An approximation method of strength ratio calculation of laminated composite material based on evolutionary artificial neural network

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***Abstract*—Traditionally, classic lamination theory is widely used to compute properties of composite materials under in-plane and out-of-plane loading from a knowledge of the material properties of the individual layers and the laminate geometry. In this study, a systematic procedure is proposed to design an artificial neural network for a practical engineering problem, which is applied to calculate the strength ratio of a laminated composite material under in-plane loading, in which the genetic algorithm is proposed to optimize the search process at four different levels: the architecture, parameters, connections of the neural network, and active functions.**

Keywords*—*Classic Lamination Theory; Genetic Algorithm; Artificial neural network; Optimization

I. Introduction

Fiber-reinforced composite materials have been widely used in a variety of applications, which include electronic packaging, sports equipment, homebuilding, medical prosthetic devices, high-performance military structures, etc. because they offer improved mechanical stiffness, strength, and low specific gravity of fibers over conventional materials. The stacking sequence, ply thickness, and fiber orientation of composite laminates give the designer an additional 'degree of freedom' to tailor the design with respect to strength or stiffness. Classical lamination theory(CLT) and failure theory, e.g., Tsai-Wu failure criteria, is usually taken to predict the behavior of a laminate from a knowledge of the composite laminate properties of the individual layers and the laminate geometry.

However, the use of CLT needs intensive computation which takes an analytical method to solve the problem, since it involves massive matrix multiplication and integration calculation. Techniques of function approximation can accelerate the calculation process and reduce the computation cost. Artificial neural network(ANN), heavily inspired by biology and psychology, is a reliable tool instead of a complicated mathematical model. ANN has been widely used to solve various practical engineering problems in applications, such as pattern recognition, nonlinear regression, data mining, clustering, prediction, etc. Evolutionary artificial neural networks is a special class of artificial neural networks, in which evolutionary algorithms are introduced to design the topology of an ANN, and can be used at four different levels: connection weights, architectures, input features, and learning rules. It is shown that the combinations of ANN's and evolutionary algorithm [1] can significantly improve the performance of intelligent systems than that rely's on ANN's or evolutionary algorithms alone.

The rest of this paper is organized as the following: section II introduces the CLT and the failure criteria, which is used to check whether the composite material fails or not in the present study; section III covers the design of artificial neural network for a function approximation; section IV reviews the use of the genetic algorithm in the design of neural network architecture, and the techniques of parameters optimization during the training process; section V presents the result of the numerical experiments in different cases; in the conclusion part, we present and discuss the experiment results.

II. Classic lamination theory and Failure theory

A. Classic Lamination Theory

CLT is based upon three simplifying engineering assumptions: Each layer's thickness is small and consists of homogeneous, orthotropic material, and these layers are perfectly bonded together through the thickness; The entire laminated composite is supposed to be under in-plane loading; Normal cross-sections of the laminate is normal to the deflected middle surface, and do not change in thickness. Fig. 1 shows the coordinate system used for showing an angle lamina. The axis in the 1-2 coordinate system are called the local axis or the material axis, and the axis in the x-y coordinate system are called global axis.

Special cases of laminates, i.e., symmetric laminates, cross-ply laminates, are important in the design of laminated structures. A laminate is called an angle ply laminate if it has plies of the same material and thickness and only oriented at $+\theta$ and $-\theta$ directions. A model of an angle ply laminate is as shown in Fig. 2.

1) Stress and Strain in a Lamina: For a single lamina under in-plane loading whose thickness is relatively small, suppose the upper and lower surfaces of the lamina are free

TABLE I: Comparison of the carbon/epoxy, graphite/epoxy, and glass/epoxy properties

Property	Symbol	Unit	Carbon/Epoxy	Graphite/Epoxy	Glass/Epoxy
Longitudinal elastic modulus	E_1	GPa	116.6	181	38.6
Traverse elastic modulus	E_2	GPa	7.67	10.3	8.27
Major Poisson's ratio	v_{12}		0.27	0.28	0.26
Shear modulus	G_{12}	GPa	4.17	7.17	4.14
Ultimate longitudinal tensile strength	$(\sigma_1^T)_{ult}$	MP	2062	1500	1062
Ultimate longitudinal compressive strength	$(\sigma_1^C)_{ult}$	MP	1701	1500	610
Ultimate transverse tensile strength	$(\sigma_2^T)_{ult}$	MPa	70	40	31
Ultimate transverse compressive strength	$(\sigma_2^C)_{ult}$	MPa	240	246	118
Ultimate in-plane shear strength	$(\tau_{12})_{ult}$	MPa	105	68	72
Density	ρ	g/cm^3	1.605	1.590	1.903
Cost			8	2.5	1

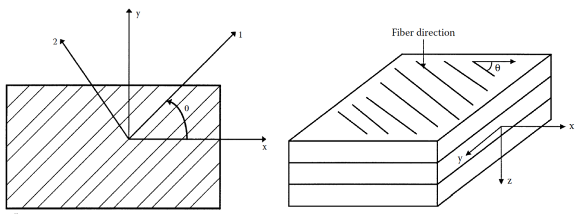


Fig. 1: The left diagram shows the local and global axis of an angle lamina, which is from a laminate as shown in the right diagram.

