WHITE PAPER

AI FEASIBILITY STUDY: OPTIMIZING CRASH PERFORMANCE USING PHYSICSAI

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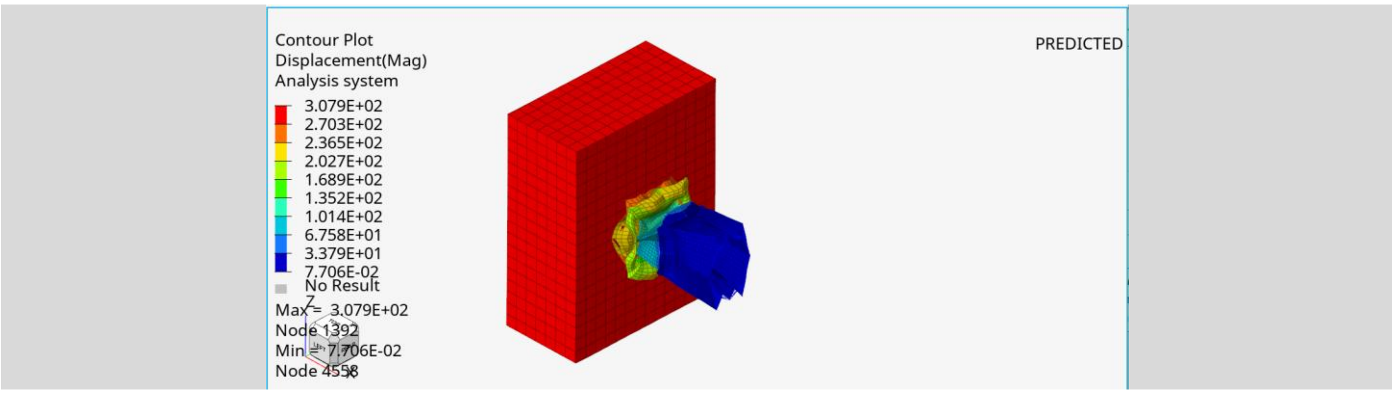

Introduction

Crush zone management is an important aspect of automotive safety design. During a collision, the crush zone helps control the forces passed onto passenger sections by absorbing much of the kinetic energy involved. The design principle involves maximizing the energy absorbed by the vehicle and restricting intrusion for occupant safety. This whitepaper instructs readers how to use Altair® PhysicsAI™ to design rails — a key component of crush zone design. It outlines how AI models were trained on 450 finite element analysis (FEA) crash simulations (each with different rail geometry) and then validated using another 50 simulations. It also outlines how Altair® HyperStudy® was used to create a workflow to optimize the rail's design using PhysicsAI. The paper highlights that AI model results showed good consistency with FEA model results when compared via R-squared values, visual inspections, and Pareto fronts. Thus, the paper suggests that PhysicsAI models can effectively perform early-stage rail design evaluations and optimizations while returning results 5 times faster than traditional FEA workflows.

Challenges

Engineers face significant challenges modeling transient, large deformation simulations, such as automobile crash testing, as they are complex and computationally expensive. Even when assessing simple rail geometry engineers are often committed to long CAE design cycles that require the assistance of highly skilled CAE analysts. This long design cycle restricts the number of design variants that engineers can evaluate due to economic and time constraints. However, engineers can streamline their workflows by creating surrogate models such as AI and reduced order models (ROMs). As these models provide results quickly, and with less computational costs, engineers can rapidly evaluate rail, crush zone, and assembly designs without the need for time consuming FEA computations.

For decades, engineers used ROMs as the surrogate model of choice to replace 3D FEA models. However, ROMs can suffer from low fidelity, require a 3D model to be parameterized, and are unable to provide transient results over time. For example, ROMs fail to predict 3D fields, curves, and key performance indicators (KPIs) when rail, crush zone, and assembly geometry vary greatly. To assess highly transient crash events, engineers need surrogate models that offer high fidelity, low-computation time, and accurate results over the duration of the crash event.

PhysicsAI aims to fill that role with its geometric deep learning engine and AI modeling workflows. The following proof-of-concept evaluation assesses PhysicsAI's transformer-based deep learning method — known as a transformer neural simulator (TNS) — to see if it meets these challenges. It also assesses how the AI models produced via the software perform when predicting crash results. The purpose of this assessment is to outline the feasibility of using PhysicsAI to optimize rail geometry based on crash performance.

Problem Formulation

Since the focus of this proof-of-concept study is to assess the feasibility of using PhysicsAI to help design rail cross sections, simple rectangular cross sections were used. Other traditional parameters of crush zones (such as crush initiating features or the use of overlapping C-shaped members) were not part of the scope. Once feasibility is established, further studies with more realistic parameters can be conducted.

