POST FATIGUE LIFE PREDICTION OF GLARE SUBJECTED TO LOW-VELOCITY IMPACT

Alireza Sedaghat 1, Majid Alitavoli 2*, Abolfazl Darvizeh 3, Reza Ansari Khalkhali 4

1- PhD Student, Faculty of Mechanical Engineering, Guilan University, Rasht, Iran, Email: sedaghat.alirezaz@gmail.com, Tel:+989113438227
2- Associate Professor, Faculty of Mechanical Engineering, Guilan University, Rasht, Iran, Email: tavoli@guilan.ac.ir, Tel: +989111352269
3- Full Professor, Faculty of Mechanical Engineering, Guilan University, Rasht, Iran, Email: adarvizeh@guilan.ac.ir, Tel: +989113310486
4- Full Professor, Faculty of Mechanical Engineering, Guilan University, Rasht, Iran, Email: r_ansari@guilan.ac.ir, Tel: +989116135929

*Corresponding author: Majid Alitavoli: Faculty of Mechanical Engineering, Guilan University, rasht, Iran, E-mail: tavoli@guilan.ac.ir

Abstract
In this study, at first, the dynamic of progressive failure of Glass-Fiber-Reinforced aluminum laminates (GLARE) under low-energy impact with intra lamianar damage models implementing strain-based damage evolution laws, Puck failure criteria using ABAQUS-VUMAT, were modeled. For interface delamination, bilinear cohesive model; and for aluminum layers the Johnson-Cook model was implemented; and the fatigue life of the fiber metal laminates of GLARE subjected to impact was obtained and the numerical and experimental results of the model were compared with each other. With regard to the very good match between the numerical and experimental results, the results of the finite element model were generalized and expanded, and with the use of the multilayer neural network, the numerical model was extracted and then, by applying the meta-innovative algorithm, the maximum fatigue life of GLARE was determined at the highest level with very low-velocity impact, and the best configuration of three-layer GLARE was selected. The findings indicated that the best configuration of hybrid composite GLARE based on conventional commercial laminates that can tolerate low-velocity impacts with 18J impact energy and a 349MPa fatigue load with a frequency of 10Hz was [Al/0-90-90-0/Al/0-90-0/Al/0-90-90-0/Al] with 13016 cycle life time.

Keywords: GLARE, fatigue life, multilayer neural network, genetic algorithm.
1. Introduction

GLARE belongs to a family of fiber-metal laminates composed of alternate layers of prefabricated reinforced composites (prepreg) with unidimensional glass fibers and Aluminum 2024 sheets first invented for aeronautical applications[1].

Today, GLAREs are presented with 6 different standard classes (Table1), GLARE 1 to GLARE 6. (Figure 1) shows a general view of the GLARE.

Among glass fibers, GLARE has good adhesive properties. Glass fibers have high strengths against the compressive loading. For this reason, fiber failure in glass fibers is rarely observed during fatigue loading. It also has more advantages including high compressive and tensile strength, good impact behavior and high residual strength [2]. Good adhesion between resin and glass fibers in GLARE has made the fabrication of fibers in both sides possible. Considering this fact, GLARE is suitable for structures subjected to bilateral stresses. It seems that these characteristics have led to various potential applications. They have many advantages such as weight saving, good impact resistance, and damage tolerance [3-5]. Impact-related damage is one of the important issues in aerial structures. Inability in early detection of internal damages of composite layers, which sometimes extends from damages’ area, still is a serious safety issue.

Therefore, the accurate prediction of the internal impact damage is very necessary. Generally, failure mechanics is used for the simulation of plates’ failure, and fracture mechanics is used for modeling the plates’ post-impact damages. These two theories have been combined with stall measure and plasticity for analyzing non-linear behavior. In continuous failure mechanics, every consistency equation for damaged materials can somehow be similar to intact materials except that conventional stress which has been replaced with the effective stress [6,7].

