Machine Learning-Based Forecasting of Preliminary Failure Intensity in Three-Dimensional Woven Composites Using Yarn Failure Metrics

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The implementation of Machine Learning (ML) methods, with an emphasis on yarn failure indicators, to anticipate the first failure intensity in three-dimensional woven composites. The study addresses failure analysis in 3D woven composites, integrating machine learning techniques and yarn failure metrics. Traditional failure criteria exhibit limitations in predicting failure under multiaxial loads. The main objective is to use Support Vector Machines (SVM) to construct a exact forecasting model for the initial failure intensity in 3D woven composites while taking Multiscale analysis and yarn failure indicators into account. It makes use of several failure criteria, such as the Hashin and Tsai-Wu criteria. The study uses an all-encompassing methodology that combines microscale and mesoscale analysis. SVM is used to predict failures, while the Mechanics of Structure Genome (MSG) model is used to boost computational efficiency. The SVM model outperforms conventional mesoscale models in forecasting failure intensity, as evidenced by the results. Better predictions are provided by the recommended model, which also works faster in terms of computing time. With the use of SVM-based models, the limits of traditional criteria are overcome in this study, which highlights the potential of these models to improve the precision of failure criteria for Multiscale analysis and experimental data in 3D woven composites.

Keywords: 3D woven composites, Failure analysis, Yarn failure metrics, Multiscale analysis;

Mechanics of Structure Genome (MSG) model, Initial failure intensity.

1. Introduction

The unique class of materials known as composites is created by macroscopically integrating two or more components, with the benefit of customization for particular uses (Tang et al 2022). Conventional laminates can have limited inter-laminar strength, but in an effort to increase dominance resistance by stitching techniques, interlaminar performance is frequently reduced (Liu et al 2023). Several three-dimensional (3D) fabrics have surfaced offering advantages such as increased impact resistance, structural stability, and fracture toughness. Weft, and binder threads, is unique among 3D woven composites (Zhou et al 2020). Binder yarns weave the warp and weft together, with the warp yarn oriented in the knitting direction and the weft yarn spanning the transverse direction (Chen et al 2021). Though 3D woven composites have many amazing qualities, their intricate production methods bring inherent uncertainties at different phases, which result in stochastic behaviour in their macro-mechanical characteristics. These uncertainties can arise at the constituent (micro-scale), ply (mesoscale), or component (macro-scale) levels and can be caused by material choices, production techniques, and service duration (Sun et al 2021). In general, uncertainties propagate from lower-scale materials, which store more uncertainty than higher-scale ones. The investigators are beginning to evaluate composite performance from a probabilistic standpoint because of the realization that 3D woven composites are inherently variable. As previously stated, there are two main categories of uncertainty in the manufacturing process of composites: lavatory and epistemic. Efforts to expand knowledge lessen epistemic uncertainty, which arises from ignorance of system and environmental factors (Dahale et al 2023). However insecurity characterizes the irreducible variability of system variables, especially those related to composite materials, which include production variances, properties of the fiber and matrix, and more. Research endeavors that tackle uncertainties often concentrate on component attributes and manufacturing procedures by using micro-mechanical models and representative elements (Tarfaoui et al 2019). Comparing 3D woven composites to two-dimensional (2D) ones reveals several clear benefits, such as increased mechanical stability, higher damage tolerance, and enhanced interlaminar fracture toughness (Guo et al 2021). Layer-to-layer (LTL) and Through-The-Thickness (TTT) interlocks are the two main categories into which three-dimensional woven composites can be further divided a full cell model with material thickness taken into account was developed (Zhou et al 2021). To assess the impact of fiber thickness and breadth regarding the stiffness parameters of 3DWOC-LTL, the inner arrangement of cells was used as the unit cell to reduce computational complexity. An integrated cell model with surfaces and interiors method, which strikes a compromise between computing efficiency and accuracy requirements, was created to take the place of the complete cell model in recognition that ignoring surface structural properties might lead to erroneous predictions (Dang et al 2023).