$+\theta$
$-\theta$
$\dots$
$-\theta$
$+\theta$

Fig. 2: Model for angle ply laminate

from external loading. According to Hooke's law, the three-dimensional stress-strain equations can be reduced to two-dimensional stress-strain equations in the composite material. The stress-strain relation in local axis 1-2 is

$$\begin{bmatrix} \sigma_1 \\ \sigma_2 \\ \tau_{12} \end{bmatrix} = \begin{bmatrix} Q_{11} & Q_{12} & 0 \\ Q_{12} & Q_{22} & 0 \\ 0 & 0 & Q_{66} \end{bmatrix} \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \gamma_{12} \end{bmatrix} \tag{1}$$

where Q_{ij} are the stiffnesses of the lamina. And they are related to engineering elastic constants as follows:

$$\begin{aligned} Q_{11} &= \tfrac{E_1}{1-v_{12}v_{21}}, \\ Q_{22} &= \tfrac{E_2}{1-v_{12}v_{21}}, \\ Q_{66} &= G_{12}, \\ Q_{12} &= \tfrac{v_{21}E_2}{1-v_{12}v_{21}}, \end{aligned} \tag{2}$$

where E_1, E_2, v_{12}, G_{12} are four independent engineering elastic constants, which are defined as follows: E_1 is the longitudinal Young's modulus, E_2 is the transverse Young's modulus, v_{12} is the major Poisson's ratio, and G_{12} is the in-plane shear modulus.

Stress strain relation in the global x-y axis is

$$\begin{bmatrix} \sigma_x \\ \sigma_y \\ \tau_{xy} \end{bmatrix} = \begin{bmatrix} \bar{Q}_{11} & \bar{Q}_{12} & \bar{Q}_{16} \\ \bar{Q}_{12} & \bar{Q}_{22} & \bar{Q}_{26} \\ \bar{Q}_{16} & \bar{Q}_{26} & \bar{Q}_{66} \end{bmatrix} \begin{bmatrix} \varepsilon_x \\ \varepsilon_y \\ \gamma_{xy} \end{bmatrix} \tag{3}$$

where

$$\begin{aligned} &\bar{Q}_{11} = Q_{11}cos^4\theta + Q_{22}sin^4\theta + 2\left(Q_{12} + 2Q_{66}\right)sin^2\theta cos^2\theta, \\ &\bar{Q}_{12} = \left(Q_{11} + Q_{22} - 4Q_{66}\right)sin^2\theta cos^2\theta + Q_{12}\left(cos^4\theta + sin^2\theta\right), \\ &\bar{Q}_{22} = Q_{11}sin^4\theta + Q_{22}cos^4\theta + 2\left(Q_{12} + 2Q_{66}\right)sin^2\theta cos^2\theta, \\ &\bar{Q}_{16} = \left(Q_{11} - Q_{12} - 2Q_{66}\right)cos^3\theta sin\theta - \left(Q_{22} - Q_{12} - 2Q_{66}\right)sin^3\theta cos\theta, \\ &\bar{Q}_{26} = \left(Q_{11} - Q_{12} - 2Q_{66}\right)cos\theta sin^3\theta - \left(Q_{22} - Q_{12} - 2Q_{66}\right)cos^3\theta sin\theta, \\ &\bar{Q}_{66} = \left(Q_{11} + Q_{22} - 2Q_{12} - 2Q_{66}\right)sin\theta^2 cos\theta^2 + Q_{66}\left(sin\theta^4 + cos\theta^4\right). \end{aligned} \tag{4}$$

2) Stress and Strain in a Laminate: For forces and moment resultants acting on laminates, such as in plate and shell structures, the relationship between applied forces and moment and displacement can be given by

$$\begin{aligned} \begin{bmatrix} N_x \\ N_y \\ N_{xy} \end{bmatrix} &= \begin{bmatrix} A_{11} & A_{12} & A_{16} \\ A_{12} & A_{22} & A_{26} \\ A_{16} & A_{26} & A_{66} \end{bmatrix} \begin{bmatrix} \varepsilon_x^0 \\ \varepsilon_y^0 \\ \gamma_{xy}^0 \end{bmatrix} \\ &+ \begin{bmatrix} B_{11} & B_{12} & B_{16} \\ B_{11} & B_{12} & B_{16} \\ B_{16} & B_{26} & B_{66} \end{bmatrix} \begin{bmatrix} k_x \\ k_y \\ k_{xy} \end{bmatrix}, \end{aligned} \tag{5}$$

where N_x, N_y refers to the normal force per unit length; N_{xy} means shear force per unit length; ε^0 and k_{xy} denotes mid plane strains and curvature of a laminate in x-y coordinates

The mid-plane strain and curvature is given by

$$
\begin{aligned}
A_{ij} &= \sum_{k=1}^{n} (\overline{Q_{ij}})_k (h_k - h_{k-1}) i = 1,2,6, j = 1,2,6, \\
B_{ij} &= \frac{1}{2} \sum_{k=1}^{n} (\overline{Q_{ij}})_k (h_k^2 - h_{k-1}^2) i = 1,2,6, j = 1,2,6, \\
D_{ij} &= \frac{1}{3} \sum_{k=1}^{n} (\overline{Q_{ij}})_k (h_k^3 - h_{k-1}^3) i = 1,2,6, j = 1,2,6.
\end{aligned}
\tag{6}
$$

The [A], [B], and [D] matrices are called the extensional, coupling, and bending stiffness matrices, respectively. The extensional stiffness matrix $[A]$ relates the resultant in-plane forces to the in-plain strains, and the bending stiffness matrix $[D]$ couples the resultant bending moments to the plane curvatures. The coupling stiffness matrix $[B]$ relates the force and moment terms to the midplain strains and midplane curvatures.

