Optimum Design Methodology of Multiple Design Parameters for Laminated Composite Materials Using Discrete Optimum Method

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January 13, 2022
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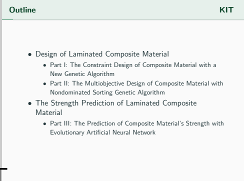
Hello, everyone, my name is zhang, welcome to my thesis defense, Thank you for finding this room and coming here. Thank you for your support and attendence. I am here to tell the result of my research over the last three years. Without any further ado, let's begin.



My presentation concerns two aspect of laminated composite material: the first is the design. item We dicuss two different situations for the design of laminated composite material, the first is the constraint design, the second is the multiple objective design. The second aspect is the strenght prediction of laminated composite material. Now we are going to talk about the frist problem.

Optimum Design Methodology of Multiple Design Parameters for Laminated Composite Materials Using Discrete Optimum Method

Part I: Background KIT

- Advantages of composites material
  - strength
  - stiffness
  - fatigue
  - impact resistance, thermal conductiviy, etc.

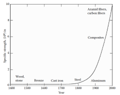


Figure 1: Composite Material(Source: Eager, T.W. and Whither advanced 1991)

Composite material gains more and more influence in commerical industry because of its excellant mechanic performance in stiffness, stength etc., over conventional materials. Figure 1 shows how composites and other traditional materials in terms of specific strength. It is obvious that the composites is better than traditional composites in terms of specific strength.

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Part I: Background
KIT

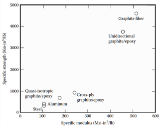

Figure 2: Specific modulus (Msi-in3/lb). (Source: Autar K. Kaw 2006)

laminated composite material is an assembly of layers of composite materials which can be joined to provide required engineering properties. There is possible by replacing conventional metal alloys with composite material. Figure 2 shows specific strength as a function of specific modulus for various fibers, metals, and composites. It is straightforward than laminated composites have advantage over traditional materials.

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Optimum Design Methodology of Multiple Design Parameters for Laminated Composite Materials Using Discrete Optimum Method

Part I: Background KIT

- Target: strength
- Constraints: weight Cost etc.
- Variable: ply operation, number of plies, material

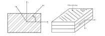

Figure 3: Laminated Composite Material

However, in practice, we need to tailor the structure of laminated composite material to satisfy practical requirements. such as the weight and cost. The design of this sequence is determined by several variables, the ply thickness, the number of layers, the ply oritentation. And all these variables are discrete in practice. So in nature the design of laminated composite material is a constrained optimization with discrete variables.

- 1. formulate the objective function, assume it is $f(x)$.
- 2. to satisfy the constraints, adding punishment items $\phi_1(x), \phi_2(x), \cdots, \phi_n(x)$
- 3. reformulate the objective functions as $f(x) + c_1\phi_1(x) + c_2\phi_2(x) + \cdots + c_n\phi_n(x)$

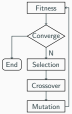

Figure 4: GA process

One of the most natural way to solve this problem is to adopt genetic algorithm, because it doesn't require the variable to be continuous. This classical method works in the following step 1. formulate the objective function. 2. append all the constraints to the objective function as punishment items 3. reformulate the objective function. In this formula, the coefficient c subscript 1 is coefficient whose value is from 0 to 1.

The drawback of this method is that genetic algorithm is proposed for unconstrained problem, you have to reformulate the objective function.

Two Techniques

- mating pool classification
- Self-adaptive mutation

Therefore, we proposed a new genetic algorithm with two Techniques, the first is mating pool classification, and the second is self-adaptive mutation operator. The advantage of this method is that We don't need to reformulate the objective function.

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Optimum Design Methodology of Multiple Design Parameters for Laminated Composite Materials Using Discrete Optimum Method

└─Part I: Methodology KIT

- 1. formulate the objective function, assume it is $f(x)$.
- 2. to satisfy the constraints, maintaining different groups in the population
- 3. do not change the objective function $f(x)$.

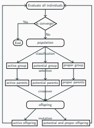

Figure 5: General flowchart of proposed GA model.

