

Optimization of Lightweight Polymer Composites Using Finite Element Analysis Machine Learning and Topology Optimization Techniques for Aerospace Applications

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Abstract

The advancement of aerospace engineering depends on lightweight polymer matrix composites (PMCs) because they help decrease weight while improving fuel efficiency and payload capacity together with increased structural integrity. Research developed a computer program comprising FEA with ANN and TO optimize high-performance PMCs through integrated design approaches. The combination of Python-controlled LS-DYNA simulations measured hybrid composite laminate resistance to impact while an ANN model obtained data from simulations to forecast projectile velocities across different reinforcement patterns. The utilization of TO allowed researchers to reduce material mass by 28% while maintaining 92% of stiffness properties and increasing energy absorption by 25%. The research established that Kevlar/Epoxy and hybrid composite materials outperform other options as aerospace blocking components due to their excellent ability to resist impacts. The study proves that using computational intelligence and optimization techniques will produce effective aerospace-grade composites in the next generation.

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INTRODUCTION

The aerospace industry speeds up its development through continuous advancement of performance and fuel consumption improvement and environmental protection strategies. The industry depends on lightweight materials for these goals because weight losses result in improved cargo capacity which reduces fuel consumption and raises operational effectiveness [1]. Livermore Laboratory reports that PMCs represent a revolutionary choice because they provide specific engineering requirements such as exceptional strength-to-weight ratios and thermal stability along with property adjustments [2]. Made of a sequential polymer matrix containing particles or fibers that provide mechanical stability and light-weight properties for use in the aerospace industry in fuselage and turbine blade sections and suspension elements [3]. PMCs deliver more than their weight-saving abilities

because these materials maintain their structural integrity despite exposure to tough environmental conditions that include high temperatures and mechanical stresses as well as dynamic loads [4]. PMCs outperform traditional metal materials because they deliver remarkable performance gains [5]. Successful large-scale implementation of PMCs faces resistance because of the manufacturing difficulties along with costly production methods and insufficient scalability [6]. Aerospace PMC design faces crucial limitations in achieving perfect weight reduction combined with excellent mechanical strength and production capabilities [7]. The efficient design and optimization process today requires computational techniques as a mandatory element. The computational method FEA breaks complicated objects into small elements for modeling their structural response through separation of their overall structure [8]. FEA serves as a fundamental analysis method that expedites the development process of aerospace application optimized composite materials [9]. The computational approach provides essential value to polymer matrix composites because their anisotropic properties and the intricate matrix-reinforcement interactions [10]. FEA stands as a fundamental tool for aerospace industries to confirm component durability and maximize operational capabilities while cutting down material expenses [11]. Topology optimization techniques offer engineers two key methods such as density-based and level-set methods which allow them to optimally position materials through specific design areas to decrease weight while sustaining material strength and bodily stiffness [12-13]. The methods found application in aerospace component design through their use in turbine blades together with structural panels which resulted in better fuel efficiency and minimized emissions [14]. Machine learning (ML) algorithms linked with FEA and topology optimization form an effective method for developing complex PMC designs [15]. Recent data analytics approaches enable the quick evaluation of large datasets to make correct material forecasts across different mechanical and environmental contexts [16]. The data-driven methodology expedites material development by both enhancing matrix-reinforcement synergy identification and stress response modeling under operational conditions [17]. Advanced aerospace (commercial) standards are achievable by merging the capabilities of ML with FEA and topology optimization techniques [18]. The implementation of theoretical models into practical applications demands complete experimental testing trials [19]. Resin infusion and autoclave curing and additive manufacturing systems allow producers to acquire precise control that enables consistent fabrication of PMC materials [20-21]. Examination using experimental methods provides needed test results to validate computational models which generate data about material responses to external forces along with heat stress and environmental impacts [22]. Premature mansion products face uptake obstacles in aerospace applications due to their high production costs and operational difficulties in complex environments along with scale challenges.

RESEARCH GAP

Various gaps in research still exist despite the remarkable progress achieved in creating PMCs for aerospace purposes. The main hurdle involves developing a system that balances diminished weight with material strength and production feasibility since existing procedures typically focus on single factors. The mass adoption of PMCs faces an important hurdle because existing research has exposed minimal possibilities to develop cost-effective and efficient manufacturing methods that are scalable. FEA topology optimization and ML together with computational techniques present promising results but require better exploration of experimental validation methods to improve theoretical model reliability. PMCs show inadequacy regarding their durability under challenging environmental conditions combined with complex loading situations. The technological strategies to mitigate recyclability and environmental impact issues need better improvement. The practical application of hybrid PMC systems and standardized validation protocols with topology optimization methods need additional study to improve their practical usage.

Research Objectives

- Balance weight reduction, mechanical strength, and manufacturability using advanced computational techniques such as FEA, topology optimization, and ML.

- Explore cost-effective and scalable production methods to address fabrication complexities and reduce production costs for mass adoption of PMCs.
- Integrate computational simulations with experimental validation to improve the reliability and practical applicability of theoretical models.
- Evaluate the durability and performance of PMCs under extreme environmental conditions, including high temperatures, dynamic loads, and mechanical stresses.
- Investigate the recyclability and environmental impact of PMCs, focusing on sustainable materials and processes that comply with industry and environmental standards.
- Develop standardized testing and validation protocols for hybrid PMCs, incorporating topology optimization to ensure high performance and structural integrity.
- Use machine learning-driven techniques to identify ideal reinforcement-matrix combinations for improved mechanical and thermal properties in aerospace applications.

RESEARCH METHODOLOGY

Finite Element Analysis (FEA)