Fracture mechanics can predict initiation and the growth of delamination phenomena based on the overall energy release rate. Although there are general frameworks, still no general model for the simulation of the GLARE’s impact mechanics has been suggested. There have been several numerical simulations represented in this area. A suitable impact model can be developed for GLARE only if the specific and basic role of constitutive materials in the impact reaction and the energy-absorbance feature is determined. Liao and Liu [8] investigated the absorbed energy among the constitutive materials of GLARE under the low-velocity impact.

Fatigue crack growth in the GLAREs can be classified into two main mechanisms: crack growth at the metal layers and delamination at the fiber-metal interface. In fact, these two have a balanced mechanism called a coupling process. Fatigue crack growth in GLAREs can be described with Linear Elastic Fracture Mechanics (LEFM). This theory states that, like metals, the crack growth rate of GLAREs is related to the stress concentration factor of the crack tip, but this influence is not so simple because stress concentration factor in GLAREs is itself influenced by fibers’ bridging which itself is initiated because of the delamination process in the metal-fiber interface. When cracks in metal layers start growing, fibers remain intact over the crack length. These fibers create a load transfer pass over the crack and restrain crack opening. Therefore, less force is transferred around the crack tip in metal layers that this, in turn, reduces the stress concentration factor of the crack tip [9-18]. Considering the present metaheuristic algorithms, the multilayer perceptron neural network was selected for modeling due to their high performance in educability and the possibility of approximating non-linear results. Genetic algorithm is a general method of optimization that employs genetic evolution for problem-solving. The input is the problem that should be solved, and the solutions are encodes according to a certain pattern, and a metric called fitness function which randomly selects and evaluates every candidate solution. In the following, a short summary of the neural network and genetic algorithm has been presented [19-24].

1.1. Multilayer Neural Network
Back-propagation algorithm (BP) is used for training the feed-forward multilayer neural network commonly known as perceptron multilayer networks (MLP). The Error backpropagation algorithm included two main passes. The first one was forward pass in which the input vector was provided to MLP network, and its effects were propagated forward through the network from the hidden layer to the output layer, and the output layer presented in the output layer created the real response of the MLP network. The second pass was called backward in which, in contrast to the forward pass, the parameters of the MLP network were changed and adjusted. This adjustment was conducted according to the error correction law, and the error signal was created in the networks’ output layer. The error vector was the difference between the desired response and the real response of the network. The calculated error value distributed over the whole network in the backward pass through the network layers. As this distribution was against the communication pass for synapse weights, the term “error back propagation” was used for this algorithm. One of the problems the researchers are faced while training neural network has been over-consistency. This means the training error level is very low in networks but the error level is very high for test data, and the network preserve training data samples and therefore it does not have the generalizability power for new data. To solve this problem, data were divided into three training, validation and test sets [19]. At the remaining part of the algorithm, the parameters of network were arranged in a way that the real response of the network got as close as possible to the desired response [20]. (Figure 2)

1.2. Optimizations with genetic algorithm

In most of the optimization problems in engineering, the optimization of more than one target function has been of great importance for designers, and there have been generally several inconsistent target functions that simultaneously should be optimized by the designer. In contrast to single-objective problems that there is just one extremum for the problem, a set of design vectors are obtained for these problems as solutions called Pareto, and the designer selects one of these points on demand. Another solution is to solve such problems according to a direct approach with a combination of the highest probability through the investigation of the direct display results by using indirect display decoding [21-23].

Genetic algorithm considers every optimization problem as an evolutionary one. This algorithm selects a set of possible values to find optimum values for parameters. Then, through performing evolution process over this population, they were gradually changed in such a way that they reach to the optimum value. The genetic algorithm needed a primary population at first. It evolved this primary population through the genetic change of their chromosomes in a way that, through the creation of new generations, it gradually found the solution of the optimization problem. This algorithm simulated three main operators in order to evolve this population including: mutation, crossover and selection.