The model setup was designed to assess the performance of a rail, intended to be part of a crush zone, during crash scenarios. In this case, the rail was 500 mm long with a hollow rectangular cross-section. The rail was fixed at one end. On the other end, it was impacted by a 300 kg rigid column moving at a velocity of 70 km/h.

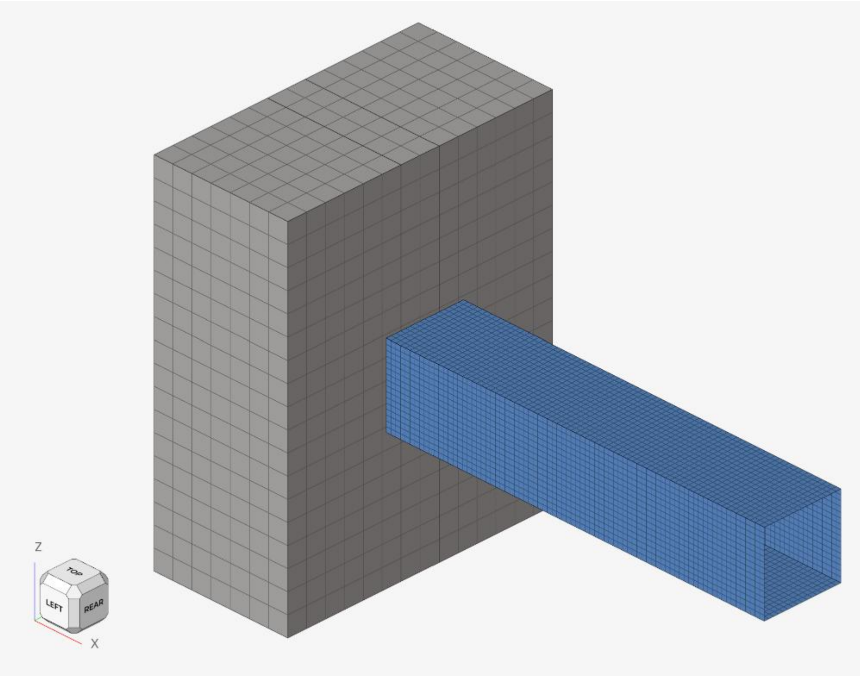

Figure 1 – Rail is fixed on one end. The other end is impacted by a rigid moving column.

HyperStudy helped synthetically generate AI training and validation data by developing a design of experiment (DOE) workflow. The DOE governed the rail's cross-sectional attributes through 45 independent shape-morphing variables (in the radial direction) as well as a variable to control the material thickness. The initial sectional perimeter of the rail was 101.6 mm; this value was constrained to change ±3 mm from the base value. The rail's material thickness varied between 1 mm and 4 mm. It was made of steel using the software's default material properties. All rail geometries evaluated in this study maintained the same aforementioned length.

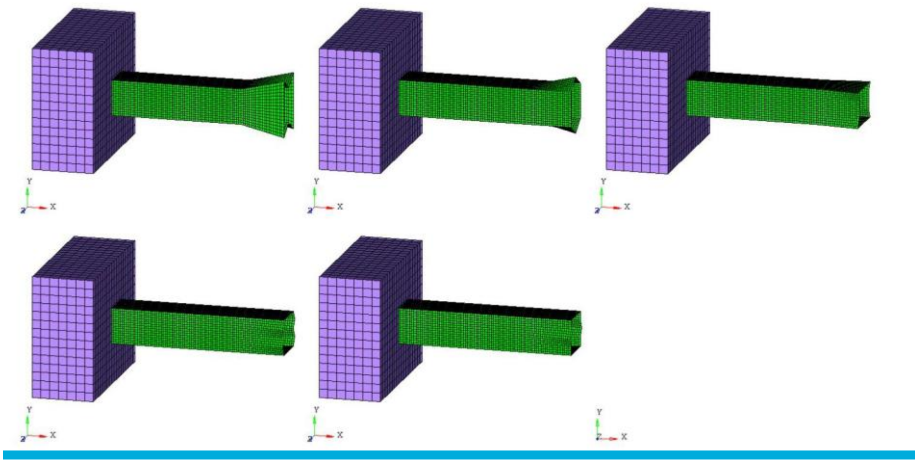

Figure 2 – Five shape morphing patterns applied to the rail.