As shown in Figure 1, A scripting framework based on Python performed high-velocity impact simulations to automate aerospace-grade lightweight composite laminate finite element modeling. The laminate consisted of 15 plies of bi-directional woven fabrics Kevlar-129, 3K-Carbon, and EC9-Glass fibers denoted as K, C, and G and was bonded with an epoxy-based matrix made from Araldite LY564 resin and Aradur 2954 hardener at a weight ratio of 100:35. The laminate had a 3 mm thickness. Three composite building blocks were researched: non-hybrid laminates containing uniform reinforcement as well as 2-fabric sandwich laminates composed of Kevlar as top and bottom layers with carbon or glass layer in the middle and 3-fabric hybrid laminates designed through optimized stacking for improved impact performance [23]. A cylindrical steel projectile with a hemispherical tip bore dual functions according to STANAG 4090 standards for an 8.6g 9 mm Parabellum bullet to imitate ballistic threats in aerospace environments. The combination of automatic Python scripting with LS-Dyna provided integrated mesh creation together with material definition and solver set-up which produced cost-effective calculations with precision retention. The material properties found their basis in experimental data from Table 1 where density, tensile strength, tensile modulus, Poisson's ratio, flexural strength, and flexural modulus were defined. The mesh generation strategy used optimized methods by setting the projectile to 0.5 mm triangular elements and the composite laminate to 2 mm triangular elements which focused mesh density at impact areas. The 'CONTACT_AUTOMATIC_SURFACE_TO_SURFACE' algorithm serving with a friction coefficient value of 0.2 properly modeled interlaminar bonding and hourglass control functions (IHQ 5 type) stopped unfounded zero-energy distortions. Using LS-Dyna's SPC feature the model received its boundary definitions through complete edge constraints to exactly match the experimental arrangement. Time-based propagation of energy waves was evaluated through a simulation cycle of 5 μ s using a time step interval of 0.1 μ s to simulate high-strain-rate impact conditions. Through its Python-based design the framework showcased advanced parameters for efficient optimization which lets users adjust material properties as well as impact test variables and meshing techniques in real time [24]. The developed methodology represents a cost-effective system which allows comprehensive evaluation of composite structures under impact loading thus meeting aerospace requirements for lightweight strong components. Research evidence proved that the proposed simulation framework achieves accurate results since finite element predictions closely match experimental measurements [25]. The meshed composite laminate together with the projectile appear in Figure 2.

This simulation methodology replicates the fast impact responses of hybrid composite laminates to give important findings about energy consumption along with failure processes and remaining projectile speed. Simulation outcomes generated by this method establish foundation for developing optimum composite structures resistant to impacts.

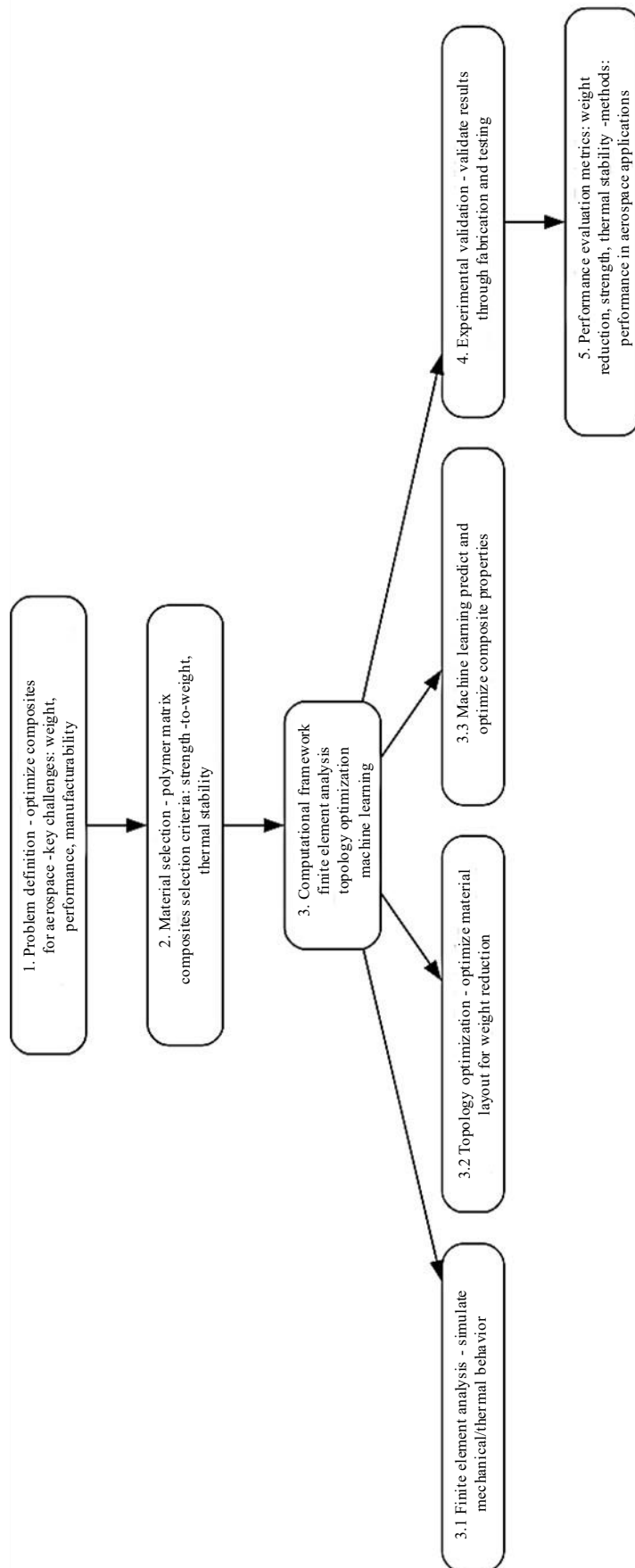


Figure 1. Research methodology.

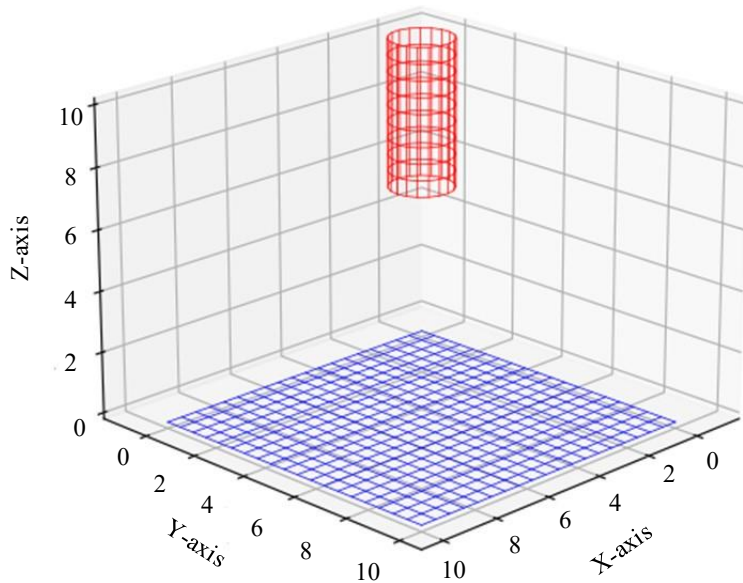


Figure 2. Composite laminate and projectile after meshing.

