



Prediction of impact performance of fiber reinforced polymer composites using finite element analysis and artificial neural network

Clifton Stephen¹ · Dinu Thomas Thekkuden² · Abdel-Hamid I. Mourad² · B. Shivamurthy³ · Rajiv Selvam¹ · Sai Rohit Behara¹

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Abstract

In this study, a methodology combining finite element analysis (FEA) and artificial neural network (ANN) through multilayer perceptron architecture was utilized to predict the impact resistance behavior of hybrid and non-hybrid fabric reinforced polymer (FRP) composites. A projectile at 250 m s^{-1} impact velocity was considered for the high velocity impact simulations. The Kevlar, carbon and glass fabric-based epoxy composites were modelled and the impact tests were performed through finite element simulations. The residual velocity results from FEA were used as training data for the ANN prediction. The ANN predicted results were in good agreement with FEA results with a maximum variation of about 6.6%. In terms of impact resistance, composite laminates with more Kevlar layers exhibited enhanced performance compared to other samples. Neat Kevlar/epoxy (K/K/K) exhibited the best impact resistance performance in terms of lowest residual velocity and highest energy absorption of 101.84 m s^{-1} and 222.86 J , respectively. Whereas, neat glass/epoxy (G/G/G) specimens registered the highest projectile residual velocity (165.13 m s^{-1}) and lowest energy absorption (158.99 J) compared to all other specimens. 2-fabric sandwich composite K/G/K exhibited a low residual velocity of 115.27 m s^{-1} and high energy absorption of 218.53 J , which is the second best among all specimens. Comparatively, the 3-fabric hybrid composites registered intermediate impact resistance results lower than that of Kevlar rich specimens, but significantly higher than neat G/G/G composite, thus, proving the effectiveness of hybridization in enhancement of impact performance compared to neat glass composite. Overall, the chosen methodology yielded significantly accurate results for the prediction of impact behavior of FRP composites.

Keywords Fiber reinforced polymer composites · Stacking sequence · Impact performance · Prediction · Artificial neural network · Finite element analysis

1 Introduction

Multi-layered fabric reinforced polymer (FRP) composites are becoming increasingly popular materials for usage in aerospace, defense and other ballistic applications due to their durability and impact resistance properties [1]. Over the past two decades, research studies have substantiated the enhancement in structural and tribological properties of FRP composites over other conventional materials [2]. Such multi-layered composites having different fabric reinforcements also known as hybrid-fabric composites offer versatility in terms of superior strength, stiffness and weight offered by each orthotropic layer [3]. Optimization of stacking sequence of such hybrid fabric reinforced composites leads to development of composites capable of offering enhanced ballistic resistance and high specific strength both of which are important parameters in the selection

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✉ B. Shivamurthy
shiva.b@manipal.edu

¹ Department of Mechanical Engineering, School of Engineering and Information Technology, Manipal Academy of Higher Education, P.O. Box 345050, Dubai, UAE

² Department of Mechanical Engineering, United Arab Emirates University, P. O. Box 15551, Al Ain, UAE

³ Department of Mechanical and Industrial Engineering, Manipal Institute of Technology, Manipal Academy of Higher Education, Manipal 576104, India

of advanced aerospace and defense grade materials. High velocity impacts are generally of the velocity range between 10 and 1000 m s⁻¹. Such impacts are further classified as low ballistic (10–350 m s⁻¹) and high ballistic (350–1000 m s⁻¹) velocities. The materials considered in this study fall under the former category and they are used for structural applications or as sacrificial cladding to protect primary structures [4]. Also, these materials can be used for drones and other aerial vehicles that operate at low ballistic velocities.

Kevlar, carbon and glass fabrics are some of the most commonly used synthetic reinforcements in hybrid composites due to easy availability, enhanced mechanical performance and cost benefits [5]. Structural components consisting of above said reinforcements fabricated in various stacking sequences have been widely studied for use in ballistic applications [6, 7]. However, the development and experimental testing of these materials involve high material and labor cost. Thus, alternative methods such as finite element analysis (FEA) have been increasingly used in recent decades to simulate various mechanical as well as impact tests [8, 9]. Similarly, machine learning techniques offer alternate methods to predict the behavior of such composite materials when subjected to various mechanical characterization tests. These modern, data-driven, theoretical and computational tools have enabled accurate solving of engineering problems for various materials under specific conditions [10].

Through available literature it can be noted that, the stacking sequence of composites is an important parameter that affects their impact behavior. Apart from the effect on mechanical and ballistic performance, hybridization also offers cost benefits by incorporating cheaper reinforcements such as glass fabrics into Kevlar and carbon-based composites which are more expensive [11, 12]. Randjbaran et al. [13] developed composites hybridizing Kevlar, glass and carbon fabrics in an epoxy matrix formulation. They fabricated hybrid fabric composite laminates by reinforcing Kevlar, carbon, and glass fabrics in the epoxy matrix in five stacking sequences such as (i) K/C/G/K/G/C, (ii) G/C/K/C/K/G, (iii) K/G/C/G/C/K, (iv) G/K/C/C/G/K and (v) K/C/G/G/C/K. These laminates were subjected to high-velocity impact tests at 184 m s⁻¹ impact velocity. They observed that specimen types (ii) and (iv) showed the best penetration resistance compared to other specimens. The stacking sequence of fabrics was reported to affect the impact behavior considerably even though all the tested specimens consisted of all three types of reinforcements. Kevlar in the internal layers and glass fabric on the impact face was observed to provide better impact resistance compared to other combinations.