At the crossover, a child chromosome was produced through the breeding of two-parent chromosome such that some genes of the two selected chromosomes allocate instead of each other’s. The crossover has had many methods including single-point and multi-point crossover. These crossover points were created with the help of random numbers. During mutation, some of the randomly selected genes had random changes. For example, in binary encoding, zeroes might be changed to one and vice versa.

This way, the primary population changed, and a new population was produced. This new population was created by children. During the selection, one set of chromosomes was chosen from their previous population based on their fitness and also with random numbers. The fittest chromosome had more chance to survive for the next generation. The selected population took its parents’ position. There have been different methods for selection. In this study, a fortune wheel
method was used for the genetic algorithm. All crossover, mutation, fitness and selection stages were common among all genetic algorithms. The procedure of performing the genetic algorithm has been represented in (Figure 3).

For multi-objective optimization problem-solving, there existed various methods, and each of them had their specific strengths and weaknesses. Weight coefficient method which is one of the least complicated methods for multi-objective optimization problem-solving was used in this study. In this method, the target functions of the problem were combined with each other through their weight coefficients, and the final target function was produced. The value of every target function’s weight coefficient depended on its importance, i.e. more important target functions received larger weight coefficients [23, 24]. In this method, a multi-objective optimization problem was turned to a single-objective one.

In this method, the major issue was that the obtained solution point according to the values of weight coefficient was one of Pareto chart’s points. Therefore, by changing the weight coefficients, one point of the Pareto chart could be found in each perform [24].

2. Materials and methods

In the present investigation, the post-impact fatigue life of GALRE was analyzed with the simulation of impact test and tension-tension fatigue test, and then a new model was developed, considering the good consistency between the numerical and experimental results. Then, the obtained models by Abaqus software were used in a four-layer perceptron neural network and a numerical model for its results was obtained. Next, the numerical results of the neural network were used for optimization of the genetic algorithm in order to obtain a three-layer arrangement for GLARE to reach the maximum fatigue life at the highest-level low-velocity impact. In the following, the experimental methods have been described respectively.

2.1. Numerical method for GLARE low energy Impact

For predicting the mechanical behavior of the aluminum layer, the Johnson-Cook relation without temperature consideration was used [25]:

$$
\sigma = \left[ A + B \left( \hat{\varepsilon}_{pl} \right)^n \right] \left[ 1 + C \ln \frac{\hat{\varepsilon}_{pl}}{\varepsilon_o} \right]
$$

Where A, B and C are material parameters, $\hat{\varepsilon}_{pl}$ is an equivalent plastic strain, $n$ is material constant. A damage parameter $\psi$ was used for simulation of the ductile damage of the aluminum layer.

$$
\psi = \sum \left( \frac{\Delta \hat{\varepsilon}_{pl}}{\bar{\varepsilon}_{pl}} \right)
$$

$$
\bar{\varepsilon}_{pl} = \left[ d_1 + d_2 \exp \left( d_3 \frac{p}{q} \right) \right] \left[ 1 + d_4 \ln \frac{\hat{\varepsilon}_{pl}}{\varepsilon_o} \right]
$$

Where $d_1$ to $d_4$ is a material parameter and $p/q$ is the hydrostatic pressure per deviatoric stress.

2.2. Composite damage model

The intra-laminar damage model had the ability to prognosticate the intralaminar failure of a composite material, and the results from the relations have been shown by Donadon et al. [26] and
Appruzzese and Falzon [27]. Damage variables represented the amount of local damage in a Representative Volume Element (RVE) of the composite material. In one dimension, the definition of damage variable $d$ led to the effective stress $\bar{\sigma}$ or the stress computed over the section of the RVE. For an undamaged pristine material $d = 0$, while $d = 1$ denoted the complete failure. Lemaitre and Chaboche expressed that the constitutive law of damaged material could be derived from the principle of strain equivalence.