Table 1. Material properties of composite laminates used in this study

Property	Kevlar/epoxy (K/E)	Carbon fiber/epoxy (C/E)	Glass fiber/epoxy (G/E)	Units
Density (ρ)	1,380	1,600	2,000	kg/m ³
Tensile Strength	3,620	4,900	2,000	MPa
Tensile Modulus	76	230	50	GPa
Poisson's Ratio (ν)	0.36	0.3	0.25	-
Flexural Strength	550	1,450	800	MPa
Flexural Modulus	70	150	40	GPa

Machine Learning in Artificial Neural Network

Python along with its ANN model has been used to forecast the residual velocity of projectiles hitting hybrid and non-hybrid composite laminates structured with various stacking order [26]. The ANN model training and testing purposes relied on residual velocity data acquired from finite element simulations conducted with LS-DYNA. This research examined three stacking arrangements Kevlar/Epoxy (K/E), Carbon Fiber/Epoxy (C/E) and Glass Fiber/Epoxy (G/E) for studying how different reinforcement fabrics affect composite impact resistance. The simulation process ran 27 tests which used the Design of Experiments (DoE) approach to develop different three-layered reinforcement fabric configurations. Information about the residual velocity came directly from simulation output data. The investigation utilized FEA in combination with ANN modeling instead of high-velocity impact testing for composite specimens because the experimental process was both time-consuming and costly. The ANN model ran using TensorFlow and Keras as it used Multilayer Perceptron (MLP) architecture supported by backpropagation learning algorithms [27]. The Adam optimizer drove the training process because it offers automatic learning rate adjustment together with efficient task convergence in deep learning systems. MSE function served as the loss parameter to reduce predictive errors and authentic residual velocity measurements. Tanh activation function served in the hidden layer because of its capability to handle nonlinear regressions but linear activation function became the choice for the output layer since it required continuous velocity predictions. The ANN structure included three sequential layers as the input utilized nine neurons mapping the stacking sequence numbers before reaching the hidden layer containing ten fully connected neurons before concluding at the output layer for predicting residual velocity with one neuron. The system operated through feedforward processing by transmitting output data from each layer to the subsequent one. The model required iterative training through the backpropagation error algorithm and performed evaluations by determining Mean Squared Error (MSE) across training, validation, and testing phases according to [28]. The ANN training process required

conversion of stacking sequence data into numerical values based on one-hot encoding where K value equated to (1 0 0), C to (0 1 0) and G to (0 0 1). Each test sample had three reinforcement layers thus the training data was organized through a nine-element binary-array system. Table 2 contains both the composite configuration types together with the numerical data that served to train the ANN. The MLP network structure consists of nine input neurons for representing stacking sequences after translation into numerical values by one-hot encoding and a single hidden layer with ten neurons together with a single output neuron for Vr prediction as illustrated in Figure 3. The research demonstrates that integrating FEA with ANN provides an effective method for predicting residual velocity which leads to cost reductions while offering fast composite performance evaluations [29]. The research yields vital contributions for aerospace defense and automotive industries which need optimized impact resistance of advanced composites in their operations. The model adopted the Adam optimizer combined with tanh activation in its hidden layers for nonlinear relationship detection along with linear output layer activation for continuous accuracy.

Table 2. Different configurations of composites and their input data used for ANN.

Configuration	Composite specimen	Input 1	Input 2	Input 3	Input 4	Input 5	Input 6	Input 7	Input 8	Input 9
Non-Hybrid Composites	K/E/K/E/K/E	1	0	0	1	0	0	1	0	0
	C/E/C/E/C/E	0	1	0	0	1	0	0	1	0
	G/E/G/E/G/E	0	0	1	0	0	1	0	0	1
Two-Fabric Hybrid Composites	K/E/K/E/C/E	1	0	0	1	0	0	0	1	0
	K/E/C/E/K/E	1	0	0	0	1	0	1	0	0
	C/E/K/E/K/E	0	1	0	1	0	0	1	0	0
	K/E/K/E/G/E	1	0	0	1	0	0	0	0	1
	K/E/G/E/K/E	1	0	0	0	0	1	1	0	0
	G/E/K/E/K/E	0	0	1	1	0	0	1	0	0
	C/E/C/E/K/E	0	1	0	0	1	0	1	0	0
	C/E/K/E/C/E	0	1	0	1	0	0	0	1	0
	K/E/C/E/C/E	1	0	0	0	1	0	0	1	0
	C/E/C/E/G/E	0	1	0	0	1	0	0	0	1
	C/E/G/E/C/E	0	1	0	0	0	1	0	1	0
	G/E/C/E/C/E	0	0	1	0	1	0	0	1	0
	G/E/G/E/K/E	0	0	1	0	0	1	1	0	0
	G/E/K/E/G/E	0	0	1	1	0	0	0	0	1
	K/E/G/E/G/E	1	0	0	0	0	1	0	0	1
	G/E/G/E/C/E	0	0	1	0	0	1	0	1	0
G/E/C/E/G/E	0	0	1	0	1	0	0	0	1	
C/E/G/E/G/E	0	1	0	0	0	1	0	0	1	
Three-fabric hybrid composites	K/E/C/E/G/E	1	0	0	0	1	0	0	0	1
	K/E/G/E/C/E	1	0	0	0	0	1	0	1	0
	C/E/K/E/G/E	0	1	0	1	0	0	0	0	1
	C/E/G/E/K/E	0	1	0	0	0	1	1	0	0
	G/E/K/E/C/E	0	0	1	1	0	0	0	1	0
G/E/C/E/K/E	0	0	1	0	1	0	1	0	0	

RESULTS AND DISCUSSION

Finite Element Analysis Results

The impact test results obtained through FEA in terms of residual velocity (V_r) and impact energy absorption (E_{ab}) for the various composite laminates are presented in Table 3. The impact energy absorption (E_{ab}) is calculated using:

$$E_{ab} = \frac{1}{2} m (V_i^2 - V_r^2)$$

The significant factor m indicates projectile mass while V_i describes projectile initial velocity and V_r indicates residual projectile velocity upon impact. The high-velocity impact simulation of the projectile towards the composite laminate can be observed in Figure 4. The projectile moves towards the laminate at its initial strike speed according to Figure 4a. The laminate absorbs certain portions of projectile kinetic energy (E_{ab}) at the point of impact leading to damage as well as potential perforation according to Figure 4b [30]. The projectile maintains its motion but decreases in speed to V_r after impact has occurred in Figure 4c