Ansari et al. [14] fabricated epoxy based FRP composite laminates using Kevlar and glass fabrics in non-hybrid and hybrid orientations by manual wet lay-up method and

subjected to impact tests at projectile velocities in the range of 200–300 m s⁻¹. Through high-velocity experimental and FEA results, they reported that hybridization had a considerable effect on the impact performance of the FRP composite laminates. From all combinations of laminates like glass/Kevlar/epoxy hybrid fabric composite, neat glass/epoxy and neat Kevlar/epoxy that were tested, Kevlar/epoxy laminate with glass fabric sandwiched between them offered the best penetration resistance.

Muhi et al. [15] conducted experimental and finite element simulation studies to investigate the effect of hybridization of reinforcements such as Kevlar and glass fabrics in an epoxy matrix composite on its ballistic performance. For the fabrication of the composite laminates by hand-lay-up method, glass fabric of 0.3 mm thick with areal density 400 g m⁻² and Kevlar fabric of 0.45 mm thick and areal density 530 g m⁻² were used as reinforcement. They conducted high-velocity impact experiments on two types of samples, the first type had only E-glass fabric with epoxy while the second type had Kevlar-29 plies hybridized with E-glass fabric and epoxy matrix in different stacking positions. They investigated the effect of stacking position on the ballistic performance of these composites. A Steel bullet with incident velocity of 176 m/s was fired on the laminate specimen. The residual velocity of the bullet was measured, and the damage to the laminate was predicted and recorded. They concluded that hybridization with Kevlar fabric enhanced resistance to penetration. Similarly, as the Kevlar layer was pushed from the front face towards the back, the energy absorption increased, reaching the highest when Kevlar fabric was the last layer.

Extensive works have been carried out to study the effect of fabric hybridization on impact performance using finite element study, but validation of such results using machine learning techniques has not been reported widely. Stacking sequence of composites is a categorical input, thus the optimization of such categorical data cannot be carried out using conventional optimization tools. Meanwhile, Artificial neural networks (ANN) have been successfully employed by various researchers to study the dynamic and quasi-static behavior of composites. Birecikli et al. [16] used ANN to predict the failure in glass fiber composites when subjected to tensile loads. Malik et al. [17] predicted the low velocity impact behavior of composites through ANN. Naderpour et al. [18] predicted the compressive strength of FRP-based concrete slabs. Bezerra et al. [19] and Galatas et al. [20] used ANN to predict the mechanical properties of composite structures. Similarly, ANN has also been used for high velocity impact studies on carbon fiber-based composites by Fernandez et al. [21] and Artero-Guerrero et al. [22] to predict the effect of stacking sequence and fiber orientation respectively.

2 Methodology

In this study, high velocity impact behavior of non-hybrid and hybrid fabric composites consisting of Kevlar, carbon and glass fabrics was studied using a combination of FEA and Artificial neural network (ANN), which is a machine learning algorithm. The composites of different stacking sequences were modelled using Solidworks software and the finite element simulations were performed on Ansys LS-Dyna finite element software tool. A total of 27 types of all possible combinations of hybrid and non-hybrid composite laminates were considered for the study utilizing the above said fabric reinforcements. Prediction of impact behavior of FRP composites using ANN requires the high velocity impact test results as input data to train and validate the algorithm to produce accurate results. In this study, the input data was derived from FEA results. Out of the 27 possible composite combinations, 22 laminates were subjected to high velocity impact simulation at impact velocity (V_i) of 250 m s^{-1} using a hemispherical ended projectile and the residual velocity (V_r) of the projectile was recorded. This impact velocity was selected for the tests as it falls under the low-ballistic velocity range in which the considered composites find application. The V_r value of the projectile can be used to measure the impact energy absorption (E_{ab}) offered by the composite laminate. Impact energy absorption offered by the composite is calculated using the difference between impact and residual energies of the projectile. The residual velocity data for the 22 chosen composite laminates were used as input data for ANN to train and validate the algorithm. After sufficient accuracy was reached, the output data in terms of predicted residual velocity was compared to FEA results. Also, the accuracy of the predicted residual velocity values was further validated by performing high velocity impact simulations on the remaining 5 composite combinations and their results were compared and reported.

The uniqueness of ANN lies in its ability to learn from previous experiences and managing to extract key outputs based on a set of input data that has been fed [23]. In the current problem, the impact performance data of the non-hybrid and hybrid laminates in various stacking sequences is required to train and validate the ANN tool. Performing experimental high velocity impact tests to generate the required data involves high equipment and labor cost and thus is unfeasible [24]. Therefore, finite element simulation models were developed and used to perform impact tests.

