Design optimization of laminated composite structures using artificial neural network and genetic algorithm

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Abstract

In this paper, an efficient method for performing minimum weight optimization of composite laminates using artificial neural network (ANN) based surrogate models is proposed. By predicting the buckling loads of the laminates using ANN the use of time-consuming buckling evaluations during the iterative optimization process are avoided. Using for the first time lamination parameters, laminate thickness and other dimensional parameters as inputs for these ANN models significantly reduces the number of models required and therefore computational cost of considering laminates with many different numbers of layers and total thickness. Besides, as the stacking sequences are represented by lamination parameters, the number of inputs of the ANN models is also significantly reduced, avoiding the curse of dimensionality. Finite element analysis (FEA) is employed together with the Latin hypercube sampling (LHS) method to generate the database for the training and testing of the ANN models. The trained ANN models are then employed within a genetic algorithm (GA) to optimize the stacking sequences and structural dimensions to minimize the weight of the composite laminates. The advantages of using ANN in predicting buckling load is proved by comparison with other machine learning methods, and the effectiveness and efficiency of the proposed optimization method is demonstrated through the optimization of flat, blade-stiffened and hat-stiffened laminates.

Keywords: composite laminates; lamination parameters; optimization; artificial neural network; genetic algorithm

Acronyms	
ANN	artificial neural network
ACA	ant colony algorithm
DQM	differential quadrature method
DT	decision tree
FEA	finite element analysis
GA	genetic algorithm
HSA	harmony search algorithm
LHS	latin hypercube sampling
LR	linear regression
MAPE	mean absolute percentage error
MLR	multiple linear regression
MS2LOS	multi-scale two-level optimization strategy
NURBS	non-uniform rational basis spline
PSO	particle swarm optimization
RDT	regression decision tree
RF	random forest regression
SA	simulated annealing algorithm

1. Introduction

Laminated composite structures are widely used in the aerospace, marine, automotive and civil industries because of their outstanding structural performance. The most significant benefit of using these over conventional materials is that they can be designed to meet different structural requirements by tailoring their stacking sequences [1]. Hence, the optimization of composite laminates is an essential part of design, leading to cost reduction or improvement of structural performance.

As ply orientations are usually limited to a set of values (e.g. 0°, 90°, +45° and −45°) and the thickness of an individual ply is fixed in practice, the optimization design of laminated composite structures usually leads to a discrete optimization problem, for which several optimization methods have been developed, such as the genetic algorithm (GA) [2–4], particle swarm optimization algorithm (PSO) [5], hybrid GA-PSO algorithm [6–9], ant colony algorithm (ACA) [10–12], simulated annealing algorithm

(SA) [13], permutation search algorithm [14], and harmony search algorithm (HSA) [15], etc. Since laminates are generally used in the form of thin-walled structures, they are also vulnerable to buckling, and in most cases the critical constraint for the optimization is a buckling constraint. In order to obtain the buckling performance of a laminate during the optimization process, the utilization of analytical methods has attracted great interest, because of their low computational cost and ease in implementation. However, the application of the analytical methods is limited to simple structural types and specific boundary and loading conditions. As a powerful structural analysis method, FEA is able to provide accurate results, for a wide range of geometries, boundary and loading conditions but it incurs a high computational cost especially in an iterative optimization where a huge number of structural analyses are required, making the optimization computationally expensive. Therefore, developing faster yet still reliable methods to substitute for FEA in the optimization is necessary. The highly efficient design package VICONOPT [16] based on the exact strip method and the Wittrick-Williams algorithm [17] were developed and utilized for the optimization of composite laminates [18,19], and has been proved to be 150 times faster than FEA [16]. The application of the isogeometric analysis method [20], differential quadrature method (DQM) [21], finite strip method [22] and surrogate modelling methods, such as the non-uniform rational basis spline (NURBS) hypersurface [23–25], modified Shepard's method [26], and radial basis function [27], to the optimization process have also been considered.

With the rapid popularization of machine learning methods, the utilization of artificial neural network (ANN) for obtaining the structural performance of composite laminates has attracted great interest from researchers. In the work of Bisagni and Lanzi [28], ANN was first employed for the post-buckling optimization of stiffened composite laminates. The structural performance of different configurations was obtained by an ANN model which was trained based on the results of FEA, with the number of layers in the skin and stiffeners and the layout of stiffeners as inputs. Results showed that the utilization of ANN significantly improves the efficiency of the optimization process. Abouhamze and Shakeri [29] conducted layup optimization of laminated cylindrical panels using ANN and GA. Based on training data obtained from FEA, an ANN model was developed to obtain the buckling loads and natural frequencies of six-layer symmetric laminates during a GA optimization. Reddy et al. [30] developed an ANN model to obtain the stress and deflection of composite laminates with the stacking sequences as inputs. The trained ANN model was then combined with a GA to minimize the deflection and stress of the laminates. Marin et al. [31] conducted a geometric optimization of stiffened composite laminates subject to mechanical and hygrothermal loads, ANN was used within a GA to improve the computational efficiency. In the work of Pitton et al. [32], ANN was combined with PSO for the buckling load maximization of variable stiffness cylindrical shells. Eight input parameters including dimensional parameters and ply angles were employed in the ANN model for which FEA was employed to create the training data. Singh and Kapania [33] investigated the application of ANN to accelerate the buckling optimization of a curvilinearly stiffened panel. Peng et al. [34] performed a multi-scale uncertainty optimization to maximize the natural frequency of hybrid composite laminates using ANN and GA with stacking sequences and material patches as design variables. The combination of ANN with GA has also been employed for the optimization of deployable shell laminates [35] and composite angle grid plates [36].

As discussed above, the high-performance ANN models are important tools for the optimization of composite laminates, especially for large complex composite laminates (e.g. complex structural type, large number of layers, etc). Mallela and Upadhyay [37] developed an ANN model for the buckling load prediction of stiffened composite laminates subject to in-plane shear based on four parameters: orthotropy ratio, smeared extensional stiffness ratio, extensional stiffness to shear stiffness ratio, and ratio of rigidities as inputs. Atilla et al. [38] employed ANN to evaluate vibration and buckling responses for composite laminates with cut-outs in which the number, size and location of the cut-out were used as inputs for the ANN model based on the results of FEA. Tian et al. [39] combined ANN with the transfer learning method to improve accuracy for shell buckling prediction problems. In the work of Sun et al. [40], both the buckling load and buckling failure mode of stiffened composite laminates subject to compression were predicted. As the predictions of buckling load and buckling failure mode are regression and classification problems respectively, two kinds of ANN models were correspondingly developed. In the work of Kaveh [41], the application of random forest regression (RF), regression decision tree (RDT), multiple linear regression (MLR) and ANN to the buckling capacity prediction of variable stiffness composite cylinders under bending-induced loads were compared, concluding the ANN to be the best method for this buckling prediction problem.

