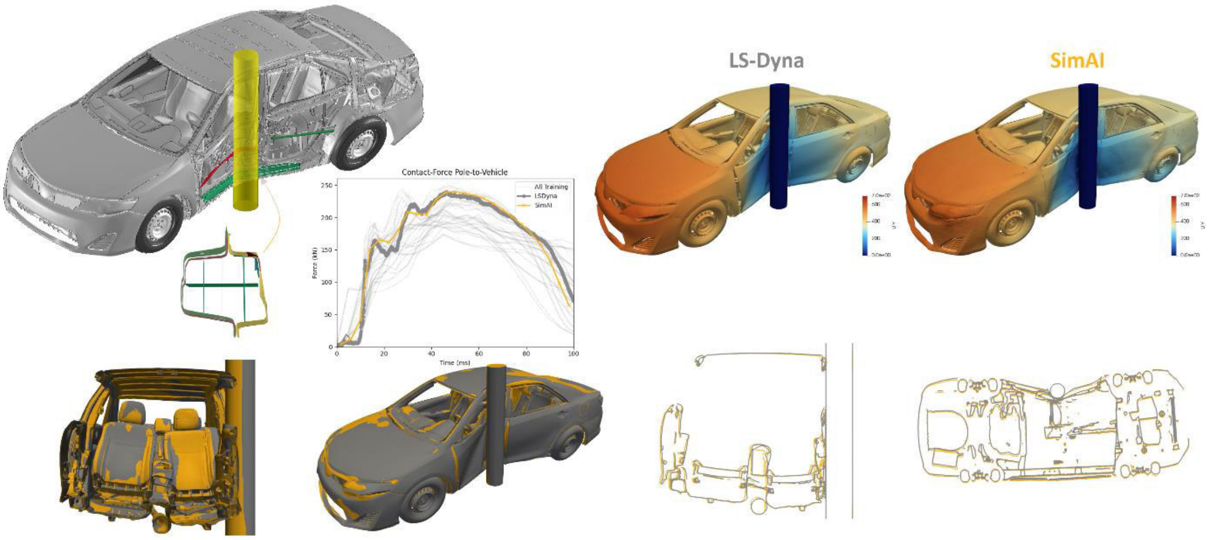


Fig.6: Prediction of deformation and force-time responses for a completely new design.

4.3 Testing on geometries generated by SimAIs design exploration tool

The seven new geometries in Fig. 2, generated using the SimAI design exploration tool as described in Section 2.1, are used as rocker inlay profiles, and the generated geometries are tested for side impact using the same SimAI model used throughout this study. These seven design explorations are also simulated using LS-Dyna to provide a basis for comparison. This comparison is first shown in Fig. 7 using the time-force responses, which show that most of SimAI's predictions are sufficiently accurate for the purposes of quantitative design optimization. From these seven geometries, we select the first and sixth, as these are the best and worst predictions in this set. The background curves in these diagrams are the same background curves shown in Fig. 4. These results are promising for the use of accelerated design exploration cycles, in which the new geometries are proposed by SimAI's geometry exploration tool and the crash event predictions are made again by SimAI without leaving the SimAI environment. By defining appropriate objective functions, this tool can perform quantitative optimization cycles and develop designs that open up new ways of thinking for designers.