Guo et al (2021) used in 3D woven composites in structural design depends heavily on the thorough comprehension and evaluation of uncertainties arising from automated production processes. Calculated models have to be combined with measurements regarding statistical error and transmission techniques to resolve these inherent problems. Yaacoub et al (2020) proposed some circumstances; nevertheless, the integration can provide serious difficulties and computational time limits. Peng et al (2021) evaluated a unique Multiscale approach for estimating variability integrating sensitivity analysis, broad and finite element analysis is introduced. Zheng et al (2020) explored the main goal of assessing 3D interlocking weaved composites' and warp reinforced LTL (WRLTL). To produce the required dataset, a two-step numerical simulation is used to train and evaluate the model. Li et al (2020) addressed the model allows for the establishment of a framework that reduces the amount of computing resources needed to evaluate the significance of each determining the variance in macroscopic features. Behera et al (2022) provided that affects the material's tensile reaction, and the sensitivity data is a useful tool for reducing on a macro scale. Perera et al (2021) described the growing application of 3D woven composites in the automotive and aviation industries, which offer improved mechanical stability, superior damage tolerance, and increased interlaminar fracture toughness, calling for the creation of effective modelling tools for their analysis and design. Montemurro et al (2021) evaluated to anticipate mechanical reactions and characterize failure behaviours of 3D woven composites; the work provides a general multi-scale analytical model. Lee et al (2019) used the predictive power of the model is evaluated for several unit cell model schemes, and it is verified using available experimental and numerical data. Predicting composites' mechanical reactions is most accomplished using the technique. Xiang et al (2020) proposed the correlations between the number of weft layers and mechanical qualities and yarn density are suggested to be quantified using exponential and linear models, respectively. The findings emphasize the usefulness of the analytical model in assisting with the examination and development of different three-dimensional woven composites.

2. Multiscale preliminary failure assessment

2.1. Initial strength constants

The weight at which the highest failure index occurs inside a structure reaches a value of one and is referred to as the "initial failure load" (O_cr). The failure index is computed at different sites using the equivalent stress field in 3D 〖(σ〗_ji) when it is subjected to an arbitrary load (P). If O_cr = ∝ O represents the initial failure load, then 〖ασ〗_ji is a linear analysis that indicates the matching stress field.

$$e(〖ασ〗\_ji)=\propto e(σ\_ji) \qquad (1)$$

The expression of material failure conditions is represented by the function e(.) in this paragraph. The failure criterion definition states that at the failure point, ∝e must equal one. This requirement can be written as follows:

$$\propto = \frac{1}{e} \qquad (2)$$

The first failure load can be calculated by defining ∝_min as the smallest ∝ among all the spots.

$$O_{cr} = \propto_{min} O \qquad (3)$$

In this case, the strength ratio, represented by ∝, is quite important. ∝_min is the numerical representation of the first failure load when P= 1. In general, 12 strength constants are found for 12 loading cases. These include tensile strengths in the W, Z, and Y, directions, compressive strengths in the W^' Z^' Y^'directions, and shear strengths in the trio of principal geometry planes w_1,w_2,w_3 〖(w〗_2-w_3, 〖w_1-w〗_3,w_1-w_2)with the caveat that sign dependence can be present for shear strengths because of woven composites' non-symmetric structure.

2.2 Multiscale examination of 3D woven composites

Microscale components of a yarn are its fibers and matrix; mesoscale components are homogenized yarns and matrices. To separate the failure analysis from the micro and mesoscale, a Multiscale modeling approach is often used. A yarn's fibers and matrix are part of the microscale, whilst homogenized yarns and matrices make up the mesoscale. In the woven mesoscale model, strength constants simplify by ignoring stress gradients and are given as three-dimensional measurements. Efficiency is ensured by the use of mesoscale yarn failure criteria in conjunction with microscale computation in decoupled Multiscale analysis. Completely united at every yarn constituent integration point, microscale modeling is necessary for Multiscale analysis. Mesoscale models provide strain/stress fields, while microscale models use local stress fields to analyze failure. Microscale modelling is necessary for integration sites in yarn pieces, and fields are averaged to lessen the impacts of stress concentration. For a more thorough study, the MSG solid model projects microscale stress fields to the mesoscale. Using the maximum main stress and fiber failure criteria, the failure criterion computes strength ratios for matrix and fiber.

