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

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***Abstract*—Traditionally, classic lamination theory(CLT) 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(ANN) 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. 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(EANNs) 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 EA's 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.

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

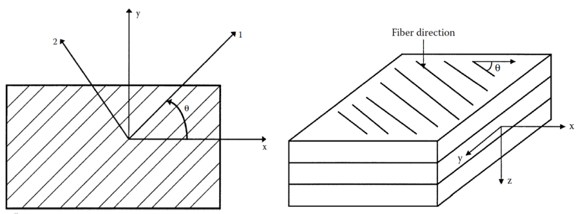

Fig. 1: The left diagram shows the local and global axis of an angle lamina, which is from a laminate as shown in the right diagram.

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

Fig. 2: Model for angle ply laminate

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 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 [1], [2], [3], [4], [5], [6], [7], [8], can be classified into two classes: one is called independent failure mode criteria which includes the maximum stress failure theory[9], maximum strain failure theory because their failure envelop are rectangle; another is called quadratic polynomial which includes Tsai-Wu[10], [11], 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,

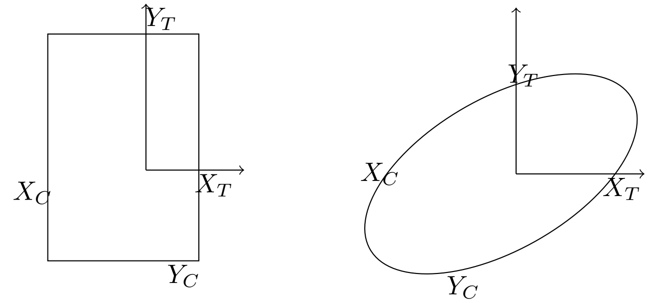

Fig. 3: Schematic failure surfaces for maximum stress and quadratic failure criteria

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

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

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

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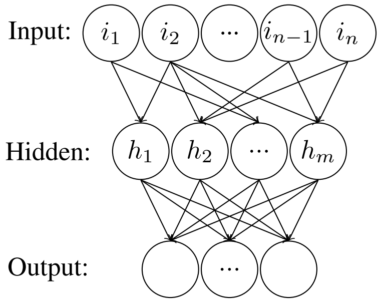

Fig. 4: Network diagram for the two-layer neural network. The input, hidden, and output variables are represented by nodes, and the weight parameters are represented by links between the nodes. Arrows denote the direction of information flow through the network during forward propagation.

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[12]. Therefore, a two-layer feedforward ANN is proposed in the present study. Fig.4 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 transfer 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, recpectively.

B. Transfer function

The transfer function is one of the critical parts of an ANN. Liu [13] et al. claims that the performance of NNs with different transfer functions is different, even if they have the same architecture. A generalized transfer 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 display the most widely adopted transfer 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.5, which derives from the previous 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 accoring 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 Figure 4. The search space is parametrized by: (i) the number of nodes m(possibly unbounded) in hidden layer, to narrow down the search space, the assumptions is that m less than n; (ii) the type of operation every nodes 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 toplogy, the aim is to find an optimal ANN architecture for a specfic problem. The architecture of a neural network determines the information processing capability in 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. Figure 5 summarizes different these four levels of evolution in ANN's.

TABLE II: Different Activation Functions

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	$f(x) = max0, x$	$(0, +\infty)$	10
Softplus	A family of S-shaped functions	$f(x) = ln(1 + e^{x})$	$(0, +\infty)$	11

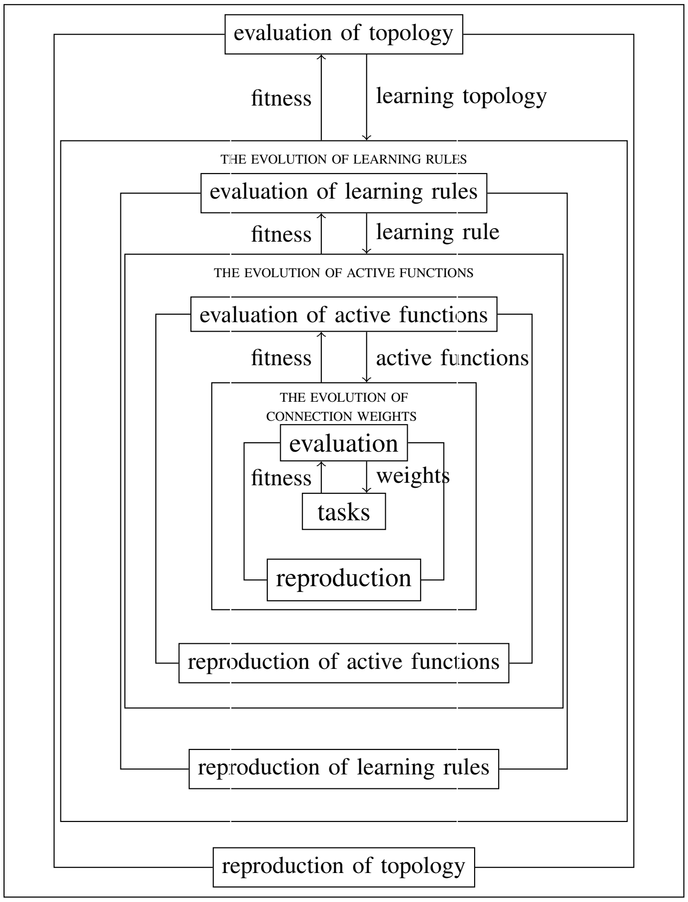

Fig. 5: A general framwwork for EANN

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 a 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 a activation function, such as "01" means a sigmoid fuction. 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.