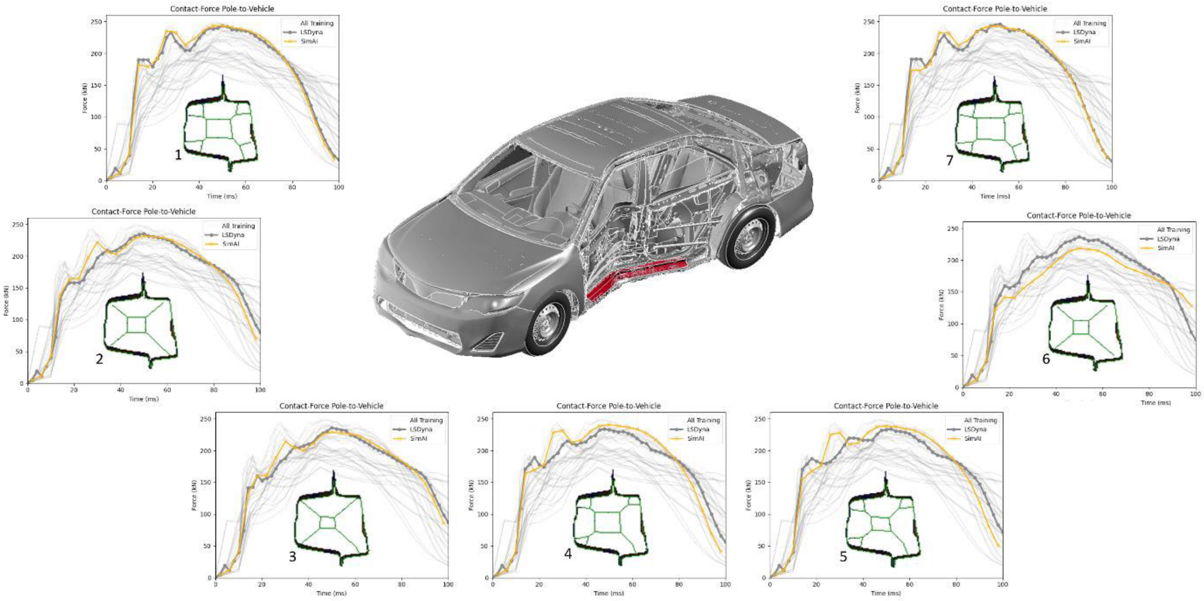
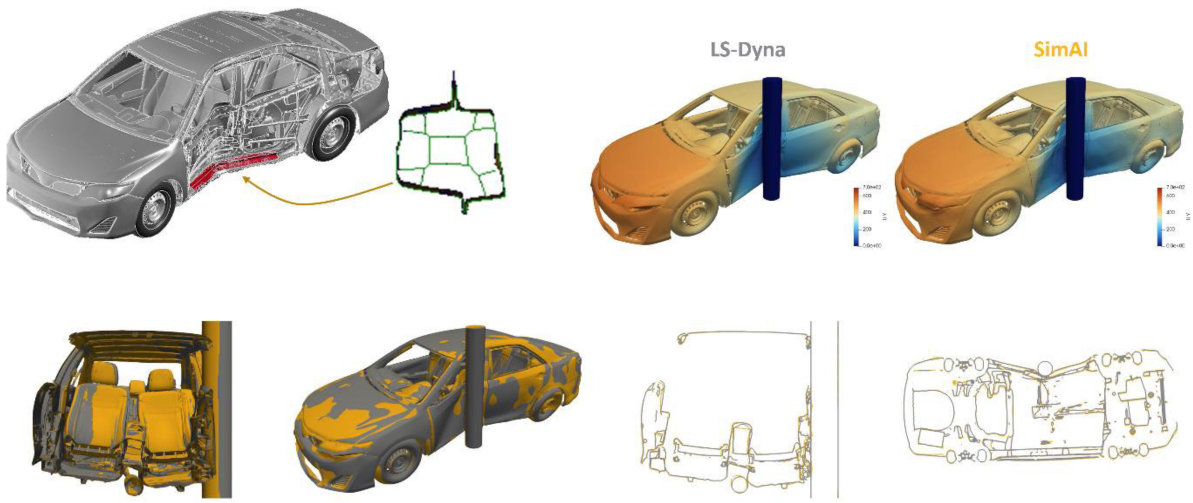
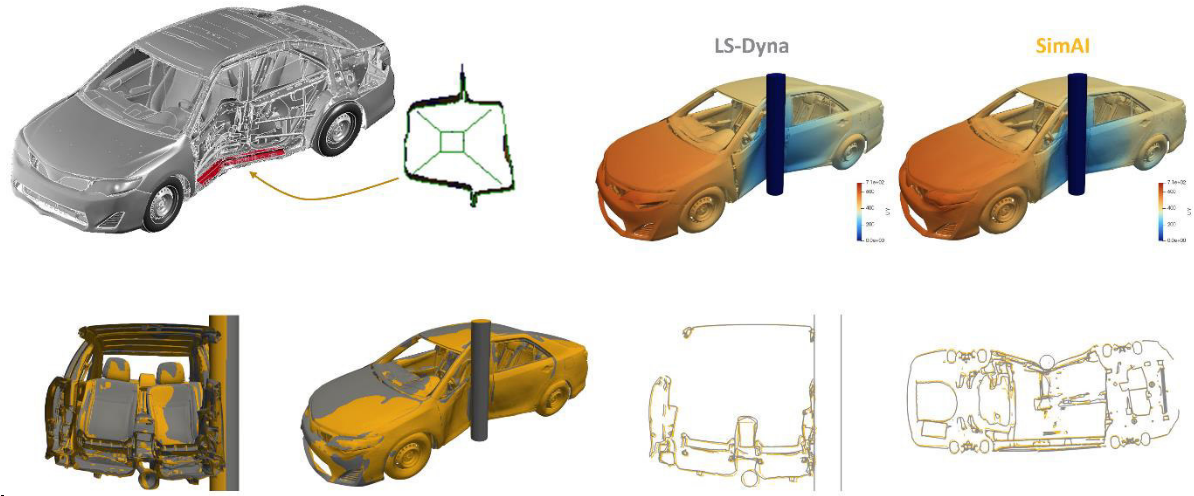