For the buckling prediction of composite laminates with large numbers of plies, the use of ply angles as inputs incurs the curse of dimensionality as well as difficulties in training the ANN model, reducing the predictive performance. More importantly, as the number of inputs for an ANN model is fixed, the trained ANN model can only be used to predict the buckling load of laminates with same number of plies if the ply angles are used as inputs.

The stiffness matrix of composite laminates can be expressed as a linear function of a small and constant number of lamination parameters [42] or polar parameters [43,44], instead of the conventional set of equations with a large number of ply angles. The use of lamination parameters or polar parameters usually divides the optimization into two stages. In the first stage the lamination parameters or polar parameters are optimized to obtain the best structural performance. After that, the second stage of the optimisation searches the stacking sequences to match the optimized lamination parameters or polar parameters obtained in the first level. Lamination parameters have been widely used for the optimization of flat laminates [18], stiffened laminates [45,46], blended laminates [47,48], and variable angle tow laminates [49]. Montemurro et al. [43,44,50] conducted a series of research on polar parameters which are directly related to the symmetries of the tensor. Based on these polar parameters, a multi-scale two-level optimization strategy (MS2LOS) was developed for optimizing flat laminates [51], stiffened laminates [52,53], blended laminates [52,54,55], and variable angle tow laminates [56,57].

As the number of lamination parameters and polar parameters are constant and independent of the number of plies in the composite laminates, they are more suitable as inputs for the ANN model compared with ply angles. In the work of Koide et al. [58] and Hajmohammad et al. [59], lamination parameters were employed as inputs for an ANN model to predict the buckling load of composite laminates. However, the laminate thickness was kept constant in these studies. Because the stiffness matrix of the laminate is determined based on both the lamination parameters and the laminate thickness, the developed ANN models can only be used to predict buckling load of laminates with predefined thickness, and hence cannot be used for the minimum weight optimization problem where the laminate thickness should be varied.

In the present work, a methodology for the minimum weight design of laminated composite structures is proposed. Firstly, ANN models are developed to obtain the buckling loads of composite laminates based on the results of FEA. In order to make the ANN models usable for a weight minimization problem where laminates with different numbers of layers and total thickness need to be evaluated, the use of lamination parameters, laminate thickness and other dimensional parameters as inputs for the ANN models is investigated. The superiority of the ANN is illustrated through comparison with other machine learning methods. The developed ANN models are then used for the evaluation of the buckling constraint during an optimization carried out using GA. The aim of this work is to study the performance of the developed ANN models and demonstrate their advantages in the minimum weight optimization of laminated composite structures. This paper is organized as follows: in section 2, the lamination parameters are introduced. Details of the proposed ANN models and GA are given in section 3. Section 4 presents the results obtained for three laminated composite structures. Conclusions are given in Section 5.

2. Lamination parameters

Classical laminate theory [1], presents the stress-strain relationship for a composite laminate as:

$$\begin{bmatrix} \mathbf{n} \\ \mathbf{m} \end{bmatrix} = \begin{bmatrix} \mathbf{A} & \mathbf{B} \\ \mathbf{B} & \mathbf{D} \end{bmatrix} \begin{bmatrix} \boldsymbol{\varepsilon}^0 \\ \boldsymbol{\kappa} \end{bmatrix}, \tag{1}$$

where $\mathbf{n}$ and $\mathbf{m}$ are vectors of in-plane forces and moments per unit width, $\mathbf{A}, \mathbf{B}$ and $\mathbf{D}$ are in-plane, coupling and out-of-plane stiffness matrices, $\boldsymbol{\varepsilon}^0$ is a vector of in-plane strains and $\boldsymbol{\kappa}$ is a vector of mid plane curvatures.

The stiffness matrices $\mathbf{A}, \mathbf{B}$ and $\mathbf{D}$ can be expressed in terms of 12 lamination parameters $\xi_j^k \left(j=1,2,3,4; k=\mathrm{A},\mathrm{B},\mathrm{D} \right)$ [60] and material stiffness invariants $\mathbf{u}$ as shown below:

$$\begin{bmatrix} A_{11} \\ A_{22} \\ A_{12} \\ A_{66} \\ A_{16} \\ A_{26} \end{bmatrix} = h \begin{bmatrix} 1 & \xi_1^{\mathrm{A}} & \xi_2^{\mathrm{A}} & 0 & 0 \\ 1 & -\xi_1^{\mathrm{A}} & \xi_2^{\mathrm{A}} & 0 & 0 \\ 0 & 0 & -\xi_2^{\mathrm{A}} & 1 & 0 \\ 0 & 0 & -\xi_2^{\mathrm{A}} & 0 & 1 \\ 0 & \xi_3^{\mathrm{A}}/2 & \xi_4^{\mathrm{A}} & 0 & 0 \\ 0 & \xi_3^{\mathrm{A}}/2 & -\xi_4^{\mathrm{A}} & 0 & 0 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \\ u_5 \end{bmatrix}, \tag{2}$$

$$\begin{bmatrix} B_{11} \\ B_{22} \\ B_{12} \\ B_{66} \\ B_{16} \\ B_{26} \end{bmatrix} = \frac{h^2}{4} \begin{bmatrix} 0 & \xi_1^{\mathrm{B}} & \xi_2^{\mathrm{B}} & 0 & 0 \\ 0 & -\xi_1^{\mathrm{B}} & \xi_2^{\mathrm{B}} & 0 & 0 \\ 0 & 0 & -\xi_2^{\mathrm{B}} & 0 & 0 \\ 0 & 0 & -\xi_2^{\mathrm{B}} & 0 & 0 \\ 0 & \xi_3^{\mathrm{B}}/2 & \xi_4^{\mathrm{B}} & 0 & 0 \\ 0 & \xi_3^{\mathrm{B}}/2 & -\xi_4^{\mathrm{B}} & 0 & 0 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \\ u_5 \end{bmatrix}, \tag{3}$$

$$\begin{bmatrix} D_{11} \\ D_{22} \\ D_{12} \\ D_{66} \\ D_{16} \\ D_{26} \end{bmatrix} = \frac{h^3}{12} \begin{bmatrix} 1 & \xi_1^{\mathrm{D}} & \xi_2^{\mathrm{D}} & 0 & 0 \\ 1 & -\xi_1^{\mathrm{D}} & \xi_2^{\mathrm{D}} & 0 & 0 \\ 0 & 0 & -\xi_2^{\mathrm{D}} & 1 & 0 \\ 0 & 0 & -\xi_2^{\mathrm{D}} & 0 & 1 \\ 0 & \xi_3^{\mathrm{D}}/2 & \xi_4^{\mathrm{D}} & 0 & 0 \\ 0 & \xi_3^{\mathrm{D}}/2 & -\xi_4^{\mathrm{D}} & 0 & 0 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \\ u_5 \end{bmatrix}, \tag{4}$$

where h is the thickness of the laminate, the material stiffness invariants $\mathbf{u}$ and stiffness properties $\mathbf{Q}$ are expressed as:

$$\begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \\ u_5 \end{bmatrix} = \frac{1}{8} \begin{bmatrix} 3 & 3 & 2 & 4 \\ 4 & -4 & 0 & 0 \\ 1 & 1 & -2 & -4 \\ 1 & 1 & 6 & -4 \\ 1 & 1 & -2 & 4 \end{bmatrix} \begin{bmatrix} Q_{11} \\ Q_{22} \\ Q_{12} \\ Q_{66} \end{bmatrix}, \tag{5}$$

$$\begin{cases} Q_{11} = E_{11}{}^2 / (E_{11} - E_{22}\upsilon_{12}{}^2), \\ Q_{22} = E_{11}E_{22} / (E_{11} - E_{22}\upsilon_{12}{}^2), \\ Q_{12} = \upsilon_{12} Q_{22}, \\ Q_{66} = G_{12}, \end{cases} \tag{6}$$

where E_{11} is the longitudinal Young's modulus, E_{22} is the transverse Young's modulus, G_{12} is the shear modulus, and υ_{12} is the major Poisson's ratio.
The lamination parameters are obtained by the following integrals:

$$\begin{bmatrix} \xi_1^k \\ \xi_2^k \\ \xi_3^k \\ \xi_4^k \end{bmatrix} = \int_{-h/2}^{h/2} Z^k \begin{bmatrix} \cos 2\theta \\ \cos 4\theta \\ \sin 2\theta \\ \sin 4\theta \end{bmatrix} dz, k = \mathrm{A, B, D}, \begin{cases} Z^{\mathrm{A}} = 1/h, \\ Z^{\mathrm{B}} = 4z/h^2, \\ Z^{\mathrm{D}} = 12z^2/h^3, \end{cases} \tag{7}$$

where θ represents the ply angle at depth z below the mid-surface. The $\xi_4^k \left(k = \mathrm{A, B, D}\right)$ are zero when the ply orientations are limited to 0°, 90°, +45° and -45°. The coupling lamination parameters $\xi_i^{\mathrm{B}} \left(i = 1, 2, 3, 4\right)$ are zero for symmetric laminates.

3. Methodology

The methodology is divided into two steps and is based on the utilization of lamination parameters. Initially, predictive models which are able to obtain the buckling loads of a range of laminated composite structures are developed based on a database generated using FEA and the Latin hypercube sampling (LHS) method. After that, the developed ANN models are employed within a GA to obtain optimal stacking sequences and structural dimensions to minimize the weight of laminated composite structures. The framework of the proposed methodology is shown in Fig. 1. This section presents the details of the whole process regarding the generation of the database and the development of the ANN models and GA.

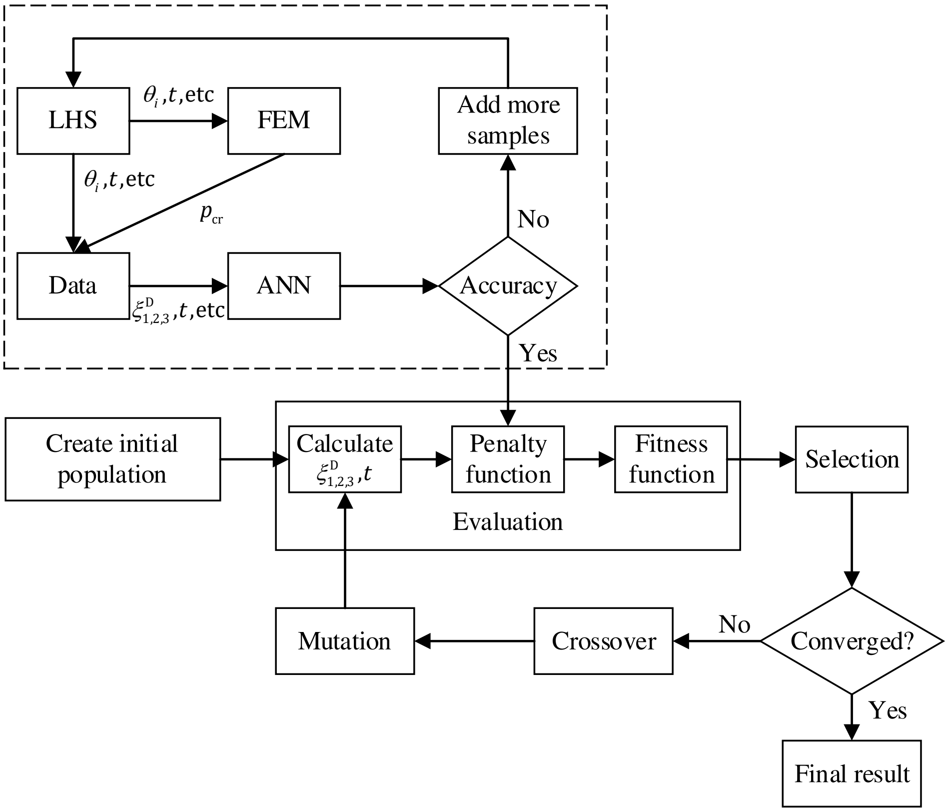


Fig. 1. Framework of the proposed methodology.

3.1 Artificial neural networks

ANN, inspired by the biological neuron system is a powerful method for the prediction of non-linear and complex relations. The development of ANN model requires a training process, during which the ANN model is taught to capture the relations between the inputs and outputs. As ANN solves new problems based on the knowledge gained from the previously solved problems, the preparation of the data for training and testing is an important part in the development of an ANN model.

3.1.2 Data description

The ANN models in this work are to be used for minimum weight optimization where composite laminates with different numbers of layers and total thicknesses need to be evaluated. In order to avoid developing a large number of ANN models each of which corresponds to one fixed number of layers, lamination parameters, laminate thicknesses and other dimension parameters (e.g. stiffener depth, width, etc) are used as inputs. Because the ANN models are to be used to obtain buckling loads p_{cr}, only the bending lamination parameters $\xi_i^D \left(i=1,2,3,4\right)$ relating to the bending stiffness matrix **D** are required, and since the ply angles are limited to 0°, 90°, +45° and -45°, the value of ξ_4^D is zero, resulting in only the three bending lamination parameters $\xi_i^{\mathrm{D}}\left(i=1,2,3\right)$ being utilized in this study. The finite element software ABAQUS [61] is employed to perform buckling analyses to determine the buckling load of each data sample in the database. The large number of buckling analyses are conducted through the use of python scripts.

In order to obtain uniformly distributed data across the design space, the LHS method is employed to determine the combinations of inputs for each of the ANN models. As the lamination parameters are discretely distributed in their feasible region, not all values of lamination parameters correspond to an actual stacking sequence [62]. Therefore, stacking sequences rather than lamination parameters are randomly selected by LHS, with the corresponding lamination parameters then calculated using Eq. (7) to be used as inputs for the ANN models. The lamination parameters of laminates with smaller numbers of layers can be easily overlapped in the feasible region by those for the laminates with larger numbers of layers. The feasible region of lamination parameters is filled more densely by laminates with larger numbers of layers. Hence, the number of layers in the laminates generated for the training process is taken as equal to the upper limit of the number of layers for the optimization to ensure the generated database is able to represent the whole design space. Different laminate thicknesses in the database are achieved by reducing layer thickness rather than deleting layers with constant thickness, in such a way that the design space can be adequately represented and the data generation process is simplified, avoiding the generation of a large number of stacking sequences for each possible number of layers. Additionally, in order to increase the efficiency of the training process as well as the prediction accuracy, the parameters in the database are normalized. Moreover, the generated database is divided into a training dataset and a testing dataset, with the percentages of samples allocated to each set to 80% and 20%, respectively.