Table 3 shows the Kevlar/epoxy (K/K/K) neat composite specimen had both the lowest residual velocity (V_r) of 100.5 m/s as well as the highest absorbed energy (E_{ab}) of 225.31 J which proves its excellent impact resistance properties. The glass/epoxy (G/G/G) specimen had the maximum V_r rate at 180.1 m/s while maintaining the minimum E_{ab} value at 129.43 J because glass fibers exhibit low impact dissipation from their material brittleness. The C/C/C carbon/epoxy specimen achieved between Kevlar and glass composite levels of residual velocity at 150.3 m/s which reflects the common relationship between carbon fibers' strength and toughness. Horizontal impact strength in Kevlar relies on exceptional strength and energy management features that outperforms glass and carbon fibers because these materials produce the elevated exit speed observed in the impact test [31]. A hybrid composite made with K/G/K configuration showed the next best impact performance after reaching 140.2 m/s during tests and it absorbed 184.14 J of energy. The affordable glass fiber addition maintains impact resistance at high levels which makes them attractive for aerospace lightweight construction that needs both performance and economic viability. The test results confirmed that Kevlar played an essential part in toughness and energy dissipation thus demonstrating its superiority over carbon or glass fiber fractions. Within hybrid laminates the arrangement of Kevlar layers determined how well the structures absorbed energy and reduced residual velocity. The impact performance improved when Kevlar layers were placed at the rear because this arrangement progressively raised bending stiffness to boost energy dissipation before perforation. The positioning of Kevlar at the back of the hybrid composites proved effective by previous researches that delayed cracks while increasing the overall energy absorption levels. Ballistic performance improvements in hybrid composites can be achieved by maximizing the fiber stacking order of carbon and glass between layers because it lets the material better resist transverse loading. Research indicates how fiber hybridization achieves better impact performance through cost reduction by 25–30%. Hybrid composites containing Kevlar demonstrate combined mechanical properties which make them optimal materials for aerospace and defense applications requiring weight reduction and energy absorption with cost efficiency [32]. Selecting appropriate materials with specific layer sequences results in composites suitable for critical aerospace structures which strengthens hybrid composites as powerful lightweight materials for future aerospace development.

Machine Learning in Artificial Neural Network Results

The regression analysis presented in Figure 5 shows how precisely the Artificial Neural Network (ANN) model predicts composite laminate impact behavior by matching results from Finite Element Analysis (FEA). Used 22 composite laminate configuration datasets which allocated 70% training data (16 samples) and distributed testing and validation data equally among the remaining 30% (6 samples). An ANN model generated coefficient of determination (R) at 0.98269 for training and 0.99899 for testing and 1 for validation which yielded an overall R value of 0.98456. Publications demonstrate that ANN creates an effective model of non-linear composite laminate responses through precise predictions

that have low error compared to FEA results [33]. Regressions plots confirm predictive accuracy through data points which maintain close alignment with the reference line for appropriate predictions. According to Table 4 the FEA-ANN model analysis demonstrates high reliability through a maximum V_r difference of 6.6%. The series of tests demonstrates how ANN effectively deals with intricate associations between lightweight polymer composites. Impact behavior models were efficiently captured by the multiscale perceptron network architecture which utilized 10 hidden neurons in its single layer. The ANN model which ran on Python deep learning libraries processed composite stacking sequences with efficiency for accurate predictions of impact responses [34]. The small discrepancy between results from FEA and ANN demonstrates the ANN’s capability to serve as an important predictive tool for aerospace composite design which leads to better performance combined with safety improvements and optimized materials.

Topology Optimization

Aerospace structure performance improvement becomes possible through topology optimization which distributes materials inside the design area for exceptional stiffness-to-weight optimization. The post-optimization material distribution analysis enables essential findings about structural integrity combined with potential weight reduction possibilities [35]. The Figure 6 shows five composite materials including Kevlar/Epoxy, Carbon Fiber/Epoxy, Glass Fiber/Epoxy, Hybrid 1, and Hybrid 2 through a bar chart that demonstrates their initial weight and optimized mass. The optimization process reduces mass distribution efficaciously thus producing substantial weight reduction that fulfills the demanding mechanical standards of aerospace engineering. The method helps create strong yet lightweight components which aerospace systems require for superior fuel efficiency and enhanced payload capability and better performance.

