

EFFICIENT SIMULATION AND UNCERTAINTY QUANTIFICATION OF PROGRESSIVE CRUSHING IN COMPOSITE LAMINATES

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Abstract

This study introduces a computational, data-driven framework for simulating the variability observed in progressive crush tests of composite laminates. A large virtual dataset is generated using efficient finite element analyses (FEA) of flat coupon carbon fibre–reinforced polymer (CFRP) laminates subjected to axial crushing. This dataset enables a systematic global sensitivity analysis to identify the FEA input parameters that most strongly influence the structural crush response. These insights guide the development of machine-learning surrogate models capable of rapidly predicting the crush behaviour of composite specimens with minimal computational cost. Leveraging these surrogate models, uncertainty quantification is performed using a Markov Chain Monte Carlo (MCMC) scheme to estimate parameter distributions that reproduce experimentally observed response variations. The proposed framework provides a scalable pathway for probabilistic assessment of progressive crushing in composite structures. By enabling fast surrogate-based predictions and statistically grounded parameter calibration, the methodology substantially reduces computational cost and accelerates the certification workflow for CFRP materials and components.

Keywords: Crushing, Composites, Finite element analysis, Machine learning, Uncertainty quantification

1. Introduction

Fibre-reinforced polymers (FRPs) are often preferred over metallic components in aerospace structures owing to their excellent energy-absorption capability paired with low structural weight. To deploy aerospace-grade composite laminates safely and effectively, it is essential to characterise and simulate the failure mechanisms that govern their structural response under extreme loading. During axial crushing of FRP laminates, the overall energy dissipation is governed by two dominant macroscopic failure modes: splaying and fragmentation [1]. These modes originate from the failure of the FRP's constituents where fibre-dominated fracture primarily drives fragmentation, and matrix-related cracking and interlaminar delamination lead to splaying. Accurate simulation and prediction of these mechanisms is critical when assessing crashworthiness or impact-driven failure in aerospace composite substructures.

However, performing physics-based finite element (FE) simulations of full-scale composite components under crushing or other high-intensity loading scenarios remains highly challenging [1]. The difficulty arises from the inherently nonlinear and multiaxial material behaviour, large deformations, and complex contact interactions. Consequently, many current industrial FE models still rely on empirical tuning parameters, which, while improving numerical stability, reduce the physical fidelity and predictive robustness of the analysis.

To address these challenges, continuum damage mechanics (CDM) models offer a promising pathway. By preserving mesh continuity while progressively reducing material stiffness in a smeared manner, continuum models provide a computationally efficient framework for representing distributed

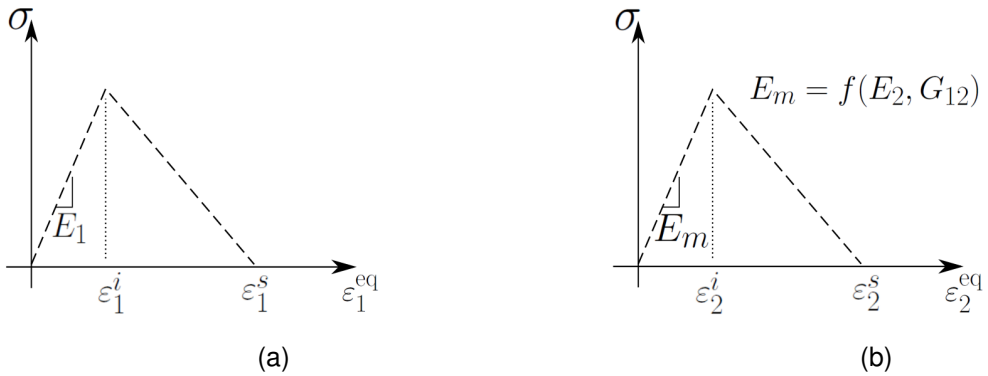


Figure 1 – CODAM2 input parameters to simulate ply-level material behaviour illustrated by corresponding stress–strain responses in the (a) longitudinal and (b) transverse direction.

damage without necessitating explicit modelling of every crack or delamination. This approach enhances the feasibility of simulating large aerospace structures while maintaining a physically motivated basis for material degradation.