B. Failure criteria for a lamina

Failure criteria for composite materials are more difficult to predict due to structural and material complexity in comparison to isotropic materials. The failure process of composite materials can be regarded from microscopic and macroscopic points of view. Most popular criteria about the failure of an angle lamina are in terms of macroscopic failure criteria, which are based on the tensile, compressive, and shear strengths. According to the failure surfaces, these criteria [2], [3], [4], [5], [6], [7], [8], [9], can be classified into two classes: one is called independent failure mode criteria which includes the maximum stress failure theory[10], maximum strain failure theory because their failure envelop are rectangle; another is called quadratic polynomial which includes Tsai-Wu[11], [12], Chamis, Hoffman and Hill criteria because their failure surfaces are of ellipsoidal shape. In the present study, the two most reliable failure criteria are taken, Maximum stress and Tsai-wu. Both of these two failure criteria are based on the stresses in the local axis instead of principal normal stresses and maximum shear stresses, and four normal strength parameters and one shear stress for a unidirectional lamina are involved. The five strength parameters are

$(\sigma_1^T)_{ult} =$ ultimate longitudinal tensile strength(in direction 1),

$(\sigma_1^C)_{ult} =$ ultimate longitudinal compressive strength,

$(\sigma_2^T)_{ult} =$ ultimate transverse tensile strength,

$(\sigma_2^C)_{ult} =$ ultimate transverse compressive strength, and

$(\tau_{12})_{ult} =$ and ultimate in-plane shear strength.

1) Maximum stress(MS) failure criterion: Maximum stress failure theory consists of maximum normal stress theory proposed by Rankine and maximum shearing stress theory proposed by Tresca. The stress applied on a lamina can be resolved into the normal and shear stress in the local axis. If any of the normal or shear stresses in the local axis of a lamina is equal or exceeds the corresponding ultimate strengths of the unidirectional lamina, the lamina is considered to be failed. That is,

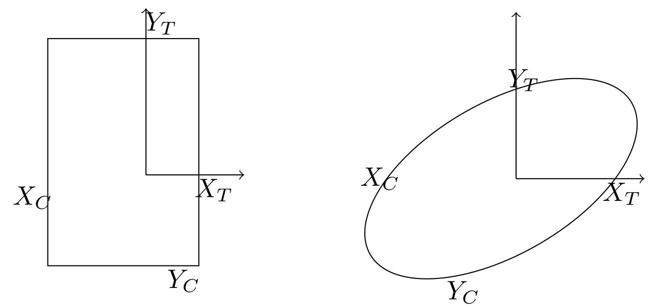


Fig. 3: Schematic failure surfaces for maximum stress and quadratic failure criteria

$$
\begin{aligned}
\sigma_1 \geq (\sigma_1^T)_{ult} \quad &or \quad \sigma_1 \leq -(\sigma_1^C)_{ult}, \\
\sigma_2 \geq (\sigma_2^T)_{ult} \quad &or \quad \sigma_2 \leq -(\sigma_2^C)_{ult}, \\
\tau_{12} \geq (\tau_{12})_{ult} \quad &or \quad \tau_{12} \leq -(\tau_{12})_{ult},
\end{aligned}
\tag{7}
$$

where σ_1 and σ_2 are the normal stresses in the local axis 1 and 2; τ_{12} is the shear stress in the symmetry plane 1-2.

2) Tsai-wu failure criterion: The TW criterion is one of the most reliable static failure criteria derived from the von Mises yield criterion. A lamina is considered to fail if

$$
\begin{aligned}
H_1\sigma_1 + H_2\sigma_2 + H_6\tau_{12} + H_{11}\sigma_1^2 + H_{22}\sigma_2^2 \\
+ H_{66}\tau_{12}^2 + 2H_{12}\sigma_1\sigma_2 < 1
\end{aligned}
\tag{8}
$$

is violated, where

$$
\begin{aligned}
H_1 &= \frac{1}{(\sigma_1^T)_{ult}} - \frac{1}{(\sigma_1^C)_{ult}}, \\
H_{11} &= \frac{1}{(\sigma_1^T)_{ult}(\sigma_1^C)_{ult}}, \\
H_2 &= \frac{1}{(\sigma_2^T)_{ult}} - \frac{1}{(\sigma_2^C)_{ult}}, \\
H_{22} &= \frac{1}{(\sigma_2^T)_{ult}(\sigma_2^C)_{ult}}, \\
H_{66} &= \frac{1}{(\tau_{12})_{ult}^2}, \\
H_{12} &= -\frac{1}{2}\sqrt{\frac{1}{(\sigma_1^T)_{ult}(\sigma_1^C)_{ult}(\sigma_2^T)_{ult}(\sigma_2^C)_{ult}}}.
\end{aligned}
\tag{9}
$$

H_i is the strength tensors of the second-order; H_{ij} is the strength tensors of the fourth-order. σ_1 is the applied normal stress in direction 1; σ_2 is the applied normal stress in direction 2; τ_{12} is the applied in-plane shear stress.