2.1 Finite element analysis

To perform high velocity impact simulations, firstly, the composite laminates consisting of various stacking

sequences of reinforcement fabrics were modelled using Solidworks 2020 computer-aided design (CAD) tool. The composite laminate was modelled to a thickness of 3 mm and consisting of 15 plies of bi-directional, woven fabric having an areal density of about 200 gsm. Kevlar-129, 3K-Carbon and EC9-Glass fabrics denoted as K, C and G respectively, were used as reinforcements. The fabric plies were bonded using a matrix formulation consisting of Araldite LY564 epoxy resin and Aradur 2954 hardener in a mixing ratio of 100:35 by weight. The model consisted of 3 main layers, with each layer made of a certain reinforcement fabric and epoxy matrix. The main layer was further divided into 5 sub-layers, with each sub-layer modelled as a block consisting of the reinforcement fabric ply and the epoxy matrix and stacked one on top of each other. Each main layer consisted the same type of reinforcement for all 5 sub layers. In non-hybrid composites, all three main layers constituted the same reinforcement, whereas in 2-fabric sandwich, the top and bottom main layers consisted Kevlar, and the middle main layer was made up of either carbon or glass fabrics. In 3-fabric hybrid, each main layer constituted different fabric types depending on which reinforcement was to be used for the front, middle and back layers. The fabric plies were assembled to form the laminate using an Assembly feature on the CAD software. A cylindrical shaped steel bullet with a hemispherical tip was chosen as a projectile for the impact simulations. The projectile dimensions were selected based on STANAG 4090 [25] standard for 9 mm Parabellum bullet with a mass of 8.6 g. The laminate and projectile models were then saved as a .IGES file format to be exported to the simulation software.

The post-impact projectile residual velocity (V_r) values were obtained through the finite element simulation performed using Ansys LS-Dyna software. This software was chosen due to its capability to solve complex problems which may be highly non-linear, using explicit and implicit time integration. Also, a large library of materials is readily available with their failure modes, which makes it a very handy tool to perform impact simulations. The software finds its applications in various sectors such as aerospace, automobile, defence etc. In this study, the composite material properties were defined using Ansys Composite Prepost (ACP), while LS-Dyna plug-in within the ANSYS software was used as the solver. The simulation results were analysed using the post-processor in LS-PREPOST. Material properties of the composites such as density, tensile and flexural properties were obtained from experimental tests performed on the laminates and provided in Table 1.

The selection of mesh size impacts the accuracy of the FEA results and simulation run time, thus requires optimum selection. Among the available types of mesh shapes and

Table 1 Material properties of composite laminates used in this study [26]

Material property	Type of composite layer		
	K/E	C/E	G/E
ρ (kg m ⁻³)	1052	1357	1641
σ_t (MPa)	402	615	346
E_t (GPa)	8.4	17.9	12.0
μ	0.37	0.31	0.25
Toughness ($\times 10^{-3}$ Jmm ⁻³)	42.3	41.6	18.7
σ_f (MPa)	177	761	265
E_f (GPa)	15.2	51.1	17.6

K/E, Kevlar/epoxy; C/E, carbon/epoxy; G/E, glass/epoxy; ρ , density; σ_t , tensile strength; E_t , tensile modulus; μ , Poisson's ratio; σ_f , flexural strength; E_f , flexural modulus

dimensions, a triangular mesh of 0.5 and 2 mm sides was selected for the bullet and composite laminate respectively as shown in Fig. 1. This selection of mesh parameters was made taking into consideration the available processor capacity and time consumption for simulation.

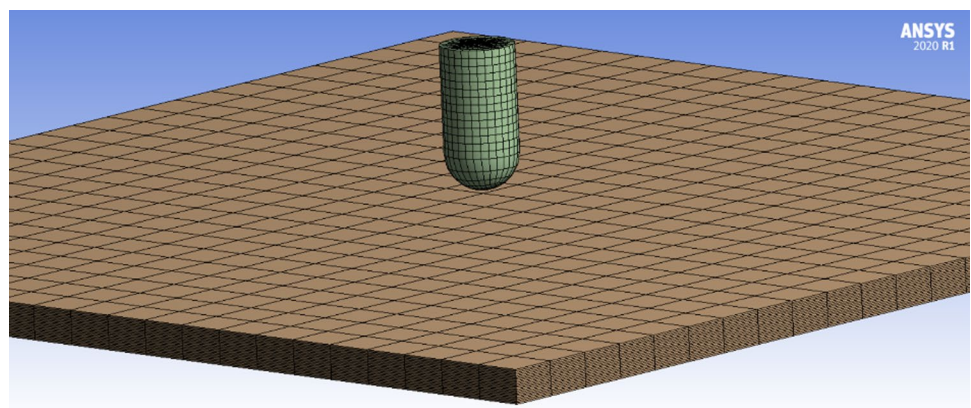
To model the bonding between layers of the composite laminate, 'CONTACT_AUTOMATIC_SURFACE_TO_SURFACE' option with a coefficient of friction value of 0.2 as suggested by LS-Dyna was selected. Similarly, 0.1 and 5 s were selected as the step-time (time taken for the impact energy wave to propagate through a discretized element) and simulation termination time respectively. Hourglass control feature of IHQ 5 type was activated considering the recommendation of LS-Dyna tool when carrying out impact simulations. When hourglass is not defined, the elements undergo severe zero-energy deformation, without displaying actual damage experienced by the composite laminate. Material models commonly used in such simulations 'MAT_RIGID_' and 'MAT 18_POWER_LAW_PLASTICITY_' were opted for the bullet and composite laminates respectively. Also, to emulate the experimental impact test set up where the composite laminate is fixed in a holding device to restrict

any rotational or linear movement, the laminate was fixed on the four edges using 'SPC' feature on LS-Dyna. The methodology followed in this study for FEA has been reported through published work to provide accurate results when compared with experimental results [27].