An additional advantage of CDM is its computational efficiency, which enables the generation of large virtual datasets through systematic variation of FE input parameters. This, in turn, motivates the application of uncertainty quantification (UQ) to represent the inherent variability observed in the mechanical response of FRP composites [2, 3]. By inferring appropriate probabilistic distributions for sensitive FE parameters based on experimentally measured scatter, the variability in crush response can be realistically captured. Because UQ procedures typically require tens of thousands of model evaluations, machine learning surrogate models are introduced to provide the necessary computational speed-up [4, 5].

In this work, we present a comprehensive computational framework capable of simulating the crush response of FRP laminates, including their variability. Key FE input parameters are treated as probabilistic quantities, and their underlying distributions are efficiently estimated by combining physics-based FE modelling with fast machine learning surrogate predictions. The resulting methodology has significant potential to accelerate the design and certification of FRP composite structures, where accounting for inherent material and structural uncertainties is essential.

2. Methodology

The following study investigates flat coupons of quasi-isotropic $[90/\pm 45/0]_{2s}$ Hexcel HexPly IM7/8552 Carbon Fibre Reinforced Polymer (CFRP) laminates subjected to axial crush tests. As part of the Composite Materials Handbook 17 (CMH–17) Crashworthiness Working Group [6] activities, the experimental tests were conducted at the University of Utah [7].

2.1 Finite Element Analysis

Progressive failure in CFRP laminates is simulated through the strain-based COMposite DAMage Model (CODAM2) [8], available as MAT219 in the commercial FE software LS-DYNA [9]. Using strains evaluated in each ply of the laminate, CODAM2 takes into account ply-based material behaviour that adhere to preserving the characteristic fracture behaviour of the laminate. Figures 1(a) and (b) present the model inputs and the corresponding stress–strain responses in the longitudinal and transverse directions, respectively. The objective of this study is to characterise the statistical distributions of these finite element input parameters in order to represent the uncertainty observed in axial crush experiments of quasi-isotropic IM7/8552 CFRP laminates.

Figure 2 illustrates the FE modelling of the test configuration to analyse flat CFRP coupon specimens subjected to axial crushing [1]. A prescribed velocity of $v = 4\ m/s$ is applied to the upper row of elements in the composite specimen, while two rigid support plates ensure guided, purely vertical motion of the laminate prior to impact against a rigid plate. The upper 20 mm region of the coupon is laterally constrained by fixing the translational degrees of freedom in the y- and z-directions. Because the analysis is performed under quasistatic conditions, the mass of the impactor is neglected.

A constant imposed velocity is therefore sufficient to initiate and sustain the crushing process. A sawtooth trigger is incorporated at the impacted end of the specimen to promote stable, progressive crushing behaviour consistent with typical composite crash modelling practices. Contact interactions are represented by a friction coefficient of $\mu = 0.2$ between the coupon and the impact plate, while the interfaces between the coupon and the guiding support plates are modelled as frictionless. Based on previous mesh topology studies, a skewed mesh with an element-edge inclination of 10° is employed. The characteristic element length is set to 1.0 mm, providing a balance between computational efficiency and adequate resolution of crushing-induced damage. Note that the CFRP laminate is modelled using a single shell element through the thickness, a common approach for capturing the global crushing response of thin composite plates.