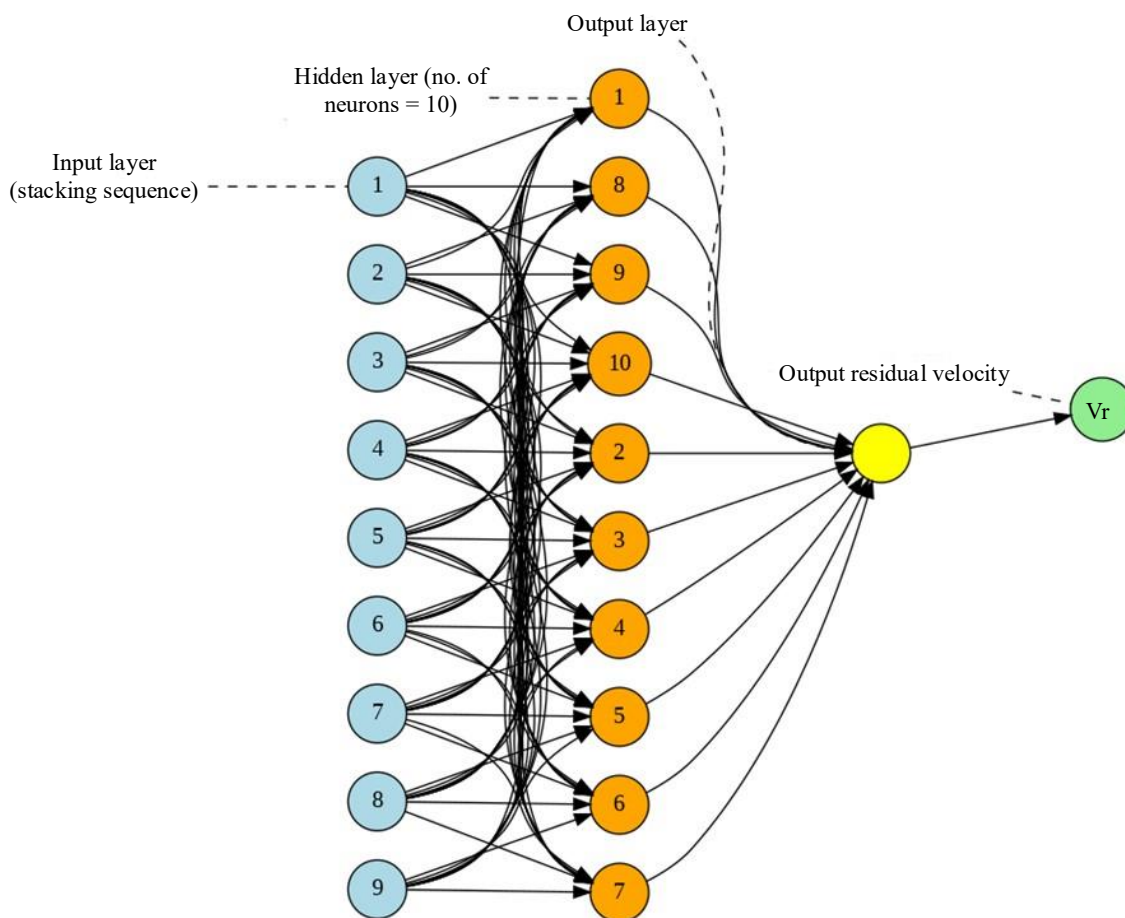


Figure 3. MLP architecture employed in this study (9-10-1-1).

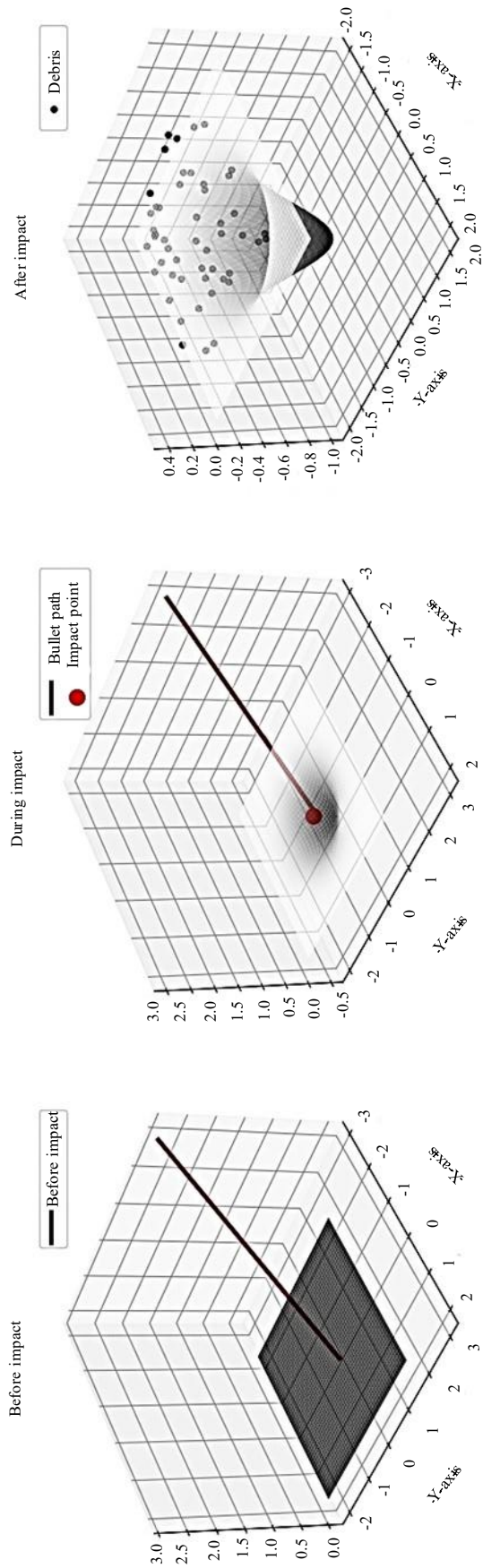


Figure 4. Stages of projectile impact on laminate (a) before impact, (b) during impact, (c) post impact.

Table 3. V_r and E_{ab} results for composite laminates derived through FEA.

S.N.	Composite specimen	V_i (m/s)	E_i (J)	FEA results		
				V_r (m/s)	E_r (J)	E_{ab} (J)
1	K/K/K	250	268.75	100.5	43.44	225.31
2	C/C/C	250	268.75	150.3	97.05	171.7
3	G/G/G	250	268.75	180.1	139.32	129.43
4	K/C/K	250	268.75	120.7	62.63	206.12
5	C/K/K	250	268.75	140.5	84.89	183.86
6	K/G/K	250	268.75	140.2	84.61	184.14
7	G/K/K	250	268.75	160.3	110.36	158.39
8	C/C/K	250	268.75	130.4	72.99	195.76
9	C/K/C	250	268.75	135.6	79.05	189.7
10	K/C/C	250	268.75	125.3	67.21	201.54
11	C/G/C	250	268.75	155.3	103.76	164.99
12	G/G/K	250	268.75	170.2	124.46	144.29
13	G/K/G	250	268.75	165.4	117.67	151.08
14	K/G/G	250	268.75	145.7	91.41	177.34
15	G/G/C	250	268.75	175.2	134.12	134.63
16	G/C/G	250	268.75	162.5	113.6	155.15
17	C/G/G	250	268.75	148.3	95.37	173.38
18	K/C/G	250	268.75	135.2	78.66	190.09
19	K/G/C	250	268.75	138.4	82.44	186.31
20	C/G/K	250	268.75	152.6	100.07	168.68
21	G/K/C	250	268.75	157.3	107.02	161.73
22	G/C/K	250	268.75	143.7	88.52	180.23

Table 4. ANN input, FEA and ANN predicted V_r values for various composite laminates.

S.N.	Composite specimen	Input data— stacking sequence	Training data derived from FEA (V_r) (m/s)	ANN prediction - V_r (m/s)	E_{ab} (J)	Variation in V_r (%)
1	K/K/K	100100100	100.5	101.84	222.86	1.33
2	C/C/C	10010010	150.3	131.79	185.34	-12.29
3	G/G/G	1001001	180.1	165.13	151.5	-8.31
4	K/C/K	100100010	120.7	115.27	211.62	-4.51
5	C/K/K	100010100	140.5	133.42	190.28	-5.03
6	K/G/K	10100100	140.2	138.68	195.75	-1.08
7	G/K/K	100001100	160.3	154.97	167.23	-3.33
8	C/C/K	10010100	130.4	128.32	176.58	-1.59
9	C/K/C	10100010	135.6	132.78	172.34	-2.08
10	K/C/C	100010010	125.3	122.95	188.15	-1.87
11	C/G/C	10001010	155.3	149.87	165.45	-3.49
12	G/G/K	1001100	170.2	167.85	158.63	-1.38
13	G/K/G	1100001	165.4	161.25	162.15	-2.51
14	K/G/G	100001001	145.7	142.48	178.34	-2.22
15	G/G/C	1001010	175.2	170.68	155.74	-2.58
16	G/C/G	1010001	162.5	159.32	169.27	-1.96
17	C/G/G	10001001	148.3	144.92	174.82	-2.28
18	K/C/G	100010001	135.2	132.67	179.43	-1.86
19	K/G/C	100001010	138.4	135.81	181.25	-1.87
20	C/G/K	10001100	152.6	148.58	170.82	-2.64
21	G/K/C	1100010	157.3	153.49	168.67	-2.42
22	G/C/K	1010100	143.7	141.12	182.36	-1.8