3) Strength ratio: The safety factor, or yield stress, is how much extra load beyond is intended a composite laminate will take. The strength ratio is defined as

$$
SR = \frac{\text{Maximum Load Which Can Be Applied}}{\text{Load Applied}} \tag{10}
$$

.

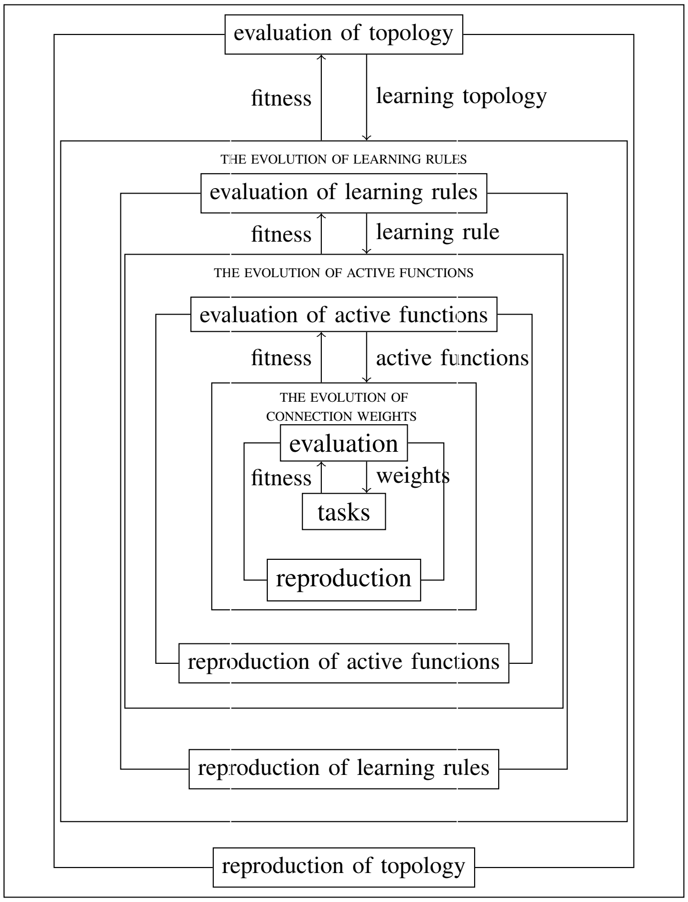


Fig. 4: A general framwwork for EANN, in which fitness refers to the corresponding value of objective function.

III. Evolutionary Artificial Neural Network

A. General neural network

In this paper, the feedforward ANN is adopted in the current study, since it is straightforward and simple to code. For function approximation through an ANN, Cybenko demonstrated that a two-layer perceptron can form an arbitrarily close approximation to any continuous nonlinear mapping[13]. Therefore, a two-layer feedforward ANN is proposed in the present study. Fig. 5 shows a general framework for a two-layer NN, in which the number of nodes in the hidden layer and the connection with inputs, are critical in the design of an ANN. For nodes in the hidden layer, we can think of them as feature extractors or detectors. Therefore, nodes within it should partially be connected with the inputs of an ANN, since the unnecessary connections would increase the model's complicacy, which will reduce an ANN's performance. Because we treat the nodes in the hidden layer as feature extractors, so the number of nodes in this layer should be less than the number of inputs. For the nodes in the last layer, every node should be fully connected with nodes in the previous layer, since we think of the nodes in the hidden layer as features. The rest, which affects a NN's performance, are activation function, and ANN's training method. In the following section, we denote the ith node in the input layer, and the hidden layer, as i_i, and h_i, respectively.

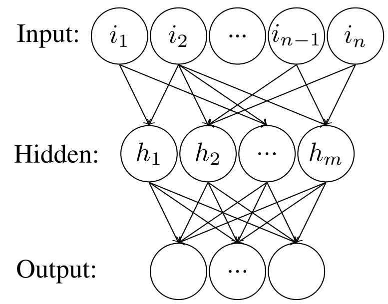


Fig. 5: Network diagram for the two-layer neural network. The input, hidden, and output variables are represented by nodes, and the weight parameters are represented by links between the nodes. Arrows denote the direction of information flow through the network during forward propagation.

B. Activation function

The activation function is one of the critical parts of an ANN. Liu [14] et al. claims that the performance of neural networks with different activation functions is different, even if they have the same architecture. A generalized activation function can be written as

$$y_i = f_i(\sum_{j=1}^{n} w_{ij}x_j - \theta) \tag{11}$$

where y_i is the output of the node i, x_j is the jth input to the node, and w_{ij} is the connection weight between adjacent nodes i and j. Tab. II displays the most widely adopted activation functions in the design of an ANN, which is used for the current study.