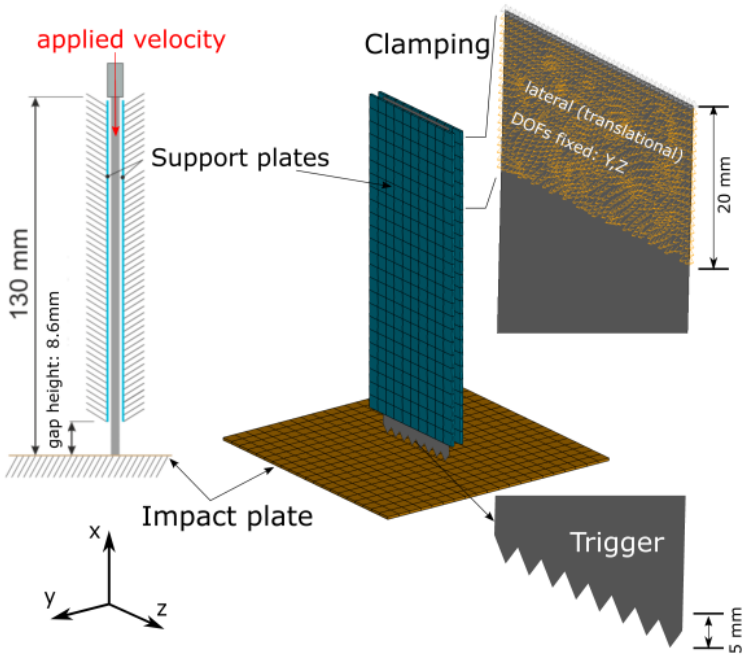


Figure 2 – Illustration of finite element model to simulate progressive axial crushing of $[90/\pm 45/0]_{2s}$ carbon fibre reinforced polymer laminates, including boundary conditions, loading configuration, and trigger mechanism [1].

The combination of the CODAM2 material model with the efficient axial crush modelling results in comparatively fast computation times, with a single analysis requiring only 3–5 minutes on a standard workstation. This computational efficiency enables the exploration of data-driven approaches to represent experimentally observed uncertainty in the composite crush response.

2.2 Data Analysis and Machine Learning Surrogate Modelling

Uncertainty quantification requires a very large number of model evaluations, making direct FE analyses computationally impractical. Consequently, fast surrogate models are needed to replace or augment FE simulations. A crucial first step is identifying the most influential FE input parameters [10], as this reduces the dimensionality of the problem and greatly facilitates the development of effective machine learning models.

Building on the outcomes of the sensitivity analysis, a computationally efficient machine learning–based surrogate model will be developed. This model will incorporate the identified influential FE input parameters and establish their relationship with key crush-related response metrics. Leveraging this rapid evaluation framework, comprehensive uncertainty quantification can then be performed.

2.3 Uncertainty Quantification

Bayes' rule [11] in Equation (1) can estimate the posterior density $p(x|y_{\text{test}})$, where x denotes sensitive FE inputs, and y_{test} the experimental data such that

$$\underbrace{p(x|y_{\text{test}})}_{\text{posterior}} \propto \underbrace{p(x)}_{\text{prior}} \quad \underbrace{p(y_{\text{test}}|x)}_{\text{likelihood}} \quad . \tag{1}$$

Bayes' rule states that the posterior density is proportional to the product of assumed prior densities $p(x)$ of the FE inputs and the likelihood $p(y_{\text{test}}|x)$. The likelihood is evaluated by the machine learning surrogate model $\mathscr{M}$, and is assumed to follow a normal distribution such that

$$p(y_{\text{test}}|x) = \mathscr{N}\left((y_{\text{test}} - \mathscr{M}(x)), \sigma_{\text{test}}\right), \tag{2}$$

where the experimental data follow a normal distribution $y_{\text{test}} \sim \mathscr{N}(\mu_{\text{test}}, \sigma_{\text{test}})$, with mean μ_{test} and covariance σ_{test}, representing the average measured value from experiments and variations, respectively.

3. Results: Calibration

In this study, the experimental data are derived from axial crush tests conducted at the University of Utah as part of the CMH-17 working group activities on crashworthiness [7]. Figure 3 presents three representative force–displacement curves obtained from these experiments. From these tests, the specific energy absorption (SEA) is calculated as

$$\text{SEA} = \frac{P_{\text{crush}}}{\rho A}, \tag{3}$$

where P_{crush} denotes the mean crush force during stable progressive crushing (taken here over the displacement range of 6 mm to 15 mm), ρ is the material density, and A is the cross-sectional area of the flat coupons. Based on these experiments, a mean value of $\mu_{\text{test}} = 46.7$ kJ/kg and an assumed standard deviation of $\sigma_{\text{test}} = 1$ kJ/kg are extracted for use in the uncertainty quantification framework, as defined in Equation (2).