Figure 4 shows the flowchart of the proposed genetic algorithm: the feature of this method is as follows: 1. classify the population into three different groups according to the constraints, we will talk about how to classify the population later. 2. Then selection parents from these differen groups.

- An individual is active if it is far smaller than the numerical value of these constraints. A group is consist of active individuals are called as active group.
- An individual is potential if it is close but smaller than the numerical value of these constraints. The corresponding group is refered as potential group.
- An individual is proper if it satisfy all the constraints. Its counterpart group is written as proper group.

Here is some definition and terminology:

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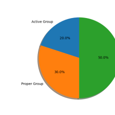
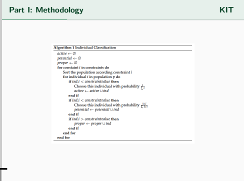
Part I: Methodology KIT

Figure 6: Parents

- acitve group: individual is used to increase the diversity of the population
- potential group: individual doesn't fulfill constraint
- proper group: individual meet constraint



The role of different group is different.



Here we provide an algorithm to implement the mating pool classification, for every individual in the population. Compare its constraint value with the threshold, if it is smaller than the constraint, select it as the active individual or potential individual with some probability. If it satisfy all the constraint, then select it as the proper individual.

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Part I: Methodology KIT

Table 1: Group Classification,and strength ratio constraint is 2.

Layup	Strength Ratio	Group
$[0_3/90_2]_s$	0.72	Active Individual
$[0_2/90_2]_s$	0.49	Active Individual
$[0_1/90_5]_s$	0.29	Active Individual
$[0_6/90_4]_s$	1.45	Potential Individual
$[0_5/90_3]_s$	1.20	Potential Individual
$[0_9/90_8/\bar{90}]_s$	2.10	Proper Individual

Here is a small example of mating pool classification, suppose there are six individuals in the population. With their constraint are in the second column of the table. For the first three, they are far smaller than constraints, so they are belong to the active group; For the third one, it satisfy the constraint, so it belongs to the proper group. For the fourth individual and fivth individual, there are possible they become a proper, so they belong to the potential group.

Optimum Design Methodology of Multiple Design Parameters for Laminated Composite Materials Using Discrete Optimum Method

$$\text{md} = [CT_1, \cdots, CT_{n-1}, CT_n] - [ICV_1, \cdots, ICV_{n-1}, ICV_n]$$

- md means mutation direction.
- CT_i denotes the i-th constraint, such as weight, strength ratio.
- ICV_i denotes individual's i-th constraint value, such as, weight, strength ratio of current individual.

The second technique in the genetic algorithm is self-adaptive mutation operator, which means it can adjust the mutation according to the constraint value. In this formula, the CTn represents constraint, ICVn denotes the corresponding individual's constraint value. We get a mutation vector from this formula, which can be used to direct the mutation of the chromosome.

Part I: Methodology KIT

- length mutation =

$$\begin{cases} LMC * [0, \sum_{i=1}^{N} md_i] & \text{if } \sum_{i=1}^{N} md_i > 0 \\ LMC * [\sum_{i=1}^{N} md_i, 0] & \text{if } \sum_{i=1}^{N} md_i < 0 \end{cases}$$

LMC stands for length mutation coefficient, it's a positive integer.

- $P(AM) =$

$$\begin{cases} 0.5, \ \text{AM} = [0, AMC \sum_{i=1}^{N} (|CT_i - CV_i|)] \\ 0.5, \ \text{AM} = [AMC \sum_{i=1}^{N} (-|CT_i - CV_i|), 0] \end{cases}$$

AMC stands for angle mutation coefficient.

The mutation is consist of two parts: length mutation and angle mutation. for the angle mutation, we increase the length of the chromosome when the sum of entries in the mutation is great than zero. Because the individual's strength is in proportion to the length. For the angle mutation, we just random change the angels with fifty probability, because there is clear relation between the ply oritentation and the strength.