C. Weights learning

The weight training in an ANN is to minimize the error function, such as the most widely used mean square error function, which calculates the difference between the desired and the prediction output values averaged overall examples. Gradient descent algorithm is widely adopted to reduce the value of an error function, which has been successfully applied in many practical areas. However, this class of algorithms is plagued by the possible existence of local minima or "flat spots" and "the curse of dimensionality." One method to overcome this problem is to adopt a genetic algorithm(GA)

IV. Methodology

For an angle ply laminate, given the laminate's lay-up, material properties, in-plane loading, etc., we can compute its strength ratio based on Tsai-Wu failure theory or maximum stress theory. To model this function, we propose an ANN framework shown in Fig. 4, which derives from the previous

TABLE II: Examples of widely used activation functions in the design of artificial neural network.

Type	Description	Formula	Range	Encoding
Linear	The output is proportional to the input	$f(x) = cx$	$(-\infty, +\infty)$	00
Sigmoid	A family of S-shaped functions	$f(x) = \frac{1}{1+e^{-cx}}$	$(0, 1)$	01
ReLU	A piece-wise function	$f(x) = max\{0, x\}$	$(0, +\infty)$	10
Softplus	A family of S-shaped functions	$f(x) = ln(1 + e^{x})$	$(0, +\infty)$	11

two-layer model. There are sixteen inputs of this ANN, which are in-plane loading N_x, N_y, and N_{xy}; design parameters of a laminate, two fiber orientation θ_1 and θ_2, ply thickness t, total number of plies N; five engineering constants of composite materials, E_1, E_2, G_{12}, and v_{12}; five strength parameters of a unidirectional lamina. Two outputs are strength ratio according to MS theory and strength ratio according to Tsai-Wu theory.

The work involved in the evolution process of ANN consists of three parts: search space, which includes the ANN's topology, transfer function, etc.; search strategy, which details how to explore the search space; performance estimation strategy refers to the process of estimating this performance.

A. Search Space

We propose a GNN framework as shown in Fig. 5. The search space is parametrized by: (i) the number of nodes m(possibly unbounded) in the hidden layer, to narrow down the search space, the assumption is that m less than n; (ii) the type of operation every node executes, e.g., sigmoid, linear, gaussian. (iii) the connection relationship between hidden nodes and inputs; (IV) if a connection exists, the weight value in the connection.

Therefore, evolution in EANN can be divided into four different levels: topology, learning rules, active functions, and connection weights. For the evolution of topology, the aim is to find an optimal ANN architecture for a specific problem. The architecture of a neural network determines the information processing capability in an application, which is the foundation of the ANN. Two critical issues are involved in the search process of an ANN architecture: the representation and the search operators. Fig. 4 summarizes these four levels of evolution in an ANN.

B. Search Strategy

To use the GA method in this work, we need to represent the ANN, devise a fitness function that determines how good a solution is, and decides the genetic search operators, including selection, mutation, and crossover.

For the representation of an ANN, encode the h_i node as an eighteen digits binary string. The initial sixteen digits in the string correspond to the connections between i_i and h_i, with '1' implying there exists a connection between them, with '0' implying no connection exists. The last two digits in the string refer to an activation function, such as "01" which means a sigmoid function. Tab. III are examples of the binary representation of ANNs whose architecture is as shown in Fig. 7.

For the objective function, treat the multiplicative inverse of the mean squared error, which is the difference between the target and actual output averaged overall examples, as the fitness function.

The crossover between individuals results in exploiting the area between the given two parent solutions. In the present study, we search the local area by combining the genes of half number of nodes from both parents. Fig. 7 illustrates the crossover operator: Fig. 7 (c) is the child of Fig. 7 (a) and Fig. 7 (a), the connection relationship of hidden nodes with inputs are from both parents, and the corresponding activation functions are also from both parents. In the binary representation Tab. III, we can see that the first two rows of the child are the same as the first two rows of parent P_1, and the last six rows of the child are the same as the first six rows of parent P_2.

C. Performance estimation strategy

The simplest approach to this problem is to perform a standard training and validation of the architecture on a dataset, however, this method is inefficient and computationally intensive. Therefore, much recent research[15] focuses on developing methods that reduce the cost of performance estimation. In this work, during the GA process, we adopt the following straightforward and efficient method to estimate the performance of an ANN: first, train a neural network one hundred times on the training dataset; second, do the validation test; estimate the neural network's performance according to its fitness of objective function on the test dataset.

V. EXPERIMENT

In the previous section, we present the details of our strategies for designing an ANN. In this section, we explain the details of the preparation of the training dataset, and validation dataset.