$$\mathrm{e} = \frac{\sigma_{11}}{\mathrm{W}} = 1, \quad \text{if } \sigma_{11} > 0$$

$$\mathrm{e} = \frac{|\sigma_{11}|}{\mathrm{W}'} = 1, \quad \text{if } \sigma_{11} < 0 \tag{4}$$

The parameters W and W^' denote the fiber's tensile and compressive strengths. Creating a failure criterion using an SVM model aims to provide a functional expression that can replace the microscale Finite Element Analysis (FEA) process in an efficient and fundamentally similar way.

$$\mathrm{e}\left(\overline{\sigma}_{\mathrm{ji}}\right) = \alpha \tag{5}$$

2.3. Developing the yarn failure criteria

Support Vector Machines (SVM) in a Multiscale analysis are used to develop yarn failure criteria. High-dimensional feature space-based systems, or SVMs, provide precise and effective failure criteria without supposing a particular functional shape. The computational efficiency is improved by combining this method with microscale modelling and the use of Mechanics of Structure Genome (MSG) models. SVMs may be used to optimise failure analysis methods for advanced material design, as shown by the derived criteria, which show higher accuracy in predicting early failure intensity in 3D woven composites.

2.3.1 Support Vector Machines (SVM)

SVM are high-dimensional feature space feature-based intelligent systems that use a set of linear functions. These systems are trained via an algorithm based on optimization theory, which incorporates a statistical learning theory-derived learning bias. SVM is useful not just for classification tasks but also for solving functional approximation and regression problems. Considering a training batch of data T={[w_j,z_j]∈R^m×R,j=1,……,k} SVR is to develop a function k that most accurately represents the system responses within e, which can be stated as follows and consists of T pairs of data points;

$$z = e(w) =< w.\varphi(w) > +a \quad (6)$$

Where Z∈Rthe system response and W∈ R^n are the n-dimensional vectors forming the inputs. The weight vector is denoted by w, and the bias term is represented by a. φ(w) provides the connection between the parameter area k and R at another level.

$$K^{\varepsilon}(w, z, e) = |z - e(w)| = \max(0, |z - e(w)| - \varepsilon) \quad (7)$$

Where ε is an accuracy measure that indicates the tube's radius surrounding the approach of regression and e is a function with real values on the input domain W w∈W,z∈R.

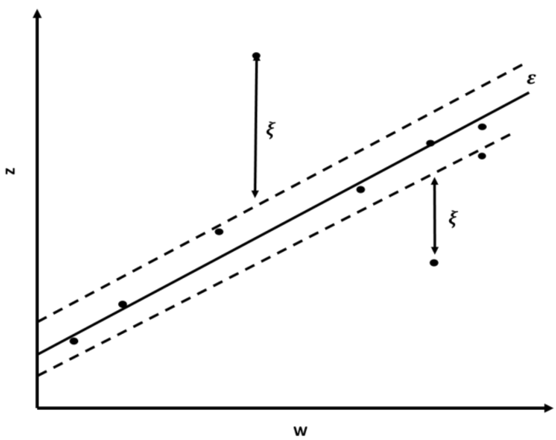

Figure 1One-dimensional linear regression problem's sensitive band [Source: Author]

