Research on Buckling Load Prediction of Composite Stiffened Plates Based on BP Neural Network

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Abstract: In view of the complexity of the composite stiffened plate structure, a prediction model between the properties and geometric parameters of the composite stiffened material and the buckling load is established based on the BP neural network. Firstly, the finite element model of composite stiffened plates was established by using Abaqus software, and the buckling load under axial load was studied. Secondly, 500 experimental samples were drawn using the Latin hypercube experiment method, and the corresponding values were obtained based on the software Buckling load value. Finally, 450 experimental samples are selected as the training set and the remaining 50 samples are used as the test set to establish a BP neural network prediction model. The results show that the method of using BP neural network to predict buckling load is effective and correct.

Key words: composite stiffened plate; prediction; BP neural network

1. Introduction

Composite materials are widely used in the aerospace field because of their high specific strength and specific modulus, good fatigue fracture and corrosion resistance \cite{1,2}, such as the proportion of composite materials on Boeing 787 has reached 50%. During the use of the aircraft, under the action of force, the common failure mode is buckling instability \cite{3,4}. Therefore, the prediction research on the buckling load of composite stiffened plates has important engineering application value.

Scholars at home and abroad have carried out research on this. From the perspective of parameters such as stiffener size and interface element strength, etc. from Liu Congyu et al. \cite{5} from the perspective of the ply sequence of stiffened plates, Zhang Changxing et al. \cite{6} from the perspective of the ply sequence of stiffened plates, Zhao Weitao et al. \cite{7} From the perspective of the ultimate compressive strength correlation, Song Gang et al. \cite{8} studied the buckling of composite materials from the load and compression angles of stiffened plates. Carlos et al. \cite{9} considered the reliability-based design of composite stiffened plates in the post-buckling state, and improved the bearing capacity of post-buckling by changing the stacking order of the skin layer and the reinforcing layer. Sobey et al. \cite{10} proposed a fast analysis method of composite structure reliability based on Monte Carlo simulation, and obtained the reliability of the material. Marcin et al. \cite{11} can calculate and analyze the effect of specific component material parameters on the overall effective performance of composite materials through
sensitivity analysis of homogenized material tensor. Xue et al. [12] proposed an analysis method for top-hat reinforced structural composite plates based on reliability analysis. Guo et al. [13] proposed an improved response surface method for the analysis of buckling reliability and sensitivity of composite stiffened plates, and analyzed the composite stiffened plates under axial compression load. CHEN et al. [14] conducted a buckling analysis of composite stiffened plates. Based on the structural reliability of composite materials, sensitivity analysis was performed on parameters such as material properties and better results were obtained. Plate buckling load prediction is valuable. Based on the above research, a prediction model for the properties and geometric parameters of composite reinforced materials and buckling loads is established based on the BP neural network.

2. Composite stiffened plate model

This article uses a T-shaped composite material stiffened plate model[15], as shown in Figure 1. The composite material stiffened plate: length La = 280mm, width Wa = 160mm, stiffener spacing Sa = 100mm, wing width W = 24mm, web height H = 20mm, the thickness of the single-layer board is 0.125mm. Material properties: $E_1 = 130000$ MPa, $E_2 = 10000$ MPa, $G_{12} = G_{13} = 4850$ MPa, $G_{23} = 3620$ MPa, $v_{12} = 0.31$.

Stacking sequence of skin and stiffener: Skin: (0/90/45/-45/45/90/0), a total of 8 layers, a total thickness of 1mm; stiffener: (0/90/45/0/-45/-45/0/45/90/0), a total of 10 layers, The total thickness is 1.25mm.

![Figure 1. Composite stiffened plate model](image1)

Based on the Abaqus finite element software, a finite element model of composite stiffened siding is established. In order to improve the calculation efficiency, the skin and stiffener are modeled with S4R shell elements, and the skin and stiffener are connected using tie. The boundary conditions Setting: One end of the load is open and the degree of freedom in the load direction is applied, and the other end is fixed. The buckle calculation module is used to perform eigenvalue buckling analysis of the finite element model. The first-order mode is shown in Figure 2.

![Figure 2. First-order buckling modes of stiffened plates](image2)

It can be seen from Table 1 that the error between the buckling load and the experimental results obtained by the method in this paper is only 1.6%, which meets the actual requirements of the project. Therefore, the rationality and accuracy of the modeling method in this paper are proved.

| Table 1. Calculation results of axial compression of stiffened plates |
|---------------------------------------------------------------|
| Buckling load(KN) | This article | Experiment [15] | error |
|-------------------|--------------|-----------------|-------|
| 4.97              | 4.89         | 1.6%(✓)        |       |
3. Prediction model
The material properties \( (E_1, E_2, G_{12}, G_{13}, G_{23}) \) and geometric parameters \( (LT, \Theta, W, H) \) selected in this study are random variables. The parameters and ranges of random variables are shown in Table 2. Before predicting the model, these variables must be sampled first. The Latin hypercube experimental method can evenly extract samples in the space area. Therefore, this study uses the Latin hypercube experimental method to randomly select 500 test samples and select 450 groups. The samples are used as training samples for model fitting, and the remaining 50 groups of samples are used as test samples for testing the model's fitting accuracy.