The relationship existing between the stress tensor $\bar{\sigma}$ and true stress tensor $\sigma$ was:

$$\sigma = D \sigma$$  \hspace{1cm} (4)

Where $D$ is damage matrix:

$$D = \begin{bmatrix} 
1/(1-d_{11}) & 0 & 0 & 0 & 0 & 0 \\
0 & 1/(1-d_{22}) & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 1/(1-d_{12}) & 0 & 0 \\
0 & 0 & 0 & 0 & 1/(1-d_{23}) & 0 \\
0 & 0 & 0 & 0 & 0 & 1/(1-d_{31}) 
\end{bmatrix}$$  \hspace{1cm} (5)

the stress tensor $\bar{\sigma}$ and strain tensor $\varepsilon$ were related as:

$$\bar{\sigma} = C \varepsilon$$  \hspace{1cm} (6)

The relationship between the stress increment tensor $\Delta \sigma$ and strain tensor $\Delta \varepsilon$ was as follows:

$$\Delta \sigma = C \left[ D \left( \Delta \varepsilon - \Delta \varepsilon^{in} \right) - \Delta D \left( \varepsilon - \varepsilon^{in} \right) \right]$$  \hspace{1cm} (7)

Where $\varepsilon^{in}$ is an inelastic strain, $D$ and $\Delta D$ are the damage and incremental damage matrices expressed by Donadon et al. [26].

2.3. Material properties

For simulating the finite element model with intralaminar and interlaminar damage together with a wide range of lamina properties, it was required to describe material behavior; and (Tables 2 and 3) show all the material properties used in this research.

2.4. Finite element modeling

Numerical modeling was conducted by ABAQUS-VUMAT for evaluation of the impact-related damage of GLARE specimens. A C3D8R solid hexagonal element was used. The Johnson-Cook model was implemented for aluminum layers. The dynamic penalty method was used to simulate the contact between the GLARE and impactor. Due to the excessive distortion of elements, an enhanced stiffness relaxation was employed to control hourglassing phenomena. Intralaminar damage models with Puck failure criteria were implemented. The bilinear cohesive model was used to predict the delamination, and finite-thickness cohesive element was established for the delamination interface between the two layers.

2.5. Fatigue crack growth in FMLs

Mechanism of fatigue crack growth in FMLs has been a complex phenomenon. To characterize this phenomenon and develop an analytical method, several simplifying assumptions were
required. However, the suggested method according to the real crack growth phenomenon should be still accurate. The SIF at crack tip was expressed as:

\[ K_{\text{tip}} = K_{\text{farfield}} + K_{\text{bridging}} \quad (8) \]

The SIF expression, caused by the far field stress applied in the Al layers, by the linear elastic theory for monolithic metals was [13]:

\[ K_{\text{farfield}} = S_{\text{al}} \sqrt{\pi a} \quad (9) \]

### 2.6. Bridging stress calculation

The fibers in FMLs were insensitive to fatigue. They transferred a significant part of the load over the crack, and restrained the crack opening, as shown in fig. 4. Due to this restraining, the crack opening in GLARE was smaller as compared to the monolithic metal. This mechanism resulted in smaller crack-tip SIF as compared to the monolithic metal, for equal crack length and applied load. (Figure 4)

The crack opening of a fatigue crack in infinite FMLs at the location \( x \) along the crack could be expressed as

\[ v_{\infty}(x) - v_{br}(x) = \delta_f(x) + \delta_{pp}(x) \quad (10) \]

Where \( v_{\infty}(x) \), \( v_{br}(x) \), \( \delta_f(x) \) and \( \delta_{pp}(x) \) represented the crack opening displacement caused by the far field stress, bridging stress in aluminum layer, the elongation of the fibers over the delaminated length and the deformation of the glass/epoxy prepreg layer, respectively. The crack opening displacement far from crack caused by the far field stress was:

\[ v_{\infty}(x) = 2 \frac{S_{\text{al}}}{E_{\text{al}}} \sqrt{a^2 - x^2} \quad (11) \]

\( E_{\text{al}}, S_{\text{al}} \) and \( a \) are the elastic modulus of aluminum, far-field stress of aluminum layer and crack length; respectively.