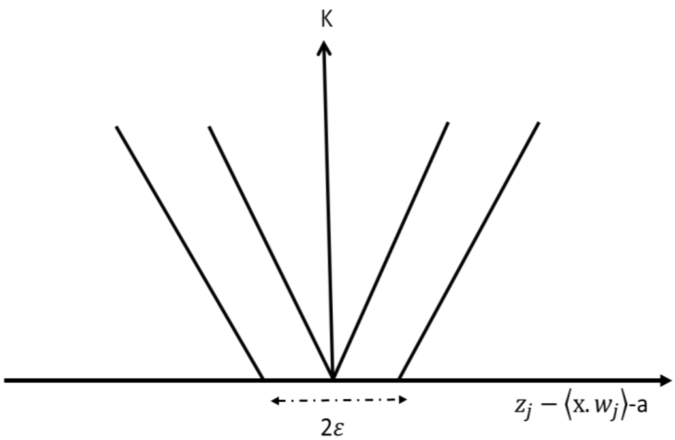

Figure 2The loss that is linearly insensitive to ε for both 0 and non-zero [Source: Author]

The amount spent on training points due to mistakes is measured by the variables with slack ξ in Figure 1. For every point inside the band, these are zero. The form of linear losses insensitive to ε as a function for both zero and non-zero ε is shown in Figure 2. The primary problem for optimizing the regressor's generalization performance can be formulated as follows

$$\text{minimize } \frac{1}{2}|x|^2 + D\sum_{j=1}^{k}(\xi_j + \hat{\xi}_j)$$

$$\text{subject to } \left(< x.\varphi(w_j) > +a\right) - z_j \leq \varepsilon + \xi_j$$

$$z_j - \left(< x.\varphi(w_j) > +a\right) \leq \varepsilon + \hat{\xi}_j$$

$$\xi_j, \hat{\xi}_j \geq 0, j = 1,2, \dots \dots, k \qquad (8)$$

Where Dis is a predetermined value and ξ,ξ are not working variables that indicate limits on the system's outputs, both upper and lower.

2.4 Model verification and failure forecasting

To record the beginning, accumulation, and spread of the composite's damage, use the notation DD-EE-FF. Pure matrix tensio, pure matrix compression, fiber tension, fiber compression, matrix tension, and matrix compression are a few of the failure types.

2.4.1 Three-dimensional woven composites (3DWOC) -During the thickness

The predictions show good agreement with finite element (FE) and real data, indicating that ELE-based mechanical response and progressive failure analysis are accurate. The damage begins in sub-cell 31's WFYE under tensile stress. Similarly, under weft tensile loading, damage starts in sub-cell 33's BYE and ends with FT damage in sub-cells 11, 13, 15, and 17's WFYE. The expected failure sequence is confirmed by numerical findings and experimental observations.

2.4.2 Three-dimensional woven composites- Layer to layer (3DWOC-LTL)

ELE strength is used to analyze the mechanical response and failure patterns of 3DWOC-LTL (T300 carbon fibers, HCGP-1 matrix), which shows different failure sequences in the warp and weft tensile loading. The analytical model's accuracy and logical consistency are validated using simulations and experimental validations. However, as previously reported in studies, 3DWOC-WRLTL, which uses T700 fibers (weft, warp), T300 fibers (binder), and TDE-86 epoxy resin, offers comprehensive progressive failure predictions under warp tensile loading. Table 1 shows the fiber properties, matrices, and geometry parameters for the 3DWOC that is being studied

Table 1Geometric parameters for TTT- 3DWOC, LTL- 3DWOC, and WRLTL- 3DWOC [Source: Author]

Sections	TTT - 3DWOC			LTL - 3DWOC		WRLTL - 3DWOC		
	weaving yarn	Woven thread	Binder thread	weaving yarn	Binder thread	weaving yarn	Woven thread	Binder thread
L_i	3	2	1	5	4	8	7	7
$N_i(K)$	11	11	1	2	2	11	11	2
$d_i(\mu m)$	6.92	6.92	6.92	7.0	7.0	7.0	7.0	7.0
$W_e(mm)$	2.14	1.83	0.36	1.21	1.00	1.60	1.60	0.80
$G_i(mm)$	2.54	2.20	2.20	2.85	1.00	3.32	3.32	3.32
$h_i(mm)$	0.33	0.38	0.11	0.15	0.13	0.31	0.31	0.15

3. Results

3.1 Mesoscale and meso-microscale analysis

The mesoscale model uses its matrix's greatest main stress criterion. Apart from the SVM-derived failure criterion, additional criteria like as maximal tensile (Maximum pressure). Mesoscale Plain Weave Composites Model, Figure 3.