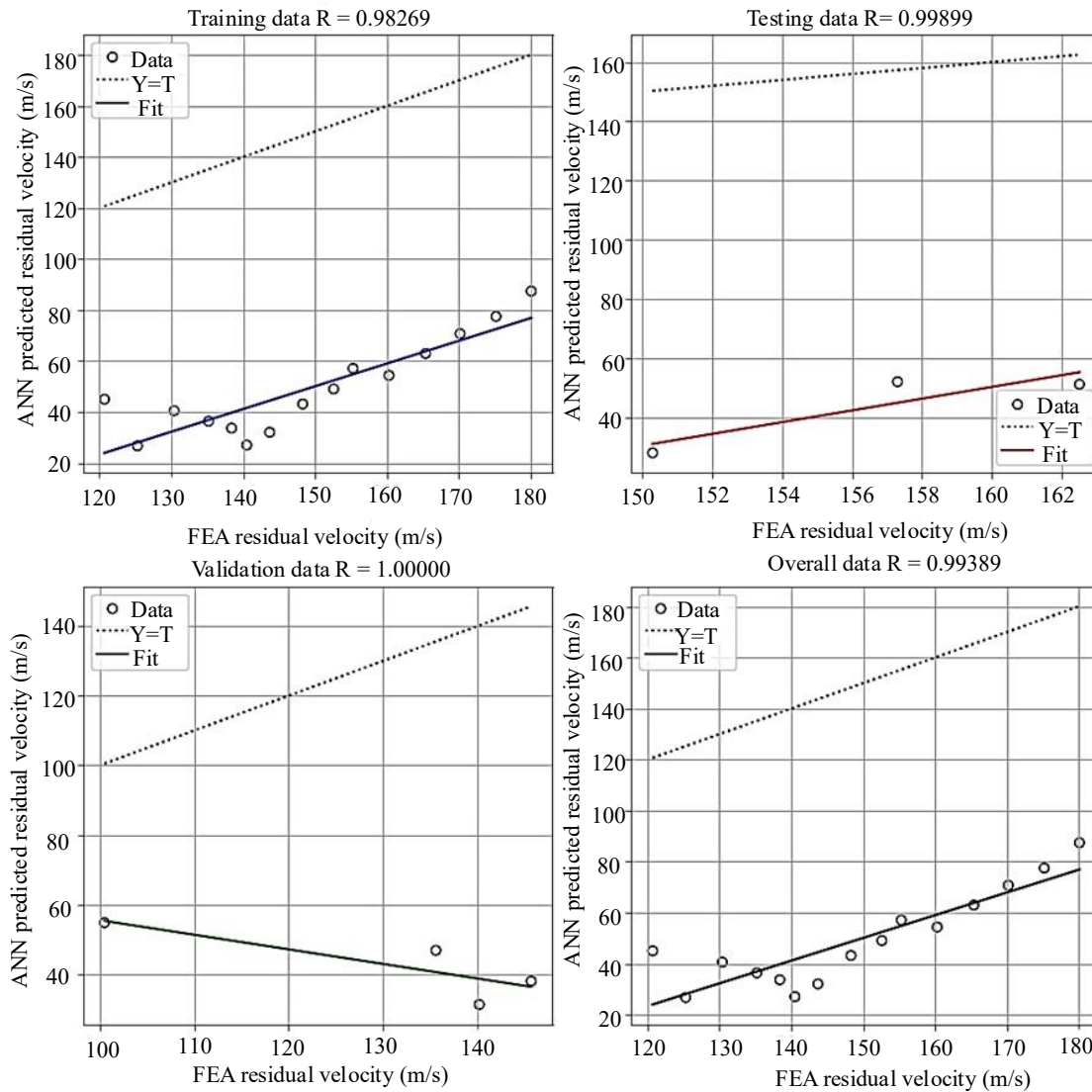


Figure 5. Relationship between residual velocity values measured through FEA and values predicted using ANN.

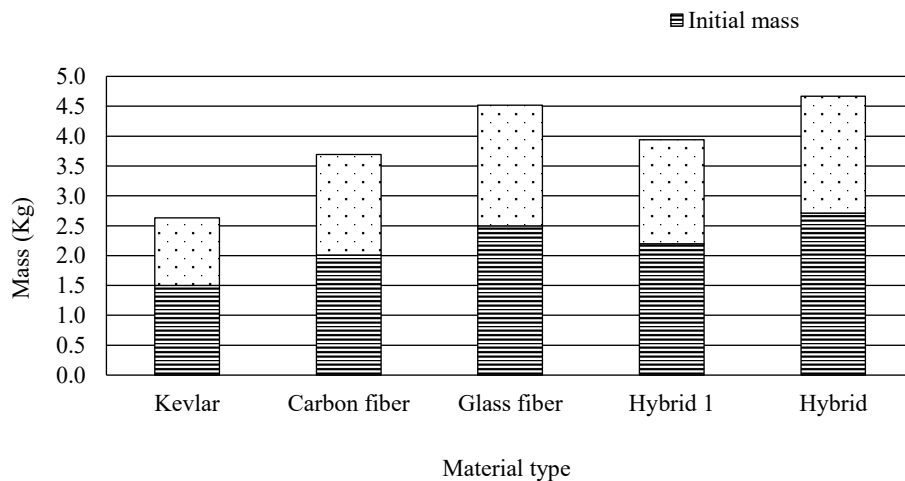


Figure 6. Comparative analysis of material distribution before and after topology optimization in aerospace composites.