3.1.3 Development of ANN models

In this study, Keras [63], a python-based open-source package, is used for the development of the ANN models. An ANN generally contains one input layer, one output layer and a number of hidden layers in between, each of which is composed of a certain number of neurones. As shown in Fig. 2, the neurones are interconnected with each other in the preceding layer and the subsequent layer. As the inputs of the ANN models in this study are bending lamination parameters $\xi_i^{\mathrm{D}}\left(i=1,2,3\right)$, laminate thickness t and dimensional parameters, the number of neurones in the input layer depends on the type of laminated composite structure, while there is only one neurone in the output layer, which is the buckling load p_{cr}. The number of hidden layers and the number of neurones in each hidden layer are determined by trial-and-error process. Except for the neurones in the input layer, the input to a neurone is a weighted linear combination of the outputs of the neurones in the preceding layer with a bias. After the input is received by a neuron, it is processed and converted to an output based on the activation function. This output is then passed through to the neurones in the subsequent layer. In this study, the linear activation function which outputs the same value as is input is applied to the output layer, while the softplus activation function expressed in Eq. (8) is applied to the rest of the layers.

$$\text{softplus}(x) = \log(\exp(x) + 1), \tag{8}$$

where x represents the input of the neurone. During the training process, the inputs are fed in the forward direction. After the output is obtained at the last layer, the error between the obtained output and the target output is converted into a loss function. In order to ensure the accuracy of the prediction, the loss function is minimized by iteratively optimizing the interconnection weights and biases based on a back propagation algorithm. In this study, the Adam optimizer [64] which is available in Keras is employed to minimize the loss function represented by the mean square error. This error estimator, shown in Eq. (9), was selected as the most commonly used error estimator, and also the one which gave the best performance.

$$\text{loss} = \frac{1}{n}\sum_{i=1}^{n}(t_i - p_i)^2, \tag{9}$$

where n is the number of data samples in the training database, t_i and p_i are the target values obtained by the FEA and ANN models for the i^{th} sample, respectively.

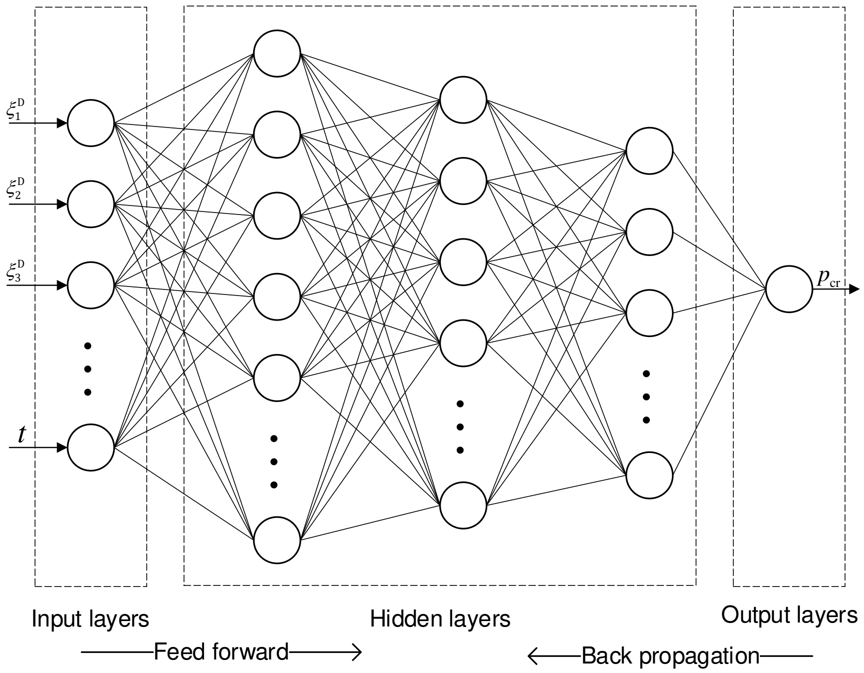


Fig. 2. The structure of an artificial neural network.

After the training process, the performance of the trained ANN models is evaluated using the testing database against the coefficient of determination (R^2) and the mean absolute percentage error (MAPE), which are expressed in Eq. (10) and (11), respectively.

$$R^2 = 1 - \frac{\sum_{i=1}^{n_t} (t_i - p_i)^2}{\sum_{i=1}^{n_t} (t_i - \bar{t})^2}, \quad (10)$$

$$\mathrm{MAPE} = \frac{1}{n_t} \sum_{i=1}^{n_t} \frac{|t_i - p_i|}{t_i}, \quad (11)$$

where n_t is the number of data samples in the testing database and $\bar{t}$ is the mean of the target values. An ANN model with better prediction ability will have a value of R^2 approaching 1 and a value of MAPE approaching 0.

3.2 Contrasting methods

In this study, linear regression (LR), decision tree (DT) and random forest (RF) methods are also developed for the prediction of the buckling loads of laminated composite structures. The three contrasting methods are popular machine learning methods for prediction problems. LR assumes a linear relationship between the inputs and outputs, hence the outputs are obtained from a linear combination of the inputs [65]. DT is proposed based on a tree-like model in which attributes are represented by internal nodes, and the branches of the nodes represent the values for the attribute tested. The results are predicted by learning decision rules from the attributes [66]. RF is developed by merging multiple decision trees together, and outputs the mean value of the outputs of individual trees [67]. The python scikit-learn package which offers a variety of machine learning functions is employed for the development of the three contrasting methods. The inputs and output of the three methods are set to be the same as those of the ANN. The parameters for training are determined based on trial-and-error procedure. Moreover, the database used for the training and testing of the three contrasting methods is the same as that for ANN.