The definition of the Maximum pressure conditions for loss is as follows:

$$e = \frac{\sigma_{11}}{W} = 1 \qquad e = \frac{\sigma_{22}}{Z} = 1 \qquad e = \frac{\sigma_{33}}{Y} = 1 \tag{9}$$

$$e = \frac{|\sigma_{11}|}{W'} = 1 \quad e = \frac{|\sigma_{22}|}{Z'} = 1 e = \frac{|\sigma_{33}|}{Y'} = 1 \tag{10}$$

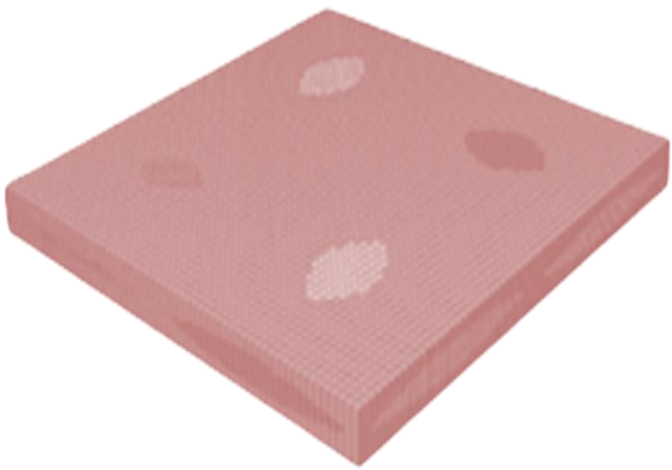

Figure 3 Mesoscale model for plain weave composites [Source: Author]

When there are compressive stresses, and

$$e = \frac{|\sigma_{23}|}{Q} = 1 e = \frac{|\sigma_{13}|}{S} = 1 \quad e = \frac{|\sigma_{12}|}{T} = 1 \tag{11}$$

The substance is subject to shear pressures.

This is one way to express the Tsai-Wu failure criterion:

$$e = E_1\sigma_{11} + E_2\sigma_{22} + E_3\sigma_{33} + E_{11}\sigma_{11}^2 + E_{22}\sigma_{22}^2 + E_{33}\sigma_{33}^2 + 2E_{12}\sigma_{11}\sigma_{22} + 2E_{13}\sigma_{11}\sigma_{33} + 2E_{23}\sigma_{22}\sigma_{33} + E_{44}\sigma_{23}^2 + E_{55}\sigma_{13}^2 + E_{66}\sigma_{12}^2 = 1 \tag{12}$$

Benchmark findings are obtained by evaluating the SVM-based yarn failure criterion using a thorough meso-micro scale study. The beginning strength constants are found by macroscale laminate analysis. Using microscale MSG dehomogenization and maximum primary stress requirements, yarns are analyzed to determine the minimal strength ratio (α2 and α3) and matrix strength ratio (α1). The beginning strength (αP) for textile composites is computed using a 2D MSG microscale model. As the 3D stress field is recovered at the microscale by the MSG model from a 2D domain, computational efficiency rises. Using a microscale square-packed model, effective stiffness and strength constants for yarns are obtained in Figure 4.