Hereafter, the SIF at the crack tip for a crack with an arbitrary delamination shape was determined; the crack growth rate could be obtained with the empirical Paris relation [28] for the aluminum layer:

\[ \frac{da}{dN} = C_{\text{cg}} \Delta K_{\text{eff}}^{n_{\text{eg}}} \quad (12) \]

\[ \Delta K_{\text{eff}} = \left(1-R^{1/35}\right)K'_{\text{tip}} \sqrt{\frac{a\pi}{W}} \quad (13) \]

\[ K'_{\text{tip}} = \beta_{\text{dixon}} \times \beta_{\text{impact}} \times K_{\text{tip}} \quad (14) \]

Where

\[ \beta_{\text{dixon}} = \frac{1}{\sqrt{1 - \left(\frac{2a}{W}\right)^2}} \quad (15) \]

\[ \beta_{\text{impact}} = \frac{1}{\sqrt{1 - \left(\frac{2v_{\text{impact}}}{v_{\text{ballistic}}\right)^2}} \quad (16) \]
Where $v_{\text{impact}}$ and $b_{\text{ballistic}}$ are impactor velocity and ballistic limit of GLARE types which were investigated by Seyed Yaghoobi et al. [29] By using eq. 4, crack growth life of GLARE could be calculated as:

$$N = \int_{a_c}^{a} \frac{1}{C_{\text{cg}}AK_{\text{eff}}^{n_{\text{cg}}}} \, da$$

(17)

2.7. Specimens
For a GLARE 5 2.1 and 4 3/2, the thickness of the Aluminum layer was 0.4mm, and the thickness of the composite layer was 2.2mm with a 3mm total thickness.

2.8. Low-velocity impact testing
The impact test was conducted by a drop-weight impact tower with a velocity range of 1.87-2.39m/s (Figure 5 and 6). After the first impact, a pneumatic braking system was activated, and the impactor was prevented to hit the specimen again. The specimen was clamped between the top and bottom steel plates of the fixture with 75×225mm² with a 50 mm diameter circular opening at the center of each plate. The impactor was a 10 mm diameter steel hemispherical with a mass of 6.29kg.

2.9. Post-impact fatigue testing
The tension-tension fatigue tests were conducted by a SANTAM-50 machine at 5 levels of 175, 232, 291 and 349 MPa with an $R=0.05$ stress ration and a frequency of 10Hz (Figures 7 and 8).

3. Findings
A total of 64 simulating cases were used in ABAQUS software that has been listed in (Table 4). Three variables were used for designation. The variables were the designs of different GLARE configurations. Every location could have one out five GLARE types, and zero values presented in the table indicated the non-existence of any GLARE in that location. Taguchi method was used for model designing. Model designing was conducted with the maximum impact energy and the maximum imposed fatigue stress.

4. Results and discussion

4.1. evaluation of the finite element
A set of low-velocity impact test was conducted for the evaluation of deformation and distortion in GLAREs. Comparative studies were conducted by the results of experiments on GLARE 5 2.1 and 4 3/2 for the evaluation of prediction models. A 50×200mm² GLARE specimen was clamped between the top and bottom of the steel plates. A steel spherical impactor with a 10 mm diameter and a mass of 6.29kg were used for 11J and 18J impact energies. The comparison between the prediction model for the contact time history for a GLARE 5 2/1 and 4 3/2 showed that it had a good consistency with the experimental results as has been represented in (Figures 9-13). According to (Figure 9), considering the predicted pattern for this problem that the stress concentration is higher in the encountered area, a graded meshing was used in order to have a more accurate dynamic analysis in the impactor area with the GLARE surface. After the collision of the impactor with GLARE, the force values in central elements increased intensely and reached
to the maximum level. This maximum limit occurred when the GLARE 5 2/1 was in its extreme deflection and after that, the impactor start dissociating from GLARE surface and the force decreased to reach zero, i.e. the complete separation. (Figure 11) shows the impact force-time history curves for GLARE 5 2/1 and 4 3/2 in 18 J impact energy. Some numerical oscillation showed up near the peak force in the curves, mainly because of the dynamic response and numerical effect. In the present investigation, a numerical filtering technique was applied and the output sampling time was 0.005 ms at about 2ms and 2.2 ms time for GLARE 5 2/1 and GLARE 4 3/2 specimens; respectively, the impactor reached to the lowest end, and then started to rebound until there was a complete separation between the impactor and laminate at about 3.7 ms and 3.5ms time; respectively. A relatively good agreement was found between the numerical and experimental results considering the impact force-time curves. For both numerical and experimental results between GLARE 4 3/2 and GLARE 5 2/1, the higher peak force and less contact time belonged to GLARE 4 3/2. This was because of the number of aluminum layers which had higher stiffness and impact resistance. (Figure 12) shows the maximum central displacement and permanent central displacement related to the lowest end of the impactor and the zero-impact force at the end of the impact; respectively. It was so because GLARE 4 3/2 absorbed more energy due to the number of its aluminum and composite layers compared to GLARE 5 2/1, while its displacement was lower. Therefore, it can be concluded that in response to a very slow velocity impact, with an increasing number of composite and aluminum layers in GLARE, more energy was absorbed and the displacement decreased. 