Altair® Radioss® produced the FEA transient crash simulations for each geometry generated by the DOE. Symmetrical conditions were applied along the two planes perpendicular to the cross-section of the beam to ensure computational efficiency. It was understood that buckling of a rail is a non-symmetrical phenomenon, however this simplification enables fast evaluation while maintaining an acceptable level of accuracy for most KPIs within a proof-of-concept study. The rail was meshed with 1280 shell elements. The transient crash simulations studied consisted of a total time span of 20 milliseconds with 100 frames in the animation. The DOE generated a total of 500 FEA simulation results. The AI models were trained using 450 randomly selected simulations. The remaining 50 simulations validated the AI models.

Experiments and Results

Three separate PhysicsAI models were trained using the TNS architecture and 450 randomly selected FEA results. One model predicted the rail's displacement while the other two predicted the impact force and internal energy, respectively. GPUs trained the AI models over time spans that varied between three to four hours. Note that total intrusion, plastic strain contour, or pulse (deceleration over time) are other parameters that may be assessed in future studies after the proof-of-concept analysis.

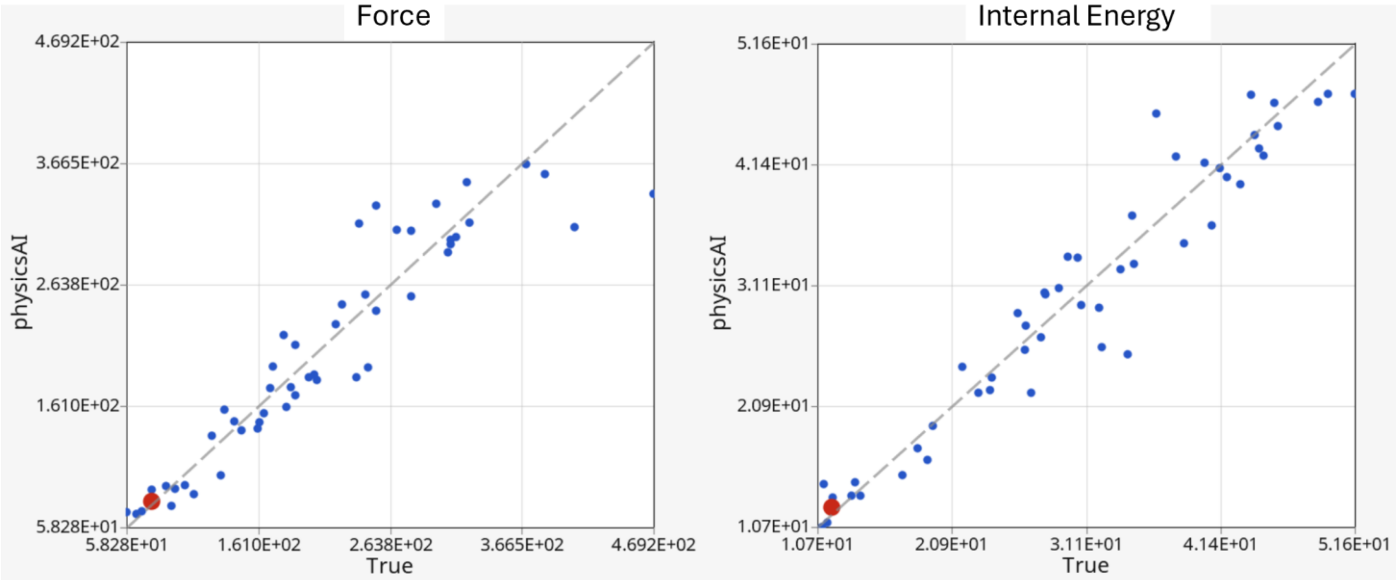

Figure 3 – Simulated (true) vs AI predicted (PhysicsAI) impact force (left) and internal energy (right).

Figure 3 highlights the results from the AI models for the impact force and internal energy and compares them to the FEA validation results. The spreads in Figure 3 closely aligns to a 45-degree diagonal, thus those two AI models returned accurate results when compared to the FEA results.

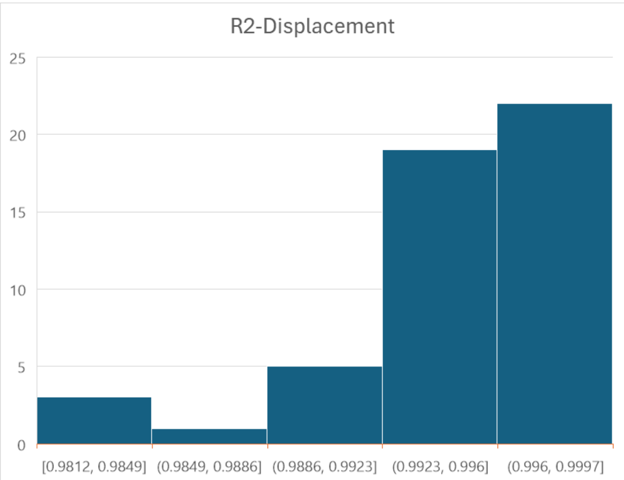

Figure 4 – A histogram chart of R-squared values for each of the 50 validation geometries. The R-squared values for each geometry were calculated by comparing the displacement results for each node as calculated by the FEA and AI models.