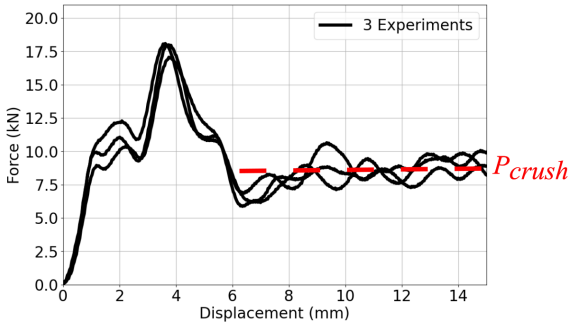
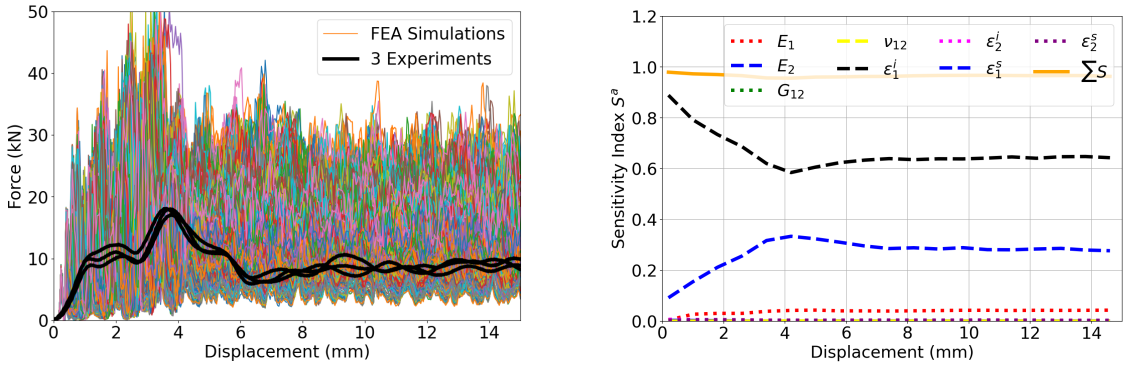


Figure 3 – Experimental force–displacement responses from axial crush tests of flat CFRP coupons conducted at the University of Utah [7].

The efficient FE modelling framework outlined in Section 2.1 is applied across a broad range of CODAM2 input parameters to generate a comprehensive dataset, following a similar approach to that presented in [10]. Figure 4(a) shows the resulting force–displacement responses obtained from 1,500 FE simulations. This extensive dataset forms the basis for a global sensitivity analysis [10], enabling the quantification of the influence of individual CODAM2 input parameters on the predicted crush response. The results of this analysis are summarised in Figure 4(b), where a sensitivity index greater than zero indicates that the corresponding parameter has a measurable effect on the force–displacement behaviour. It is observed that all material properties associated with the longitudinal (fibre) direction are influential to various degrees, including the elastic modulus E_1 as well as the damage-related parameters, namely the initiation strain ε_1^i and the saturation strain ε_1^s (see Figure 1 for an illustration of these parameters).



(a) (b)

Figure 4 – (a) Force–displacement responses from 1,500 FE simulations obtained by varying CODAM2 input parameters, and (b) results of the global sensitivity analysis, highlighting the influence of individual CODAM2 input parameters on the crush response.

Consequently, a machine learning–based surrogate model can be developed to efficiently approximate the FE response. The three most influential CODAM2 input parameters are related to the resulting SEA values obtained from the 1,500 FE simulations shown in Figure 4(a). In this study, Gaussian Process Regression (GPR) is employed, as it has been demonstrated to provide high accuracy and efficiency for relatively small datasets (e.g. [12]). It is noted, however, that alternative surrogate modelling approaches, such as linear or polynomial regression, could also be considered. Figure 5 presents a parity plot demonstrating that the GPR surrogate model accurately predicts the SEA as a function of the three sensitive CODAM2 inputs, achieving a coefficient of determination R^2 exceeding 98%. This surrogate model is denoted as $\mathscr{M}$ in Equation (2) and forms the basis for the uncertainty quantification framework.