2.2 Artificial neural network

In the present work, an artificial neural network (ANN) model was developed to predict the residual velocity of bullets passing through hybrid and non-hybrid composite laminates fabricated using different stacking sequences after high velocity impacts. The residual velocity data used for training, testing, and validating neural network model was collected from the finite elemental approach performing the numerical simulations of high velocity impact on the developed composites. The influence of fabric stacking sequence of reinforcement fabrics such as Kevlar, Carbon and Glass on the impact behavior of the corresponding composites was investigated. Therefore, twenty-seven numerical runs were generated based on three reinforcement fabrics and three-layered composite specimens using design of experiment approach. For each of the runs, the residual velocity was estimated from the finite element analysis using LS Dyna. FEA and ANN are effective over experimentations for saving time and cost involved in studying the high velocity impact behavior for all the 27 specimens [22].

A multilayer Perceptron (MLP), which is a class of Feed Forward Artificial Neural Network with Backpropagation supervised learning approach, was performed using MATLAB R2020a with 'nntool' command. Levenberg–Marquardt (TRAINLM), Gradient descent with momentum weight and bias learning function (LEARNGDM) and Hyperbolic tangent sigmoid (TANSIG) were the training, adaptive learning and transfer functions, respectively. The performance of the neural network during the stages of training, testing and validation was evaluated using 'Mean Squared Error (MSE)'. The MLP neural network consisted of three layers namely, input, hidden and output layers. The

Fig. 1 Composite laminate and projectile after meshing

hidden layer consists of 10 neurons. This is a feed forward network, where each neuron was connected to all nine inputs from the preceding layer. All the three layers mentioned above were inter-connected within the network. The output of each layer formed the output for the next layer, till the output of the last layer (output layer) was the desired result of the network. ANN employs a learning algorithm that utilizes recursive differential equations as learning laws to continuously learn during each stage. The output results were continuously improved by training the neural network to be aware of the environmental conditions, past experience and aim of the study during each stage and every iteration of the learning process. MLP also consisted of a back propagation error algorithm to minimize the mean squared error in the predicted output results during the learning process using the numerical iteration process [28].

The input data fed to train the ANN for predicting the residual velocity prediction is the stacking sequence of the fabric which is in a categorical form. To predict residual velocity results in terms of numerical values, the input

data must also be in numerical form. In this study, one hot encoding method was utilized to convert the composite stacking sequence, which is in categorical form into a one-hot numeric array [29]. In this method, the categorical data such as stacking sequence was to be converted into binary codes (0 s and 1 s). For this, Kevlar layer was assigned a binary code (1 0 0), similarly, carbon layer and glass layers were assigned binary codes (0 1 0) and (0 0 1), respectively. These codes together formed nine inputs considering that each composite consisted of 3 layers of reinforcement fabric in different stacking sequences. Table 2 shows the stacking sequence and the one hot encoded numerical, binary code input data for all the specimen types used in this study.

In this study, the ANN architecture with Multilayer perceptron (MLP) with feed-forward network and back propagation error method that is most commonly used in similar studies [21] has been followed to predict the residual velocity (V_r) of the projectile after impact. Figure 2 shows the MLP architecture with the nine inputs (stacking sequence converted to numerical input value using one hot encoding

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

Configuration	Composite specimen	Stacking sequence (One hot encoded—numerical array) input								
		Input 1	Input 2	Input 3	Input 4	Input 5	Input 6	Input 7	Input 8	Input 9
Non-hybrid composites	K/K/K	1	0	0	1	0	0	1	0	0
	C/C/C	0	1	0	0	1	0	0	1	0
	G/G/G	0	0	1	0	0	1	0	0	1
Two-fabric hybrid composites	K/K/C	1	0	0	1	0	0	0	1	0
	K/C/K	1	0	0	0	1	0	1	0	0
	C/K/K	0	1	0	1	0	0	1	0	0
	K/K/G	1	0	0	1	0	0	0	0	1
	K/G/K	1	0	0	0	0	1	1	0	0
	G/K/K	0	0	1	1	0	0	1	0	0
	C/C/K	0	1	0	0	1	0	1	0	0
	C/K/C	0	1	0	1	0	0	0	1	0
	K/C/C	1	0	0	0	1	0	0	1	0
	C/C/G	0	1	0	0	1	0	0	0	1
	C/G/C	0	1	0	0	0	1	0	1	0
	G/C/C	0	0	1	0	1	0	0	1	0
	G/G/K	0	0	1	0	0	1	1	0	0
	G/K/G	0	0	1	1	0	0	0	0	1
	K/G/G	1	0	0	0	0	1	0	0	1
Three-fabric hybrid composites	G/G/C	0	0	1	0	0	1	0	1	0
	G/C/G	0	0	1	0	1	0	0	0	1
	C/G/G	0	1	0	0	0	1	0	0	1
	K/C/G	1	0	0	0	1	0	0	0	1
	K/G/C	1	0	0	0	0	1	0	1	0
	C/K/G	0	1	0	1	0	0	0	0	1
	C/G/K	0	1	0	0	0	1	1	0	0
	G/K/C	0	0	1	1	0	0	0	1	0
	G/C/K	0	0	1	0	1	0	1	0	0

