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ITJ

ISSN 1812-5638

INFORMATION TECHNOLOGY JOURNAL

ANSI*net*

Asian Network for Scientific Information
308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

A Neural Network Method Applied in Prediction Eigenvalue Buckling for Sandwich Plates

¹Liu Xiaoman, ¹Du Guojun and ²Niu Xiaoxia

¹Department of Engineering Mechanics, Yanshan University, Qinhuangdao, China

²College of Information and Technology Engineering, Yanshan University, Qinhuangdao, China

Abstract: The sandwich plate as a kind of composite materials was served in the field of aerospace, transportation, construction, packaging and so on. Sandwich plates due to the particularity of structure, applied in the accidental limit load will product damage or long time used will generate fatigue abrasion, these all make the sandwich plates whole or partial stiffness deterioration, results in early failure. In order to forecast critical load fast. The Radial basis function networks (RBFNNs) is employed as the calculate tool of the critical load for given geometric and physical parameters. Firstly using ANSYS finite element eigenvalue buckling method to analyse the square honeycomb sandwich plate buckling behavior, study on effect of honeycomb sandwich plate buckling in different size parameters and material properties. Secondly, Intelligent simulation by a large number of numerical data, All the models developed are of acceptable accuracy within the data range, considering the complexity and nonlinear of the property correlation of composite sandwich plate. The natural frequency should be optimization training in the genetic algorithms which can improve the prediction accuracy. The results show that: increased reasonably core high and increased face plate thickness and cell-wall thickness, reduced single length of cell size, selecting the fit elasticity modulus of core material will enable increased ability to resist buckling of honeycomb sandwich plates. Buckling behavior of honeycomb sandwich plates were more sensitive when change core high and face-plate thickness.

Key words: Eigenvalue buckling, neural network, sandwich plates, radial basis function networks (RBFNNs)

INTRODUCTION

Composite laminate structures of static, dynamic theoretical analysis and computing applications, as well as viscoelastic polymer material with sandwich plates and shell structures which uses a special process to become mechanics applications research stage. Sandwich plates due to the particularity of structure, applied in the accidental limit load will product damage or long time used will generate fatigue abrasion, these all make the sandwich plates whole or partial stiffness deterioration, result in early failure. Especially when the sandwich plates under compression load, the structure is the most prone to occur the buckling behavior, so, it is very important to analysis the buckling of sandwich plates for the safe use of the structure. The works (Liu, 2001; Li, 2006) and papers (Du *et al.*, 2007, 2008) are on the large amplitude vibration of sandwich plates with initial deflection and uniform distributed load. Neural network technology used in composite sandwich plates of various performance prediction and optimization of composite materials at home and abroad in recent board application issues a research hotspot direction (Shi *et al.*, 1998; Hensman *et al.*, 2010; Haykin, 2009), Artificial intelligence applied to the field of engineering structural optimization,

damage identification, life assessment studies and other fields to become a major trend of intelligent (Sliseris and Rocens, 2013; Sliseris and Rocens, 2012; Murugan and Friswell, 2013), The Radial basis function networks (RBFNNs) is employed as the calculate tool of the critical load for given geometric and physical parameters. The design of artificial neural networks (ANNs) is motivated by analogy of highly complex, non-linear and parallel computing power of the brain.

ANNs and RBFNNs have recently been introduced into the field of polymer composites (Sliseris and Rocens, 2013). It is a promising field of research in predicting experimental trends and has become increasingly popular in the last few years as they can often solve problems much faster compared to other approaches with the additional ability to learn from small experimental data (Hassan *et al.*, 2009)

The prediction results of ANNs were compared and checked with the experiments. Firstly using ANSYS finite element eigenvalue buckling method to analyse the square honeycomb sandwich plate buckling behavior, study on effect of honeycomb sandwich plate buckling in different size parameters and material properties. Secondly, intelligent simulation by a large number of numerical data and the natural frequency

