Surrogate Modeling in the Automotive Industry

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With around 2.2 million jobs, the automotive industry is Germany's largest industrial value-adding sector. A modern vehicle is a highly complex mechatronic system that increasingly acts and reacts autonomously.

Simulation and modeling play a key role in bringing such systems to the road in a cost-efficient, safe, and regulation-compliant way. While conventional simulation pipelines have enabled physically grounded crash analysis for decades, it is surrogate models—i.e., efficient approximations of complex simulations—that now facilitate rapid prototyping, design optimization, and real-time onboard evaluation. This is particularly relevant in holistic approaches to vehicle safety, where the entire chain—from occupant simulations for injury prediction and comfort analysis to full-vehicle crash simulations—is considered. Below, we present three application scenarios that we have explored in recent years, partly in collaboration with partners from the automotive industry:

Model Reduction for NVH Analysis of Flexible Multibody Systems

For analyzing the NVH behavior (Noise, Vibration, Harshness) of flexible multibody systems, automated model reduction is essential. Techniques such as the Craig-Bampton method, Krylov subspace approaches, or modal reduction allow nonlinear flexible bodies to be efficiently integrated into simulations, see [2]. Over the years we developed our in-house software Morembs [1] to cluster those methods, build interfaces to commercial software solutions and export those models.

Structural Optimization in Crash Simulations

Crash simulations pose a unique set of challenges for surrogate modeling due to their highly nonlinear and transient dynamics, non-continuous boundary conditions (e.g., contact and impact), and limited accessibility of underlying simulation models, which are often embedded in commercial software. These aspects call for tailored surrogate modeling approaches. In the context of data-driven modeling, latent space embeddings have proven effective in capturing the complex dynamics of high-fidelity simulations in a compact, low-dimensional, and information-rich representation [6]. Such representations ease the learning process and improve generalization for downstream tasks using black-box machine learning models.

To further exploit the structure of crash data, we applied geometric deep learning techniques—such as graph neural networks—that can leverage spatial correlations inherent in irregular and mesh-based simulation outputs. Multi-scale and hierarchical learning schemes enable efficient encoding of both local (micro-scale) and global (macro-scale) features, mitigating common limitations of neural network architectures such as spectral bias. The effectiveness is shown for the structural response of a simplified crash scenario which could reduce computational costs by up to four orders of magnitude [7].

Surrogate Models as a Bridge Between Simulation Models in Human Body Models

In addition to pure computational acceleration, surrogate models are an enabling technology for the transfer of properties between different simulation models. In many scenarios, multiple models represent the same physical system but differ in key aspects such as evaluation time, fidelity, interpretability, and how they handle complex features like contact mechanics. By learning to predict relevant output quantities in a representation compatible with the target model, a surrogate model can serve as a proxy—effectively bridging the gap between these diverse simulations.

This allows for the transfer of useful characteristics from one model to another. Moreover, surrogate models provide differentiable metamodels that replicate the input-output behavior of complex simulations. This not only makes them useful for integration with gradient-based algorithms but also significantly reduces computation time during the online phase. Thanks to these capabilities, surrogate models are particularly well-suited for tasks such as optimization (e.g., optimal control), inverse problems (e.g., parameter identification), and sensitivity analysis. For example, within the EMMA4Drive project, we used such surrogates to learn human–seat interactions in autonomous driving scenarios, enabling us to develop a human body model capable of predicting human-like motion of occupants [3, 4, 5].

References

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