A. Dataset Preparation

For composite material, it is impossible to obtain massive training data from the practical scenario. Therefore, we use classical lamination theory and failure theory, which follows a two-step procedure: first, evaluate the stress and strain according to classic lamination theory; second, substitute them into the corresponding equation to get the strength ratio. We repeat this procedure to yield 14000 points uniformly distributed over

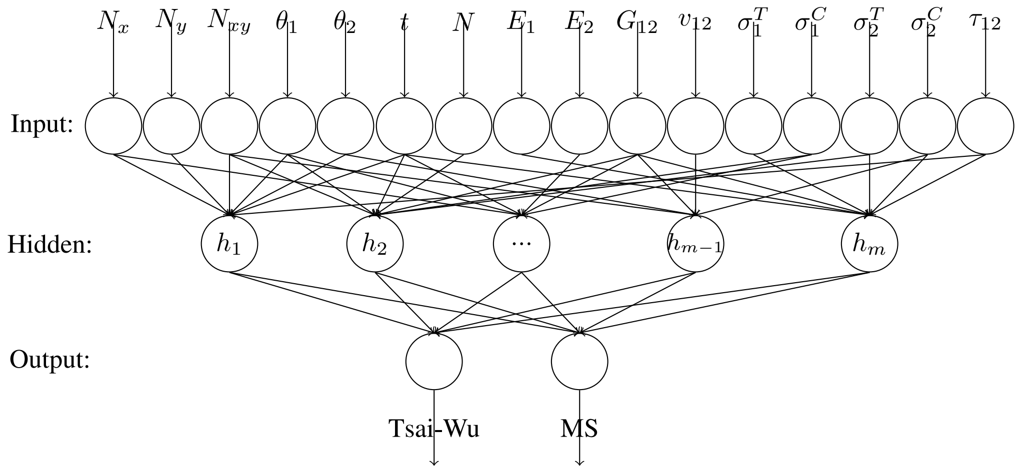


Fig. 6: Diagram for modeling the target function of strength ratio calculating for an angle ply laminate.

TABLE III: The binary representation of parent 1, parent 2, and child corresponding to Fig.5(a), (b) and (c), with $i_1, i_2, \cdots, I_{16}$ denote sixteen inputs and $h_1, h_2, \cdots, h_{12}$ refer to nodes in the hidden layer. 1 represents an edge from the input node to hidden node, and 0 represents no edge from input nodes to hidden node.

Hidden	Nodes	i_1	i_2	i_3	i_4	i_5	i_6	i_7	i_8	i_9	i_{10}	i_{11}	i_{12}	i_{13}	i_{14}	i_{15}	i_{16}	f	f
P1	h_1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	1	1	0	0
	h_2	0	1	1	1	0	0	0	1	0	0	1	1	0	0	0	0	1	1
	h_3	1	0	0	1	0	1	1	0	1	1	0	0	1	0	0	0	0	0
	h_4	0	0	1	0	1	0	0	0	0	1	0	1	0	0	1	0	0	1
	h_5	0	0	0	0	0	1	0	1	0	1	0	1	0	1	1	1	0	1
P2	h_1	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	1	0
	h_2	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	h_3	1	1	1	1	0	0	0	0	1	1	1	1	0	0	0	0	1	1
	h_4	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0
	h_5	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	0	1
	h_6	0	0	0	0	0	1	0	1	0	1	0	1	0	1	1	1	0	1
	h_7	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0
	h_8	0	0	0	0	0	1	0	0	0	1	0	0	0	1	0	1	0	0
	h_9	0	0	0	0	0	1	0	1	0	1	0	1	0	0	0	0	0	1
	h_{10}	0	1	1	1	0	0	0	0	1	1	1	1	0	0	0	0	1	1
	h_{11}	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	1	1
	h_{12}	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0	1	1
Child	h_1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	1	1	0	0
	h_2	0	1	1	1	0	0	0	1	0	0	1	1	0	0	0	0	1	1
	h_1	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	1	0
	h_2	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	h_3	1	1	1	1	0	0	0	0	1	1	1	1	0	0	0	0	1	1
	h_4	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0
	h_5	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	0	1
	h_6	0	0	0	0	0	1	0	1	0	1	0	1	0	1	1	1	0	1

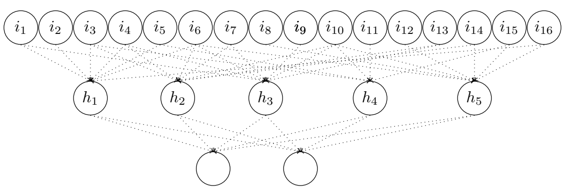
the domain space. We define the domain of the corresponding inputs as follows: the range of in-plane loading varies from 0 to 120; the range of fiber orientation θ is from -90 to 90; ply thickness t is 1.27mm, the number of plies range N is from 4 to 120. Three different composite material is used in this experiment, as shown in Tab. I. Fig. IV shows part of the training data, which are randomly selected from the generated training dataset. To speeds up the learning and accelerate convergence, the input atttributes of the dataset are rescaled to between 0 and 1.0 by a linear function.