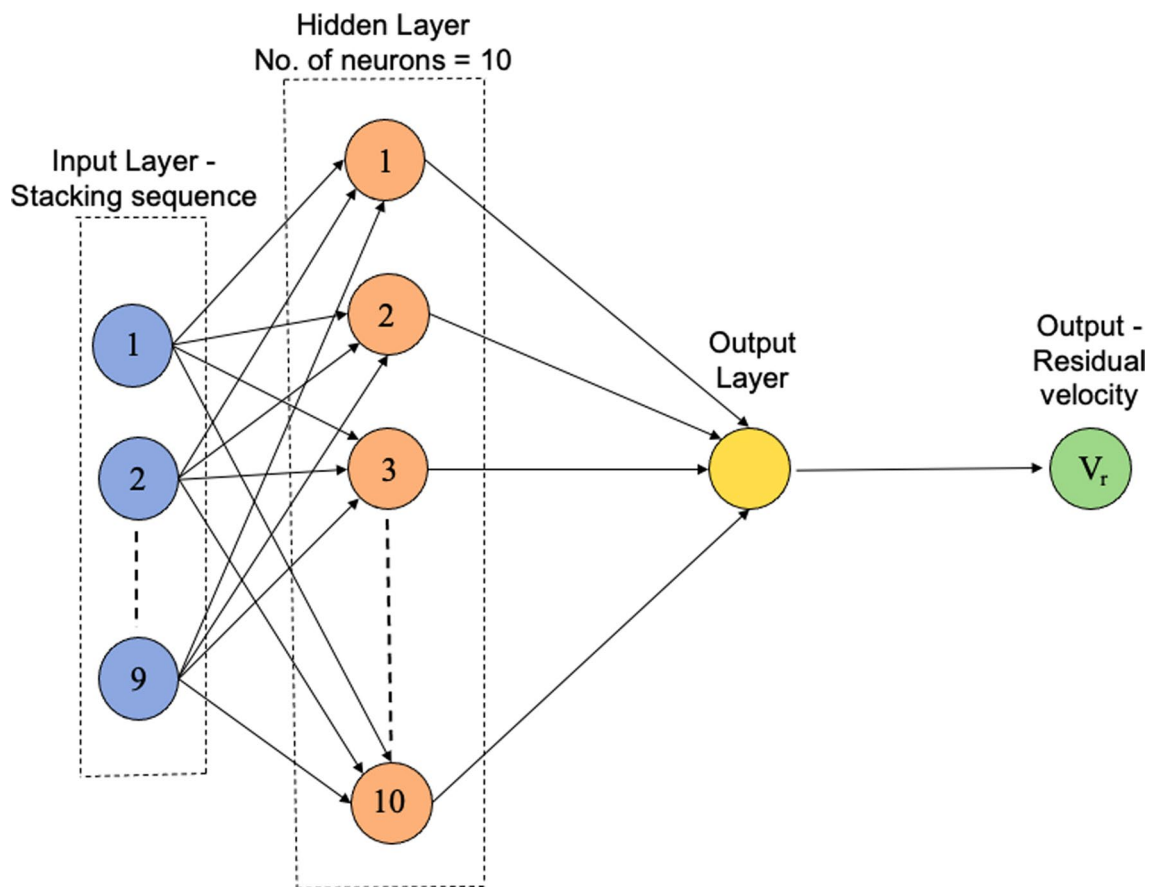


Fig. 2 MLP architecture employed in this study (9-10-1-1)

method as presented in Table 2), one hidden layer consisting of 10 neurons, 1 output layer, and finally the V_r output.

3 Results and discussion

3.1 Finite element analysis results

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

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

where m is the projectile mass and V_i and V_r are the incident and residual velocities of the projectile before and after impact, respectively.

Figure 3 depicts the impact of projectile on the laminate observed through simulation of high velocity impact. Figure 3a shows the projectile directed towards the impact face of the laminate at impact velocity (V_i). Figure 3b depicts the impact event during which some kinetic energy

possessed by the projectile is absorbed by the laminate (E_{ab}) leading to its damage and perforation. Impact energy absorption (E_{ab}) is an important factor to measure the ballistic impact resistance behavior of any material [30]. E_{ab} is thus defined as the difference in the projectile kinetic energy before and after an impact event. Figure 3c shows the bullet travelling at a residual velocity (V_r) after passing through the laminate post impact. In this study, all laminates were completely perforated during impact and exhibited V_r values which are presented in Table 3.