(Figure 13) shows the post-impact fatigue for GLARE 5 2.1 for different impact energy levels, and different tension-tension fatigue tests. As the figure clearly shows, with an increase in the impact energy at a certain level of tensile stress in the fatigue test, the fatigue life of specimen decreased. This was due to the damage caused by the low-velocity impact. Also, with increasing tension stress in fatigue with keeping the energy level constant, the fatigue life of GLARE was reduced. The reason for this was that the damage level of the composite and aluminum layers of GLARE increased. Therefore, with the simultaneous increase of the impact on the GLARE and the tension stress level of fatigue, the fatigue life of GLARE was definitely reduced.

4.2. the results of numerical modeling with neural network

An MLP multilayer perceptron neural network was used for numerical modeling. Four layers with 8 hidden neurons produced a neural network. Of 64 primary data, 70% was used for training, 15% for testing and 15% for validation; and the improvement procedure has been shown in (Figure 10). Also, the difference between real outputs of the obtained neural network with 64 primary data has been shown in (Figure 14).

As can be seen in (Figure 15), the blue points are fatigue lifetime of different GLARE predicted by the neural network, while the red points are modeled fatigue lifetime by the finite element method. As can be seen, these two matched in many points. Therefore, this figure clearly shows that the neural network has been able to accurately predict GLARE specimen lifetime according to the primary data.

4.3. optimization

Considering obtained models with multilayer perceptron neural network, a metaheuristic optimization was used.
1- Design variables: permutation of different GLAREs; 2- design constraint: 3 permutation and 5 different GLAREs; 3- design objective: maximizing fatigue life. Genetic algorithm was applied for these aims.

The number of primary population was 30, and the number of optimization generations was 80. Due to the 85% crossover probability, and a 15% mutation probability, the optimization procedure chart has been shown in (Figure 15). According to (Figure 16), after the ninth generation of optimization, the two relative compatibility and optimized graphs converged to each other, and the compatibility was optimized after the tenth generation. Also, a lifetime of 13016 cycles was obtained for an impact energy of 18J (the maximum of very low impact energy) and a 350MPa tension-tension fatigue stress (the maximum exerted stress for tension-tension fatigue) for a GLARE with the first order equal to 5, the second layer equal to 3 and the third layer equal to 5; respectively. It should be mentioned that GLARE 5 fatigue life in these loading conditions is 9873 cycles and comparing to new hybrid composite design the improvement is 31.83% and comparing to [Glare 3/GLARE 5/ GLARE 3] multilayer composite arrangement the improvement is 30.16%