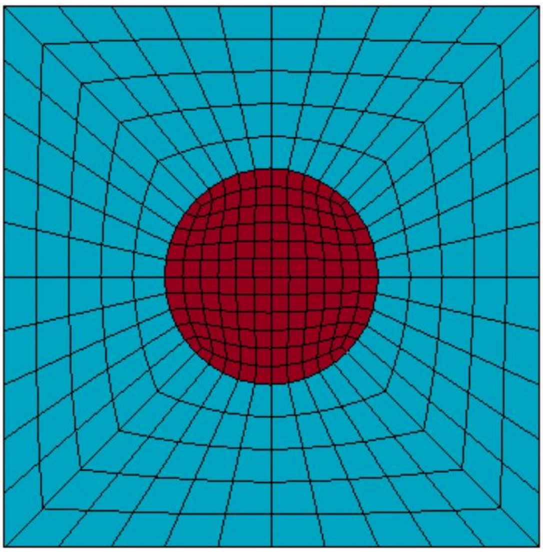

Figure 4. Square packed model at microscale [Source: Author]

3.2 Comparing mesoscale and meso-micro-scale models

Mesoscale analysis, especially using SVM, exposes the weakness of the yarn strength ratio in comparison to the matrix ratio. Out of all the models, SVM has the best accuracy. Various strength constants exhibit a notable loss of accuracy in traditional mesoscale models, particularly under Z' stress. Table 2 displays the yarn's elastic constants and effective strength constants (MPa).

Table 2. Elastic yarn constants and effective yarn strength constants (MPa) [Source: Author]

Material	Yarn
E_1 (MPa)	139700
$E_2 = E_3$(MPa)	9537
$G_{12} = G_{13}$(MPa)	4700
G_{23}(MPa)	3060
$v_{12} = v_{13}$	0.252
v_{23}	0.259
X	1518.86
X'	1215.09
Y=Z	49.21
$Y' = Z'$	178.29
R	56.96
S=T	41.80

The damage initiation sites revealed by several models, such as SVM and meso-micro, are comparable. Critical failure start sites are successfully identified by SVM, which matches Hashin and Tsai-Wu criteria with very few modifications. Because sub-scale modeling assumes certain equations and coefficients, traditional criteria based on microscale modeling produce a variety of forecasts. However, the accuracy is improved by simply developing a failure criterion based on SVM without assuming a particular functional form and by combining data from microscale models, as shown by the results in Table 3.

Table 3. Initial constants of strength (MPa) [Source: Author]

Model	Meso-micrometer range	SVM	Hashin	Tsai-Wu	Maximum stress	Difference (SVM)	Difference (Hashin)	Difference (Tsai-Wu)	Max-stress Diff
X = Y	149.81	146.54	143.81	147.50	150.60	2.18%	4.01%	1.54%	0.53%
$X' = Y'$	294.25	281.48	267.83	234.71	253.46	4.34%	8.98%	20.23%	13.86%
Z	39.91	38.73	32.63	36.22	38.06	2.95%	18.25%	9.24%	4.64%
Z'	144.60	140.78	200.48	210.55	137.89	2.64%	38.65%	45.61%	4.64%
R=S	22.94	22.86	24.03	23.41	24.10	0.35%	4.76%	2.06%	5.05%
T	19.10	18.92	19.34	19.23	19.36	0.92%	1.24%	0.67%	1.35%

3.3 Analysis of Computational Efficiency

For strength constants under six instances, meso-micro scale modeling required 8.1 hours of work. 0.32 hours for the same SVM mesoscale modeling. After sampling and microscale analysis of MSG, the SVM model took 8.3 hours to complete. Little time is needed for

Tensor training. It can take hours for a novice and minutes for an expert to alter a hyper parameter, depending on the user's knowledge level. Not include hyper parameter modification; the comparison is limited to computing time. In terms of loading scenarios, Figure 5 shows the computation time for SVM and meso-micro size models. The yarn failure criterion requires a one-time 8.3-hour computation for the initial SVM model. For a variety of computationally demanding analyses, the suggested SVM model provides an effective method for creating failure envelopes with little loss of accuracy.