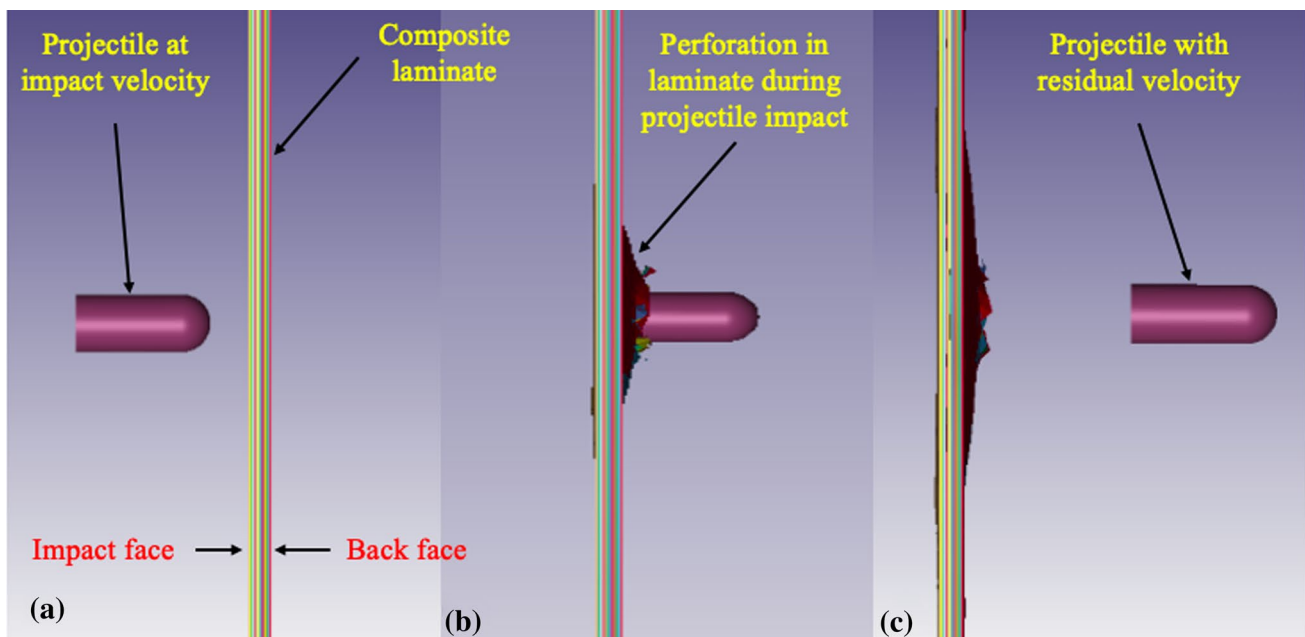
From Table 3, it can be noted that, neat Kevlar/epoxy (K/K/K) specimen exhibited the least V_r of 101.84 m s⁻¹ and highest E_{ab} of 222.86 J for the projectile compared to all other hybrid and non-hybrid composite laminates. The highest V_r of 165.13 m s⁻¹ and least E_{ab} of 151.50 J for the projectile was exhibited by neat G/G/G specimen. C/C/C specimen had a V_r of 131.79 m s⁻¹ which is between that of neat Kevlar/epoxy and glass/epoxy specimens. The highly brittle nature of carbon and glass fibers compared to that of Kevlar led to their higher projectile V_r . The second-best composite after K/K/K was K/G/K sandwich composite with V_r and E_{ab} values of 115.27 m s⁻¹ and 211.62 J, respectively. This reinforcement combination is ideal for structural

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

Sl. No	Composite specimen	V_i (m s ⁻¹)	E_i (J)	FEA results	
				V_r (m s ⁻¹)	E_{ab} (J)
1	K/K/K	250	269.37	101.84	224.15
2	C/C/C			131.79	194.07
3	G/G/G			165.13	151.50
4	K/C/K			127.62	198.72
5	C/K/K			127.62	198.72
6	K/G/K			115.27	211.62
7	G/K/K			127.62	198.72
8	C/C/K			131.66	194.21
9	C/K/C			131.65	194.22
10	K/C/C			131.65	194.22
11	C/G/C			137.24	187.76
12	G/G/K			140.10	184.35
13	G/K/G			151.29	170.33
14	K/G/G			151.29	170.33
15	G/G/C			155.19	165.19
16	G/C/G			153.63	167.26
17	C/G/G			137.24	187.76
18	K/C/G			127.62	198.72
19	K/G/C			153.63	167.26
20	C/G/K			130.71	195.28
21	G/K/C			153.63	167.26
22	G/C/K			130.75	195.23

applications considering the fact that glass fabrics are far cheaper and easily available compared to Kevlar fabrics and their impact performance is comparable to that of K/K/K. It was also observed that specimens with more Kevlar plies exhibited better impact resistance behavior compared to other specimens.

The position of Kevlar layer in the hybrid composite specimens also had an effect on the impact behavior of the laminates. Specimens with Kevlar plies in the rear layers showed enhanced E_{ab} and lower V_r compared to specimens with glass and carbon layers in the rear layers. This trend was also observed by researchers such as Muhi et al. [15] who conducted impact studies on hybrid fabric composites. They noted that as the Kevlar layer is pushed from the front face towards the back, the energy absorption increases, reaching the highest when Kevlar fabric is the last layer due to the increasing bending stiffness of the laminate when Kevlar is on the rear layer. Similarly, Randjbaran et al. [13] through ballistic impact experiments reported that, for hybrid composites comprising Kevlar, carbon and glass fabrics, the stacking of carbon and glass in the middle layers was more efficient for ballistic applications. Srivathsan et al. [31] through their studies on Kevlar/glass/epoxy hybrid composites, reiterated that the outermost fabric layers contribute its properties in transverse loading conditions. Thus, it is evident through literature, the hybridization in FRP composites is beneficial in terms of good performance for transverse loading and reduction of 25–30% in material cost [27].