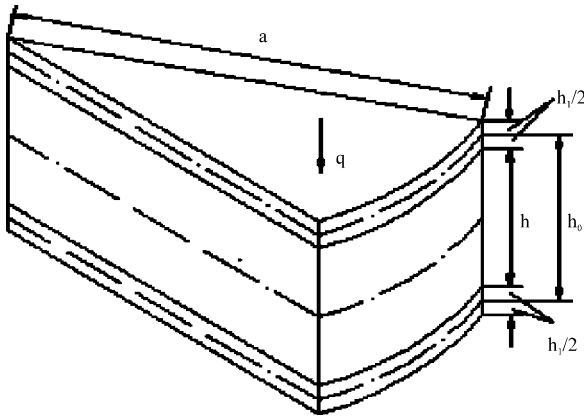


Fig. 1: A sandwich circle plate in the polar-coordinates systems

should be optimization training in the genetic algorithms which can improve the prediction accuracy (Liu *et al.*, 2011).

PROBLEM STATEMENT AND PRELIMINARIES

Definition: Figure 1 shows a sandwich circle plate in the polar-coordinates systems. Where radius of plate is a, r is the radial coordinate. Uniform distributed loading is q_0 . Having tiny static deflection is w_0 , m is the area density of sandwich plate.

With excitation, live deflection is \bar{w} , then the total deflection is $w = w_0 + \bar{w}$, stress is $\sigma_r = \sigma_{r0} + \bar{\sigma}$, Ψ is the angle between the link line of two arbitrary opposite points in medium section of the top and the bottom faces and the normal of circular sandwich plates before deformed. $\psi = \psi_0 + \bar{\psi}$ Uniform distributed load is $q = q_0 + \bar{q}$. According to static equilibrium function given in reference (Shi *et al.*, 1998), with the boundary conditions BC of the plates, here $v_0 = 0, \sigma_{r0} = 0$. The basis control and physical kinematical equations of sandwich plates with initial deflection are governed in the classical theory by:

$$R_1 = m \frac{d^2 \bar{w}}{dt^2} - 2h_1 \frac{d}{dr} \left[r \bar{\sigma}_r \left(\frac{dw_0}{dr} + \frac{d\bar{w}}{dr} \right) \right] - G_2 h_0 \frac{d}{dr} \left[r \left(\bar{\psi} + \frac{d\bar{w}}{dr} \right) \right] - \bar{q} r = 0$$

$$R_2 = D \frac{d}{dr} \left[\frac{1}{r} \frac{d}{dr} (r \bar{\psi}) \right] - G_2 h_0 \left(\bar{\psi} + \frac{d\bar{w}}{dr} \right) = 0$$

$$R_3 = \frac{d}{dr} \left[\frac{1}{r} \frac{d}{dr} (r^2 \bar{\sigma}_r) \right] + \frac{E}{2r} \left(\frac{d\bar{w}}{dr} \right)^2 + \frac{E}{r} \frac{dw_0}{dr} \frac{d\bar{w}}{dr} = 0$$

where, h_0 is distance between middles of up and down surface layer and h_1 is thickness of surface layer., E is a modulus of longitudinal elasticity of surface layer and G_2 is a shear modulus, D is the bending stiffness of sandwich plate., w is the deflection of the middle layer and σ_{r0} is the radial stress, u is the displacement in the middle layer. Based on spatial mode assumption, where initial deflection is $w_0 = f_0(1 + C_1 \rho^2 + C_2 \rho^4)$, discrete time and space and live deflection is:

$\bar{w} = h_0 \phi(t)(1 + C_1 \rho^2 + C_2 \rho^4)$ There are the basis control and physical kinematical equations of sandwich plates in “Reissner” hypothesis.

$$\left. \begin{aligned} \frac{\partial M_x}{\partial x} + \frac{\partial M_{xy}}{\partial y} - Q_x &= 0 \\ \frac{\partial M_{xy}}{\partial x} + \frac{\partial M_y}{\partial y} - Q_y &= 0 \\ \frac{\partial Q_x}{\partial x} + \frac{\partial Q_y}{\partial y} + q &= 0 \end{aligned} \right\} \quad (1)$$