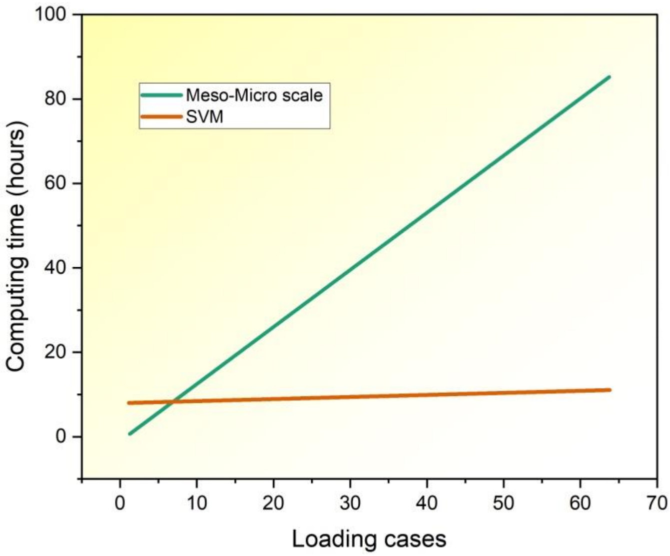

Figure 5. The computing time of the SVM model and its meso-micro size [Source: Author]

Benchmarking confirms that the suggested model is accurate and effective, and it correlates well with the outcomes. Accuracy decline in certain constants is observed in traditional criteria. By underlining the shortcomings of conventional criteria, the suggested criterion provides more precise predictions under multiaxial loads. Assumptions at the root of traditional criteria's inaccuracy can exist. Applying an SVM model can improve the precision of developing failure criteria for Multiscale analysis and experimental data.

4. Conclusion

The yarn failure metrics and a Multiscale analysis methodology, this study demonstrates the efficacy of a Support Vector Machine (SVM)--based model for forecasting the initial failure intensity in 3D woven composites. When compared to conventional mesoscale models, the SVM model exhibits higher accuracy, which overcomes the shortcomings in failure predictions under intricate multiaxial stresses. Mechanics of Structure Genome (MSG) model integration improves computing performance and guarantees a solid and trustworthy analysis. The research highlights the usefulness of SVM in developing accurate failure criteria for Multiscale evaluations and experimental data related to composite materials. The suggested approach offers important insights into failure behavior by drawing attention to the flaws of traditional criteria. This work highlights the importance of ML techniques in optimizing failure analysis processes for better material design and dependability, to making a significant contribution to the field of predictive modeling in composite materials.

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References

1. Behera, B. K., & Kamble, Z. (2022). Advanced 3D woven profile structures and their composites for automotive applications. Polymer Composites, 43(9), 5946-5953. 10.1002/pc.26851
2. Chen, Z., Pan, S., & Zhou, Z. (2021). Experimental Study of Mechanical Behavior of 3D Angle-Interlock Woven Fabrics under Cyclic Load. Applied Composite Materials, 28, 733-751. 10.1007/s10443-021-09883-1
3. Dahale, M., Archer, E., McIlhagger, A., Ralph, C., Neale, G., & Dempsey, C. (2023). Three-dimensional woven composites. Design and Manufacture of Structural Composites, 189-206. 10.1016/B978-0-12-819160-6.00014-7
4. Dang, H., Zhang, Y., Liu, P., Zhao, Z., Tong, L., Zhang, C., & Li, Y. (2023). Progressive failure prediction of three-dimensional woven composites using a generic multi-scale analytical model. Composite Structures, 303, 116321. 10.1016/j.compstruct.2022.116321
5. Guo, Q., Zhang, Y., Li, D., Guo, R., Ma, M., & Chen, L. (2021). Effect of bias yarn on tensile fracture mechanism of multiaxial 3D angle-interlock woven composites. Thin-Walled Structures, 159, 107269. 10.1016/j.tws.2020.107269
6. Guo, Q., Zhang, Y., Li, D., Sun, X., Li, M., & Chen, L. (2021). Experimental characterization of the compressive properties and failure mechanism of novel multiaxial 3D woven composites. Composites Communications, 28, 100905. 10.1016/j.coco.2021.100905
7. Lee, J., Tomasek, D., Santos, T. M., May, M. D., Meuskens, I., & Kahne, D. (2019). Formation of a β-barrel membrane protein is catalyzed by the interior surface of the assembly machine protein BamA. Elife, 8, e4978710.7554/eLife.49787
8. Li, Z. G., Li, D. S., Zhu, H., Guo, Z. X., & Jiang, L. (2020). Mechanical properties prediction of 3D angle-interlock woven composites by finite element modeling method. Materials Today Communications, 22, 100769. 10.1016/j.mtcomm.2019.100769
9. Liu, X., Zhou, X. Y., Liu, B., & Gao, C. (2023). Multiscale modeling of woven composites by deep learning neural networks and its application in design optimization. Composite Structures,