**Fig. 3** Stages of projectile impact on laminate **a** before impact, **b** during impact, **c** post impact

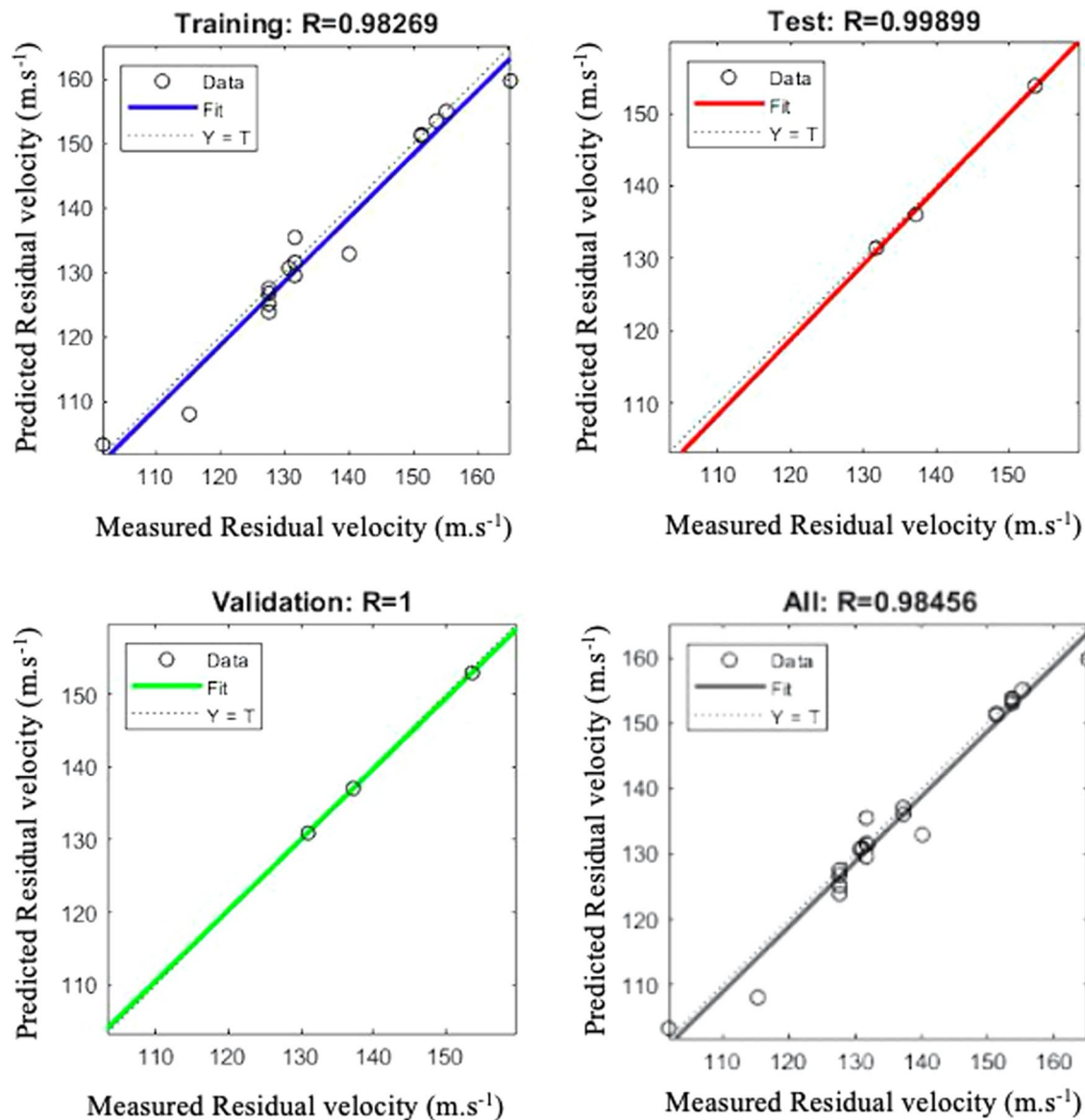


Fig. 4 Relationship between residual velocity values measured through finite element analysis and values predicted using ANN

3.2 Artificial neural network results

The regression plots represented in Fig. 4 indicate the closeness of the artificial neural network (ANN) model output to the actual target from the finite element analysis (FEA) results. Out of 22 training data fed to the network, 70% of training data (#16 data) was used for training while remaining 30% was used for testing (#3 data) and validating (#3 data) the trained model. In the training stage, R value that indicates the relationship between the output and target is obtained for training, testing and validation. An overall R value of 0.98456 is obtained where the individual R values for the training, testing

and validation are 0.98269, 0.99899 and 1, respectively. A high R value close to 1 in all stages indicated a good linear correlation between the model output and target with least error. The dotted line indicates that the model output is equal to target with zero percent error. The solid lines indicate the best data fit. In the current study, the developed ANN model network had the best fit with scattered points close to the dotted line.

