Machine learning assisted stochastic progressive failure analysis of composite laminates in a meso-macro framework

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Ravindra S. Chahar[1*], Tanmoy Mukhopadhyay[1]

[1] Department of Aerospace Engineering, Indian Institute of Technology Kanpur, Kanpur, India.
rravi@iitk.ac.in(RSC), tanmoy@iitk.ac.in(TM)

Abstract

Quantification of uncertainty in composite materials has been a challenge in terms of complexity and computation time. This is due to the nonlinear behaviour of composite materials and multiple failure mechanisms occurring simultaneously. This study develops a high fidelity surrogate model to quantify the uncertainty in matrix cracking in 90-degree plies of a composite laminate efficiently. The surrogate model is trained by continuum damage mechanics-based user subroutine (UMAT) coupled with the gaussian processes assisted finite element method. High fidelity surrogate model-based uncertainty propagation can effectively replace physics-based models and the global response of the composite laminates can be predicted accurately and cost-effectively. Using the proposed computational model, progressive failure of blunt-notched GLARE specimen is investigated considering stochasticity in applied strain following a multi-scale framework.

Key words: *Continuum Damage Mechanics; High fidelity Surrogate Model; Gaussian Processes; Stochastic Analysis*

1 Introduction

In recent years, machine learning methods are being widely used for solving complex structural problems [1, 2, 3]. Fibre-reinforced composites are of major interest in aerospace, automobile and marine applications because of their outstanding mechanical properties. The global response of the composite laminates remains uncertain due to various sources of uncertainty [4]. Uncertainty in the composite laminates may be built up from manufacturing defects (such as matrix voids, ply thickness variations, fibre dimension variations) and damages during service life. Uncertainty in material and geometric properties which are the results of manufacturing imperfections significantly affect the global response of composite laminate [5]. An additional factor of safety is added in the design to account for such uncertain global responses, which may lead to either extra conservative or an unsafe design. Gaussian process is a powerful machine learning-based algorithm for uncertainty quantification in complex engineering systems [6]. It is a probabilistic method for fitting the data points using possible functions and giving a reliable estimate for uncertainty in the predicted functions. In this paper, Gaussian process-based machine learning method has been used for the representation of nonlinear constitutive behaviour of composite laminate. The proposed method has been implemented for quantification of matrix damage uncertainty in 90-degree plies of blunt notched fibre metal laminate.

2 Numerical Modeling

The onset and evolution of composite laminate damage as shown in figure 2 is predicted using failure criteria proposed by P Linde [7]. The output of finite element simulation is fiber and matrix damage which is represented by damage variables D_f and D_m, respectively. The applied strain and damage variable are taken as training data points for training the surrogate model using Gaussian processes and predictions are made at new data points. We assume that the data obtained from the finite element simulations $D = \{x_i, y_i\}$ of i=1,....,n are generated from an unknown function, $f(x)$. The function is assumed as a gaussian process having mean as zero and a covariance function, k, i.e.

$$f(x) \sim GP\left(0, k\left(x, x^{'}; \theta\right)\right) \tag{1}$$

The covariance function is:

$$k\left(x, x^{'}; \theta\right) = \alpha^2 exp\left(-\frac{1}{2}\sum_{d=1}^{D}\frac{\left(x_d - x_d^{'}\right)^2}{\beta_d^2}\right) \tag{2}$$

where $\theta = (\alpha, \beta)$ are the hyper-parameters and D is the dimension of input variables. The hyper-parameters θ and the noise variance σ^2 are trained by maximizing the log marginal likelihood, i.e.

$$log\, p\,(y|x, \theta) = -\frac{1}{2}\, log\, |K| - \frac{1}{2}\, y^T K^{-1} y - \frac{n}{2} log\, 2\pi \tag{3}$$

Predictions are made using the conditional distribution [6]. Which is

$$f\,(x^*)\,|y \sim \mathcal{N}\left(k\,(x^*, x)\, K^{-1} y, k\,(x^*, x^*) - k\,(x^*, x)\, K^{-1} k\,(x, x^*)\right) \tag{4}$$