First, randomly initialize the population, partial training every ANN, For the evolution of the topology,

Fig. **??** shows three ANNs.

C. Performance estimation strategy

The simplest approach to this problem is to perform a standard training and validation of the architecture on dataset, however, this method is inefficient and computational intensive. Therefore, much recent research[14] foces on developing methods that reduce the cost of performance estimation.

V. Experiment

In the previous section we present the details of our strategies for designing an ANN. In this section, we describe the details of training dataset prepartion, and evaluation.

A. Dataset Preparation

Equation 3 takes an analytical approach to model the relationship between stress and strain. We sample this function to yield 14000 points uniformly distributed over the domain space.

The range of in-plane loading is from 0 to 120; the range of fiber orientation θ is from -90 to 90; ply thickness t is 1.27mm, number of plies range N is from 4 to 120; Three different material is used in this experiment, as shown in table I. Figure IV shows part of the training data.

In order to speeds up the learning and accerlate convergence, the input atttributes of the data set are rescaled to between 0 and 1.0 by a linear function.

VI. Result and Discussion

We have conducted experiment by the use of the generated data set. This data set is randomly partitoned into a training set and a test.

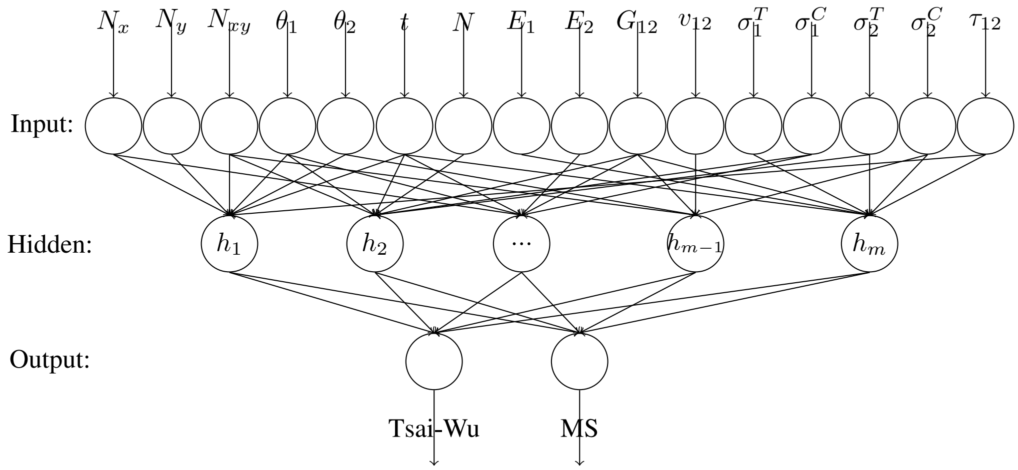

Fig. 6: Diagram for modeling the target function of strength ratio calculating for a angle ply laminate

TABLE III: Binary representation of parent 1, parent 2 and child corresponding to Fig 4(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 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
	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
P1	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
	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
P2	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
	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
Child	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

Figure **??** shows five ANNs with different topologies, quite different results have been observed when different architectures are adopted. It is clear that architecture whose mean of average difference is less than the rest.

Table V shows part of the valudation.

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.

VII. Conclusion

We review the use of GA and ANN 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 and Tsai-wu failure theories. To obtain

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

TABLE V: Comparsion between practical and simulation

Input				Output			
				CLT		ANN	
Load	Laminate Structure	Material Property	Failure Property	MS	Tsai-Wu	MS	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

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 complex analytical mathematical model.

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 for the other type of laminated composite material.

ACKNOWLEDGMENT

The work has partly been supported by China Scholarship Council(CSC) under grant no. 201806630112

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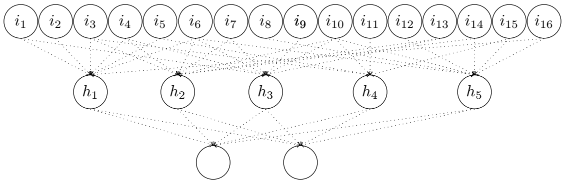
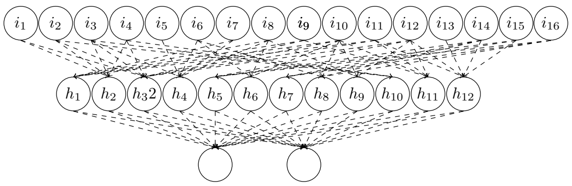
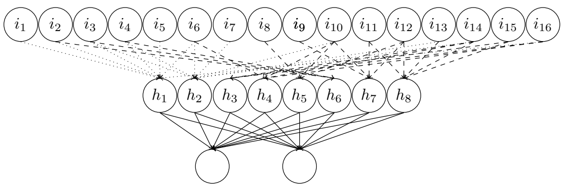


(a) Parent 1



(b) Parent 2



(c) Child

Fig. 7: Examples of three ANN, 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.

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