The validation of the displacement AI model required comparing the displacements of each node within a given geometry as calculated by an FEA simulation and the AI model, respectively. The FEA and AI model displacements for each corresponding node were cumulated into a single R-squared value for each of the 50 validation geometries. When these R-squared values equal one, it represents an exact match between the FEA and AI results. The resulting 50 R-squared values for each validation test are plotted within a histogram in Figure 4. The values are all above 0.98, with the median being 0.9949. This suggests that the displacement AI model showed excellent accuracy when compared to the FEA test data.

In addition to the above quantitative evaluation, the predicted displacements were visually inspected to ensure compliance in terms of the rail's deformed shape at different frames during the animation of the crash event (Figure 5). ROMs are unable to produce full 3D displacement fields for each frame, so demonstrating PhysicsAI's ability to do this shows its advantages over traditional ROMs. Figure 5 shows the AI models produce fairly good predictions for the non-linear, transient deformations, buckling, and impact at each frame. However, there are minor differences in the deformed shape of the rail at the opposite end of the wall. After this proof-of-concept analysis is completed, future studies can aim to address these differences.

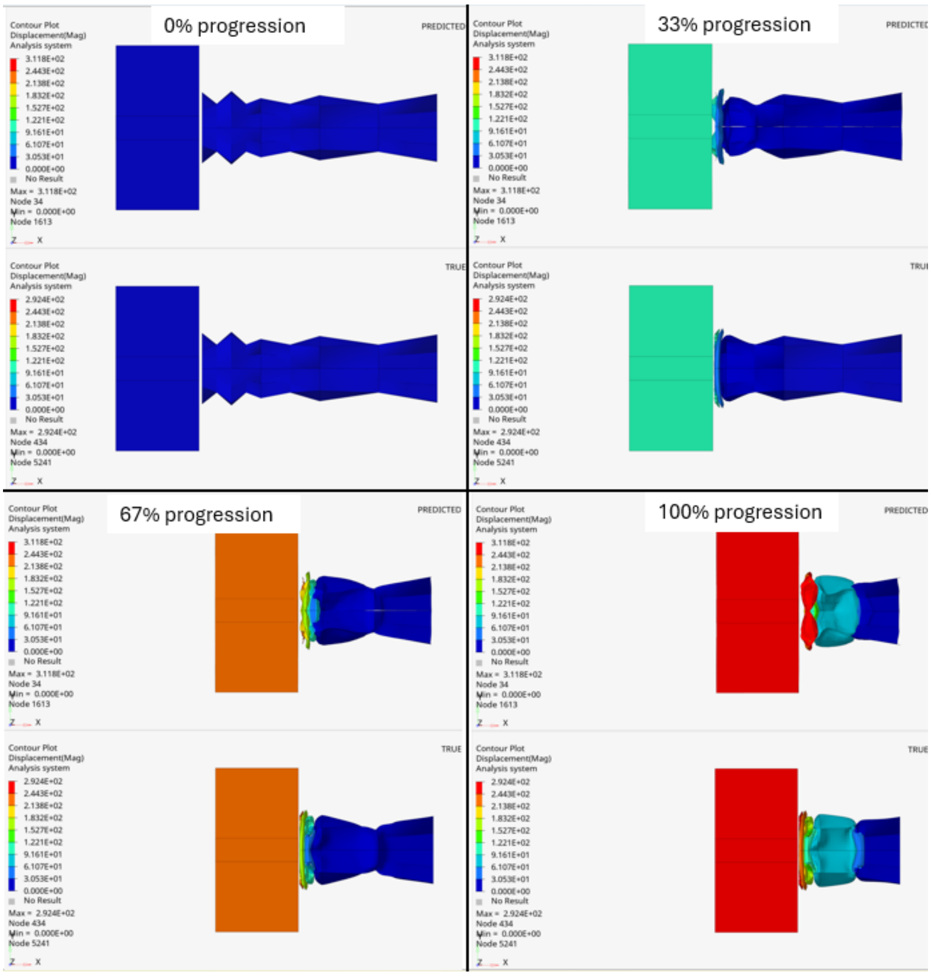

Figure 5 - Crash progression plots comparing FEA simulated (true) vs AI (predicted) displacement results at 0% progression (top-left), 33% progression (top-right), 67% progression (bottom-left), and 100% progression (bottom-right) for a single geometry.