3 Results and Discussion

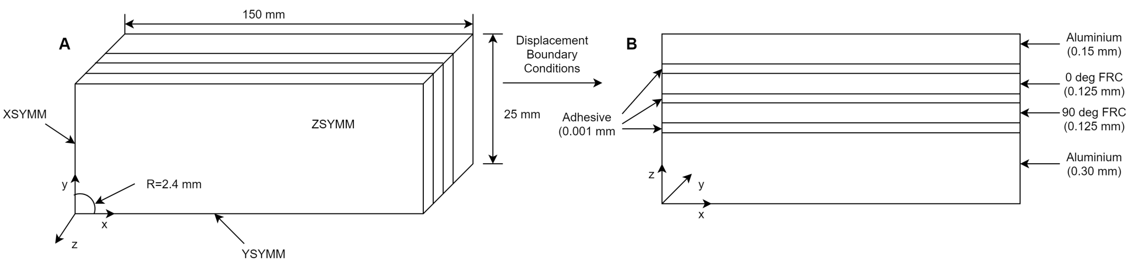


Figure 1: Boundary conditions and geometry of blunt-notched fibre metal laminate. (A) One-eighth part of the model with symmetric boundary conditions. **(B)** The fiber metal laminate consists of GLARE 3 (3/2-0.3) material having total thickness of 1.406 mm.

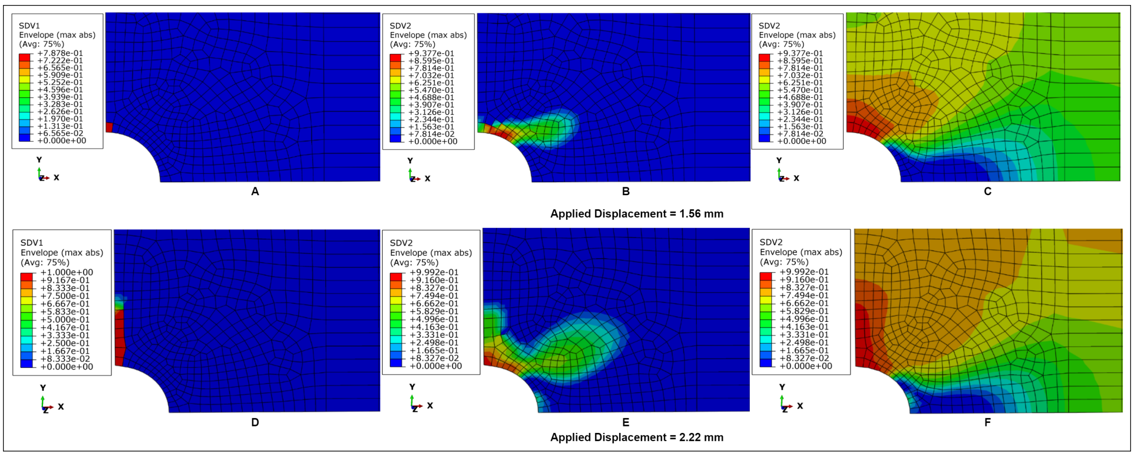
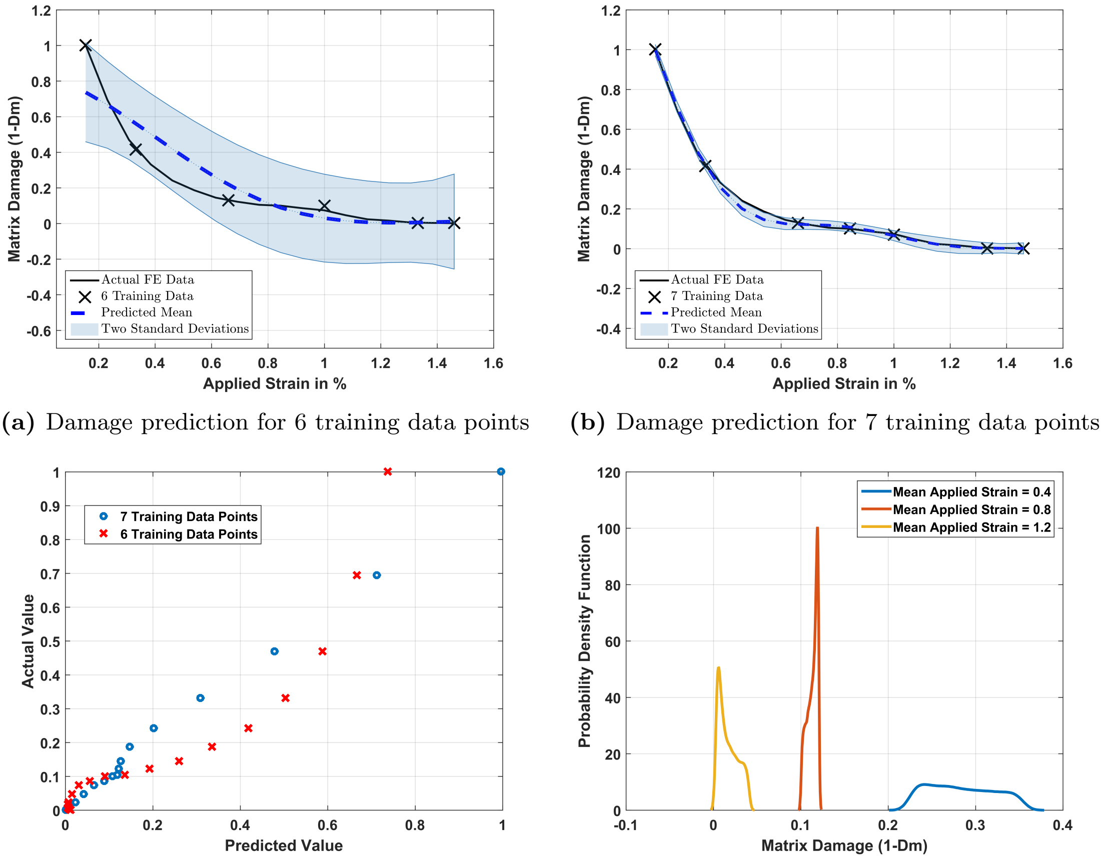