When $R = \infty$, the basic equation of free vibration equations:

$$\frac{D}{2} (1 - \nu_f) \nabla^2 f - C f = 0 \quad (2)$$

$$D \nabla^2 \omega + \left(1 - \frac{D}{C} \nabla^2 \right) (2D_f \nabla^4 \omega - \rho \bar{\omega}^3 \omega) = 0 \quad (3)$$

$$D = \frac{E_f (h+t)^2 t}{2(1-\nu_f^2)}, D_f = \frac{E_f t^3}{12(1-\nu_f^2)}, C = G_c \frac{(h+t)^2}{h}$$

E_f is the elastic modulus of surface layer. ν_f is the Poisson’s ratio of surface layer. G_c is the sandwich shear modulus.

Brief introduction of RBFNNs: RBFNNs have three-layer architecture with no feedback, as shown in Fig. 2. The input layer is made up of N nodes (N dimension of the input vector $x=(x_1, x_2 \dots x_N)$?RN); their connections to the hidden nodes are not weighted and implement a fan-out of the input components to the hidden layer. This last consists of H hidden neurons (radial basis units), with radial activation functions. A typical choice for this function is the Gaussian function which has a peak at the center c and decreases monotonically as the distance from the center increases. So, the output of the h-th hidden neuron, $ah(x)$, is a radial basis function that defines a spherical receptive field in RN given by the following equation:

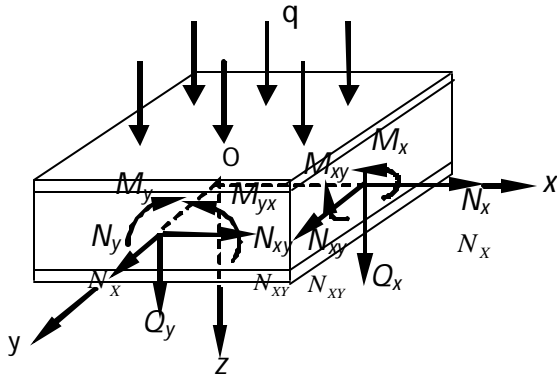


Fig. 2: A sandwich circle plate in the polar-coordinates systems

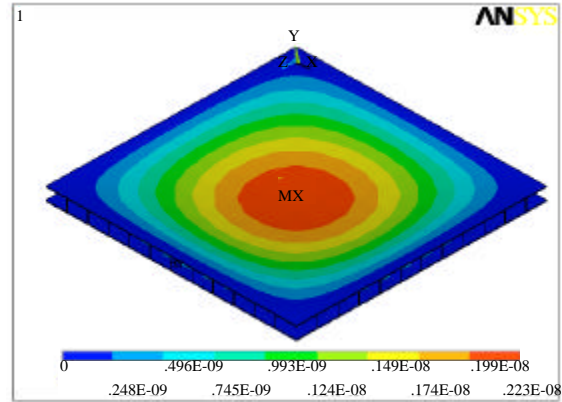


Fig. 4: Sandwich plate bending deformation maps

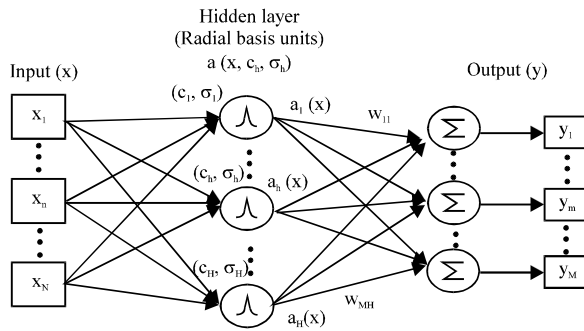


Fig. 3: Structure of the radial basis function network

$$y_m(x) = \sum_{h=1}^H w_{mh} a_h(x) \quad m = 1, 2, \dots, M \quad (4)$$

The output layer is made up of M linear summation units, linked to the hidden layer by weighted connections w_{mh} . Hence, the network output is a vector $y(x) = (y_1(x), y_2(x), \dots, y_M(x))^T$, where the m-th component $y_m(x)$, is given by the following equation:

$$y_m(x) = \sum_{h=1}^H w_{mh} a_h(x) \quad m = 1, 2, \dots, M \quad (5)$$

In this study such network was used as a classifier; consequently the dimension M of the output layer is equal to the number of fault classes to be detected. Here, the RBFNNs was simulated by using MATLAB 6.5 neural network toolbox. The general design function newrb is adopted. Structure of the radial basis function network is Fig. 3.

Numerical analysis: Ansys is employed as the instrument of supporting the train samples. We choice

Table 1: Buckling loads of different cell-spacing (Mpa)

Cell-spacing	h = 0.03	h = 0.025	h = 0.02
0.01	36.58	34.29	27.86
0.02	11.92	10.55	8.61
0.03	5.78	4.96	4.60
0.04	3.63	2.89	3.79
0.05	2.62	1.97	2.79
0.06	2.07	1.31	1.17

Table 2: Buckling loads of different sandwich height (Mpa)

Sandwich-height	c = 0.03	c = 0.04	c = 0.05
0.020	6.60	4.79	3.79
0.022	6.23	4.18	3.32
0.025	5.96	3.89	2.97
0.028	5.84	3.75	2.79
0.030	5.69	3.57	2.62
0.032			
0.035	5.46		
5.320	3.33		
3.220	2.54		
2.380			

Table 3: Buckling loads of different sandwich's modulus (Mpa)

Sandwich modulus	c = 0.03	c = 0.04	c = 0.05
206	26.78	14.21	8.84
150	21.28	10.80	6.64
108	16.89	8.39	5.17
82.0	13.11	6.36	3.96
68.0	11.67	5.64	3.56
55.0			
28.3	9.17		
5.52	4.36		
2.59	2.78		
1.67			

shell93 element, use 3D solid modeling, study on effect of honeycomb sandwich plate buckling in different size parameters and material properties (Table 1-3). Bending load shows in Fig. 4.

The prediction results of ANNs were compared and checked with the experiments. Studing on effect of honeycomb sandwich plate buckling in different size parameters and material properties, the Input values are

Table 4: Prediction results of ANN (Mpa)

Cell-spacing	Target (A)	Predict (B)	Error rate (%)
0.01	36.58	30.86	17.9
0.02	11.92	10.61	11.1
0.03	5.78	6.60	14.1
0.04	3.63	4.79	31.0
0.05	2.62	3.79	44.0
0.06	2.07	2.37	14.4

Table 5: Prediction results of ANN (Mpa)

Cell-spacing	Target (A)	Predict (C)	Error rate (%)
0.01	36.58	35.29	3.50
0.02	11.92	11.25	3.10
0.03	5.78	5.96	3.11
0.04	3.63	3.79	4.40
0.05	2.62	2.87	9.50
0.06	2.07	2.11	1.90

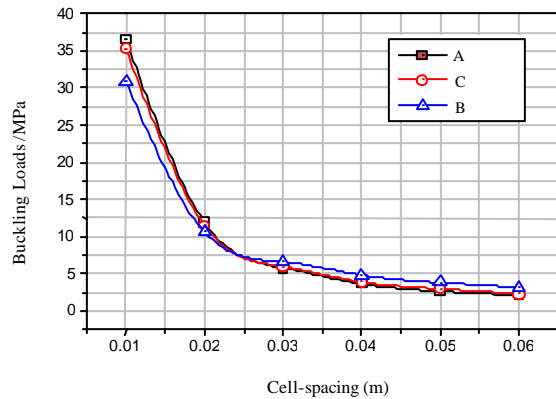


Fig. 5: Functions compared curves of prediction results

cell-spacing, Sandwich height and Sandwich's Modulus; Secondly, Intelligent simulation by these large numbers of numerical data.