| Variable | Label | Mean | Range          |
|----------|-------|------|----------------|
| \( E_1 \) [MPa] | \( x_1 \) | 130000 | [123500, 136500] |
| \( E_2 \) [MPa] | \( x_2 \) | 10000 | [9500, 10500] |
| \( G_{11} \) [MPa] | \( x_3 \) | 4850 | [4607.5, 5092.5] |
| \( G_{12} \) [MPa] | \( x_4 \) | 4850 | [4607.5, 5092.5] |
| \( G_{23} \) [MPa] | \( x_5 \) | 3620 | [3439, 3801] |
| \( LT \) [mm] | \( x_6 \) | 0.125 | [0.11875, 0.13125] |
| \( \Theta \) [°] | \( x_7 \) | 45 | [41.9985, 48.0015] |
| \( W \) [mm] | \( x_8 \) | 24 | [21.6, 26.4] |
| \( H \) [mm] | \( x_9 \) | 20 | [18, 22] |

Due to the complexity of the composite structure, there is an implicit function relationship between the selected 9 parameters and the buckling load. In order to clearly describe the relationship between the parameters and the buckling load, a high-precision model is required for fitting. It has strong non-linear mapping ability [16], and also has high prediction accuracy. Therefore, this paper chooses BP neural network to establish a prediction model.

3.1. Data normalization
Before setting up a prediction model, you need to normalize the original data. Due to the inconsistency of the units of the input data, the range of the input data varies widely, resulting in a slow convergence of the neural network and a long training time. The role of pattern classification may be too large, while the input of a small data range is too small, which greatly affects the performance of the neural network, reduces the prediction accuracy, and transforms the input data into common transformation formulas such as (1):

\[
C_{ij} = \frac{c_{ij} - c_{i\text{min}}}{c_{i\text{max}} - c_{i\text{min}}} \tag{1}
\]

In the formula: \( C_{ij} \) is the normalized parameter, \( c_{ij} \) is the input data, \( c_{i\text{min}} \) is the minimum value of the corresponding column of the input data, and \( c_{i\text{max}} \) is the maximum value of the corresponding column of the input data. The normalized range of \( C_{ij} \) is [0, 1].

3.2. BP neural network prediction model
BP neural network is a kind of multilayer feedforward neural network [17], which can carry out error backpropagation and perform weighted summation for each input unit. Use the sample data to train and learn the network, and continuously adjust the weights and thresholds to reflect the mapping between
the input and output. The resulting neural network model can predict the output value corresponding to a given input.

The schematic diagram of the BP neural network is shown in Figure 3. The model consists of three parts, namely the input layer, the hidden layer and the output layer. The input layer variables are $E_1, E_2, G_{11}, G_{12}, G_{23}, \theta, LT, W, H$. The output layer is $y_p$ (buckling load). Generally, for a neural network with only one hidden layer, adjusting the number of nodes in the hidden layer can fit a non-linear function with higher accuracy. Therefore, this paper uses a three-layer multi-input single-output BP network with a hidden layer to build a prediction model. In the process of network design, it is very important to determine the number of hidden neurons. Too many neurons in the hidden layer will increase the amount of network calculations and easily cause over-fitting problems; too few neurons will affect the network performance and fail to achieve the expected results.

Figure 3. BP neural network schematic

The number of hidden neurons in the network is directly related to the complexity of the actual problem, the number of neurons in the input and output layers, and the setting of the expected error. It can be selected by referring to formula (2), where $M$ is the number of neurons in the input layer, $L$ is the number of neurons in the output layer, and $a$ is an arbitrary constant between $[0,10]$.

$$d = \sqrt{M + L + a}$$

(2)

In this study, the hidden layer function uses the Tansig function, the output layer transfer function uses the Purelin function, the training algorithm uses trainbfg, the maximum training number of the neural network is set to $1e+4$ times, the training accuracy requirement is set to $1e-3$, and the learning rate is set to $1e-4$, training the established neural network model.

3.3. Evaluation of model indicators

This paper uses the mean square error $MSE$ and the average absolute percentage error $MAPE$ to evaluate the accuracy of the BP neural network model. The smaller the $MSE$ and $MAPE$, the higher the accuracy of the model fit and the higher the accuracy of the prediction. The specific calculation formula is as follows:

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (\hat{y}_i - y_i)^2$$

(3)

$$MAPE = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100\%$$

(4)

Where $y_i$ is the real value and $\hat{y}_i$ is the predicted value of the neural network model.

3.4. Result analysis

The predicted and actual results of the BP neural network are shown in Figure 4, where the predicted maximum relative error is 9.18%, the minimum relative error is 0.15%, and the average relative error is
According to the formulas (3) and (4), the model prediction is known. The mean square error is 0.0405, and the average absolute percentage error is 3.35%. Through calculation and analysis, the BP neural network has a high fitting accuracy and can accurately predict the value of the buckling load of composite stiffened plates.

![Comparison chart](image1)

![Relative error chart](image2)

**Figure 4.** BP neural network model prediction results

4. **Conclusion**

1) The number of hidden layer neurons is 7 and trainbfg is used as a training function to establish a BP neural network. The buckling load of composite stiffened plates is predicted. The average error of prediction is 3.35%, which meets the actual requirements of engineering.

2) Using BP neural network can quickly and accurately establish the prediction model of buckling load, which can be extended to the design of composite stiffened plates and provide guidance for the design of composite stiffened plates.

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