Part I: Problem I KIT

Design of cross ply laminate with one constraint

0
90
90
0
90

Figure 7: Model for cross ply laminate

- Find $\{\theta_k, n\}$, where $\theta_k \in \{0, 90\}$
- Minimize weight
- Constraint: the strength ratio should not less than two.

The first problem is the design of cross ply laminates with one constraint, The fiber oritentation with a cross ply laminates is only consist of 0 and 90. The objective the minimization of the weight, the constraint is that the strength ratio must greater than 2.

Optimum Design Methodology of Multiple Design Parameters for Laminated Composite Materials Using Discrete Optimum Method

Part I: Methodology KIT

Classical lamination theory:

$$
\begin{aligned}
\begin{bmatrix} N_x \\ N_y \\ N_{xy} \end{bmatrix} &= \begin{bmatrix} A_{11} & A_{12} & A_{16} \\ A_{12} & A_{22} & A_{26} \\ A_{16} & A_{26} & A_{66} \end{bmatrix} \begin{bmatrix} \varepsilon_x^0 \\ \varepsilon_y^0 \\ \gamma_{xy}^0 \end{bmatrix} \\
&+ \begin{bmatrix} B_{11} & B_{12} & B_{16} \\ B_{11} & B_{12} & B_{16} \\ B_{16} & B_{26} & B_{66} \end{bmatrix} \begin{bmatrix} k_x \\ k_y \\ k_{xy} \end{bmatrix} \\
\begin{bmatrix} M_x \\ M_y \\ M_{xy} \end{bmatrix} &= \begin{bmatrix} B_{11} & B_{12} & B_{16} \\ B_{12} & B_{22} & B_{26} \\ B_{16} & B_{26} & B_{66} \end{bmatrix} \begin{bmatrix} \varepsilon_x^0 \\ \varepsilon_y^0 \\ \gamma_{xy}^0 \end{bmatrix} \\
&+ \begin{bmatrix} D_{11} & D_{12} & D_{16} \\ D_{11} & D_{12} & D_{16} \\ D_{16} & D_{26} & D_{66} \end{bmatrix} \begin{bmatrix} k_x \\ k_y \\ k_{xy} \end{bmatrix}
\end{aligned}
\tag{1}
$$

To calculate the strength ratio of laminated composite material, two theories are needed. The first is classical lamination theory, which computes the stree and strain in the materail given the load.

Part I: Methodology KIT

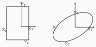


Figure 8: Schematic failure surfaces for maximum stress and quadratic failure criteria

- Maximum stress failure

$$SF_{MS}^k = \text{min of} \begin{cases} SF_X^k = \begin{cases} \frac{X_t}{\sigma_{11}}, & \text{if } \sigma_{11} > 0 \\ \frac{X_c}{\sigma_{11}}, & \text{if } \sigma_{11} < 0 \end{cases} \\ SF_Y^k = \begin{cases} \frac{Y_t}{\sigma_{22}}, & \text{if } \sigma_{22} > 0 \\ \frac{Y_c}{\sigma_{22}}, & \text{if } \sigma_{22} < 0 \end{cases} \\ SF_S^k = \begin{cases} \frac{S}{|\tau_{12}|} \end{cases} \end{cases}.$$

- Tsai-wu failure theory

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

The second is failure theory, which checks whether whether a material failure or not under certain load. Here we adopte two different failure theories, one is Tsai-wu, and the other is Maximum Stress. Because they have different failure surface.

Part I: Result
KIT

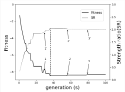


Figure 9: The variation of fitness and strength ratio as the genetic algorithm proceeds.

First, we present the process of the new genetic algorithm. In figure 9, Fitness is the negation of the individual's mass. The solid curve is the fitness of the best individual in the population in respect to the generations, and the dotted line denotes its corresponding strength ratio. If no individuals in the population satisfy the constraint, the best individual is the one with the biggest strength ratio; if not, the best individual is the one with the smallest mass.