4.4. the error evaluation of optimized model

The optimized model of this study predicted the post-impact fatigue lifetime for an impact energy of 18J (the maximum of very low impact energy) and a 350MPa tension-tension fatigue stress (the maximum exerted stress for tension-tension fatigue) as 13016 cycles. The first layer in this optimized hybrid composite was equal to GLARE 5, the second layer was equal to GLARE 3 and the third layer was equal to GLARE 5. A finite element model for this GLARE with the exact composition of the above GLARE structure was designed to validate the model with an impact energy of 18J; and then a 350MPa stress level with the same finite element method that its results had a high match with the experimental results. After that, the post-impact fatigue lifetime for this new finite element model was evaluated. This obtained lifetime was 13406 cycles that had a 3% difference relative to the neural network model optimized by the genetic algorithm (mean value error). This indicated the efficacy and trust of the neural network model optimized by the genetic algorithm. The finite element model represented for this new under-the-impact GLARE composition has been shown in (Figure 17).

5. Conclusion

The purpose of the present investigation was to maximize the fatigue life of hybrid composite GLARE with three permutation and the optimization methods were used to find minimum values. The best configuration of hybrid composite GLARE was based on conventional commercial laminates that can tolerate low-velocity impacts with 18J impact energy and a 349MPa fatigue load with a frequency of 10Hz is [Al/0-90-90-0/Al/0-90-0/Al/0-90-90-0/Al] with 13016 cycle lifetime. By the comparison between neural network model and finite element model for this GLARE, the difference for the prediction of post-impact fatigue life was 3%.

References


Alireza Sedaghat is PhD Student of Mechanical Engineering In Guilan University and Faculty Member of Islamic Azad University of Lahijan. Main research Interests Include: Impact Mechanics, Fatigue, Hybrid Composites, Biomechanics

Majid AliTavoli is Associate Professor of Faculty of Mechanical Engineering of Guilan University. His Main Research Interests Include: Metal Forming, Water jet, Innovative Design, Impact

Abolfazl Darvizeh is Distinguished Mechanical Engineering Professor Of Guilan University. His Main Research Interests Include: Design and Nature (Biomimetic Engineering), Impact Mechanics, Explosive Welding.
Reza Ansari Khalkhali is Full Professor of Faculty of Mechanical Engineering of Guilan University. His Main Research Interests Include: Mathematical Modeling, Dynamics and Vibrations, Non-Conventional Materials

![Figure 1. Fiber metal laminate (GLARE)](image)

**Table 1. commercial grades of GLARE**

<table>
<thead>
<tr>
<th>Grade</th>
<th>Sub</th>
<th>Metal Type</th>
<th>Metal Thickness (mm)</th>
<th>Fibre Layer (mm)</th>
<th>Pregreg orientation in each fibre layer (°)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GLARE 1</td>
<td>-</td>
<td>7475-T761</td>
<td>0.3-0.4</td>
<td>0.266</td>
<td>0/0</td>
</tr>
<tr>
<td>GLARE 2</td>
<td>GLARE 2A</td>
<td>2024-T3</td>
<td>0.2-0.5</td>
<td>0.266</td>
<td>0/0</td>
</tr>
<tr>
<td></td>
<td>GLARE 2B</td>
<td>2024-T3</td>
<td>0.2-0.5</td>
<td>0.266</td>
<td>90/90</td>
</tr>
<tr>
<td>GLARE 3</td>
<td>-</td>
<td>2024-T3</td>
<td>0.2-0.5</td>
<td>0.266</td>
<td>0/90</td>
</tr>
<tr>
<td></td>
<td>GLARE 4A</td>
<td>2024-T3</td>
<td>0.2-0.5</td>
<td>0.266</td>
<td>0/90/0</td>
</tr>
<tr>
<td>GLARE 4</td>
<td>GLARE 4B</td>
<td>2024-T3</td>
<td>0.2-0.5</td>
<td>0.266</td>
<td>90/0/90</td>
</tr>
<tr>
<td>GLARE 5</td>
<td>-</td>
<td>2024-T3</td>
<td>0.2-0.5</td>
<td>0.266</td>
<td>0/90/90/0</td>
</tr>
<tr>
<td></td>
<td>GLARE 6A</td>
<td>2024-T3</td>
<td>0.2-0.5</td>
<td>0.266</td>
<td>+45/-45</td>
</tr>
<tr>
<td>GLARE 6</td>
<td>LARE 6B</td>
<td>2024-T3</td>
<td>0.2-0.5</td>
<td>0.266</td>
<td>-45/+45</td>
</tr>
</tbody>
</table>