Prediction of the buckling loads

Example 1: Rectangular metal honeycomb sandwich plates, tables are ordinary steel plate, $\rho = 7800 \text{ kg m}^{-3}$, length and width are both 0.6 m, $t = 3 \text{ mm}$, $E_f = 200 \text{ GPa}$, $\mu = 0.3$, sandwich is AL, $\rho_{AL} = 2700 \text{ kg m}^{-3}$, $E_{AL} = 70 \text{ GPa}$, $\mu = 0.35$, $h = 0.03 \text{ m}$.

From Table 4 the Error rate is higher. Factors maybe nonlinear characteristics of sandwich plate which had been confirmed; the others maybe contact surface of table board and sandwich. As we know the natural frequency is the intrinsic properties of sandwich plates. So the natural frequency should be optimization training in the genetic algorithms which can improve the prediction accuracy. Compared as Table 5, compared curves as Fig. 5.

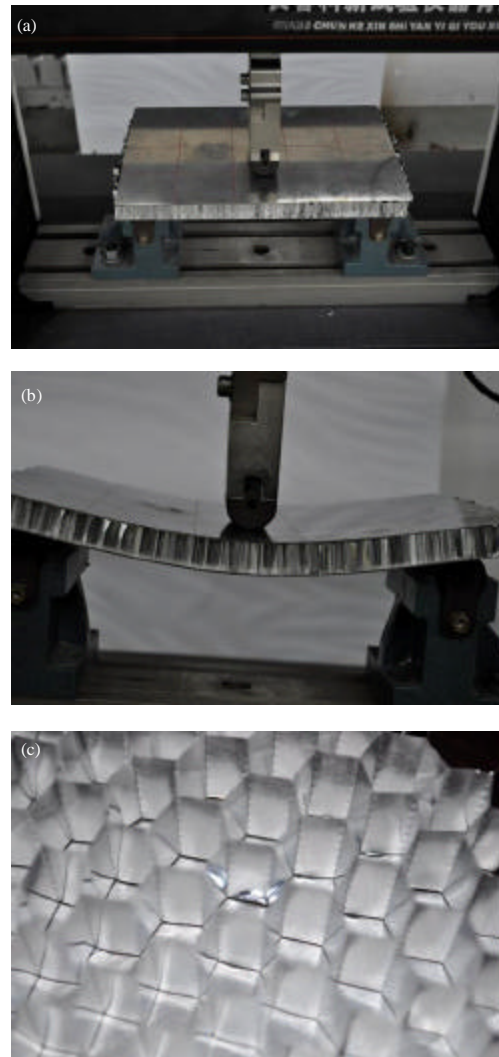


Fig. 6(a-c): Three-point bending of sandwich plate, (a) Load form, (b) Deformation and (c) Local buck

PREDICTION THE BUCKLING LOADS OF TYPICAL SANDWICH PLATES

Experiment 1: Rectangular metal honeycomb sandwich plates, Tables are ordinary steel plate, $\rho = 7800 \text{ Kg m}^{-3}$, length is 300 mm, width is 200 mm, thickness is 1 mm, weight is 881g, $E_f = 200 \text{ GPa}$, $\mu = 0.3$; sandwich is AL, $\rho_{AL} = 2700 \text{ Kg m}^{-3}$, $E_{AL} = 70 \text{ GPa}$, $\mu = 0.35$, $h = 15 \text{ mm}$, cell-spacing is 6 mm, $t = 0.1 \text{ mm}$. Three-point bending is used as Fig. 6.

In order to accuracy prediction the buckling loads of sandwich plate, the experiments must be done early like Fig. 7.