Optimum Design Methodology of Multiple Design Parameters for Laminated Composite Materials Using Discrete Optimum Method

Part I: Result KIT

Table 3: The optimum layup for the loading $N_x = 1e^6$ N when changing the length mutation coefficient, the performance of the GA can be improved when the lenght mutation coefficient is smaller.

Length mutation coefficient	Material	case	Stacking sequence	Strength ratio	Mass	Cost	Layer
1	glass-epoxy	worst	$[0_{40}/90_{26}]_s$	2.010	8.58	132	132
		best	$[90_{24}/0_{38}/\bar{90}]_s$	2.078	8.12	125	125
		average		2.012	7.83	123	123
	graphite-epoxy	worst	$[0_9/90_4/\bar{0}]_s$	2.170	1.41	68	27
		best	$[0_9/90_1/\bar{0}]_s$	2.150	1.10	53	21
		average		2.018	1.47	70	28
5	glass-epoxy	worst	$[0_{36}/90_{32}]_s$	2.009	8.84	136	136
		best	$[0_{36}/90_{26}/\bar{90}]_s$	2.003	8.12	125	125
		average		2.008	8.55	131	131
	graphite-epoxy	worst	$[0_9/90_{12}]_s$	2.006	2.20	105	42
		best	$[0_8/90_3/\bar{0}]_s$	2.001	1.20	57	23
		average		2.022	1.54	73	29

To check the effect of the coefficient of length mutation on the performance of new genetic algorithm, we run this new genetic algorithm one hundred times. The simulation results is in as shown in this table. For both of glass-epoxy and graphite epoxy, we got better simulation results if the length mutation coefficient takes a relative small value.

Optimum Design Methodology of Multiple Design Parameters for Laminated Composite Materials Using Discrete Optimum Method

Part I: Result KIT

Table 4: The optimum lay-ups for the loading $N_x = 1e6$ N

Cross Ply $[0_M/90_N]$	Choudhury and Mondal's		Current Research	
Material	Glass-Epoxy	Graphite-Epoxy	Glass-Epoxy	Graphite-Epoxy
M	68	17	78	18
N	72	18	28	8
no. of lamina(n)	140	35	106	26
SR	2.01	2.10	2.03	2.16
weight	9.10	1.84	6.89	102.5

We also compare our work with other results in other literature. As you can see from the table, we obtained better results for both cases.

Part II: KIT

- Part II: The Multiobjective Design of Composite Material with Nondominated Sorting Genetic Algorithm

The second problem is the multiple objective design of cross ply laminate.

Optimum Design Methodology of Multiple Design Parameters for Laminated Composite Materials Using Discrete Optimum Method

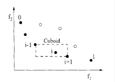


Figure 12: Crowding-distance calculation. Points marked in filled circles are solutions of the same nondominated front. (Source: Kalyanmoy DebSamir AgrawalAmrit PratapT Meyarivan, 2000)

We adopte NSGA algorithm to solve this problem, NSGA is an effective and robust method for solve multiple objective problem. In which it can maintains multiple solutions in the population. In figure 10, f1 and f2 represents two objective functions. Points marked in filled circleare solutions belong to the same frontier. Among these solutions, no individual is better than another.

Optimum Design Methodology of Multiple Design Parameters for Laminated Composite Materials Using Discrete Optimum Method

- Find $\{\theta_k, n\}$ where $\theta \in$ [0-90]
- Minimize: weight
- Maximize: strength ratio

Ther are two objective in this experiment, the first is the weight, and the second is the strength ratio.

Optimum Design Methodology of Multiple Design Parameters for Laminated Composite Materials Using Discrete Optimum Method

Part II: Experiment Setting KIT

P_1:	0	0	0	1	1	0	0	1	1	0

Figure 13: An individual's chromosome represented by binary string.

Table 6: Parameters of genetic algorithm.

Parameter	Value
Population	30
Encoding	binary
Selection strategy	Tournament
Crossover strategy	One-point
Crossover rate	0.9
Mutation strategy	Mass mutation
Mutation rate	0.1

We adopte binary string with length 10 to represent a solution for the problem, the first five digits represent the number of angle 0 in the sequence. the last five digits denotes the number of angle 90. This table shows the related parameters about the nondominated genetic algorithm.