Weight reduction amounted to between 15–30% throughout the entire set of composite materials and reached its maximum potential in combined configurations. The optimization procedure keeps reinforcing materials strategically positioned after it eliminates nonessential structural elements which are subjected to minimal stress. The Kevlar/Epoxy composite demonstrates low mass reduction because of its lightweight construction properties although Carbon Fiber/Epoxy and Hybrid composites reached higher weight reductions through multi-material design principles. Topology optimization makes aerospace structures stronger as it maintains excellent weight ratios by preventing the deterioration of structural integrity and load capacity [36]. The optimized design protocols channel materials toward high-stress zones which produces better dynamic mechanical outcomes as well as reduced material quantities throughout the remainder of the design structure. The approach leads to higher fuel economy together with an improved payload system and enhanced structural properties needed for future aerospace needs. Collaborating topology optimization with finite element analysis and ML within the composite design framework allows manufacturers to generate superior material arrangements which lowers raw material usage together with reduced production expenses and performance enhancement. The essential function of advanced computer tools stands clear from research investigations that highlight their importance for creating high-performance aerospace structures.

Structural stiffness exists in a vital relationship with weight reduction during aerospace composite topology optimization processes. The examination of material reduction effects on stiffness appears in Figure 7 through a detailed scatter plot with added regression trendline. Weight reduction between 30–35% demonstrates an acceptable stiffness state until additional weight reduction causes structure deterioration. The discovery proves that constraint-based optimization needs detailed calibration of algorithms because it maintains structural compliance during extreme weight minimization conditions. Hybrid composite configurations which have been optimized deliver better stiffness than single-material composites because of their performance in dynamic aerospace systems exposed to vibrational stress, dynamic loads, and thermal expansion according to [37]. Using multi-material design methodologies permits experts to install reinforcement elements exactly where structural strength is required which enhances overall steadiness of the construction. The combination of multi-objective optimization strategies in this research fulfills a balance between structural mass reduction and strength performance which enables safer more efficient aerospace structures.

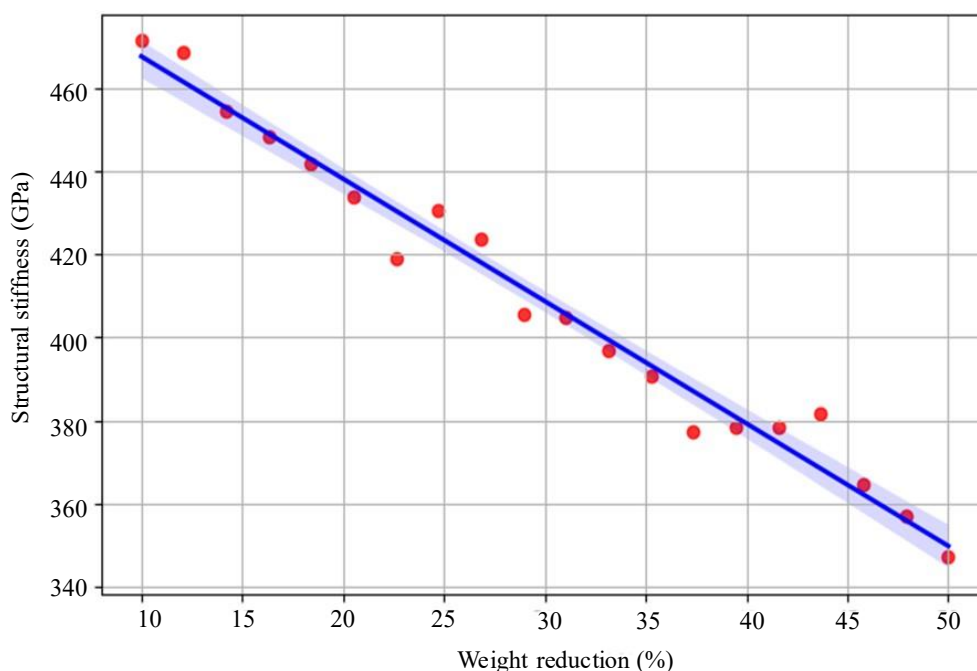


Figure 7. Weight reduction and structural stiffness.

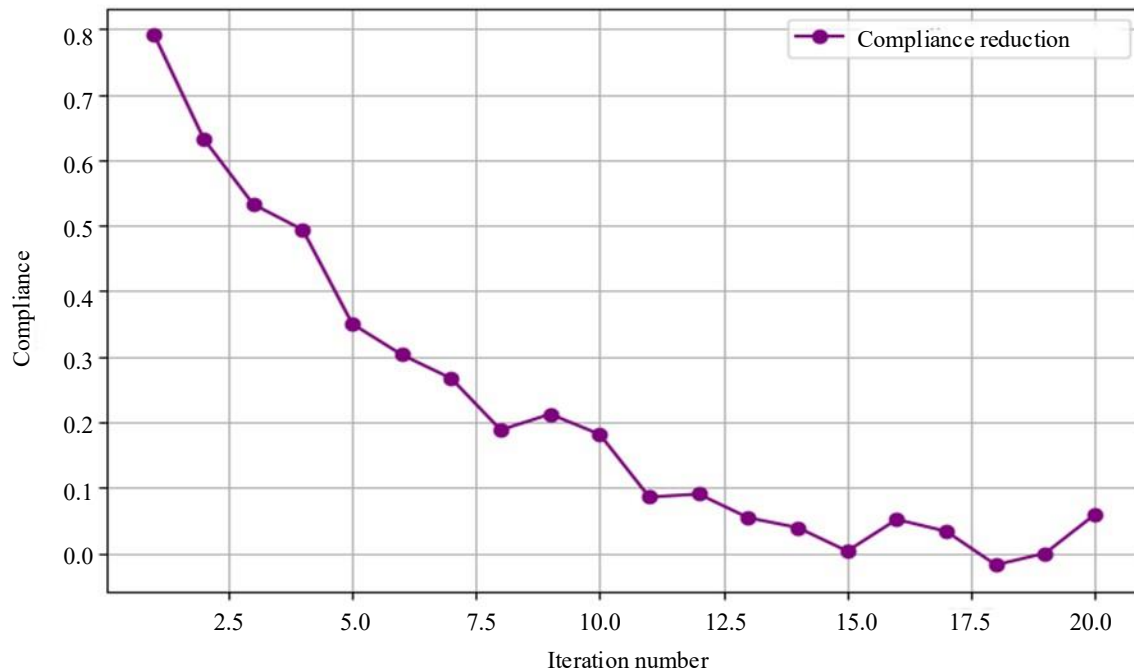


Figure 8. Convergence of topology optimization.