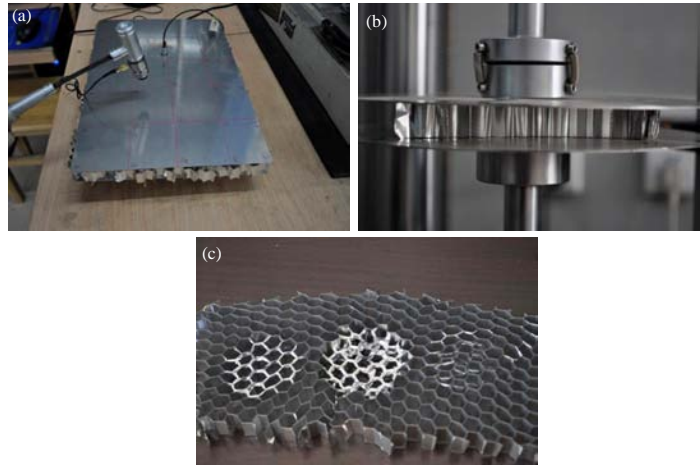


Fig. 7(a-c): Preparations of Prediction the Buckling Loads, (a) Test natural frequency, (b) Stiffness testing and (c) Process of buckling

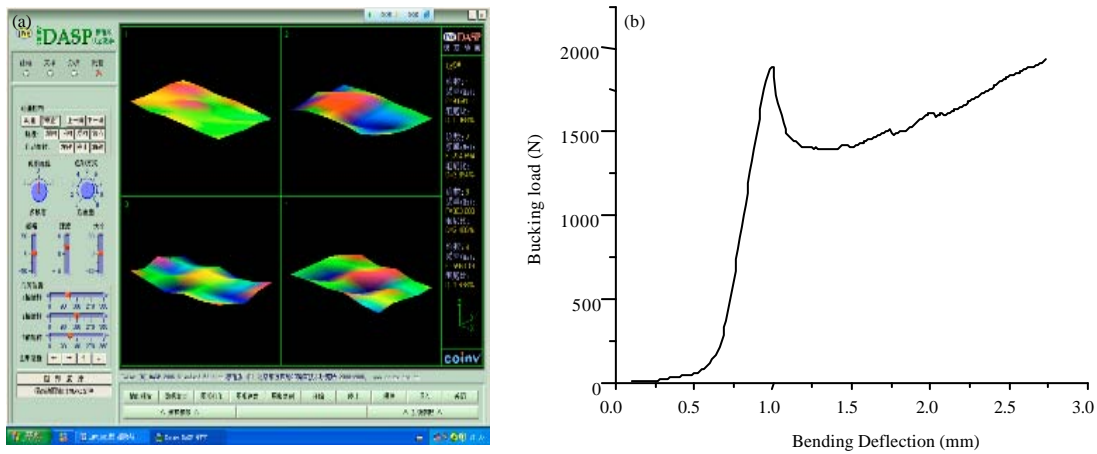


Fig. 8(a-b): Experiment Results of Sandwich Plates, (a) Modal shape of sandwich plate, (b) Buckling Curve

Table 6: Predict result (Mpa)

Prediction load (MPa)	Experimental load (MPa)	Error rate (%)
7.18	6.67	7.64

When the plate reaches the critical bending load, sandwich occurs local buckling first like Fig. 6. Sandwich occurs stage compression buckling failure, first place in intermediate as Fig. 7. Experiment natural frequency has been used to optimization training in the genetic algorithms. The bending load and shear plane of sandwich plate have been used to be calculated bending strength. Result as Table 6.

Equivalent Modulus and contact surface of table board and sandwich may cause error ratio, which should research in the future.

CONCLUSION

In this study, the Radial basis function networks (RBFNNs) is employed as the calculate tool of the critical load for given geometric and physical parameters, which can forecast critical load of sandwich plates fast. the natural frequency is the intrinsic properties of sandwich plates. So The natural frequency should be optimization training in the genetic algorithms which can improve the prediction accuracy. The results show that: increased reasonably core high and increased face plate thickness and cell-wall thickness, reduced single length of cell size, selecting the fit elasticity modulus of core material will enable increased ability to resist buckling of honeycomb sandwich plates.

ACKNOWLEDGEMENTS

This study is supported by the Natural Science Foundation of Hebei Province (E2012203090). The authors also gratefully acknowledge the helpful comments and suggestions of the reviewers, which have improved the presentation.

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