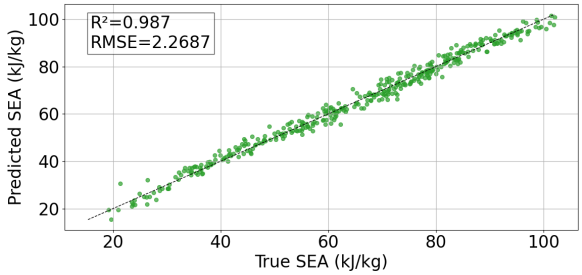


Figure 5 – Parity plot comparing Gaussian Process Regression (GPR) surrogate model predictions with FE-computed specific energy absorption (SEA), demonstrating high predictive accuracy.

To apply Bayes' rule as stated in Equation (1), prior distributions must be specified for the sensitive CODAM2 input parameters. For the longitudinal modulus E_1, a normal prior distribution is adopted with a mean of 150 GPa and a standard deviation of 7.5 GPa, based on values reported in previous studies [2, 5]. In contrast, the damage initiation strain ε_1^i and saturation strain ε_1^s are more difficult to estimate a priori. Therefore, uniform prior distributions are assumed for these parameters, following the approach in [3].

Figure 6 presents the prior and posterior distributions of the three sensitive CODAM2 input parameters, conditioned on the experimentally measured SEA with a mean of 46.7 kJ/kg and a standard deviation of 1 kJ/kg applying Markov Chain Monte Carlo method to draw random samples. The comparison illustrates how the experimental observations update the initial parameter assumptions within the Bayesian framework. This uncertainty quantification process requires thousands of model evaluations, highlighting the importance of the computational efficiency provided by the GPR surrogate model.

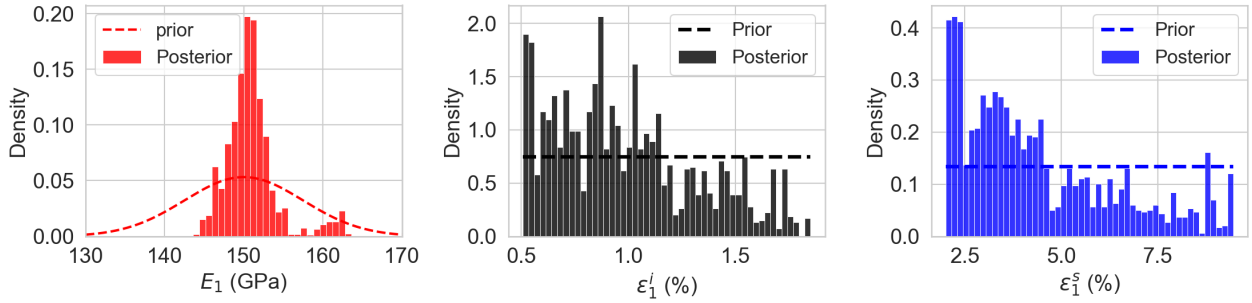


Figure 6 – Prior and posterior distributions of the three sensitive CODAM2 input parameters (E_1, ε_1^i, ε_1^s) obtained via Bayesian inference conditioned on experimental SEA data.

4. Results: Validation

It is essential to validate the posterior distributions of the FE input parameters, obtained in Figure 6, against independent crush test data. To this end, a tubular geometry, as shown in Figure 7, is simulated under progressive axial crushing. Corresponding experimental results are reported in [13]. Analogous to the flat coupon simulations presented in Figure 2, crushing is initiated by prescribing a velocity to a rigid plate, with failure triggered via a chamfered region implemented through a local reduction in shell thickness. The model employs a randomly oriented mesh with an approximate element size of 1 mm $\times$ 1 mm. To improve computational efficiency, only a quarter model is considered by exploiting symmetry conditions. The bottom nodes are fully constrained. The CODAM2 material model is applied, with the three longitudinal input parameters E_1, ε_1^i, and ε_1^s sampled from the previously identified posterior distributions. All remaining input parameters are assigned fixed nominal values, consistent with prior studies [3].