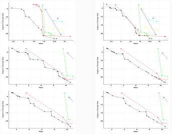


Figure 14: The vary of frontiers for graphite-epoxy as the NSGA-II algorithm proceeds.

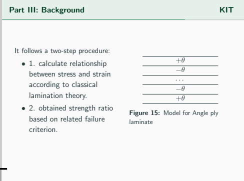
These figures shows the variation of individuals during the process of non-dominated genetic algorithm. The x axis is the weight, and y axis is the negation of the strength ratio. individuals belong to different frontiers are marked with differend color, then we connect same colored individuals with dashed line.

Optimum Design Methodology of Multiple Design Parameters for Laminated Composite Materials Using Discrete Optimum Method

Part III: KIT

- Part III: The Prediction of Composite Material's Strength

Part III focuses on using an alternative method to predict the strength of a laminated composite material.



The traditional way of doing this follows a step precedure: first, calculate the stress and strain within the laminated composite material by using of classical lamination theory. Second use failure theory to check the corresponding material failure or not. The drawback of this method is that the computation cost is high because of the involvment of matrix multplication and interal operation and interal operation. There we propose to use evolutionary artificial neural network to predict the strenght of angle ply laminate.

Optimum Design Methodology of Multiple Design Parameters for Laminated Composite Materials Using Discrete Optimum Method

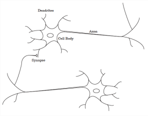


Figure 16: Schematic Drawing of Biological Neurons. (Source: 1996)

A neural network is a collection of neurons, in which the neurons are interconnected with each other. A neuron is consist of dendrite, axon, which the basic unit to process information in the human body.

Optimum Design Methodology of Multiple Design Parameters for Laminated Composite Materials Using Discrete Optimum Method

Part III KIT

Table 7: Different Activation Functions

Type	Description	Formula	Range
Linear	The output is proportional to the input	$f(x) = cx$	$(-\infty, +\infty)$
Sigmoid	A family of S-shaped functions	$f(x) = \frac{1}{1+e^{-cx}}$	$(0, 1)$
Gaussian	A coninuous bell-shaped curve	$f(x) = e^{-x^2}$	$(0, 1)$

Different active functions can be used to represent different neurons, table 5 show commonly use active functions.

Part III: Methodology KIT

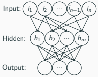


Figure 17: Neural Network Model

we proposed the following general neural network to solve the strength prediction. The feature of this neural network is as follows: neurons in the hidden layer are partly connect with the inputs, because uncecessary connection will casue overfitting. and we treat neurons in the hidden layer as the feature learned from the inputs. Therefore the neurons in the outputs layer should be fully connected with the previous layer.

Part III: Methodology KIT

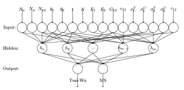


Figure 18: General Neural Network for CLT

Based on the general neural network architecture, we proposed the following structure to predict the strength of angle ply structure. There are two outputs, which are tsai wu strength ratio, and maximum strength ratio. There are 16 inputs, which are consist of four parts: the first part is the loading, Nx, Ny, Nxy the second part is the sequence of the angle ply laminate, which are two ply oritenation, ply thickness, and the number of plies. the third part is the four engineering constants, E1,E2,G12, v12 Traverse elastic modulus Major Poisson's ratio Shear modulus the fourth part is five constants about the material: Ultimate longitudinal tensile strength Ultimate longitudinal compressive strength Ultimate transverse tensile strength Ultimate transverse compressive strength Ultimate in-plane shear strength Longitudinal elastic modulus

Figure 19: Example of proposed architecture.

Table 8: The binary representation of Figure 19.

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
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

In order to adopte genetic algorithm for neural network revolution, we need to represent this neural network with a chromosome. Table 8 is the binary representation of the above neural network, with one row representing a neuron. for every neuron, if there exist a connection between the neuron and the inputs, we denote with 1, otherwise, it is zero.The last two column is the code for active function.