3.3 Optimization procedure

As the most popular method in stacking sequence optimization, GAs, which perform stochastic search based on a population of designs without the utilization of information on the gradient of the objective and constraint functions are used in this study. The aim of the optimization is to minimize the weight of laminated composite structures subject to a buckling constraint. The design variables include the stacking sequences, laminate thickness and other structural dimensions. The optimization problem can be formulated as:

$$\text{Minimize:} \quad W(\mathbf{x}), \tag{12}$$

$$\text{Subject to:} \quad G(\mathbf{x}) = \frac{N_{\mathbf{d}}}{N_{\mathbf{cr}}} - 1 \le 0, \tag{13}$$

$$x_i^{\mathrm{l}} \le x_i \le x_i^{\mathrm{u}}, i = 1,2,3,\ldots,n_{\mathrm{d}},$$

where $W(\mathbf{x})$ is the structure's mass, $G(\mathbf{x})$ is the buckling constraint, $N_{\mathbf{d}}$ and $N_{\mathbf{cr}}$ are the required buckling load and actual buckling load of the structure, respectively. $\mathbf{x}$ is the vector of design variables including ply angles which are limited to 0°, 90°, +45° and -45°, ply thickness or laminate thickness, and stiffener dimensions (if applicable). x_i^{l} and x_i^{u} are the lower and upper bounds of each design variable, respectively and n_{d} is the number of design variables. There are usually two ways to conduct minimum weight optimization of composite laminates, by reducing either the ply thickness or the number of plies where the plies have a fixed thickness. In this paper, both ways of minimum weight optimization are considered. Two chromosomes are used for each individual, the first one represents the stacking sequence by a string of genes which represent the ply angles 0°, 90°, +45° and -45° with 1, 2, 3, and 4, respectively, and the second stores the remaining design variables encoded in binary form. Several methods have been proposed for the GA optimization problem where stacking sequences with different numbers of plies are considered [68,69]. In this paper, the concept of the empty ply proposed in [70] is used to delete a ply. Apart from the ply angles 0°, 90°, +45° and -45°, the empty ply is also encoded into the first chromosome to represent a deleted ply, ensuring the chromosomes of different individuals have the same length.

For the GA optimization, optimized results are obtained by exchanging the genetic information of the chromosomes between individuals based on consecutive operations such as selection, crossover, and mutation. In this paper, the initial population is randomly generated, and the performance of the individuals is evaluated based on the objective function shown below:

$$f(\mathbf{x}) = W(\mathbf{x}) + \alpha \cdot \max\left(0, G(\mathbf{x})\right), \tag{14}$$

where α is the penalty coefficient corresponding to the buckling constraint, and the value of α is obtained using trial-and-error process. More advanced penalization methods [71,72] could also be employed herein, but are out of scope for this paper.

The developed ANN models are employed to obtain the buckling load of each individual, and the buckling constraint is implemented by the penalty method. The individual with the lower value of objective function is given the higher fitness value, which correspondingly then has more probability of being selected for reproduction. In this paper, the roulette wheel method with an elitism operation which keeps the best individual directly for the next generation is used in the selection operation. After that a two-point crossover operation executed with high probability followed by a mutation operation executed with low probability are implemented to produce a new generation as shown in Fig. 1. In this paper, the population size, probabilities of crossover and mutation are determined using a trial-and-error process. Based on the above operations, the structures are successively optimized until the stopping criterion is satisfied.

4. Applications

In order to demonstrate the effectiveness of the proposed method, minimum weight optimization is conducted for flat, blade-stiffened and hat-stiffened laminates in this section. For the generation of the database, ABAQUS is used to perform buckling analysis for the three laminates. The four-noded quadrilateral S4R shell element with six degrees of freedom at each node are employed, and the mesh size is determined based on a mesh sensitivity analysis. The laminates are assumed to be simply supported, and compression loading is applied in the longitudinal direction. The material properties shown in Table 1 are utilized. The stacking sequences of the three types of laminated composite structures are assumed to be symmetric. It should be noted that the developed ANNs and GAs are for symmetric laminates only, and lower laminate weight can be obtained if the symmetry constraint is not implemented [73]. In this section, the flat laminate is optimized by reducing the ply thickness, while the blade-stiffened and hat-stiffened laminates are optimized by reducing the number of plies with a fixed ply thickness. The value of the ply thickness shown in Table 1 is the starting value for the optimization of flat laminate, while it is fixed for the blade-stiffened and hat-stiffened laminates.

Table 1 Material properties.

E_1 (kN/mm^2)	131
E_2 (kN/mm^2)	7.1
G_1 (kN/mm^2)	3.5
ρ (kg/mm^3)	1584
ν_{12}	0.3
Ply thickness (mm)	0.125

4.1 Flat laminate

For the optimization of the flat laminate, the design variables are the ply angles and ply thickness. Since the inputs of the ANN model for the flat laminate are the three bending lamination parameters and the laminate thickness, the ply angles and ply thickness obtained in each optimization cycle are used to calculate the lamination parameters and laminate thickness, which are then used as inputs for the ANN model to obtain the buckling load of each individual. The flat laminate has dimensions of 1000 mm ×

1000 mm, and the number of plies is 32 which is fixed during the optimization. A mesh size of 50 mm is chosen. Fig. 3 shows the effect of the size of the database on MAPE, and the value of MAPE shown in Fig. 3 is the mean of five ANN results. As expected, the value of MAPE decreases as the number of samples in the database increases. It can be seen that, the required number of samples for the flat laminate is around 750, hence 750 FEA are conducted in a total computational time of about 2 hours on an i7-CPU Intel processor at 4 GHz speed. The inputs of the ANN model for the flat laminate are the three bending lamination parameters and the laminate thickness. After a trial-and-error procedure, the structure of the ANN model is determined as 4-30-30-30-30-30-1 (5 hidden layers with 30 neurones in each). Fig. 4 shows the comparisons of R^2 and MAPE between the four methods, the abscissa and ordinate represent the predicted value and target value, respectively. As expected, LR has the lowest value of R^2 and highest value of MAPE, indicating that the buckling problem for composite laminates is highly non-linear, and the buckling load cannot be accurately obtained by a linear combination of the lamination parameters and laminate thickness. It is observed that RF performs better than DT in this case, as RF achieves higher value of R^2 and lower value of MAPE. ANN obtains the best results with values of R^2 and MAPE equal to 0.996 and 0.023, respectively, achieving the highest goodness-of-fit and prediction accuracy, demonstrating its superior performance in predicting buckling load.

For the GA optimization in this case, the size of the population is 30, and the probabilities of crossover and mutation are 0.85 and 0.05, respectively. The total design load is chosen to be 4 kN, and the corresponding minimum weight is converged to 4280 g at around the 100th generation. Since GA is a stochastic method, it is run 10 times for each case in this study, and the results show that all the GA optimizations are converged well. A typical GA optimization run is shown in Fig 4 (a). In comparison with the initial laminate which is just able to carry the design load obtained during the optimization, a mass reduction of 12.5% is achieved. The ply thickness is reduced from 0.125 mm to 0.084 mm, and the optimized stacking sequence is shown in Table 2. The solution times for each buckling analysis using FEA and ANN are 10.57 seconds and 1×10^{-4} seconds, respectively. The solution time using ANN is therefore only 0.0009% of that of FEA, achieving a significant reduction in computational cost. Because the number of buckling evaluations during each GA optimization run is 9000 in this case, the utilization of ANN achieves a total time saving of 44 hours for each GA run. It should be noted that the solution time of the ANN mentioned in this paper excludes the training time, since once the ANN model is trained and established, it can be utilized any number of times.