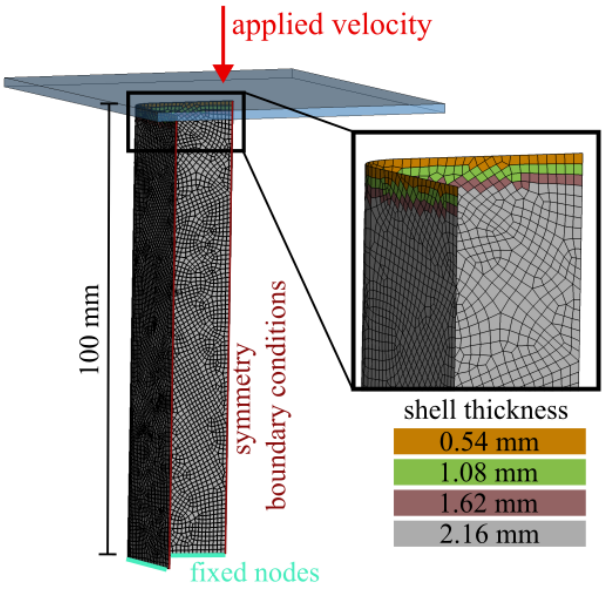


Figure 7 – Validation model for axial crushing of a CFRP tube, including geometry, boundary conditions, mesh configuration, and trigger implementation.

Figure 8 compares the force–displacement responses obtained from 100 FE simulations, based on samples drawn from the posterior parameter distributions, with the corresponding experimental measurements. It can be observed that the simulated responses generally follow the trends exhibited by the experimental curves. Importantly, as the primary objective of the proposed framework is to capture and represent uncertainty, the spread in the simulated force–displacement responses is also of particular relevance. The FE predictions exhibit a reasonable level of variability, reflecting the under-

lying uncertainty in the calibrated input parameters. While a more extensive set of experimental data would be required to rigorously validate the predicted variability, the presented results demonstrate the potential of the proposed framework. In particular, it provides a promising pipeline for leveraging efficient FE simulations in combination with data-driven techniques to predict the mechanical response of composite structures, including an explicit quantification of associated uncertainties.

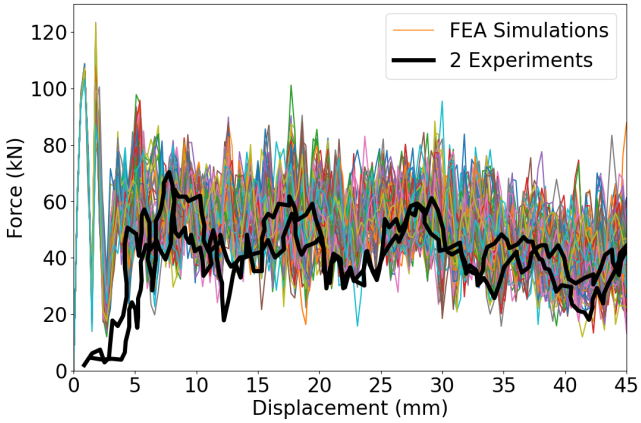


Figure 8 – Comparison of force–displacement responses from 100 FE simulations using posterior parameter samples with corresponding experimental measurements [13], illustrating predictive capability and uncertainty representation.

5. Conclusion

This work presents a comprehensive computational framework for incorporating uncertainty into finite element simulations of composite structures undergoing progressive axial crushing. The proposed pipeline integrates high-fidelity finite element modelling, machine learning–based surrogate modelling, and Markov Chain Monte Carlo techniques to infer the distributions of key input parameters. In doing so, it enables the representation of experimentally observed variability in the crushing response of composite materials.

From a broader perspective, this framework provides a pathway towards the virtual determination of material allowables, thereby supporting a shift in certification practices towards increased reliance on simulation. Such an approach has the potential to significantly reduce the extent of experimental testing required for the certification of composite structures. Nevertheless, it is important to emphasise that experimental data remains an essential component of the framework, as it underpins the calibration process and provides critical insight into the inherent variability of material behaviour.

Future work will focus on extending the modelling capabilities to incorporate more advanced damage mechanisms, particularly delamination, enabling the simulation of additional failure modes such as splaying during axial crushing. Furthermore, the selection of prior distributions within the uncertainty quantification framework should ideally be informed by physically measured variations, for example those arising from manufacturing-induced defects, to further enhance the predictive capability and physical relevance of the approach.

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