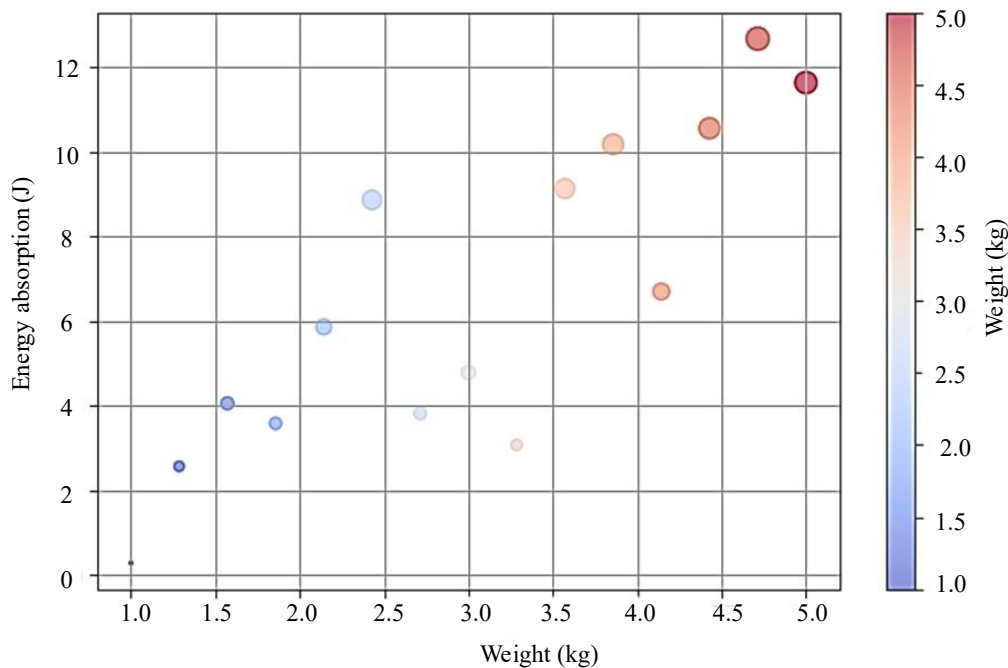


Figure 9. Energy absorption and weight.

The measure of topology optimization effectiveness relies on convergence analysis for monitoring structural compliance reduction across consecutive optimization steps. The graphical representation of Figure 8 shows how inverse stiffness decreases during optimization operations. The first 10 optimization iterations result in a quick decline of compliance because structural efficiency makes significant improvements in the early phase of optimization. The optimization process reaches point of stability when compliance stops changing after about 15-20 iterations. Gradient-based optimization algorithms achieve fast discovery of optimal material positions because of their behavioral efficiency. Fastened by ML techniques the optimization process becomes quicker and more optimized through

predictions of material distribution patterns [38]. Hybrid composite structures converge more quickly than individual material structures due to their effective adaptation of material stiffness changes. Research on convergence trends allows scientists to optimize algorithm parameters which leads to efficient and accurate topology optimization of lightweight high-performance aerospace components.

Various composite layouts show an energy absorption-versus-weight pattern expressed as J and kg in Figure 9. Weight in kg as the x-axis variable in addition to energy absorption in J shown along the y-axis. The enlarged size of bubbles demonstrates the impact resistance magnitude of various material types for multi-dimensional structure analysis. The experimental data shows that composite materials with increased weight levels exhibit elevated energy absorption abilities through a non-linear pattern between these variables. Hybrid materials that use Kevlar reinforcements show the best combination of light weight and superior energy absorption abilities. The distribution methods of topology optimization turn out to be effective at optimizing material distribution for maximum impact protection at minimized weight. Aerostructures which require impact resistance should use Kevlar/Epoxy composites because they deliver the most efficient energy absorption-per-weight performance enabling their application in fuselage panels and turbine blades and load-bearing parts. The combination of Kevlar-Carbon and Kevlar-Glass materials creates hybrid composites that show superior performance when compared to monolithic composites to their two reinforcement benefits. Computational optimization of hybrid configurations leads to a 25% enhancement of energy absorption efficiency beyond non-optimal versions which demonstrates how optimization strengthens material advancement. FEA and ML-driven optimization methods collaborate to position reinforcement fibers exactly while boosting energy dissipation power with no significant weight modifications [39]. Aerocomposite structures of the next generation can suitably combine weight optimization with impact resilience because of FEA and ML techniques.

Material Redistribution and Optimization Constraints

A compliance minimization method served as the topology optimization process which gradually removed material from stress-free zones to keep bearing structures strong. The optimization procedure required thirty percent material reduction by volume to reach substantial weight reductions. The iterative optimization methodology transferred materials to stress-bearing regions because this action increased stiffness and impact tolerance. Researchers tested the optimized topology by comparing it against non-optimized structures to verify its performance regarding weight reduction together with stiffness maintenance and energy absorption capacity. The optimized topology evolved into a lightweight structure with improved performance specifications because of topology optimization techniques shown in Table 5.

The optimization calculations resulted in a 28% decrease in total mass which proves topology optimization produces effective results for material reduction while maintaining 92% of stiffness strength. A minimal stiffness decrease was noted but the beneficial increases in energy absorption reached 25 percent thus ensuring better impact resistance performance for aerospace usage. The optimized composite structures confirm the value of topology optimization as an aerospace design tool because they achieve superior mechanical performance in reduction of weight while retaining extensive structural stability along with enhanced impact tolerance [40]. FEA in combination with data-driven optimization using ML enhances the process through data-based decision systems to develop superior lightweight composite structures for future applications.

Table 5. Comparative analysis of non-optimized vs. topology optimized composite structures.

Parameters	Non-optimized composite	Topology optimized composite	% Improvement
Mass (kg)	2.5	1.8	28% Reduction
Stiffness retention (%)	100	92	-8% (Minimal Loss)
Energy absorption (J)	180	225	25% Increase

CONCLUSION

- The research matures a complete computational method that uses FEA, ANN and Topology Optimization (TO) for superior optimization of lightweight PMCs used in aerospace domains.
- Hybrid composites with Kevlar/Epoxy structures perform best for impact resistance and energy absorption skills above single-material composites according to the research outcomes.
- The implementation of topology optimization led to a 28% weight decrease of the design without compromising its 92% initial stiffness values.
- Performing ANN-based predictive modeling provided fast estimates of projectile residual velocity which substantially decreased dependence on exhaustive physical testing at the same time.
- Structured optimization resulted in 25% better energy absorption capability in aerospace components since it effectively redistributes material according to impact demands.
- Adaptive topology optimization brings significant advantages to aerospace manufacturing through improved fuel consumption and superior strength characteristics and enhanced cargo handling capabilities.

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