Comparison of impact test results obtained through FEA and ANN is presented in Table 4. It can be noticed that most results are in good agreement with each other with a maximum variation of about 6.6%. This reiterates that, the MLP network architecture of 1 hidden layer with 10 neurons, chosen for this study to predict the impact

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

Sl. No	Composite specimen	Input data—stacking sequence	Training data derived from FEA (m s^{-1})	ANN prediction		Variation in V_r (%)
				V_r (m s^{-1})	E_{ab} (J)	
1	K/K/K	100100100	101.84	103.31	222.86	1.42
2	C/C/C	010010010	131.79	131.42	194.48	-0.28
3	G/G/G	001001001	165.13	159.77	158.99	-3.35
4	K/C/K	100100010	127.62	124.20	202.41	-2.67
5	C/K/K	100010100	127.62	126.76	199.66	-0.68
6	K/G/K	010100100	115.27	108.07	218.53	-6.66
7	G/K/K	100001100	127.62	127.55	198.79	-0.05
8	C/C/K	010010100	131.66	129.56	196.57	-1.62
9	C/K/C	010100010	131.65	131.57	194.31	-0.06
10	K/C/C	100010010	131.65	135.48	189.82	2.83
11	C/G/C	010001010	137.24	136.04	189.17	-0.88
12	G/G/K	001001100	140.10	132.92	192.78	-5.40
13	G/K/G	001100001	151.29	151.23	170.41	-0.04
14	K/G/G	100001001	151.29	151.52	170.03	0.15
15	G/G/C	001001010	155.19	155.04	165.39	-0.10
16	G/C/G	001010001	153.63	153.78	167.06	0.10
17	C/G/G	010001001	137.24	137.05	187.98	-0.14
18	K/C/G	100010001	127.62	126.89	199.51	-0.57
19	K/G/C	100001010	153.63	153.54	167.38	-0.06
20	C/G/K	010001100	130.71	130.70	195.30	-0.01
21	G/K/C	001100010	153.63	152.99	168.10	-0.42
22	G/C/K	001010100	130.75	129.75	196.35	-0.76

behavior of composites is effective in producing results that are accurate. From Fig. 4, it can be noted that the accuracy of the trained algorithm is about 98.45%.

3.3 Validation and inference

The V_r values predicted using ANN were validated through FEA results for select composite laminates (K/K/C, K/K/G, C/C/G, G/C/C, and C/K/G) to further ensure the accuracy of prediction. The results of both ANN and FEA values for the composites considered for validation are provided in Table 5.

It can be noted in Table 5, that, the ANN predicted and FEA values for V_r are in good agreement with each other with a maximum variation of about 4.2%. This variation is

acceptable for high velocity impact problems as reported in other published works [32, 33]. Thus, the methodology followed in this work to predict the impact behavior of various composite laminates using FEA and MLP-based ANN machine learning algorithm have provided an accurate measure of impact resistance without actually conducting experimental tests on such materials. ANN tool can thus be used to predict ballistic responses of various composites, such as residual velocity vs. impact velocity and impact performance curves [34].

It can be noted from both FEA and ANN results that among the three reinforcement fabrics used, Kevlar is the most suited for impact resistance applications owing to its superior impact resistance property. But Kevlar is also the most expensive among the three fabrics at 19.36 US\$ per

Table 5 Validation of ANN predicted E_{ab} values using FEA for select composite laminates

Sl. No	Composite specimen	V_i (m s^{-1})	V_r (m s^{-1}) ANN prediction	V_r (m s^{-1}) FEA results	Variation in V_r (%)
1	K/K/C	250	125.14	127.62	1.94
2	K/K/G		114.45	115.27	0.7
3	C/C/G		150.33	150.62	0.2
4	G/C/C		162.50	155.62	-4.2
5	C/K/G		138.86	135.72	-2.2

m² and next is carbon fabric with a cost of 18.36 US\$ per m². Glass fabric is the cheapest with a cost of 3.52 US\$ per m² [35]. Thus, it is ideal to use K/G/K sandwich composite with impact performance close to neat Kevlar composite for impact resistance applications where cost is the major material selection criterion. The material cost of K/G/K composite is 21% lower than that of K/K/K composite [1].

4 Conclusion

From this study on the prediction of residual velocity of projectiles post impact on various hybrid and non-hybrid composite laminates, the following conclusions can be derived:

- The proposed methodology combining FEA and ANN allows to accurately predict the residual velocity (V_r) results and thereby the impact behavior of various hybrid and non-hybrid composites.
- The ANN network trained with the data derived from FEA was able to achieve an accuracy of 98.45%. The predicted output values had a maximum variation of about 6.6% compared to FEA results. The optimum results were obtained using an MLP architecture network consisting of one hidden layer with 10 neurons.
- Through FEA and ANN results it was observed that, stacking sequence does affect the impact resistance of FRP composites. The best penetration resistance was observed in K/K/K specimen followed by specimens with Kevlar in both front and back layers.
- K/K/K composite exhibited highest impact energy absorption of 222.86 J, while G/G/G composite had the least energy absorption of 158.99 J. With energy absorption of 218.53 J, K/G/K sandwich composite exhibited energy absorption closest to neat Kevlar/epoxy specimen.
- 3-fabric hybrid composites exhibited energy absorption values significantly lower than neat Kevlar and 2-fabric sandwich composites, but higher than that of neat glass/epoxy composite.
- Though the impact energy absorption of K/G/K composite is slightly lower than K/K/K, the former is advantageous in terms of material cost savings of about 21% making it ideal for wider usage.

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Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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