B. ANN training and validation

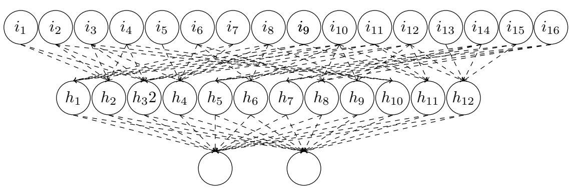
The ANN training procedure is carried out by optimising the multinomial logistic regression objective using mini-batch gradient descent[16] with momentum. The batch size is set to 1000, momentum to 0.9. the learning rate is set to 10^{-2}. As

TABLE IV: Examples of the training data

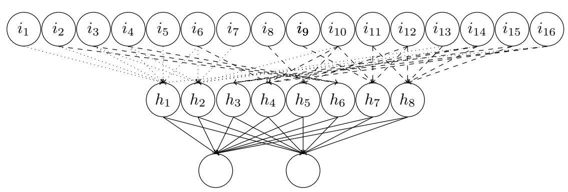
Input				**Output**	
Load	Laminate Structure	Material Property	Failure Property	MS	Tsai-Wu
-70,-10,-40,	90,-90,4,1.27,	38.6,8.27,0.26,4.14,	1062.0,610.0,31,118,72,	0.0102,	0.0086
-10,10,0,	-86,86,80,1.27,	181.0,10.3,0.28,7.17,	1500.0,1500.0,40,246,68,	0.4026,	2.5120
-70,-50,80,	-38,38,4,1.27,	116.6,7.67,0.27,4.173,	2062.0,1701.0,70,240,105,	0.0080,	0.0325
-70,80,-40,	90,-90,48,1.27,	38.6,8.27,0.26,4.14,	1062.0,610.0,31,118,72,	0.0218,	0.1028
-20,-30,0,	-86,86,60,1.27,	181.0,10.3,0.28,7.17,	1500.0,1500.0,40,246,68,	0.6481,	0.9512
0,-40,0,	74,-74,168,1.27,	181.0,10.3,0.28,7.17,	1500.0,1500.0,40,246,68,	1.3110,	3.9619



(a) Parent 1



(b) Parent 2



(c) Child

Fig. 7: Examples of three ANNs, with (a) and (b) as parent ANNs, and (c) as the child of (a) and (b). child c inherits the connection relationship part from parent 1 denoted by the darker dashed lines,and the rest from parent 2 denoted by the gray dashed line.

for the training dataset and validation dataset, We follow the 70/30 rule, with 70% of the entire data for training and 30% for validation.

C. Genetic algorithm

The genetic algorithm involves the evolution of an artificial neural network's topology, activation function, etc., in the optimizing process. The corresponding parameters are as the following. The population is 10, the percentage of parents in the population is 40%; the strategy of selecting parents is rank-based; the mutation rate of the offspring is 0.3.

VI. Result and Discussion

In this work, we propose to use an artificial neural network as an alternative way to compute the strength ratio of composite material instead of a two-step procedure, based on classical lamination and failure theory. Fig. 8 shows the changes of the fitness and error during the evolution procedure. The fitness is obtained through the performance estimation technique of an artificial neural network. As shown in this figure, fitness grows during the initial stage; then, it slowly converges as generation proceeds. It implies genetic algorithm can find a better artificial neural network with the evolution of the number of neurons in the hidden layer, connection relationship, activation functions, and connection weights.

Fig. 9 shows the rest training of the artificial neural network obtained by the GA. After the optimizing process, we get the best individual, which is a pre-trained neural network. We continue to train it with a standard gradient-based descent algorithm. The target neural network converges rapidly at first, and further training doesn't reduce the error efficiently. Then, we use the target ANN to predict the properties of laminated composite material.

To present the evaluation result of the ANN straightforwardly, we randomly select several experiment results from the validation dataset, as is shown in Tab. V. Comparing the strength ratio outputs based on CLT and ANN from Tab. V, we can see that the calculation of strength ratio can be achieved using a two-layer neural network, without the intensive computation of matrix multiplication.

TABLE V: Comparsion between practical and simulation

Input				Output			
Load	Laminate Structure	Material Property	Failure Property	CLT MS	CLT Tsai-Wu	ANN MS	ANN Tsai-Wu
-10,40,20	26,-26,168,1.27	116.6,7.67,0.27,4.17	2062.0,1701.0,70,240,105	0.342	0.476	0.351	0.492
20,-70,-30	10,-10,196,1.27	181.0,10.3,0.28,7.17	1500.0,1500.0,40,246,68	0.653	0.489	0.612	0.445
60,-20,0	82 -82,128,1.27	181.0,10.3,0.28,7.17	1500.0,1500.0,40,246,68	1.663	0.112	1.673	0.189

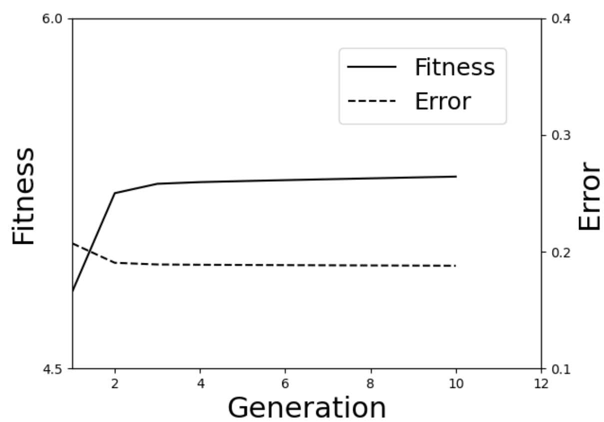


Fig. 8: Fitness and averaged sum-of-squares errors of the pre-trained artificial neural network as generations proceed.