324, 11755310.1016/j.compstruct.2023.117553
10. Montemurro, M., Bertolino, G., & Roiné, T. (2021). A general multi-scale topology optimisation method for lightweight lattice structures obtained through additive manufacturing technology. Composite structures, 258, 113360. 10.1016/j.compstruct.2020.113360
11. Peng, G. C., Alber, M., Buganza Tepole, A., Cannon, W. R., De, S., Dura-Bernal, S., ... & Kuhl, E. (2021). Multiscale modeling meets machine learning: What can we learn?. Archives of Computational Methods in Engineering, 28, 1017-1037. 10.1007/s11831-020-09405-5
12. Perera, Y. S., Muwanwella, R. M. H. W., Fernando, P. R., Fernando, S. K., & Jayawardana, T. S. S. (2021). Evolution of 3D weaving and 3D woven fabric structures. Fashion and Textiles, 8(1), 1-31.
13. Sun, Q., Zhou, G., Tang, H., Meng, Z., Jain, M., Su, X., & Han, W. (2021). In-situ effect in cross-ply laminates under various loading conditions analyzed with hybrid macro/micro-scale computational models. Composite structures, 261, 113592. 10.1016/j.compstruct.2021.113592
14. Tang, Z., Guo, L., Zheng, T., Li, Z., Sun, R., & Huang, K. (2022). A combined machine learning and numerical approach for evaluating the uncertainty of 3D angle-interlock woven composites. Composite Structures, 294, 115726.10.1016/j.compstruct.2022.115726
15. Tarfaoui, M., & Nachtane, M. (2019). Can a three-dimensional composite really provide better mechanical performance compared to two-dimensional composite under compressive loading?. Journal of Reinforced Plastics and Composites, 38(2), 49-61. 10.1177/0731684418802028
16. Xiang, Z., Chen, K., Qian, M., & Hu, X. (2020). Yarn-dyed woven fabric density measurement method and system based on multi-directional illumination image fusion enhancement technology. The Journal of The Textile Institute, 111(10), 1489-1501. 10.1080/00405000.2019.1706222
17. Yaacoub, J. P. A., Salman, O., Noura, H. N., Kaaniche, N., Chehab, A., & Malli, M. (2020). Cyber-physical systems security: Limitations, issues and future trends. Microprocessors and microsystems, 77, 103201. 10.1016/j.micpro.2020.103201
18. Zheng, T., Guo, L., Huang, J., & Liu, G. (2020). A novel mesoscopic progressive damage model for 3D angle-interlock woven composites. Composites Science and Technology, 185, 107894. 10.1016/j.compscitech.2019.107894
19. Zhou, B., Wang, H., Wang, K., Zhao, J., Zhou, H., & Huang, S. (2021). Nondestructive test technology research for yarn linear density unevenness. Autex Research Journal, 23(1), 132-141. 10.2478/aut-2021-0051
20. Zhou, W., Wente, T., Liu, D., Mao, X., Zeng, D., Torab, H., ... & Xiao, X. (2020). A comparative study of a quasi 3D woven composite with UD and 2D woven laminates. Composites Part A: Applied Science and Manufacturing, 139, 106139. 10.1016/j.compositesa.2020.106139