Fig.7: SimAIs force predictions are in line with LS-Dyna simulation results for the seven designs generated by the geometry exploration tool.



a.



b.

Fig.8: SimAI predictions versus deformations simulated by LS-Dyna for the inlay profiles 1 (a) and 6 (b) obtained by the AI-based design exploration tool.

5 Conclusion

This study demonstrates the transformative potential of AI-driven surrogate models for accelerating complex CAE workflows, particularly in the field of crash simulations in automotive engineering. By utilizing highly accurate LS-Dyna data, Ansys SimAI is able to simulate complex physical behaviors with significantly reduced computational effort. The models, which were trained with different pole positions, door beam configurations and rocker reinforcements, exhibit high predictive accuracy and generalizability, even for previously unknown geometries.

The integration of multiple data sets into a unified surrogate model further underscores SimAI's scalability and adaptability in multidimensional design spaces. This capability not only streamlines design iteration but also enables more comprehensive exploration of structural configurations without the high costs of traditional simulations. Furthermore, the platform's ability to integrate new data for continuous learning makes it a valuable tool for iterative engineering development and long-term optimization strategies.

SimAI's design exploration functionality facilitates the execution of quantitative geometry optimization studies, reducing the time required for manual design iterations by a significant fraction. Moreover, it facilitates the generation of wholly novel design variants, thereby expanding the existing design paradigm.

Overall, the results confirm that AI-based surrogates such as Ansys SimAI are more than just computational shortcuts – they are enablers of agile, data-driven design processes that can leverage both legacy and newly generated simulation data to drive innovation in vehicle safety and performance engineering.

6 Literature

[1] M. Redhe, J. Forsberg, T. Jansson, P.O. Marklund, L. Nilsson, “Using the response surface methodology and the D-optimality criterion in crashworthiness related problems” Structural and Multidisciplinary Optimization 24, (2002) 185–194.

[2] P. Friedrich, U. Reuter, M. Thiele, D. Weigert, “Application of model order reduction techniques in LS-Dyna” 11th European LS-DYNA Conference, 2017, Salzburg, Austria.

[3] E. Raponi, M. Bujny, M. Olhofer, N. Aulig, S. Boria, F. Duddeck, “Kriging-assisted topology optimization of crash structures” Comput. Methods Appl. Mech. Eng. 348 (2019) 730-752.

[4] F. Scarselli, M. Gori, A.C. Tsoi, M. Hagenbuchner, G. Monfardini, “The Graph Neural Network Model” IEEE Transactions on Neural Networks 20(1), (2009) 61-80.

[5] Fabio Parisi, Sergio Ruggieri, Ruggiero Lovreglio, Maria Pia Fanti, Giuseppina Uva, “On the use of mechanics-informed models to structural engineering systems: Application of graph neural networks for structural analysis” Structures, Volume 59, 2024

[6] Shih-Pu Kuo, Pierluigi D’Acunto, Ian F.C. Smith, “Graph Neural Networks for Fast Structural Analysis to support Interactive Design Decision-Making”, EG-ICE 2025: AI-Driven Collaboration for Sustainable and Resilient Built Environments Conference Proceedings

[7] Jie Zhou, Ganqu Cui, Shengding Hu, Zhengyan Zhang, Cheng Yang, Zhiyuan Liu, Lifeng Wang, Changcheng Li, Maosong Sun, ”Graph neural networks: A review of methods and applications”, AI Open, Volume 1, 2020, Pages 57-81

[8] https://www.ansys.com/products/simai

[9] https://www.ccsa.gmu.edu/models/2012-toyota-camry