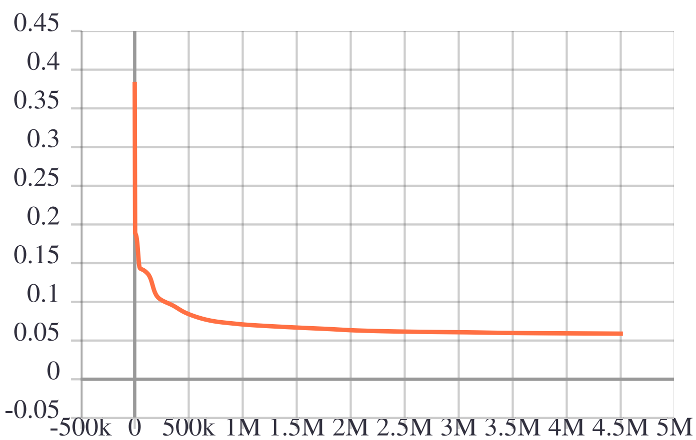


Fig. 9: The illustration of the behaviour of fitness on the training dataset during the training session.

VII. Conclusion

We review the use of genetic algorithms and artificial neural networks as an alternative approach for calculating the strength ratio of an angle ply laminate under in-plane loading, traditionally, which is obtained through CLT, and corresponding failure theories, such as Maximum stress theory and Tsai-wu failure theory. To obtain optimal architecture, we propose a two-layer ANN framework and four levels of evolution on the design of ANN. It was demonstrated that ANN is an efficient and simple tool to compute the strength ratio, instead of the complex analytical mathematical model. Our findings underline the practical applicability of ANN on the analysis of composite material.

There are more improvements we can make over the search strategy and application in the area of laminated composite material. The future work is to develop a more sophisticated ANN, which not only can predict the properties for angle ply laminate, but also the other type of laminated composite material.

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References

[1] F. Lobo, C. F. Lima, and Z. Michalewicz, *Parameter setting in evolutionary algorithms*. Springer Science & Business Media, 2007, vol. 54.

[2] T. N. Massard, “Computer sizing of composite laminates for strength,” *Journal of reinforced plastics and composites*, vol. 3, no. 4, pp. 300–345, 1984.

[3] J. Reddy and A. Pandey, “A first-ply failure analysis of composite laminates,” *Computers & Structures*, vol. 25, no. 3, pp. 371–393, 1987.

[4] C. Fang and G. S. Springer, “Design of composite laminates by a monte carlo method,” *Journal of composite materials*, vol. 27, no. 7, pp. 721–753, 1993.

[5] A. Soeiro, C. C. António, and A. T. Marques, “Multilevel optimization of laminated composite structures,” *Structural optimization*, vol. 7, no. 1-2, pp. 55–60, 1994.

[6] J. L. Pelletier and S. S. Vel, “Multi-objective optimization of fiber reinforced composite laminates for strength, stiffness and minimal mass,” *Computers & structures*, vol. 84, no. 29-30, pp. 2065–2080, 2006.

[7] P. Jadhav and P. R. Mantena, “Parametric optimization of grid-stiffened composite panels for maximizing their performance under transverse loading,” *Composite structures*, vol. 77, no. 3, pp. 353–363, 2007.

[8] S. Omkar, R. Khandelwal, S. Yathindra, G. N. Naik, and S. Gopalakrishnan, “Artificial immune system for multi-objective design optimization of composite structures,” *Engineering Applications of Artificial Intelligence*, vol. 21, no. 8, pp. 1416–1429, 2008.

[9] A. Choudhury, S. Mondal, and S. Sarkar, “Failure analysis of laminated composite plate under hygro-thermo mechanical load and optimisation,” *International Journal of Applied Mechanics and Engineering*, vol. 24, no. 3, pp. 509–526, 2019.

[10] R. Watkins and A. Morris, “A multicriteria objective function optimization scheme for laminated composites for use in multilevel structural optimization schemes,” *Computer Methods in Applied Mechanics and Engineering*, vol. 60, no. 2, pp. 233–251, 1987.

[11] P. Martin, “Optimum design of anisotropic sandwich panels with thin faces,” *Engineering optimization*, vol. 11, no. 1-2, pp. 3–12, 1987.

[12] C. M. Soares, V. F. Correia, H. Mateus, and J. Herskovits, “A discrete model for the optimal design of thin composite plate-shell type structures using a two-level approach,” *Composite structures*, vol. 30, no. 2, pp. 147–157, 1995.

[13] G. Cybenko, “Approximation by superpositions of a sigmoidal function,” *Mathematics of control, signals and systems*, vol. 2, no. 4, pp. 303–314, 1989.

[14] Y. Liu and X. Yao, “Evolutionary design of artificial neural networks with different nodes,” in *Proceedings of IEEE international conference on evolutionary computation*. IEEE, 1996, pp. 670–675.

[15] B. Baker, O. Gupta, R. Raskar, and N. Naik, “Accelerating neural architecture search using performance prediction,” *arXiv preprint arXiv:1705.10823*, 2017.

[16] Y. LeCun, B. Boser, J. S. Denker, D. Henderson, R. E. Howard, W. Hubbard, and L. D. Jackel, “Backpropagation applied to handwritten zip code recognition,” *Neural computation*, vol. 1, no. 4, pp. 541–551, 1989.