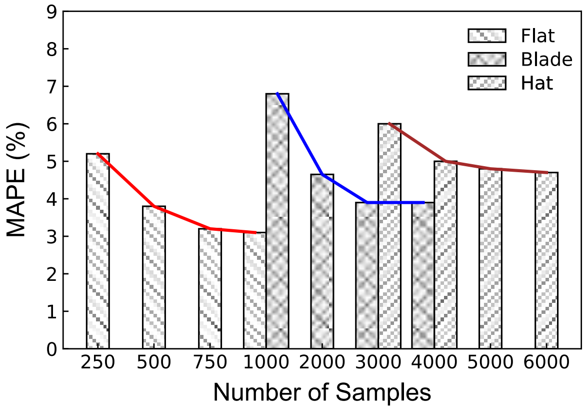


Fig. 3. The effect of size of database on MAPE.

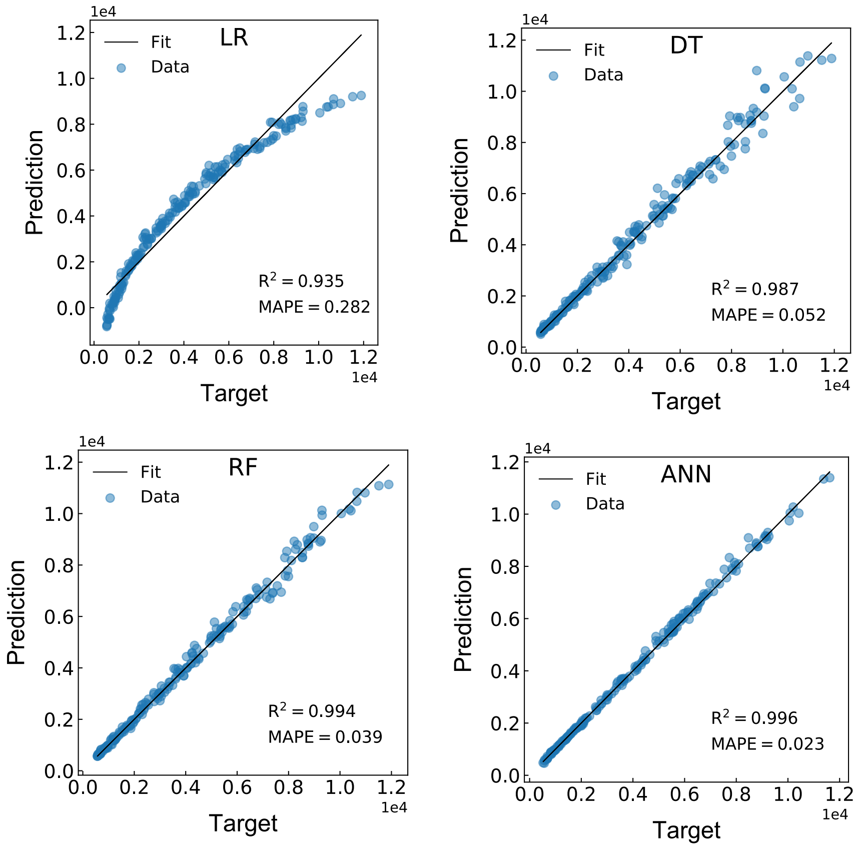
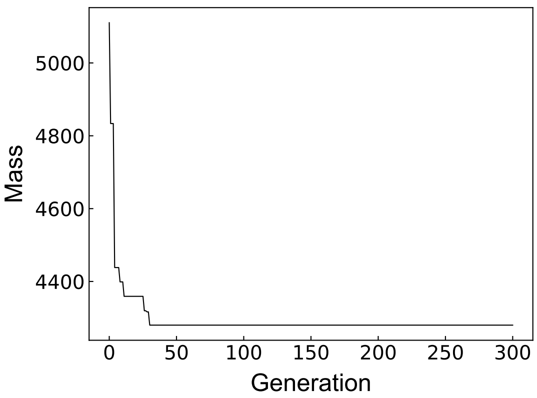


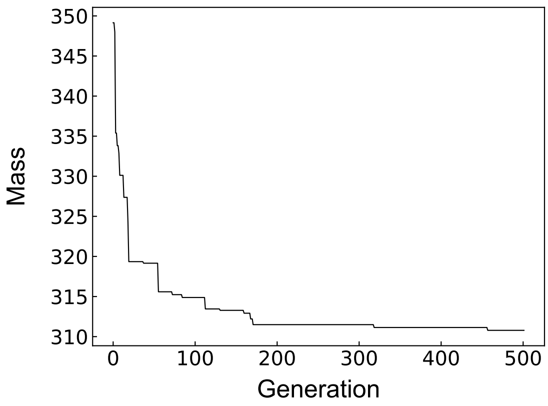
Fig. 4. Comparisons of R^2 and MAPE between different machine learning methods for flat laminate.

Table 2. Optimized stacking sequences and time saving for each GA run.

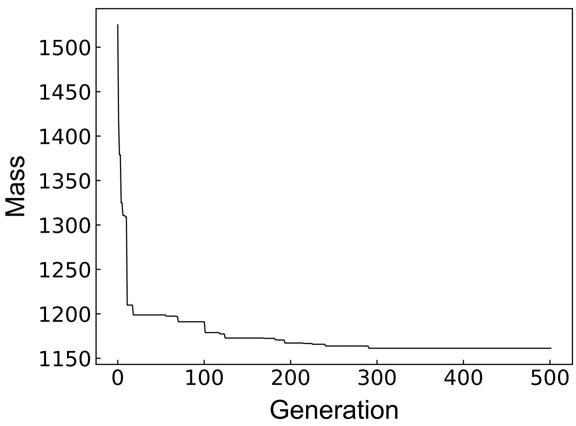
Case		Stacking sequences	Time saving (hours)
Flat laminate	skin	$[45/\text{-}45_2/45/\text{-}45/90/\text{-}45/(45/90_2)_2/0/90_2]_S$	26.4
Blade-stiffened laminate	skin	$[\text{-}45_2/90_2/45_4/90/45]_S$	184.6
	stiffener	$[\text{-}45/45/90/45/0/90/0/\text{-}45/0_2]_S$	
Hat-stiffened laminate	skin	$[45/\text{-}45_2/90/45_2/90/0]_S$	257.9
	stiffener	$[0_2/45_2/0_3/90/45]_S$	



(a) Flat lamiante



(b) Blade-stiffened lamiante



(c) Hat-stiffened lamiante

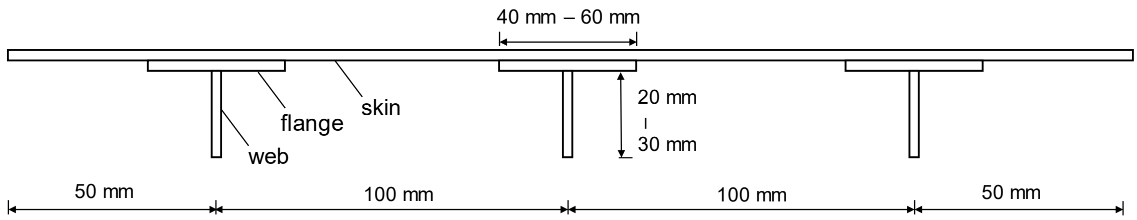
Fig. 5. Typical GA optimization runs for the three cases.