![Figure 2. Neural network model used in this study [21]](image)
Figure 3. Procedure of the genetic algorithm [20]

<table>
<thead>
<tr>
<th>Table 2. The material parameters for 2024-T3 aluminium [8]</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Elastic parameters</strong>: ( \rho = 2770 \text{kg/m}^3 ), ( E = 72.4 \text{GPa} ).</td>
</tr>
<tr>
<td>( v = 0.34 )</td>
</tr>
<tr>
<td><strong>Plastic parameters</strong>: ( A = 396 \text{MPa}, B = 689 \text{MPa} )</td>
</tr>
<tr>
<td>( C = 0.083 \text{MPa}, n = 0.34 )</td>
</tr>
<tr>
<td>( d_1 = 0.13, d_4 = 0.13, d_5 = -1.5 ).</td>
</tr>
<tr>
<td><strong>Fracture parameters</strong>: ( d_1 = 0.011, \dot{\varepsilon}_0 = 1.0 \text{s}^{-1} )</td>
</tr>
</tbody>
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<tr>
<th>Table 3. Material parameters for Glass/Epoxy composite layer. [8-10]</th>
</tr>
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<tbody>
<tr>
<td><strong>Composite layer</strong>: Youngs moduli ( E_1 = 50.6 \text{GPa}, E_2 = E_3 = 9.9 \text{GPa} )</td>
</tr>
<tr>
<td>Shear moduli ( G_{12} = G_{13} = 3.7 \text{GPa} ), ( G_{23} = 1.65 \text{GPa} )</td>
</tr>
<tr>
<td>Poisson's ratios ( \nu_{12} = \nu_{13} = 0.32, \nu_{23} = 0.063 )</td>
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<td><strong>Strength parameters</strong>: ( X^T = 2500 \text{MPa}, X^C = 2000 \text{MPa}, Y^T = 50 \text{MPa} )</td>
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<td>( Y^C = 150 \text{MPa}, S_{12} = S_{13} = 75 \text{MPa} )</td>
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<td>( S_{23} = 50 \text{MPa} ) [25]</td>
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<td><strong>Intralaminar fracture toughnesses</strong>: ( G_1^t = 81.5 \text{N/mm}, G_2^t = 14.955 \text{N/mm} )</td>
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<td>( G_3^t = 106.3 \text{N/mm}, G_{12}^t = 14.955 \text{N/mm} )</td>
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<td><strong>Interface</strong>: Interlaminar Fracture toughnesses ( G_1^c = 0.5 \text{N/mm}, G_2^c = G_3^c = 0.9 \text{N/mm} )</td>
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Figure 4. Crack bridging of the fibers and delamination of the layers

Figure 5. The impact test machine

Figure 6. Impact loading set up

Figure 7. The fatigue test machine
Table 4. The results of finite element simulation for the creation of a numerical model

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Figure 9. A complete view of the finite element modeling for GLARE 5 2/1

Figure 10. Damage cantor for the composite part of GLARE

Figure 11. Comparison between numerical and experimental results for force-time history for GLARE 5 2.1 and 4 3/2

Figure 12. Force-displacement history curve for 18 J impact energy
Figure 13. The results of post-impact fatigue for GLARE 5 2.1

![Bar chart showing energy dissipation for different GLARE configurations.]

Best Validation Performance is 511012.6193 at epoch 13

Figure 14. The improvement procedure of the neural network

![Graph showing mean squared error over epochs.]
Figure 15. The difference between the real outputs of the obtained neural network

Figure 16. Convergence of the optimization results
Figure 17. The finite element model for new GLARE