All of the aforementioned assessments demonstrate that PhysicsAI models had an accuracy level acceptable enough to evaluate an optimization workflow. Thus, HyperStudy was used to set up an optimization as a means to explore the rail's design space. For all assessments, the rail had a set aspect ratio and length, however, its cross section and material thickness could vary. The goals were to minimize the impact force and internal energy. Constraints for manufacturability were applied to the sectional perimeters, with a maximum permissible deviation of 3 mm from the perimeter's initial value of 101.6 mm. The thickness was constrained between 1 and 4 mm. The optimization workflow was then performed twice, once using the PhysicsAI models and again using traditional FEA.

Figure 6 shows the two Pareto fronts, comparing the internal energy vs maximum force, for the various design permutations assessed by FEA and PhysicsAI. Pareto fronts are used to help engineers assess optimization tradeoffs. In this case, it shows there is a limit as to how much the impact force and internal energy will be reduced because they are in trade-off. The Pareto front created using PhysicsAI had a maximum deviation of only 15% from the one created using the Radioss solver. This further suggests that PhysicsAI can return results of sufficient accuracy to drive early rail and crush zone development and optimizations.

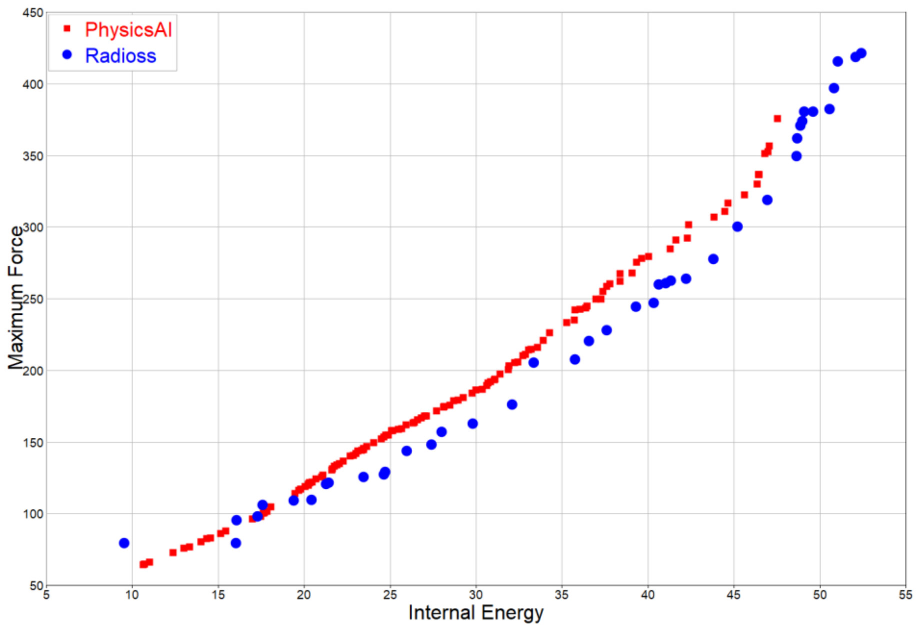

Figure 6. Pareto plots generated by PhysicsAI driven optimization (red) and FEA solver driven optimization (blue)

It should be noted that the PhysicsAI driven optimization was performed five times faster than the optimization process using traditional FEA. That suggests that AI can be used to perform quick crash-test, product, and part optimizations without significantly affecting the quality of results.

Conclusion

This white paper shows the effectiveness of using PhysicsAI models for the rapid, comprehensive design space exploration of the crush zone of a rail. PhysicsAI models predicted both qualitatively and quantitatively reliable results, such as correctly predicting the Pareto front. In addition to scalar KPI values, PhysicsAI closely matched the large-deformation, transient buckling, and folding of the rail at multiple timesteps. This is a significant advantage over ROMs which are unable to predict full 3D field predictions over the duration of a crash event. PhysicsAI can predict crash-test results using meshes or CAD models (without parameterization). Moreover, in the absence of historical training data, synthetic data can be generated using a DOE workflow derived via HyperStudy. Finally, a part optimization workflow ran five times faster when using PhysicsAI surrogate models, compared to traditional FEA solvers, without affecting accuracy.

This study serves as a proof-of-concept analysis. It shows the viability of PhysicsAI to design and optimize rail geometry for crash events. It could be taken further, in future studies, by using more detailed geometry inputs and additional KPIs that are used in the industry.

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