4.2 Blade-stiffened laminate

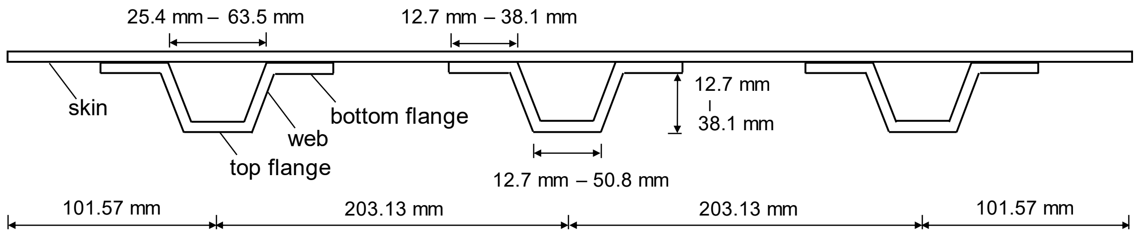
This section describes the optimization of a blade-stiffened laminate. In contrast to the optimization of the flat laminate, the optimization of blade-stiffened laminate and hat-stiffened laminate minimizes the weight by reducing the number of fixed thickness plies, correspondingly, the obtained results are more practical. The blade-stiffened laminate has dimensions of 300 mm × 300 mm, and a mesh size of 6 mm. The cross-section of the blade-stiffened laminate is shown in Fig. 6(a), and has three uniformly spaced stiffeners, with the flange and web assumed to have the same stacking sequence and hence the same thickness for simplicity. It is also assumed that the stiffener should not be thinner than the skin for the stiffened laminates in this study. The design variables are the ply angles, thicknesses of the skin and stiffener, the width of the flange and the height of the web. During the optimization, the width of the flange is varied from 40 mm to 60 mm, and the height of the web is varied from 20 mm to 30 mm.

As can be seen from Fig. 3, the required number of samples in the database for the blade-stiffened laminate is around 3000. Compared with the flat laminate, the blade-stiffened laminate requires a larger number of samples because more input features are considered. Correspondingly, 3000 FEA are conducted in a total computational time of about 22 hours. The inputs of the ANN model in this case are the bending lamination parameters, the thicknesses of the skin and stiffener, the width of the flange and the height of the web. After a trial-and-error procedure, the structure of the ANN model is determined as 4-50-50-50-50-50-1 (5 hidden layers with 50 neurones in each). As can be seen from Fig. 7, compared with the contrasting methods, ANN is shown to have the best performance with the values of R^2 and MAPE equal to 0.987 and 0.032, respectively.

For the GA optimization in this case, the size of the population is 50, and the probabilities of crossover and mutation are 0.9 and 0.05, respectively. The total design load is chosen to be 400 kN, and the corresponding minimum weight is converged to 310.78 g at around 450th generation. Fig. 4(b) shows a typical GA optimization run for the blade-stiffened laminate. Compared with the initial laminate which is just able to carry the design load during the optimization, the optimized laminate achieves a mass reduction of 6.5%. The optimized stacking sequences of the skin and stiffener are shown in Table 2, and the optimized values of the width of the flange and the height of the web are 48 mm and 26.4 mm, respectively. The solution times for each buckling analysis using FEA and ANN are 26.58 seconds and 1×10^{-4} seconds, respectively. The solution time using the ANN is therefore only 0.0004% of that of FEA. As the number of buckling evaluations during each GA optimization run is 25000 in this case, the utilization of ANN achieves a total time saving of 184.6 hours for each GA run.



(a) Cross section of blade-stiffened lamiante.



(b) Cross section of hat-stiffened lamiante.

Fig. 6. Cross section of stiffened laminates.

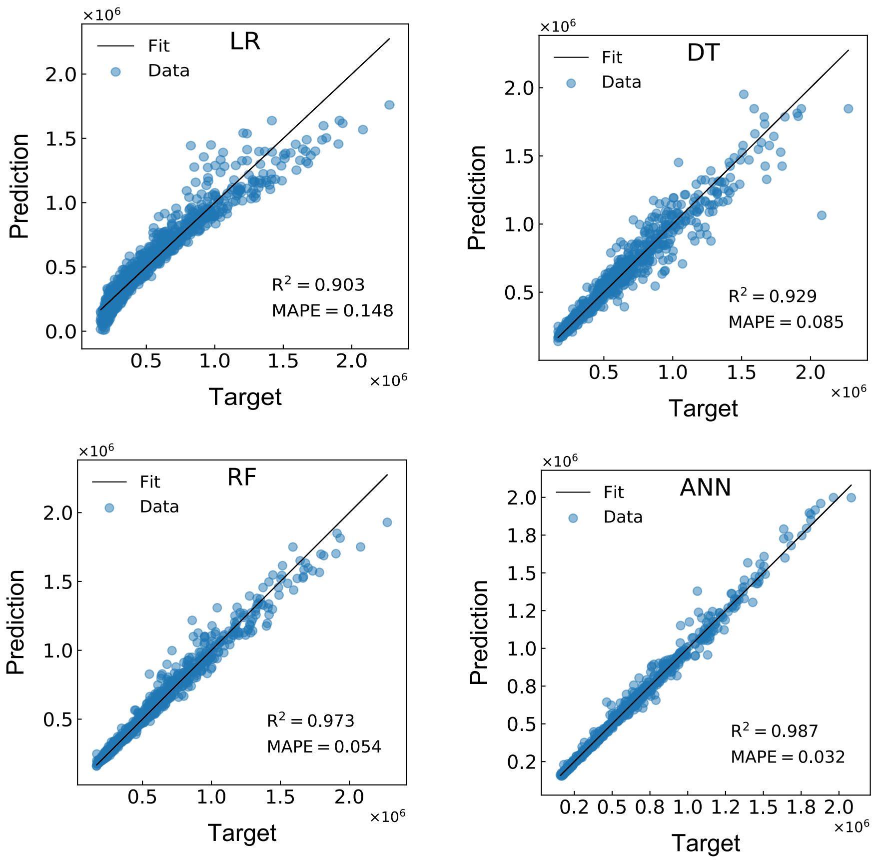


Fig. 7. Comparisons of R^2 and MAPE between different machine learning methods for blade-stiffened laminate.

4.3 Hat-stiffened laminate

The optimization of a hat-stiffened laminate is described in this section. The hat-stiffened laminate has dimensions of 609.4 mm × 609.4 mm, with the cross-section shown in Fig. 6(b). A mesh size of 8.7 mm is used. The stacking sequences of the bottom flange, top flange and web are assumed to be the same. The design variables are the ply angles, thicknesses of the skin and stiffener, the bottom hat width, the widths of the bottom and top flanges, and the height of the web. During the optimization, a typical dimensional limit for the hat stiffener is implemented, correspondingly, the bottom hat width is varied from 25.4 mm to 63.5 mm, the width of bottom flange is varied from 12.7 mm to 38.1 mm, the width of top flange is varied from 12.7 mm to 50.8 mm, and the height of the web is varied from 12.7 mm to 38.1 mm.