Figure 2: Contour plots of fiber and matrix damage in 0-degree and 90-degree plies for displacement applied in the direction of fibres. (A, D) Fibre damage in 0-degree ply, **(B, E)** Matrix damage in 0 degree ply, **(C, F)** Matrix damage in 90-degree ply at two different applied displacements.

Considering the symmetry, only one-eighth part of the laminate is modelled with geometry and boundary conditions as shown in figure 1. Displacement controlled tensile load is applied at

Table 1: Material properties of fiber-reinforced epoxy.

$E_1 (MPa)$	$E_2\,(MPa)$	$G_{12} = G_{13}\,(MPa)$	$G_{23}\,(MPa)$	ν_{12}	$X^T\,(MPa)$	$X^C\,(MPa)$
55000	9500	5500	3000	0.33	2500	2000
$Y^T\,(MPa)$	$Y^C\,(MPa)$	$S^L\,(MPa)$	$G_{ft,c}$	$G_{fc,c}$	$G_{mt,c}$	$G_{mc,c}$
50	150	50	12.5	12.5	1	1



(a) Damage prediction for 6 training data points **(b)** Damage prediction for 7 training data points

(c) Scatter plot for 6 and 7 training data points **(d)** Probability density for matrix damage

Figure 3: Matrix damage uncertainty quantification and scatter plots for present surrogate model with respect to the finite element model. (a-b) Prediction of matrix damage variable in 90-degree plies of composite laminate and uncertainty associated with the prediction. The black solid line represents the actual data generated from finite element simulation while the dashed blue line represents the predicted mean. The shaded blue region shows the uncertainty in the prediction. **(c)** Scatter plots for predicted values of present surrogate model with respect to the actual values of the finite element simulation model for 18 uniformly distributed data points. **(d)** Probability density function plot for 10000 samples considering $\pm 10\%$ stochasticity in deterministic values of applied strain.

a reference point RP (upper right corner of the model). Aluminium layers are modelled using the isotropic plasticity model available in commercial software ABAQUS and meshing is done using continuum solid incompatible mode elements (C3D8I). P Linde's failure criteria is used for modelling the fibre-reinforced epoxy layers and is implemented in ABAQUS using user subroutine (UMAT). The continuum Shell elements (SC8R) are used for meshing the fibre-reinforced epoxy layers. The material properties of Aluminum plasticity, fibre-reinforced epoxy (see table 1) and adhesive layers are taken from [8]. For initiation of delamination, adhesive layers are modelled using traction separation law and quadratic power law available in ABAQUS is used for the delamination propagation. Cohesive elements (COH3D8) are used for meshing the adhesive layers. The development of the surrogate model is done using MATLAB. Figure 2 shows that the matrix and fibre damage initiates at the tip of the notch and propagates in the direction perpendicular to the applied displacement. As shown in figure (3a-3c), the surrogate model trained with 7 data points gives better predictions over the 6 data points. The surrogate model trained with 7 data points has been used to find the probability density of matrix damage for 10000 samples considering $\pm 10\%$ stochasticity in deterministic values of applied strain. The deterministic values of applied strain are taken as 0.4, 0.8 and 1.2 (see figure 3d).

4 Conclusion

High-fidelity surrogate model has been developed to quantify the uncertainty in matrix cracking in 90-degree plies of a blunt-notched GLARE specimen following a multi-scale framework. The surrogate model is trained by Gaussian process-based machine learning method. The accuracy of the surrogate model has been investigated with respect to the finite element model for two sets of training data points. The developed surrogate model has been used to find the probability density of matrix damage for 10000 samples considering stochasticity in the applied strain.

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