The inputs of the ANN model in this case are the bending lamination parameters and thicknesses of the skin and stiffener, the bottom hat width, the widths of the bottom flange and top flange, and the height of the web. As more input features are added for the hat-stiffened laminate, the required number of samples in this case further increases to around 5000 as shown in Fig. 3. In order to generate the database, 5000 FEA are conducted and the total computational time is about 43 hours. After a trial-and-error procedure, the structure of the ANN model is determined as 4-50-50-50-50-50-50-1 (6 hidden layers with 50 neurones in each). As can be seen from Fig. 8, ANN performs better than the contrasting methods, and the values of R^2 and MAPE for the ANN are 0.987 and 0.046, respectively. Comparisons of the MAPE between the three cases show that as the number of inputs increases, the values of MAPE of ANN increase smoothly, indicating that an increase of the number of inputs slightly reduces the accuracy of the ANN prediction. The values of R^2 of the three cases achieved by ANN models are all greater than 0.98, and the value of R^2 of the hat-stiffened laminate is only 0.9% lower than that of the flat laminate. Similar comparisons using the RF, DT, and LR models show increased reductions in R^2 of 5.1%, 13.3%, and 16.0%, respectively. These comparisons demonstrate that increasing of the number of inputs has a smaller effect on the ANN models than the other three models, and the advantage of ANN model is more pronounced when larger numbers of inputs are considered. It should be noted that since the data used to train the surrogate models are generated according to the geometric constraints of these optimization problems, the developed ANN models can only be used for the optimization problems with same constraints, otherwise, the optimization performance cannot be guaranteed.

For the GA optimization in this case, the size of the population is 60, and the probabilities of crossover and mutation are 0.9 and 0.05, respectively. The total design load is chosen to be 243 kN, and the corresponding minimum weight is converged to 1163.83 g at around 180th generation. A typical GA optimization run of the hat-stiffened laminate is shown in Fig. 4(c). Compared with the initial laminate which is just able to carry the design load during the optimization, the optimized laminate achieves a mass reduction of 28% in this case. Table 2 presents the optimized stacking sequences of the skin and stiffener. The optimized values of the widths of the bottom and top flanges are 38.1 mm and 31.1 mm, respectively, and the optimized values of the bottom hat width and the height of the web are 63.5 mm and 30.7 mm, respectively. Furthermore, in this case the solution times for each buckling analysis using FEA and ANN are 30.95 seconds and 1×10^{-4} second, respectively. Therefore, the solution time of the ANN is only 0.0003% of that of FEA. The number of buckling evaluations during each GA optimization run is 30000 in this case, hence a time saving of 257.9 hours for each GA run is achieved.

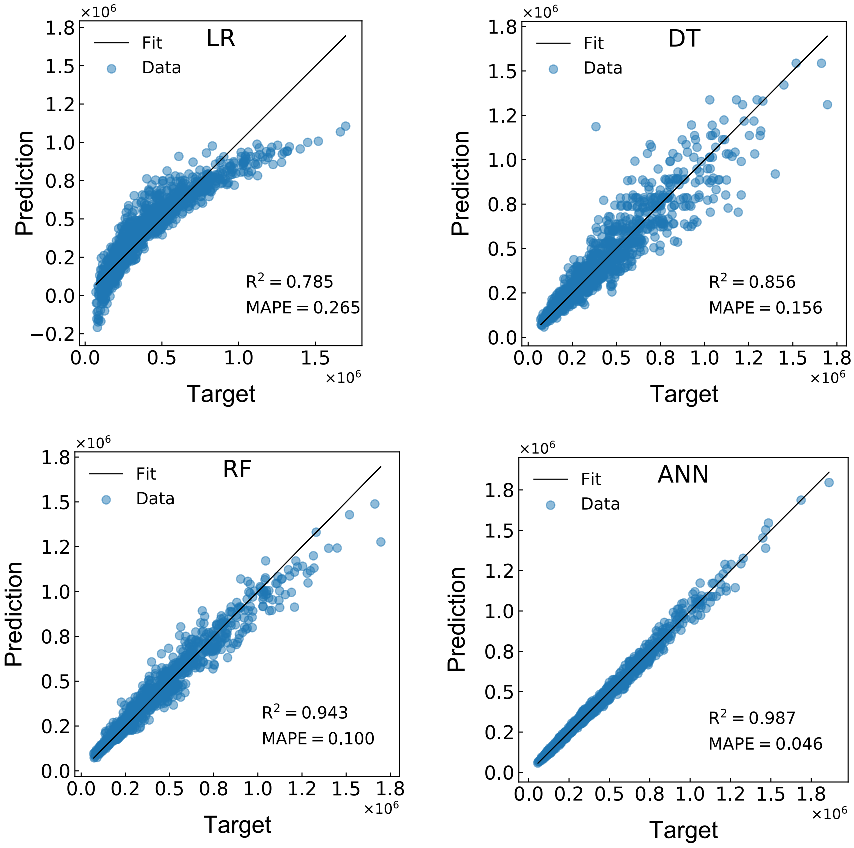


Fig. 8. Comparisons of R^2 and MAPE between different machine learning methods for hat-stiffened laminate.

5. Conclusions

This paper presents an efficient optimization method for the weight minimization of laminated composite structures subject to a buckling constraint. The lamination parameters and laminate thickness are used to replace the stacking sequences as inputs of the ANN models, which significantly reduces the number of inputs to the ANN models, and also makes the ANN models usable for the minimum weight optimization where laminates with different numbers of layers and total thicknesses need to be evaluated. To generate the required database, the LHS method is employed to determine the combinations of inputs for the ANN models, and FEA is used to obtain the buckling load of the samples in the database. The developed ANN models achieve high goodness-of-fit with values of R^2 equal to 0.996, 0.987 and 0.987 for the flat, blade-stiffened and hat-stiffened laminates, respectively. The corresponding values of MAPE are 0.023, 0.032 and 0.046, respectively, which means that the developed ANN models are able to predict the buckling loads of composite laminates with negligible errors. Comparisons of R^2 and MAPE between LR, DT, RF and ANN show that ANN has the best performance for all the cases, demonstrating its superiority in the prediction of buckling load. After the ANN models are developed, they are employed in an optimization using GAs during which large numbers of buckling evaluations are performed. The results show that all the optimizations are converged well. The solution time for each buckling analysis using ANN is only around 1×10^{-4} second, while the solution time for FEA is more than 100000 times longer, hence considerable time saving is gained from the use of ANN, suggesting that the developed ANN models represent a strong alternative to FEA in the minimum weight optimization of composite laminates. Nevertheless, as a line of future research for more complex optimization problems, the sensitivity of the optimization parameters is also recommended to be investigated, based on which more suitable and effective optimization methods and ANN models could be developed.

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